



RGNZ/MGPB

Rudarsko-geološko-naftni zbornik

The Mining-Geological-Petroleum Engineering Bulletin





Detalj iz adrenalinskog parka na eksploatacijskom polju „Hercegovac–Radlovac“ – inovativan i uspješan primjer rekultivacije površinskog kopa u Republici Hrvatskoj, koji je provela tvrtka Radlovac d.d.

Fotografirao Goran Gašparac, 2026.

Detail from the adrenaline park at the “Hercegovac–Radlovac” exploitation field – an innovative and successful example of open-pit mine reclamation in the Republic of Croatia, implemented by Radlovac d.d.

Photo taken by Goran Gašparac, 2026.



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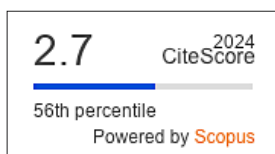
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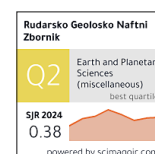
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Digital Petrographic Approach to Carbonate Reservoir Evaluation in MATLAB

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Original scientific paper



Nita Ariyanti^{1,2} , Sugeng Sapto Surjono¹ , Salahuddin Husein^{1*} ,
Marsha Khairia Alfany² , Firman Syaifuddin² , M. Irfan Mashudi³

¹ Geological Engineering Department, Universitas Gadjah Mada, Yogyakarta.

² Geophysical Engineering Department, Institut Teknologi Sepuluh Nopember, Surabaya.

³ Pertamina EP Cepu, Indonesia.

Abstract

Porosity is a crucial parameter in the characterization of carbonate reservoirs, as it directly influences fluid storage and flow behaviour. Conventional techniques for porosity assessment, such as core analysis and well logging, are often labour-intensive, time-consuming, and costly. This study proposes an automated method for porosity estimation through petrography and image analysis techniques using MATLAB. Thin-section photographs of carbonate rocks are processed through image segmentation, feature extraction, and classification procedures to quantitatively determine porosity. The estimation process relies on RGB-based image analysis, in which variations in colour intensity between the rock matrix and pore spaces are used to distinguish pore regions accurately. The RGB image analysis approach in MATLAB achieves an accuracy of 60.9% when compared with Routine Core Analysis (RCAL) data, indicating a strong correlation between the estimated and measured porosity values. This digital petrography method demonstrates higher accuracy and consistency than conventional manual image analysis, which is often influenced by human interpretation and subjectivity. By automating the image processing workflow, the method enables objective, rapid, and cost-effective porosity estimation. Despite the absence of complex computational algorithms, the MATLAB-based digital petrography technique provides a reliable and efficient alternative for preliminary carbonate reservoir characterization, especially when laboratory or well-log data are limited.

Keywords:

digital petrography; image analysis; carbonate reservoir characterization

1. Introduction

Carbonate reservoirs exhibit significant variety, leading to the considerable complexity of their reservoir rocks (Ahr, 2008; Choquette et al., 1970; Flügel, 2010; Lucia, 1995; Moore, 2001). The quality of carbonate rock reservoirs necessitates investigation due to the interrelated regulatory factors (Choquette et al., 1970; Flügel, 2010; Lucia, 1995; Slatt, 2006). The quality of carbonate rock reservoirs is influenced by various factors, including depositional facies, sedimentary environment, and diagenetic processes. In carbonate reservoirs with limited core and well-log data, digital image analysis provides an efficient alternative for petrophysical characterization (Kharitontseva et al., 2021). Further comprehensive research on these parameters is required to better explore carbonate reservoir zones (Ezeakacha et al., 2018; Saenger et al., 2016; Blunt et al., 2013).

The increasing application of AI-based image classification, particularly in complex carbonate systems, reflects the growing role of digital petrography in reservoir studies (Basso et al., 2025). Recent advances in digital reservoir characterization increasingly combine image-based analysis with artificial intelligence for more accurate reservoir evaluation. For example, Zhang et al. (2024) demonstrated the application of a neural network-assisted fracture identification system integrated with an analytic hierarchy process for tight carbonate reservoir assessment. The assessment of carbonate reservoirs is essential in hydrocarbon exploration and production, as it evaluates the potential for oil and gas extraction by examining the reservoir's characteristics, including porosity, permeability, and saturation. The RGB-based petrographic image analysis conducted in MATLAB provides a rapid, non-destructive approach for estimating carbonate rock porosity through colour-based segmentation of thin-section images. The image is subsequently segmented into binary format using the RGB colour attributes to characterize pore structures directly from standard petrographic images without re-

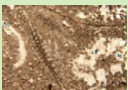
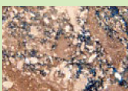
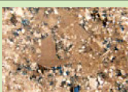
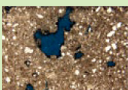
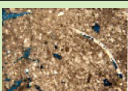
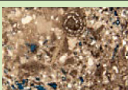
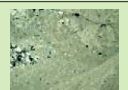
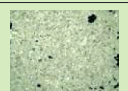
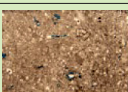
* Corresponding author: Salahuddin Husein

e-mail address: shddin@ugm.ac.id

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Table 1: Petrographic porosity in fraction and photomicrographs used as inputs for MATLAB modelling

Samples Code	Petrographic Porosity	Photomicrographs	Samples Code	Petrographic Porosity	Photomicrographs
NA-01	0.125		NA-17	0.065	
NA-02	0.105		NA-18	0.065	
NA-03	0.17		NA-19	0.025	
NA-04	0.14		NA-20	0.04	
NA-05	0.155		NA-21	0.03	
NA-06	0.2		NA-22	0.005	
NA-07	0.1		NA-23	0.03	
NA-08	0.165		NA-24	0	
NA-09	0.02		NA-25	0.04	
NA-10	0.075		NA-26	0	
NA-11	0.1		NA-27	0.015	
NA-12	0.12		NA-28	0.11	
NA-13	0.065		NA-29	0.03	
NA-14	0.065		NA-30	0.08	
NA-15	0.025		NA-31	0.12	
NA-16	0.04		NA-32	0.075	

quiring advance depth data or 3D structural information especially 3D physical porosity measurements. This approach enhances efficiency in large-scale thin-section evaluation and offers a cost-effective alternative for preliminary porosity assessment, particularly in early stage reservoir characterization. To contextualize this approach, several previous studies have explored digital and colour based methods for carbonate analysis.

Previous research has demonstrated that RGB-based image segmentation can be a valid approximation when validated against core or log data (**Hearn et al., 1984; García-Lamont et al., 2020**). Recent studies highlight that image-based rock typing provides valuable micro-scale information for reservoir characterization (**Wang et al., 2024**). Furthermore, the results can also be validated with Routine Core Analysis (RCAL) data, which provides reliable laboratory-measured porosity values to assess the accuracy of image-based estimations. However, most existing RGB based studies primarily focus on qualitative visualization or limited statistical comparison, often relying on grayscale conversion or partial colour segmentation. In contrast, the present study introduces a quantitative RGB colour attribute approach directly implemented in MATLAB to differentiate matrix and pore spaces in carbonate rocks. This method expands previous applications by integrating full-spectrum colour analysis for pixel-based porosity estimation, enabling rapid, non-destructive, and cost-efficient evaluation of carbonate textures using standard thin-section images without requiring 3D imaging or machine learning models.

2. Data and Materials

2.1. Core and RCAL Data

The primary dataset for validating image-based porosity estimations derived from petrographic thin-section analysis were these samples, which were collected from carbonate intervals in the North-East Java Basin. The carbonate samples analyzed in this study were obtained from the Prupuh Formation, which represents an Early Miocene carbonate sequence. This formation is part of the regional carbonate platform development that characterizes the lower to middle Miocene stratigraphy of East Java. The sampled interval occurs at an approximate subsurface depth of 800-1200 meters, corresponding to shallow-marine depositional settings typically dominated by bioclastic and micritic limestones. Lithologically, the core material primarily consists of packstone to grainstone textures, composed of bioclastic fragments, foraminifera, and peloidal grains, cemented by fine-grained calcite spar (**Hidayat et al., 2022**). In an effort to ascertain the fundamental petrophysical properties of specified carbonate rock core samples, including porosity, permeability, grain density, and fluid saturation, Routine Core Analysis (RCAL) was carried out to

analyze a total of 31 core plugs samples. These measurements are used as ground-truth data to verify the porosity estimations that are based on images. As a consequence of the heterogeneity of carbonate rocks, RCAL is essential for the calibration of digital analysis results and the provision of valuable insight into reservoir quality.

2.2. Thin Sections

Petrographic thin sections were prepared from core plug samples obtained from the same intervals as those employed for Routine Core Analysis (RCAL). However, the plugs for the thin sections are physically different from the ones the RCA data originates from. These thin sections facilitate the use of light microscopy to observe the rock's pore structures, mineral composition, and texture in detail. In this investigation, the thin-section images were additionally employed for digital image processing, employing RGB colour-based analysis to visually estimate porosity. Prior to RGB-based image analysis, the petrographic thin sections were initially evaluated using the Nodule petrography method, a conventional point-counting technique that provides a baseline estimation of visual porosity through manual microscopic interpretation. Petrographic data and porosity values derived from petrographic analysis are presented in **Table 1**.

3. Methodology

3.1. Workflow

In this study, the porosity of carbonate rock samples is estimated from petrographic thin-section images using an RGB-based image analysis approach implemented in MATLAB. As the images are treated as RGB frameworks, image processing operations are performed based on specific colour components that correspond to various features within the sample. MATLAB's image processing toolbox provides a comprehensive set of functions for image enhancement, segmentation, colour detection and feature extraction (**Duth & Deepa, 2018**). In this case, these tools facilitate the identification of pore spaces in petrographic images through channel specific processing and colour thresholding techniques (**Dias et al., 2020**). The RGB-based image segmentation technique follows a similar approach to that employed by **Kuang et al. (2022)**, in which differences in colour intensity between matrix and pore spaces are used to delineate porosity. **Luo et al. (2023)** demonstrated that 2D thin-section images can be effectively used to infer 3D petrophysical properties, supporting the reliability of image-based porosity estimation.

The porosity of carbonate rock samples was estimated from petrographic thin-section images in this investigation using an RGB-based image analysis approach in MATLAB. The images were processed as RGB frameworks, with colour components corresponding to pore

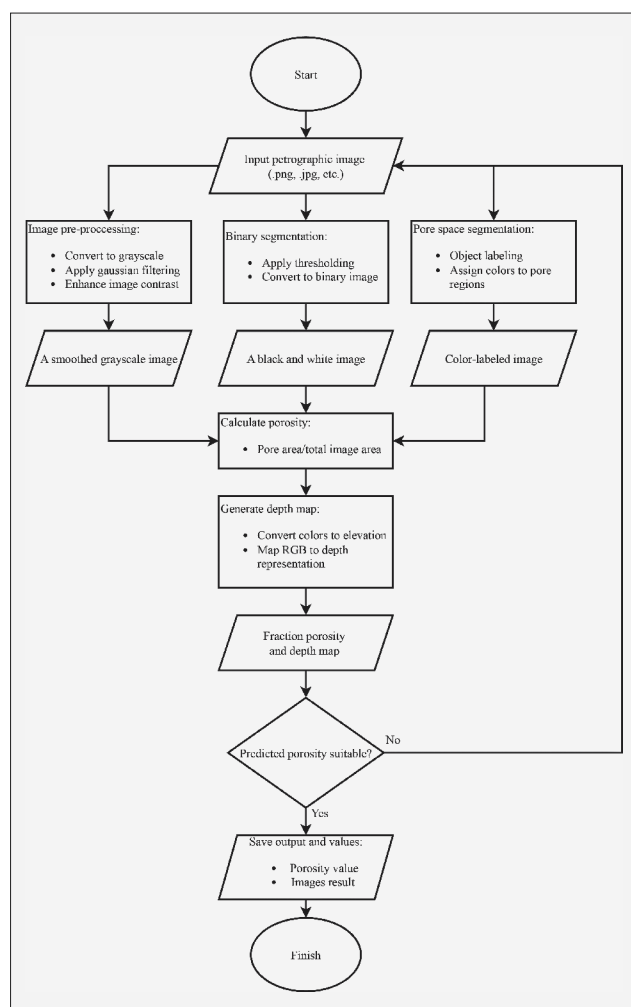


Figure 1: Image processing workflow for porosity estimation in petrographic samples using MATLAB.

and textural features. Enhancement, segmentation, and feature extraction were facilitated by MATLAB's Image Processing Toolbox (Dias et al., 2020; Duth & Deepa, 2018). The workflow commenced with the production of thin-sections from 31 carbonate core plugs of the Prupuh Kujang Formation. Thin-section images were acquired under transmitted light using a petrographic microscope equipped with a high resolution digital camera. MATLAB was used to ingest these images and preprocess them through noise reduction (median filter) and contrast enhancement (histogram equalization). In order to determine the most responsive colour component for pore detection, each image was decomposed into its Red, Green, and Blue channels. Pore segmentation was performed by utilizing Otsu thresholding and binary conversion (imbinarize) to differentiate between the solid matrix (white pixels) and pore spaces (black pixels). It should be noted that under plane polarization light (PPL), pores often appear dark or black due to the absence of transmitted light, whereas opaque minerals may also exhibit similar tones. When blue resin impregnation is used, pores are instead represented by bright blue regions, allowing more precise differentiation from opaque

minerals. Noise was eliminated and the continuity of the pore boundary was enhanced through morphological filtering (imopen, imclose, imfill). Following this, regionprops was employed to label and quantify pore regions, and label2rgb was employed to illustrate their visual distribution. The ratio of pore pixels to total image pixels was used to calculate porosity (fr). A high R^2 value was obtained, confirming a strong agreement with RCAL data, and the correlation between digital and laboratory porosity values was assessed using linear regression with polyfit and corrcoef. The automated MATLAB-based procedure guarantees the objective and reproducible quantification of pore structures, and it is consistent with the most recent advancements in AI-assisted carbonate petrography (Kuang et al., 2022; Luo et al., 2023; Faria et al., 2025).

However, in order to validate the porosity values predicted using this RGB-based method, a benchmarking process was conducted by comparing the predicted results with laboratory-measured porosity from RCAL. This comparison was further assessed using a linear regression to express the correlation between laboratory-measured porosity values and those derived from images. The coefficient of determination (R^2) was used to indicate the strength of the correlation. Automatic classification through MATLAB-based routines is in line with recent advancements employing one-class models and convolutional neural networks for carbonate thin-section analysis (Faria et al., 2025).

3.2. Depth Map

In the field of petrographic image analysis, a depth map is a visual aid that is employed to simulate changes in depth or elevation by referencing the grayscale intensity or RGB values of an image. Despite the fact that petrographic images are two-dimensional, a depth map can be produced computationally by designating pseudo-depth values to varying pixel intensities. Typically, darker areas (e.g. pore spaces) are interpreted as “deeper” and lighter areas (e.g. matrix minerals) as “shallower”. This is accomplished in MATLAB by converting the RGB image to grayscale and subsequently mapping the grayscale values to a surface or 3D geometry using functions such as surf, imagesc, or mesh. The RGB image is converted to grayscale using rgb2gray to initiate the procedure. The grayscale intensity is subsequently interpreted as a height value, with the “depth” of each pixel determined by its luminance. The contrast between the matrix and pore zones is improved by plotting these values in 3D using a colourmap (e.g. ‘jet’ or ‘parula’). This artificial depth map aids in the qualitative evaluation of heterogeneity and texture in carbonate rocks by illustrating the spatial distribution and relative geometry of porosity features, despite the fact that it does not represent actual geological depth. This method is especially beneficial in educational environments and preliminary digital rock characterization, as it provides a user-friendly

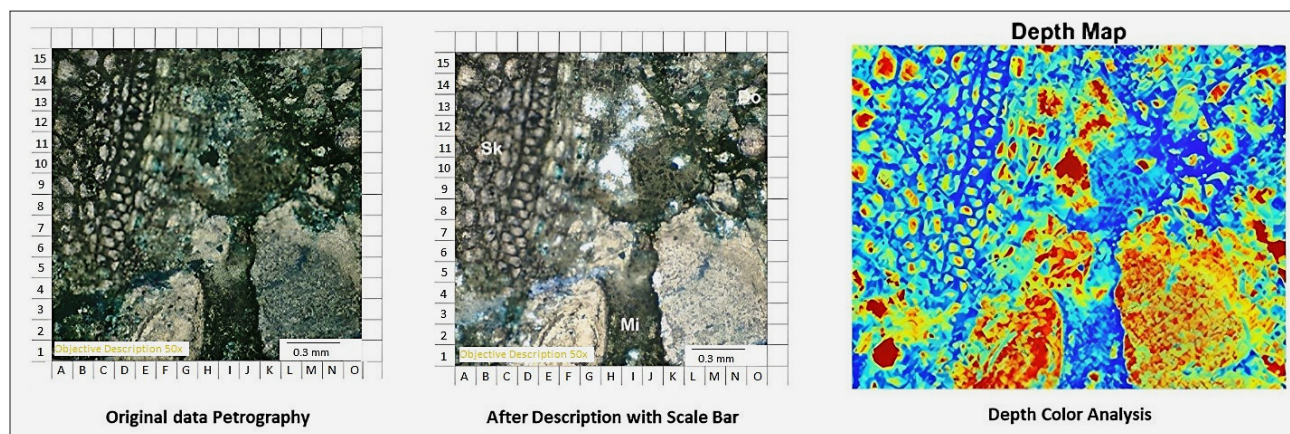


Figure 2: Petrographic image workflow for RGB-based analysis (Sample NA-24). The figure illustrates the same thin-section area at identical magnification and scale across three panels: (a) the original transmitted-light thin-section image; (b) the annotated image with descriptive mineral labels and a scale bar; and (c) the pseudo-depth map visualization generated from RGB intensity variations.

approach to analyzing the pore distribution in carbonate reservoir samples.

The depth map image depicts the variety of pore depths in a carbonate rock thin section on a colour-coded RGB scale. In this illustration, the blue areas correspond to the highest or deepest pore spaces, suggesting zones with the highest pore volume and possible reservoir quality. The green and yellow sections show intermediate pore depths, whilst the red parts represent the shallowest or least porous zones. This colour gradient, which ranges from red (low pore depth) to blue (high pore depth), provides a straightforward visual assessment of pore distribution and connection. This map allows researchers to identify heterogeneous pore structures and estimate the rock's porosity, which is critical for evaluating reservoir performance.

3.3. Petrographic Analysis

The thin-section analysis in **Figure 2** (from sample number NA-24) reveals that the rock is predominantly composed of skeletal grains, which constitute approximately 63% of the total composition. These skeletal grains include foraminiferal taxa such as Nummulites (D-H, 1–5) and Spiroclypeus (A-G, 4–15), appearing brownish to dark brown in colour, with grain sizes ranging from 0.125 mm to 1 mm. Dolomite crystals account for around 7% of the composition, characterized by colourless, fine-sized subhedral crystals (<1 mm) with three directional cleavages, low relief, and weak pleochroism (monochroic). Under cross-polarized light (XPL), these dolomites exhibit gray interference colours, typically of the fourth order, with inclined extinction and no twinning (G-I, 6–7). The matrix is dominated by microcrystalline calcite or micrite, making up 19% of the sample. It appears as fine, brownish-dark grains with subrounded to angular shapes and low relief, measuring less than 0.06 mm. Under XPL, it shows dark brown interference colours of the first order (H-J, 2–4). The remaining 11%

is composed of other constituents, including blank or pore spaces observed in areas such as H, 10–11, contributing to the porosity of the sample.

In the original transmitted-light images, pore spaces are visible as dark or opaque regions interspersed between skeletal grains and within micritic zones, appearing irregular in shape. These dark zones correspond to areas of lower RGB intensity and are therefore detected as black regions after binary segmentation. Under crossed nicols, these pores remain dark, indicating true voids rather than mineral phases. The processed images in MATLAB clearly differentiate the pore structures through enhanced contrast and thresholding, where pore spaces are represented by dark (black) pixels, and the solid matrix by bright (white) pixels. Based on both petrographic and digital interpretation, the pores can be classified into several types: (1) intercrystalline pores, which occur between dolomite crystals; (2) moldic pores, formed by the dissolution of skeletal fragments; (3) vuggy pores, represented by irregular, larger cavities; and (4) microfracture pores, characterized by thin, elongated voids cutting across grains or matrix. These pore types collectively control the connectivity and heterogeneity of the carbonate reservoir, and their distinction enhances the interpretability and accuracy of the image-based porosity estimation.

3.4. Binary Segmentation

Binary segmentation is a critical phase of digital petrography that facilitates the separation of pore spaces from the solid carbonate matrix. In order to identify and quantify pore regions, binary segmentation was implemented on petrographic thin-section images in this investigation. The RGB image was initially converted to grayscale using MATLAB's `rgb2gray` function, which reduced the image to pixel intensity values that ranged from black (0) to white (255). This conversion simplifies the dataset while maintaining the essential textural and

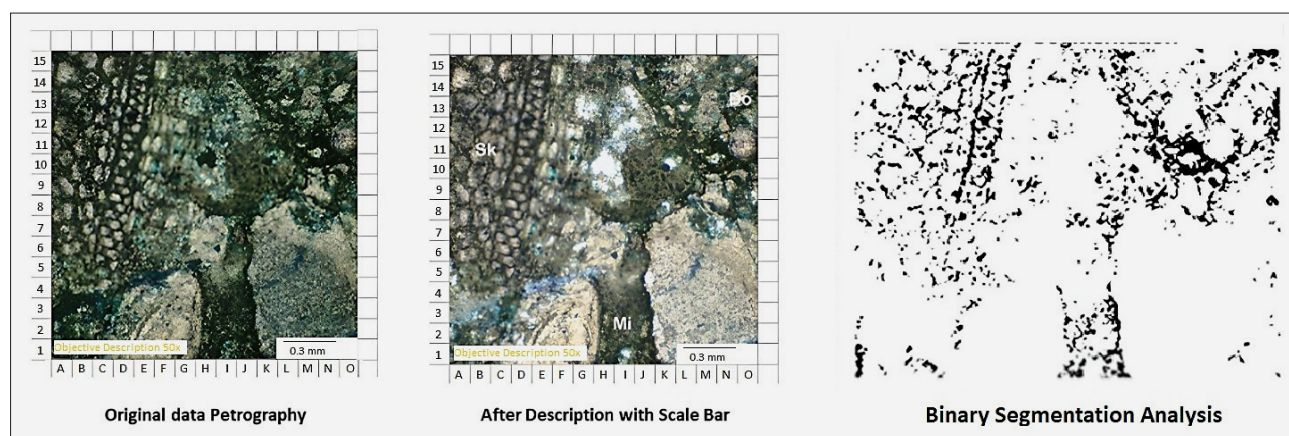


Figure 3: Comparative petrographic analysis and binary image segmentation for quantitative porosity evaluation in carbonate thin section (Sample NA-024).

luminance variations necessary for further analysis. The grayscale image was subsequently converted to a binary image using thresholding techniques, either Otsu's adaptive method (graythresh) by **Otsu (1979)** or manual threshold adjustment, contingent upon the quality of the image's contrast. The carbonate matrix is depicted as white pixels (value = 1), while pore spaces are represented as black pixels (value = 0) in the resulting binary output. This procedure effectively separates the pore framework from the surrounding solid material, enabling precise quantitative and visual differentiation. Post-segmentation, the bwlable and regionprops functions of MATLAB were implemented to identify and characterize individual pore geometries, including their shape, spatial distribution, and area. The ratio of black pixels (pores) to the total number of pixels in the image was used to calculate porosity, which was expressed as a percentage. The binary segmentation method offers a rapid, objective, and reproducible method for directly estimating porosity from thin-section images, making it an efficient alternative when laboratory or core analysis data are scarce. This method, as illustrated in **Figure 3**, demonstrates that binary segmentation not only improves pore-matrix contrast but also establishes a consistent framework for quantitative comparison with Routine Core Analysis (RCAL) results. Moreover, it facilitates the identification of micro-scale pore variability that may otherwise be disregarded in traditional petrographic evaluations, thereby facilitating a more thorough assessment of the quality of carbonate reservoirs. Binary segmentation with picture thresholding is a simple yet effective approach for carbonate reservoir assessment via image-based porosity estimation, as shown as **Figure 3**.

3.5. Pore Space Segmentation

Pore space segmentation is a critical stage in the digital quantification of porosity, during which individual pore regions are extracted, classified, and measured from the binary image. In order to eliminate minor artifacts,

bridge discontinuities, and improve the specification of the pore boundary, morphological operations such as imopen, imclose, and imfill were implemented. This refinement guarantees the precise separation of interconnected or irregularly shaped pore structures that are frequently observed in carbonate rocks as a result of diagenetic alteration and recrystallization. The quantitative parameters, including pore area, perimeter, aspect ratio, and spatial distribution, were extracted by labelling and analyzing the segmented pore regions using MATLAB's bwlable and regionprops functions. The resulting images effectively demonstrate the heterogeneity of pore systems, emphasizing regions with greater porosity and potential reservoir quality. Subsequently, the total pore area was compared to the total image area to determine porosity, resulting in a digital value that was cross-validated against Routine Core Analysis (RCAL) measurements. The segmentation procedure's reliability for quantitative pore characterization is confirmed by the close correspondence between these datasets. The integration of threshold-based and morphological segmentation techniques, as illustrated in **Figure 4**, enables the efficient and reproducible estimation of pore space geometry, thereby offering valuable insight into the microstructural heterogeneity of carbonate reservoir rocks. This method is predicated on the premise that pore spaces exhibit significantly lower intensity values than the adjacent minerals, which allows for precise segmentation based on colour or brightness, as shown as **Figure 4**.

Three primary stages comprise the RGB image analysis conducted with MATLAB: Binary Segmentation, Pore Space Segmentation, and Depth Map generation. The pseudo Depth Map serves as an initial foundation for pore identification by illustrating the intensity contrast and textural variation within the carbonate thin section. In this visualization, colour gradations correspond to relative pixel intensity values, where cooler colours (blue to green) represent lower intensity zones (interpreted as pore spaces or voids), and warmer colours (yellow to red) indicate denser mineral regions. A colour legend and

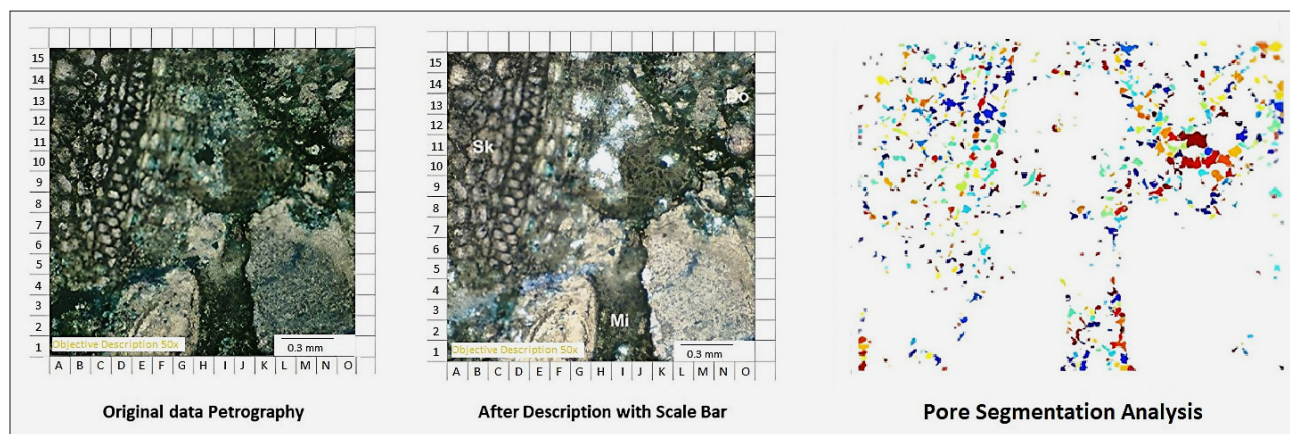


Figure 4: Petrographic Image, Annotated Description, and Pore Space Segmentation of Carbonate Sample NA-1.

scale bar were included to facilitate the interpretation of these variations in grayscale depth intensity. The pore space segmentation image depicts the spatial distribution and delineation of pore spaces, as determined by digital image processing of the carbonate thin section. Coloured regions denote segmented pore spaces, with each unique colour representing an individual pore or pore cluster identified through a connected-component labeling method. The colour variations do not represent pore type, size, or porosity magnitude, but are exclusively used to visually differentiate individual pores and avoid overlap. The white or light-toned background indicates the non-porous carbonate rock matrix. Larger continuous coloured regions denote interconnected pores or macropores, which can substantially influence effective porosity, whereas smaller isolated coloured patches represent micropores or discrete pore spaces. Quantitative porosity measurements are derived from the ratio of the total pore pixel area to the overall image area, rather than from the colour information itself.

The analysis is limited by the microscope's optical and pixel resolution, as only pores that are visibly resolved in thin-section images can be quantified. Micropores smaller than 1-2 μm remain undetected, causing underestimation compared to high-resolution 3D or micro-CT methods. In addition, the RGB-based segmentation may misclassify opaque minerals, stains, or poorly illuminated areas as pores due to similar low-intensity values. Over-segmentation and uneven lighting can further affect accuracy; thus, the method performs best on well-prepared thin sections with uniform illumination and strong optical contrast between pores and the matrix.

4. Results and Discussion

4.1. Correlation Analysis (RCAL vs MATLAB)

Building upon this single-sample comparison, porosity values estimated through MATLAB image processing were systematically compared against laboratory

measurements from a total of 31 carbonate thin-section samples. The results, as summarized in **Table 2**, illustrate the correlation and discrepancies between the digital estimations and experimental data, thereby offering valuable insight into the image-based porosity assessment's accuracy.

A linear regression analysis was used to determine the relationship between porosity values acquired from MATLAB image processing and Routine Core Analysis (RCAL) laboratory data. The scatter plot shows a significant positive correlation, with a regression equation of $y = 0.477x^{0.505}$ and a coefficient of determination (R^2) of 0.609. The strong R^2 value suggests that image-based calculations employing RGB segmentation techniques in MATLAB can explain 60.9% of the variance in laboratory-measured porosity. Recent segmentation models by **Vieira de Mello et al. (2025)** also achieved high correlation ($R^2 > 0.88$) between predicted and measured values, consistent with the accuracy obtained in this research. The slope is significantly more than one, indicating that MATLAB consistently underestimates porosity values. Nonetheless, the tight clustering of data points around the regression line demonstrates that the image-based method is a viable and efficient option for predicting porosity, which is especially useful in scenarios requiring rapid or cost-effective analysis for reservoir characterization.

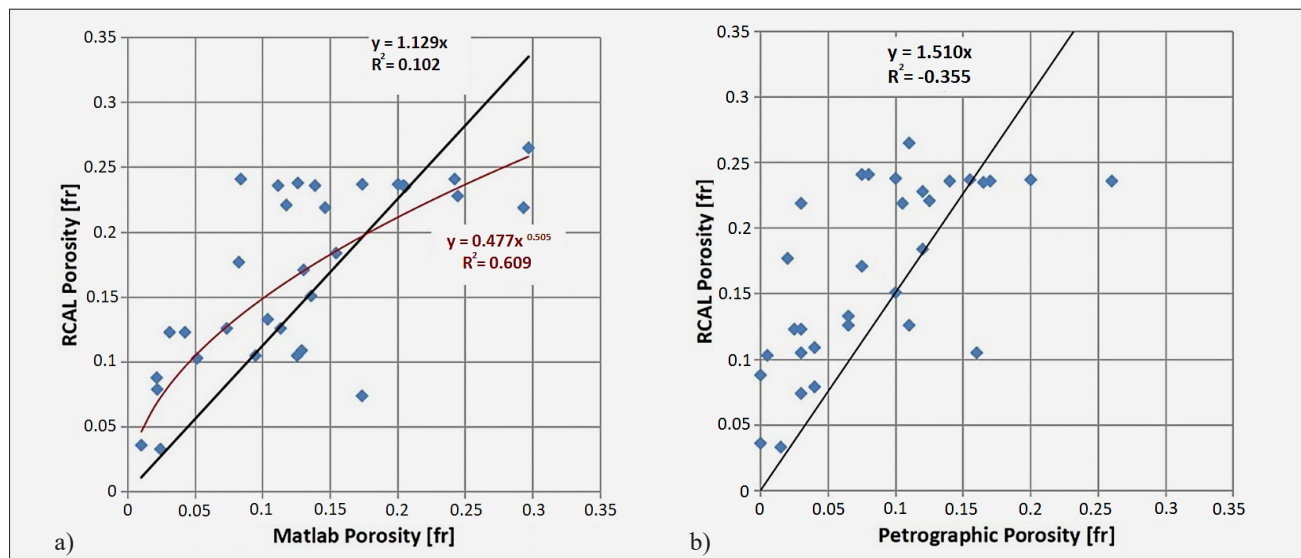
Despite the promising accuracy, some restrictions should be noted. The pattern of underestimating at increasing porosity levels suggests a nonlinearity caused by picture quality difficulties, segmentation thresholds, or differences in pore morphology that RGB-based approaches cannot fully capture. As a result, while the MATLAB-based approach is an effective preliminary tool, it may benefit from further calibration with advanced image enhancement or machine learning approaches to improve pore space recognition and account for complicated textures. Furthermore, the method's applicability should be verified across a variety of lithologies and depositional textures to provide greater reliabil-

Table 2: Comparison of predicted porosity in fraction from MATLAB and measured porosity from RCAL

Samples Code	Petrographic Porosity	MATLAB*	RCAL**	Samples Code	Petrographic Porosity	MATLAB*	RCAL**
NA-01	0.125	0.1173765	0.221	NA-17	0.03	0.173455	0.074
NA-02	0.105	0.146145	0.219	NA-18	0.005	0.05127095	0.103
NA-03	0.17	0.1112485	0.236	NA-19	0.03	0.0945311	0.105
NA-04	0.14	0.138645	0.236	NA-20	0	0.021358	0.088
NA-05	0.155	0.17366	0.237	NA-21	0.04	0.0217245	0.079
NA-06	0.2	0.200175	0.237	NA-22	0	0.00990335	0.036
NA-07	0.1	0.12588	0.238	NA-23	0.015	0.024114	0.033
NA-08	0.165	0.205445	0.235	NA-24	0.11	0.29687	0.265
NA-09	0.02	0.082184	0.177	NA-25	0.03	0.29313	0.219
NA-10	0.075	0.130173	0.171	NA-26	0.08	0.24212	0.241
NA-11	0.1	0.13573	0.151	NA-27	0.12	0.2444	0.228
NA-12	0.12	0.15425	0.184	NA-28	0.26	0.2041	0.236
NA-13	0.065	0.113139	0.126	NA-29	0.11	0.0732	0.126
NA-14	0.065	0.103535	0.133	NA-30	0.03	0.0309	0.123
NA-15	0.025	0.042258	0.123	NA-31	0.16	0.1254	0.105
NA-16	0.04	0.128745	0.109	NA-32	0.075	0.0836665	0.241

* Predicted Porosity (MATLAB)

** Measured Porosity (RCAL)

**Figure 5:** (a) Linear regression correlation between MATLAB-based image analysis and RCAL porosity measurements; (b) Linear regression correlation between RCAL porosity and petrographic porosity.

ity. Integrating this methodology with existing digital rock physics approaches could improve reservoir characterization efforts by allowing for quick porosity estimation over bigger datasets at low cost and time.

Recent advancements in digital imaging and quantitative petrography have improved the characterization of pore systems in carbonate reservoirs. Multiscale imaging approaches integrating thin-section and SCAL data have demonstrated significant improvements in understanding pore heterogeneity and connectivity (Suliman et al., 2024). These studies emphasize the importance of

digital petrography as a complementary tool for reservoir evaluation, providing a non-destructive and efficient method for porosity estimation.

Figure 5a shows a link between porosity measured from RCAL core samples and porosity approximated via MATLAB-based petrographic image processing. Since carbonate rocks have complex and varied pore systems, the linear regression reveals a poor connection ($R^2 = 0.102$), suggesting that the relationship is nonlinear. A far better fit is offered by the power-law regression ($R^2 = 0.609$), indicating that pore shape is a key factor in regu-

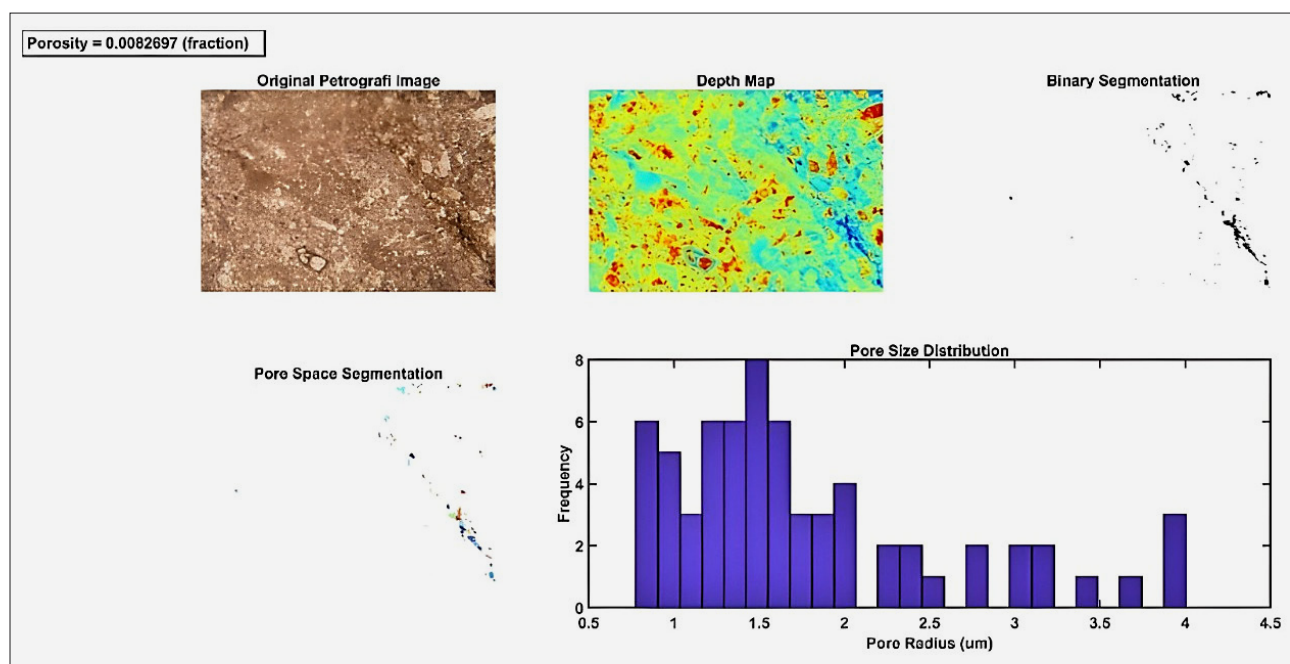


Figure 6: Pore structure characterization and porosity estimation of thin-section sample NA-22 using RGB-based petrographic image analysis.

lating porosity visible in thin-section pictures. This demonstrates that, when its nonlinear behaviour and pore geometry restrictions are appropriately taken into consideration, petrographic image analysis can approximate actual porosity.

Figure 5b shows the scatter diagram depicting the correlation between petrographic porosity obtained through RGB-based image analysis (x-axis) and porosity determined via Routine Core Analysis (RCAL) (y-axis). Each location corresponds to a distinct carbonate sample. Overall, the distribution of data points exhibits considerable dispersion, suggesting a tenuous correlation between the two methodologies. The regression line, represented as $y = 1.510x$, indicates that RCAL porosity values are typically greater than those derived from thin-section image analysis. This is expected, as RCAL measurements encompass micro-pores and interconnected pore networks that are not detectable in two-dimensional petrographic images. The negative R^2 value (-0.355) further suggests that the linear model fails to adequately characterize the relationship between the datasets, indicating a weak statistical correlation. This behaviour suggests that the current image segmentation method could underestimate porosity in samples exhibiting more intricate pore architectures. The overall scatter indicates that analyzing thin-section images in isolation is inadequate for predicting core-scale porosity in heterogeneous carbonate rocks, and that enhancements in thresholding, segmentation, or the application of supplementary techniques are necessary to increase accuracy.

Figure 7 displays a scatter diagram comparing porosity values derived from Matlab image analysis (x-axis)

and petrographic thin-section analysis (y-axis). The regression line presents the equation $y = 0.611x$, suggesting that petrographic porosity increases at a slower rate than Matlab porosity and is typically lower for the same samples. The coefficient of determination, $R^2 = 0.723$, indicates a moderate correlation, suggesting that approximately 72.3% of the variability in petrographic porosity is accounted for by the Matlab-derived porosity. The extensive dispersion of data points around the trend line indicates variability between the two methods, likely affected by factors such as grain heterogeneity, image resolution, pore-type variations, or segmentation errors. Overall, the plot indicates a modest yet positive correlation between the two porosity measurement methods, suggesting that they do not exhibit a firm correspondence and should be interpreted cautiously in reservoir characterization.

The scatter diagram depicts the correlation between petrographic porosity obtained from thin-section image analysis and laboratory-measured RCAL porosity. Overall, the data reveal a feeble and statistically insignificant correlation, as evidenced by the poorly defined trend line and the negative coefficient of determination ($R^2 = -0.355$). Although the regression slope (1.510) indicates that RCAL porosity generally increases more swiftly than petrographic porosity, the significant scatter illustrates that thin-section measurements do not consistently serve as reliable predictors of core-scale porosity. This discrepancy highlights the inherent limitations of 2D petrographic observations, which detect only pore features evident within a single plane and frequently underestimate micropores, moldic pores, or interconnected pore networks that exist in three dimensions. Converse-

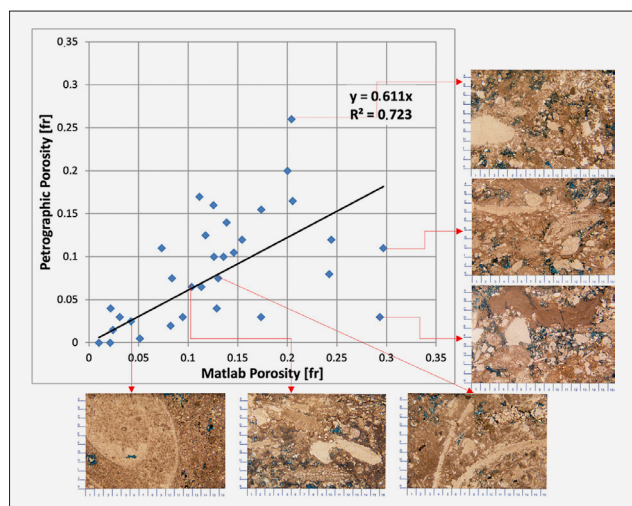


Figure 7: Representative petrographic thin-section photomicrographs provided as substitutes for unavailable samples. The selected images depict comparable lithofacies and pore structures, ensuring consistency in visual-based porosity estimation and maintaining dataset representativeness for the MATLAB analysis.

ly, RCAL measurements encompass the entire pore network at the particle scale, rendering them a more accurate reflection of the actual reservoir porosity. Consequently, the figure underscores the variability of carbonate pore structures and emphasizes that petrographic porosity alone is inadequate for precise quantitative porosity assessment without supplementary calibration or laboratory data.

4.2. Outlier sample analysis

In **Figure 6**, the porosity prediction of sample NA-22 using RGB-based petrographic image analysis resulted in a value of 0.0083, which is relatively close to the manual petrographic analysis that reported a porosity of 0. However, this value remains significantly lower than the porosity measured through Routine Core Analysis (RCAL), which reached 0.036. This discrepancy is expected, considering that porosity in RCAL, particularly using helium gas porosimetry, employs a more advanced and sensitive method. This technique relies on the principle of Boyle's law which states that the volume of gas varies inversely with pressure under isothermal conditions (Pal et al., 2018). Therefore, it is reasonable that the results do not perfectly match, as RCAL porosity measurements can detect micro-scale and connected pores that are often not visible or accessible in thin-section image analysis. Helium porosimetry is grounded in Boyle's law and is widely regarded as a benchmark for porosity measurement due to its ability to quantify effective pore volume with high accuracy. As such, while the digital prediction aligns with the trend observed in manual petrography, further calibration is necessary to bring it closer to the benchmark RCAL values.

4.3. Discussion

The findings of this investigation indicate that digital petrography based on RGB and MATLAB offers a dependable and effective method for estimating porosity in carbonate rocks, marking a significant improvement over traditional methods. The proposed image analysis approach is capable of accurately representing up to 72.3% of the variance observed in RCAL data, as evidenced by the strong correlation between image-derived porosity and laboratory-measured values ($R^2 = 0.723$), as shown in **Figure 7**. This high level of agreement confirms that the automated image segmentation and pore quantification techniques employed in this study are capable of replicating porosity trends that are typically obtained from more complex laboratory analyses. The superiority of this automated method is clearly demonstrated when compared to the manual estimation results presented in **Figure 5**. The manual petrographic porosity data exhibits a lack of correlation with RCAL measurements ($R^2 = -0.355$), highlighting the severe limitations and subjectivity inherent in visual point-counting. While the manual method failed to capture any meaningful trend, the MATLAB-based approach in **Figure 7** successfully aligned with the physical measurements. Nevertheless, despite the strong correlation in **Figure 7**, the porosity values derived from MATLAB tend to underestimate porosity at higher ranges. This underestimation is likely the result of the inherent limitations of 2D thin-section imagery, which is unable to fully capture connected or micro-scale pores that are visible in helium porosimetry measurements. Helium gas methodologies are particularly sensitive to micro-porosity, as noted by Pal et al. (2018), because the gas can penetrate small pore throats that are not resolved in digital image analysis.

Furthermore, minor discrepancies between the predicted and measured porosity may be influenced by variations in image quality, illumination, and segmentation thresholds. However, the RGB-based segmentation algorithm's robustness is substantiated by the drastic improvement in correlation coefficient from -0.355 to 0.723. In comparison to manual visual estimation, the objectivity and reproducibility of petrographic interpretations are improved by the technique's capacity to differentiate between matrix and pore spaces through grayscale intensity mapping. Additionally, this method offers a comprehensive visualization of spatial heterogeneity and pore geometry. In comparison to previous digital petrography studies (e.g. Kuang et al., 2022; Faria et al., 2025; Basso et al., 2025), the accuracy of 72.3% attained in this research is within the same performance range as more complex machine learning or deep learning approaches. This discovery implies that simpler MATLAB-based procedures can achieve comparable accuracy while being computationally efficient, provided they are calibrated correctly. Consequently, the RGB-based method is a practical alternative for preliminary reservoir characterization, particularly in data-limited situations. Overall, the digital petrography framework developed in this study illustrates

that image-based porosity estimation is not only feasible but also highly prospective for facilitating the assessment of reservoir quality in carbonate rocks.

6. Conclusions

This research assessed the application of RGB-based MATLAB image processing techniques to determine porosity in carbonate rocks and contrasted the findings with petrographic observations and Routine Core Analysis (RCAL) measurements from 31 samples. The porosity values derived from MATLAB typically align with the overall trend observed in the RCAL data, although they tend to systematically underestimate, especially in samples exhibiting higher porosity or more intricate pore architectures. Regression analysis reveals that the correlation between image-derived porosity and laboratory measurements is nonlinear, with a power-law model offering a superior fit compared to a linear model. The modest correlations among petrographic, MATLAB, and RCAL porosity underscore the limitations of 2D thin-section imaging, which is unable to comprehensively characterize micropores or three-dimensional pore connectivity as determined by helium porosimetry. Despite these limitations, the MATLAB workflow provides a consistent and practicable method for initial porosity estimation, particularly when rapid or cost-effective assessments are required. Overall, the findings indicate that digital petrography can serve as a complementary tool but cannot supplant laboratory measurements. Future advancements in segmentation, calibration, or machine learning techniques may improve the precision of image-based porosity predictions in heterogeneous carbonate reservoirs.

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SAŽETAK

Digitalni petrografski pristup procjeni karbonatnih ležišta u MATLAB-u

Poroznost je ključni parametar u karakterizaciji karbonatnih ležišta jer izravno utječe na skladištenje fluida i ponašanje toka. Konvencionalne tehnike za procjenu poroznosti, poput analize jezgre i bušotinske karotaže, često zahtijevaju mnogo posla te su dugotrajne i skupe. U ovome je radu predložena automatizirana metoda za procjenu poroznosti pomoću tehnika analize petrografskih podataka i slika korištenjem računalnoga programa MATLAB. Fotografije tankih presjeka karbonatnih stijena obrađuju se postupcima segmentacije slike, uočavanja značajki i klasifikacije kako bi se kvantitativno odredila poroznost. Proces procjene oslanja se na RGB analizu slike, u kojoj se za precizno razlikovanje pornih područja koriste razlike u intenzitetu boje između stijenske matrice i pornih prostora. Pristupom RGB analize slike u MATLAB-u postiže se točnost od 60,9 % u usporedbi s podacima rutinske analize jezgre (RCAL), što upućuje na snažnu korelaciju između procijenjenih i izmjerenih vrijednosti poroznosti. Ova metoda digitalne petrografije pokazuje veću točnost i konzistentnost od konvencionalne ručne analize slike, na koju često utječu ljudska interpretacija i subjektivnost. Automatizacijom procesa obrade slike metoda omogućuje objektivnu, brzu i isplativu procjenu poroznosti. Unatoč nedostatku složenih računalnih algoritama tehnika digitalne petrografije temeljena na MATLAB-u pruža pouzdanu i učinkovitu alternativu za preliminarnu karakterizaciju karbonatnih ležišta, posebice u slučajevima kada su laboratorijski podatci ili podatci iz karotažnih mjerenja ograničeni.

Ključne riječi:

digitalna petrografija, analiza slika, karakterizacija karbonatnih ležišta

Author's contribution

Nita Ariyanti (Dr candidate): conceptualization, data curation, investigation, software, validation, visualization, and writing original draft. **Sugeng Sapto Surjono** (Prof Dr): supervision. **Salahuddin Husein** (PhD): supervision. **Firman Syaifuddin** (Dr): software, validation, and error analysis. **Marsha Khairia Alfany** (BE): data curation and methodology. **M. Irfan Mashudi** (BE): writing, review & editing. All authors have read and agreed to the published version of the manuscript.

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Original scientific paper



Gartika Setiya Nugraha^{1*}✉, Ibnu Rusydy¹✉,
Hamzah Nailan Edward²✉, Muhammad Taufiq³✉

¹ Geological Engineering, Faculty of Engineering, Universitas Syiah Kuala, 23111 Banda Aceh, Aceh, Indonesia.

² Mining Engineering, Faculty of Science & Engineering, Western Australia School of Mines: Minerals, Energy and Chemical Engineering, Curtin University, 117 Egan St, Kalgoorlie WA 6430, Australia.

³ PT.Indonesia Pacific Energy, Jalan. Guntur No. 57, Jakarta Selatan, DKI Jakarta, 12970, Indonesia.

Abstract

The Tamiang region in Aceh, Indonesia, is geologically complex and underexplored, with limited baseline geochemical data. This study conducted a reconnaissance geochemical survey to evaluate spatial variations in metal concentrations and their geological controls. Forty stream sediment samples from various drainage systems across the region were analyzed for 22 elements (Al, As, Ba, Ca, Co, Cr, Cu, Fe, K, La, Li, Mn, Na, Ni, Pb, Sc, Sr, Ti, V, Y, Zn, Zr) using ICP-OES. Nineteen elements exhibited anomalous concentrations, with Cu, Ca, Li, and Na showing particularly high anomalies, whereas Al, Sc, and Y remained within background levels. Based on their geochemical behaviour, the elements can be grouped into major lithogenic elements such as Al, Fe, Ca, K, Na, Ti, Sr, and Zr, which reflect lithology and weathering intensity, and ore-related elements including Cu, Pb, Zn, As, Co, Ni, and Cr, which may indicate localized metal enrichment. Rare earth and high field strength elements such as La, Y, Sc, Li, Zr, and Ti provide insight into source rock composition and magmatic or weathering processes, while miscellaneous elements including Mn, Ba, and Sr show mixed lithological or secondary origins. The spatial distribution of these anomalies may suggest localized metal enrichment associated with specific lithological zones. Despite the reconnaissance scale and limited sampling density, these results provide a preliminary geochemical framework for the Tamiang region, supporting future geological and geochemical investigations and contributing to a robust scientific assessment of the area.

Keywords:

econnaissance geochemistry; stream sediments; mineral prospecting; geochemical mapping; Aceh; Indonesia

1. Introduction

Base and transition metals play a crucial role in modern industries, such as automotive manufacturing, electronics, aerospace, and construction (Cioacă et al., 2020; Eskdale et al., 2023; Yaisamut et al., 2023). Understanding their occurrence and availability is essential for sustainable industrial development, and Indonesia, with its abundant mineral resources, contributes to the global supply of these metals (Jamin et al., 2023; PWC, 2023; Tiess & Mujiyanto, 2011). The country's metal mining sector has considerable geological potential; however, it also faces the challenge of ensuring that exploration and resource development are based on reliable geological and geochemical information rather than speculative assumptions (Christie et al., 2019; Sun et al., 2024).

Regional geochemical surveys represent a cornerstone of modern exploration geoscience, providing the

baseline data necessary to delineate areas of geochemical enrichment, assess lithological variations, and guide mineral resource assessments (Cohen & Howell, 2013; Kyser et al., 2015; Saremi et al., 2024). Among various reconnaissance techniques, stream-sediment geochemical analysis is one of the most widely applied methods for detecting metal anomalies in drainage catchments (El-Makky & Sediek, 2012; Grunsky & de Caritat, 2020; Jo et al., 2024). Stream sediments integrate detrital materials derived from the weathering of source rocks upstream, thereby reflecting the overall chemical composition of the contributing geological units (Grunsky & de Caritat, 2020; Mira et al., 2020; Shirazi et al., 2022; Tonggiroh, 2020; Wardhani et al., 2018). This method is particularly effective in areas where bed-rock exposures are limited and geochemical data are scarce, making it a cost-effective and efficient approach for regional geochemical mapping.

In Indonesia, extensive research on mineral resources has primarily focused on regions with known mining activities and established ore deposits such as Papua, Kalimantan, and Sulawesi (Kramadibrata, 2013). These

* Corresponding author: Gartika Setiya Nugraha
e-mail address: setiya@usk.ac.id

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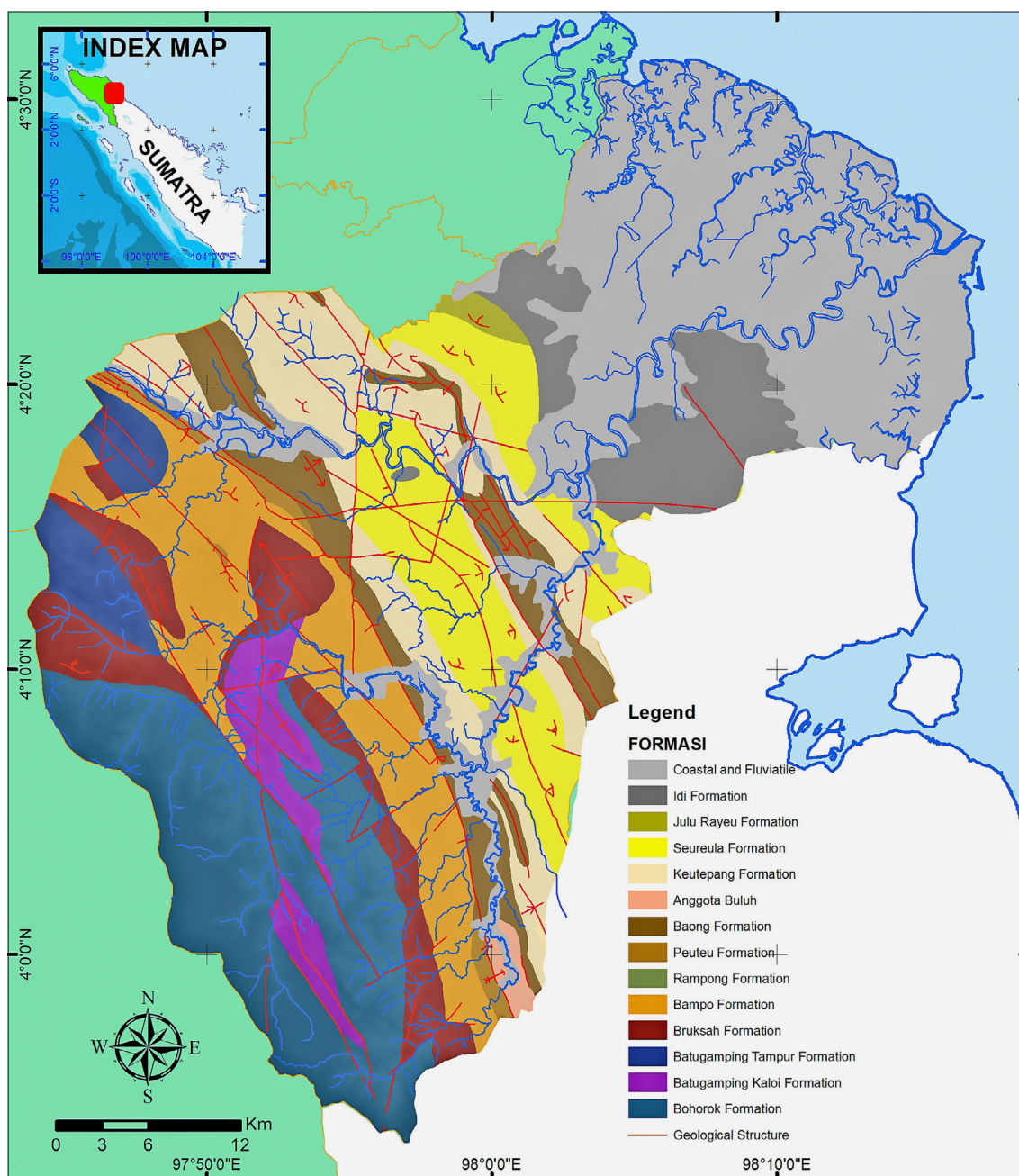


Figure 1: Regional geological map of the Tamiang, Aceh Province.
Modified and redrawn from (Cameron et al., 2007)

areas have been studied in detail due to their economic significance and the availability of geological data. Conversely, Aceh Province particularly the Tamiang region has received relatively little attention, despite its complex geological framework and potential for diverse mineralization styles. The limited availability of geochemical baseline data from this region represents a major gap in the current understanding of Sumatra's metallogenic and lithogeochemical evolution. Geologically, the Tamiang region lies in the eastern part of Aceh, within the influence of the Sumatra Fault Zone, one of the most active tectonic features in Southeast Asia (Barber et al., 2005; Cameron et al., 2007). The area comprises

pre-Paleogene metamorphic basement rocks, Paleogene intrusive bodies, and younger volcanic sequences. These lithologies are known to be associated with magmatic-hydrothermal processes that can lead to metal enrichment in various parts of Sumatra (Aida et al., 2025). Although preliminary geological mapping indicates favorable structural and lithological conditions for mineralization, there have been no systematic geochemical surveys to characterize the background element concentrations or to delineate metal distribution patterns in this region. The absence of such data limits both academic understanding and the future application of geoscientific information for resource evaluation. The stream-sedi-

ment geochemical approach provides a suitable framework for establishing a regional geochemical baseline in such underexplored areas. Through systematic sampling and multielement analysis, spatial variations in element concentrations can be evaluated in relation to underlying lithology, geomorphology, and drainage patterns. These relationships can be visualized using geospatial mapping techniques, allowing for a comprehensive interpretation of the regional geochemical framework (**Grunsky & de Caritat, 2020**).

The Tamiang region, located along the Sumatra Fault Zone, has not been systematically studied for its geochemical characteristics. The absence of baseline geochemical data hampers regional geological correlations and the identification of areas with geochemical anomalies indicative of mineralization. To address this knowledge gap, the present study conducted a reconnaissance-level stream-sediment geochemical survey in the Tamiang region, Aceh, Indonesia. The primary objective of this study is to establish baseline geochemical data for base and transition metals within the region's drainage systems. The dataset was used to evaluate spatial variations in element concentrations and to interpret their relationship with the regional geological framework. This approach contributes new information to Indonesia's regional geochemical database and enhances understanding of the lithogeochemical characteristics of eastern Aceh. The findings are expected to support future geological and mineral resource assessments and provide a foundation for subsequent geoscientific investigations in the Tamiang region, Aceh, Indonesia.

2. Geological Setting

The study area is located in the Tamiang region, Aceh Province, which lies within the northern part of the Sumatra Basin. The regional geology comprises a variety of sedimentary, volcanic, and intrusive rock units, with ages ranging from the pre-Paleogene to the Quaternary. The main lithological units include the Coastal and Fluvial deposits (Qh) consisting of gravel, sand, and clay; the Idi Formation (Qpi) with semi-consolidated gravels, sands, and clays containing vein quartz, arenites, and rhyolites; the Julu Rayeu Formation (QTjr) with rhythmic sandstone, lignitic clay, and mudstone; and the Seureula Formation (Tps) with alternating sandstone and mudstone (see **Figure 1**).

Other significant formations are the Keutapang Formation (Tuk) comprised of sandstone, carbonaceous mudstone, and minor conglomerate; the Buluh Member (Tmbb) dominated by calcareous sandstone; the Baong Formation (Tmb) with calcareous mudstone, sandstone, and glauconitic sandstone; and the Peutu Formation (Tmp) consisting of calcareous and carbonaceous mudstones and fine sandstone. The Rampang Formation (Tlr) consists of euxinic mudstone, siltstone, and volcanoclastic sandstone, indicating deposition in anoxic

marine conditions. The Bampo Formation (Tlb) is comprised of black pyritic mudstone, sandstone, and laminated siltstone. The Bruksah Formation (Tob) includes calcareous and micaceous conglomerates with thin coal beds, deposited in fluvio-deltaic environments. The Tampur Limestone (Totl) is made up of reefal limestone and dolomite with chert nodules. The Kaloi Limestone (MPkl) consists of massive limestone associated with Triassic shale, limestone, and sandstone. The Bohorok Formation (Pub) includes undated conglomerate, minor quartzite, slate, and metamorphic limestone (**Cameron et al., 2007**). This geological diversity contributes to the genesis of metal enrichments through weathering, erosion, and fluvial transport processes that mobilize metallic elements from bedrock to stream sediments.

3. Materials and Methods

3.1. Materials

This study was conducted in the Tamiang region of Aceh, Indonesia, an area known for its promising geological potential for mineral exploration. A total of 40 sampling points were selected along the Tamiang River and its main tributaries, including the Simpang Kanan, Simpang Kiri, Tamiang, and Tenggulun rivers (see **Figure 2**). Sampling locations were systematically chosen from the river mouths upstream toward the headwaters to capture a representative distribution of sediment along the drainage network.

Stream sediments represent the eroded material transported from the surrounding bedrock and reflect the characteristics of the local drainage system, making them suitable for geochemical studies. A total of 40 samples, each weighing 1 kg, were collected from 40 locations across the Tamiang rivers. Sampling was conducted along riverbanks using two distinct approaches tailored to depositional conditions. In downstream locations, particularly near river mouths with vegetated sediment surfaces (e.g. grasses), the vegetated surface was first removed, and then samples were taken from 5 to 10 cm below, to avoid organic contamination and ensure collection of true stream sediment (**Aida et al., 2025**). In upstream areas where active fluvial deposits had minimal organic cover, samples were collected directly from the sediment surface.

The collected samples were air-dried, homogenized, and sieved. The fraction passing through an 80-mesh sieve (0.177 mm), comprising silt, clay, and the finer portion of fine sand, was selected for geochemical analysis (**Shirazi et al., 2022**). This fraction excludes coarser sand and gravel, representing the mobile geochemical component relevant to mineral detection. Each sieved sample was placed into polyethylene bags and subsequently sent to the laboratory for analysis. The laboratory used for this analysis was PT Intertek Utama Services, located at Jl. Raya Bogor KM. 28, Jakarta Timur 13710, Indonesia.



Figure 2: The research location

3.2. Laboratory Methods

The metal content of stream sediments was analyzed using Inductively Coupled Plasma Optical Emission Spectrometry (ICP-OES) (Liu, 2023; Luis Manrique Carreño, 2022; Zhang et al., 2024). ICP-OES was selected for stream sediment analysis as its detection limits were suitable for the expected concentrations of target metals, while practical considerations such as local availability, cost-effectiveness, and operational simplicity further supported its use (Aida et al., 2025; Göçmengil et al., 2022; Zhang et al., 2024). Instrumental parameters, calibration standards, and quality control procedures followed standard laboratory protocols. Detection limits for each element were monitored, and replicate analyses were performed to ensure data precision and reliability.

A total of 22 elements were measured, including Al, As, Ba, Ca, Co, Cr, Cu, Fe, K, La, Li, Mn, Na, Ni, Pb,

Sc, Sr, Ti, V, Y, and Zr. For the purpose of data interpretation, these elements were grouped based on their geochemical and genetic significance: major and lithogenic elements (Al, Fe, Ca, K, Na, Ti, Sr, Zr), indicating lithology, mineral composition, and weathering intensity; ore-related (chalcophile) elements (Cu, Pb, Zn, As, Co, Ni, Cr), assessing possible mineralization or hydrothermal influence; REE and HFSE (La, Y, Sc, Li, Zr, Ti), reflecting source rock composition and magmatic or weathering processes; and miscellaneous or ambiguous elements (Mn, Ba, Sr, V), which may have mixed lithological or secondary origins.

Elements such as Sb, Mo, and W were also analyzed; however, their concentrations were predominantly below the instrument detection limits (Sb < 5 ppm, Mo < 1 ppm, W < 10 ppm) and were therefore excluded from further interpretation. All elemental data, including average concentrations, standard deviations, background levels, and anomalies, are presented in **Table 1** and further discussed in the Results section.

Table 1: Elemental concentrations in the stream sediment of the Tamiang Aceh, Indonesia

Elements	Units	Mean	Min.	Max.	Site (Max)	Standard deviation	Background	Threshold	Anomaly Location
Al	%	3.20	2.02	4.48	TM02	0.67	3.86	4.53	-
As	ppm	16	6	38	TM37	9.00	25	34	TM33, TM34, TM37, TM 38
Ba	ppm	343	207	673	TM38	121.11	464	585	TM01, TM11, TM38
Ca	%	0.20	0.04	3.58	TM22	1.05	1.25	2.30	TM20, TM21, TM22, TM23, TM32
Co	ppm	11	6	17	TM38	2.94	14	17	TM01, TM37, TM38
Cr	ppm	41	18	82	TM02	14.47	55	69	TM02, TM03
Cu	ppm	13	3	89	TM37	16.37	29	46	TM37, TM38
Fe	%	3.27	1.5	7.82	TM03	1.39	4.66	6.06	TM02, TM03, TM37
K	%	2.01	1.39	3.07	TM01	0.43	2.44	2.88	TM01, TM17
La	ppm	25	11	44	TM05	6.41	31	37	TM05
Li	ppm	24	16	42	TM02	6.09	30	36	TM02, TM03
Mn	ppm	454	160	1350	TM30	273.72	728	1001	TM28, TM30, TM32, TM37, TM38
Na	%	0.36	0.09	0.93	TM17	0.27	0.63	0.90	TM17, TM18
Ni	ppm	23	10	44	TM03	6.56	29	36	TM03
Pb	ppm	23	9	83	TM30	16.87	39	56	TM28, TM30, TM32, TM 37, TM38
Sc	ppm	6	2	9	TM21	1.67	8	9	-
Sr	ppm	56	12	144	TM22	37.60	94	131	TM21, TM22, TM32
Ti	%	0.19	0.1	0.28	TM02	0.04	0.23	0.27	TM02
V	Ppm	53.00	22	101	TM02	18.40	71	90	TM02, TM03
Y	ppm	8.00	3	13	TM02	2.59	11	13	-
Zn	ppm	70	36	152	TM38	27.77	97	125	TM02, TM03, TM30, TM31, TM33, TM37, TM38
Zr	ppm	23	10	43	TM03	8.44	31	40	TM02, TM03

3.3. Data processing and analysis

The laboratory analysis results were subjected to statistical analysis to determine mean, standard deviation, detection limit, and metal distribution, as shown in the histogram curves (Yaisamut et al., 2023). Geographic Information System (GIS, ArcGIS) was used to map the spatial distribution of metals in stream sediments from the Tamiang region, Aceh, with concentrations represented as points and color gradients indicating low-to-high values (Smith et al., 2019; Sun et al., 2019). Anomaly analysis was conducted to identify unusual metal concentrations potentially related to mineralization or other geological processes. Anomalies were defined as values significantly deviating from the background, calculated using background value = median + standard deviation and threshold = median + 2 × standard deviation (Manrique, 2022; Yaisamut et al., 2023), with values exceeding the threshold considered anomalous and further analyzed to assess their spatial patterns.

Graphical presentations focused on elements showing distinct spatial anomalies, as these are most likely to reflect geological controls such as lithological variations, structural features, or hydrothermal alteration. The con-

centrations of Cu, Zn, Pb, and Co in Tenggulun; Ca and Sr in Tamiang Hulu; La and Li in Sekerak and Bandar Pusaka; and Na and K in Rantau and Seruway were highlighted due to their geochemical significance and correspondence with regional lithologies or weathering processes (Freitas et al., 2024; Müller et al., 2025; Reinhardt et al., 2018; Xu et al., 2025; Zhao et al., 2025).

4. Results and Discussion

4.1. Elemental concentrations in the stream sediment

Table 1 summarizes the concentrations of the analyzed elements. To clarify spatial variations and maintain consistency with the subsequent geochemical interpretation, the elements were grouped into four geochemical categories: (1) major and lithogenic elements (Al, Fe, Ca, K, Na, Ti, Sr, Zr), (2) ore-related (chalcophile) elements (Cu, Pb, Zn, As, Co, Ni, Cr), (3) REE and HFSE elements (La, Y, Sc, Li, Zr, Ti), and (4) miscellaneous elements (Mn, Ba, Sr, V). This grouping provides a framework for interpreting spatial geochemical patterns in relation to lithological controls, weathering in-

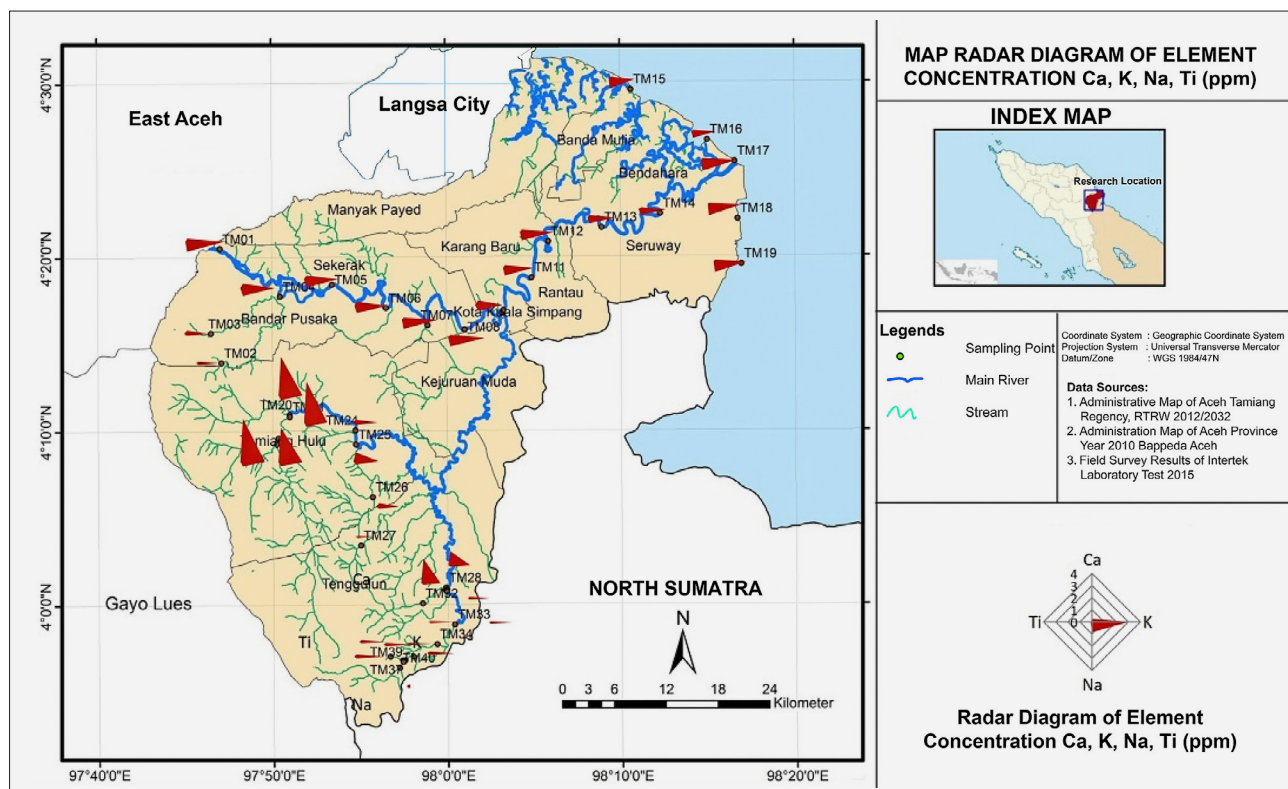


Figure 3: Spatial distribution of metal elements Ca, K, Na, and Ti in the Tamiang region, Aceh, Indonesia

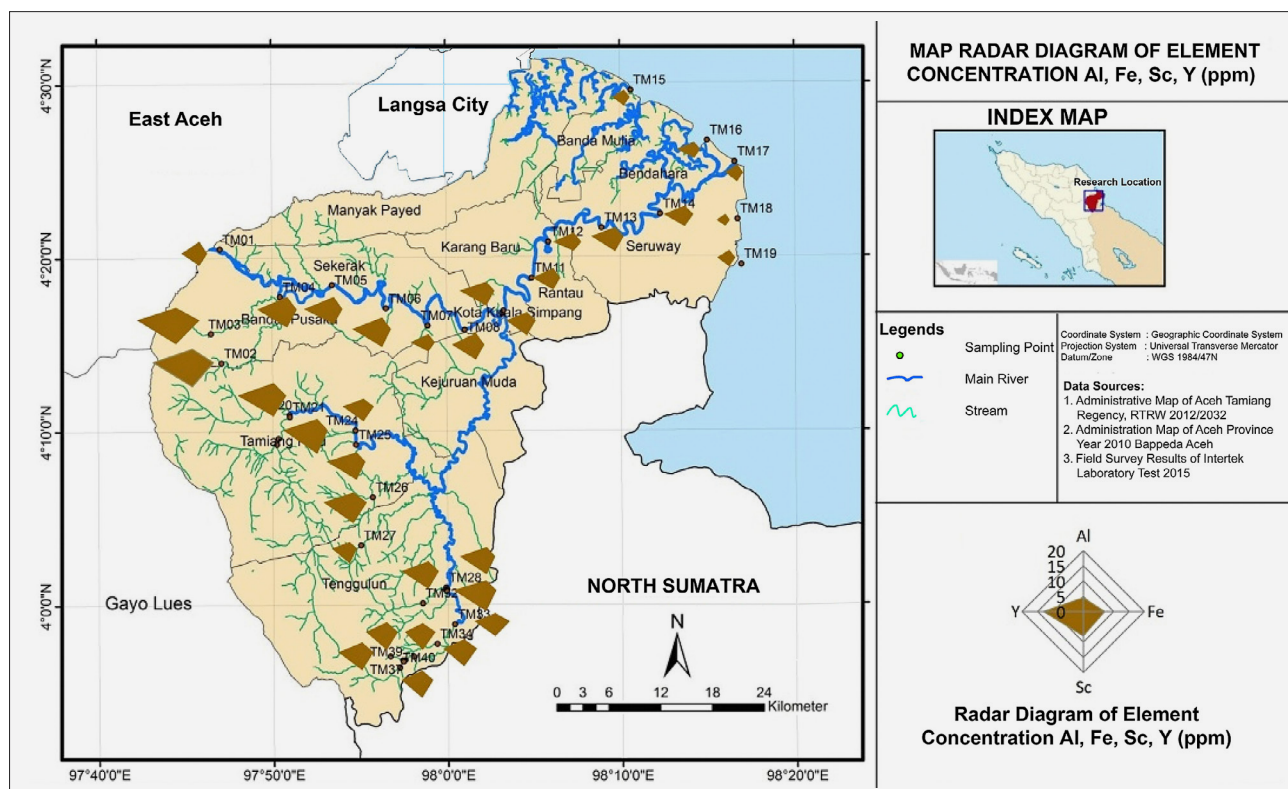


Figure 4: Distribution map of metal elements (Al, Fe, Sc, Y) in Tamiang, Aceh, Indonesia

tensity, and potential mineralization within the Tamiang region. The distinction between background and threshold values for each element provides a useful basis for

identifying geochemical variability and delineating potential anomaly zones within the Tamiang region, Aceh, Indonesia.

Major and lithogenic elements such as aluminum (Al), iron (Fe), calcium (Ca), potassium (K), sodium (Na), titanium (Ti), strontium (Sr), and zirconium (Zr) exhibit relatively consistent concentrations across most sampling sites. Aluminum did not exceed the threshold value at any location. Elevated Fe values at TM02, TM03, and TM37 correspond to lithologies enriched in iron oxides and heavy minerals (Tonggiroh, 2020). Calcium and sodium show minor anomalies at TM20–TM23, TM32, and TM17–TM18, respectively, consistent with variations in carbonate and feldspathic lithologies rather than distinct mineralization processes (Cameron et al., 2007). Sodium shows background and threshold values both below 1%, with TM17 and TM18 exceeding this limit, likely derived from feldspathic or clay-bearing sediments. Potassium anomalies occur at TM01 and TM17, exceeding its background value of 2% and threshold of 3%. Titanium exhibits an anomaly at TM02, with a background of 0.23% and a threshold of 0.27%. The presence of Ti may be associated with heavy minerals such as ilmenite or titanite (Ghadimi et al., 2016). Strontium shows anomalies at TM21, TM22, and TM32, with a background of 94 ppm and a threshold of 131 ppm. These Sr enrichments could indicate localized concentrations related to carbonate-rich lithologies or fluid-induced mobilization (Li et al., 2020; Smith et al., 2009). Zirconium anomalies at TM02 and TM03, with a background of 31 ppm and a threshold of 40 ppm, potentially indicate detrital zircon grains or resistant lithological units (Ali et al., 2022).

Ore-related (chalcophile) elements, including copper (Cu), lead (Pb), zinc (Zn), arsenic (As), cobalt (Co), nickel (Ni), and chromium (Cr), display more pronounced spatial variability. Arsenic (As), with a background value of 25 ppm and a threshold of 34 ppm, exceeded the threshold at TM33, TM34, TM37, and TM38, suggesting localized As enrichment possibly associated with sulfide-bearing lithologies (El-Makky & Sediek, 2012). Cobalt (Co) anomalies occur at TM01, TM37, and TM38 (above 17 ppm), while chromium (Cr) enrichment at TM02–TM03 (above 69 ppm) indicates possible derivation from mafic or ultramafic rocks (Maier et al., 2016). Copper (Cu) concentrations surpass the threshold of 46 ppm at TM37–TM38, and lead (Pb) anomalies are recorded at TM28, TM30, TM32, TM37, and TM38, with a background of 39 ppm and a threshold of 56 ppm. Zinc (Zn) enrichment is widespread, occurring at TM02–TM03, TM30–TM33, and TM37–TM38, exceeding its background of 97 ppm and threshold of 125 ppm. Such Zn anomalies may be linked to sulfide mineralization or remobilization by weathering (Ayari et al., 2022). The co-occurrence of Cu, Zn, and Pb at multiple sites marks zones of multi-element enrichment, though their origin cannot yet be confirmed without mineralogical evidence (Ayari et al., 2022; Saadat, 2022; Tonggiroh, 2020; Zheng et al., 2014). The poten-

tial anthropogenic contribution of Pb is considered unlikely given the absence of supporting land-use or contamination data; thus, these variations are more plausibly natural in origin (Ignatavičius et al., 2022; Saadat, 2022; Tan et al., 2018; Zheng et al., 2014). Nickel (Ni) shows a background of 29 ppm and a threshold of 36 ppm, with an anomaly detected at TM03. This localized Ni enrichment may be linked to ultramafic rock fragments or hydrothermal veins (Maier et al., 2016; Shine et al., 2022).

REE and HFSE elements (La, Y, Sc, Li, Zr, Ti) generally occur at low to moderate levels. Lanthanum (La) exhibits a minor anomaly at TM05, reflecting possible heavy-mineral accumulation or distinct lithological provenance (Fakolade et al., 2024). Both yttrium (Y) and scandium (Sc) show stable concentrations throughout the study area, with background values of 11 ppm and uniform distributions, respectively. No geochemical anomalies were detected for either element, indicating stable geochemical behaviour and strong lithological control within the region (Chassé et al., 2017; Halkoaho et al., 2020; Zhou et al., 2022). Lithium (Li) enrichment at TM02–TM03, exceeding its 36 ppm threshold, may relate to clay-rich sediments or pegmatitic sources (Cameron et al., 2007; Rohiman et al., 2024). Zirconium (Zr) anomalies at TM02–TM03 are consistent with detrital zircon grains hosted in resistant lithologies (Ali et al., 2022).

Miscellaneous elements such as barium (Ba), manganese (Mn), strontium (Sr), and vanadium (V) reveal diverse patterns. Barium anomalies at TM01 and TM11 (exceeding 585 ppm) may be associated with barite or Ba-bearing feldspar minerals transported by fluvial processes (Yaisamut et al., 2023). Manganese enrichment at TM28, TM30, TM32, TM37, and TM38 could reflect secondary precipitation under variable redox conditions in sedimentary environments (Haghighizadeh et al., 2024). Strontium anomalies at TM21–TM22 and TM32 likely indicate local carbonate-rich lithologies or fluid-induced mobilization (Li et al., 2020; Smith et al., 2009). The observed patterns provide essential baseline data for subsequent spatial interpretation presented in Section 4.2, ensuring that the discussion remains grounded in observed geochemical evidence.

4.2. Map of Metal Element Distribution in Tamiang, Aceh

Building upon the geochemical classification described in Section 4.1, the spatial distribution of elements was interpreted through four geochemical groups: (1) major and lithogenic (Al, Fe, Ca, K, Na, Ti, Sr, Zr), (2) ore-related or chalcophile (Cu, Pb, Zn, As, Co, Ni, Cr), (3) REE–HFSE (La, Y, Sc, Li, Zr, Ti), and (4) miscellaneous or ambiguous elements (Mn, Ba, Sr, V). This framework facilitates the interpretation of distribution

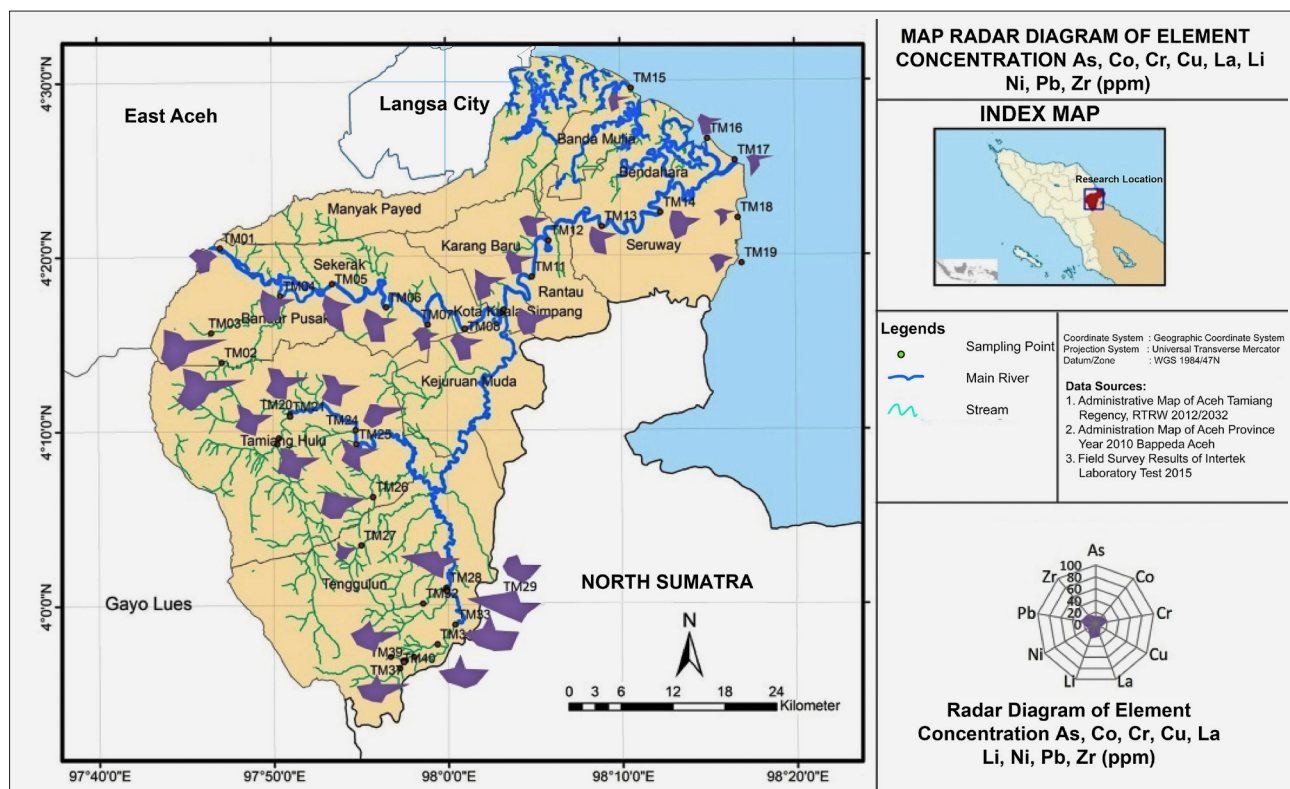


Figure 5: Distribution map of metal elements (As, Co, Cr, Cu, La, Li, Ni, Pb, Zr) in Tamiang, Aceh, Indonesia

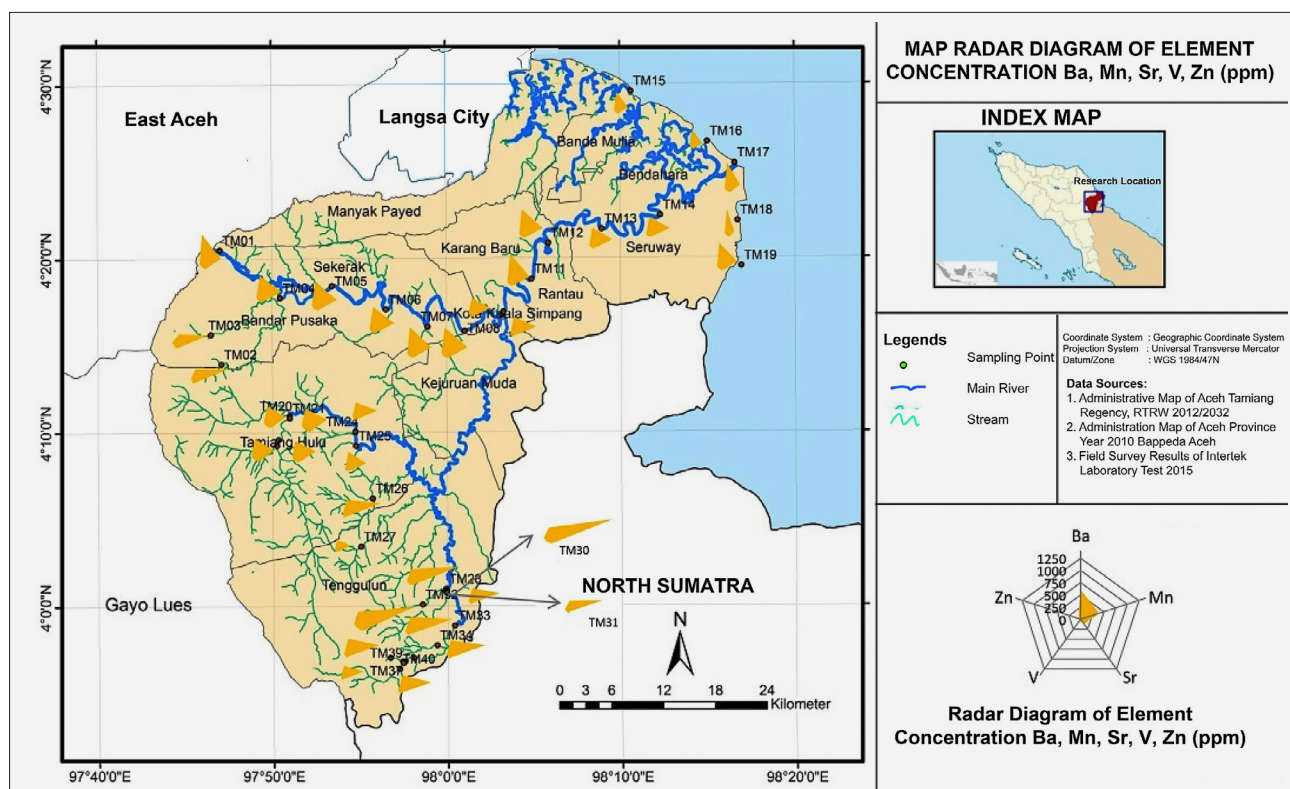


Figure 6: Distribution map of metal elements (Ba, Mn, Sr, V, Zn) in Tamiang, Aceh, Indonesia

maps (see **Figures 3–6**) by linking geochemical variations to lithological composition, weathering intensity, and potential mineralization indicators. The observed

spatial patterns suggest that the geochemical variability across the study area is primarily governed by lithology, geomorphology, and surficial processes.

4.2.1. Major and Lithogenic Elements (Ca, K, Na, Ti, Fe, Al, Sr, Zr)

Major and lithogenic elements reflect lithology, mineral composition, and weathering intensity. These elements (Ca, K, Na, Ti) display widespread but generally low enrichment, consistent with their derivation from silicate and carbonate rocks (see **Figure 3**). Their geochemical signatures mainly represent geogenic sources and weathering processes typical of tropical environments. The highest concentrations were identified in Sekerak Village, Kuala Simpang City, Rantau, and Seruway Muara within the Aceh Tamiang region, Indonesia.

In the Tamiang Hulu area, Ca is the dominant element, suggesting the possible presence of carbonate rock formations or Ca-rich sediments derived from ancient marine deposits or lithological inputs from upstream river sources (**Debruyne et al., 2016**). Meanwhile, in Tenggulun, K is the most dominant element, reinforcing the hypothesis that this element has a widespread distribution in surface materials. The dominance of Ca in Tamiang Hulu and K in Tenggulun suggests localized lithological variations that should be validated through further petrographic and mineralogical analyses (**Halkoaho et al., 2020; Morin-Ka et al., 2025**). Elevated Ca concentrations in Tamiang Hulu indicate carbonate-bearing lithologies or Ca-rich alluvial sediments, whereas higher K contents in Tenggulun likely reflect feldspar-rich parent rocks and intense silicate weathering (**Debruyne et al., 2016; Halkoaho et al., 2020; Morin-Ka et al., 2025**).

Potassium reached a maximum value of 3.07%, which may be related to the presence of feldspar minerals in the parent rocks (**Halkoaho et al., 2020**). In contrast, Na exhibited the lowest content (0.93%). The relatively low Na concentrations and broad spatial distribution suggest pervasive weathering of silicate minerals and possible inputs from carbonate rocks in the Tamiang region (**Debruyne et al., 2016**). Na exhibits lower concentrations across most of the region, implying limited sodium-bearing mineral input or higher mobility during chemical weathering (**Debruyne et al., 2016**).

Titanium shows minimal variation, reflecting its occurrence in stable minerals such as ilmenite and rutile that resist decomposition and transport (**Morin-Ka et al., 2025; PWC, 2019; Syakti et al., 2015**). Ti represents the element with the lowest overall concentration across the entire Tamiang region ($\approx 0.28\%$), consistent with its presence in weathering-resistant minerals such as ilmenite or rutile, which are generally not easily decomposed or dispersed during surface processes (**Morin-Ka et al., 2025; PWC, 2019; Syakti et al., 2015**). These spatial patterns provide insight into the geochemical conditions of the Aceh Tamiang region and can serve as indicators for evaluating mineral potential. Further studies integrating mineralogical and hydrological

data are recommended to support sustainable resource utilization and environmental management in the region.

The spatial distribution of Fe and Al was recorded mainly in the upstream reaches of the Tamiang River, particularly in the Tamiang Hulu and Tenggulun areas, reaching maximum values of 7.82% and 4.48%, respectively (see **Figure 4**). Such enrichment is characteristic of tropical lateritic environments, where prolonged weathering and secondary mineral formation result in Fe- and Al-rich regoliths (**Asonye et al., 2022; Zhou et al., 2022**). The spatial trend, with decreasing concentrations downstream, indicates limited transport and dilution effects likely caused by geomorphological constraints and sediment retention in the upper catchment area.

Zr shows elevated values (42 ppm, 44 ppm, and 43 ppm at TM02–TM03), as illustrated in **Figure 5**, with concentrations primarily in Tenggulun and Bandar Pusaka. The localized enrichment in these areas indicates the influence of lithological and geochemical processes, particularly those associated with ultramafic–mafic source rocks and secondary weathering (**Eskdale et al., 2023; Shirazi et al., 2022**). Strontium (Sr) exhibits the highest concentrations in the Tenggulun and Tamiang Hulu areas, with an average of 119 ppm, a minimum of 12 ppm, and a maximum of 144 ppm (see **Figure 6**). Sr enrichment predominantly occurs in the upstream regions of the study area, forming clear spatial clusters consistent with carbonate-bearing lithologies and the occurrence of celestite–barite mineral assemblages (**Lyons et al., 2002**).

4.2.2. Ore-related (chalcophile) elements (As, Co, Cr, Cu, Ni, Pb, and Zn)

Ore-related or chalcophile elements may indicate possible mineralization or hydrothermal influence. These elements (As, Co, Cr, Cu, Ni, Pb, and Zn) exhibit localized enrichments primarily concentrated in the Tenggulun and Bandar Pusaka areas, as illustrated in **Figures 5 and 6**. In the Tenggulun area, arsenic (As) exhibits the highest recorded value of 38 ppm at TM37. In Bandar Pusaka, chromium (Cr) reaches its maximum concentration of 82 ppm at TM02, where Co and Cu also attain their highest levels (17 ppm and 89 ppm, respectively), suggesting a shared geochemical control or mineral association (see **Figure 5**). These anomalies likely coincide with zones underlain by volcanic and intrusive lithologies, indicating possible natural geochemical dispersion from sulfide-bearing rocks (**El-Makky & Sediek, 2012; Maier et al., 2016**).

The distribution of Ni in Bandar Pusaka may reflect minor mineralization derived from igneous or metamorphic rocks, which locally enriches the soil in trace metals (**Doherty et al., 2023; Savina et al., 2023**). Lead (Pb) shows its highest concentration in Tenggulun (83 ppm at TM30, **Figure 5**). The significant accumulation

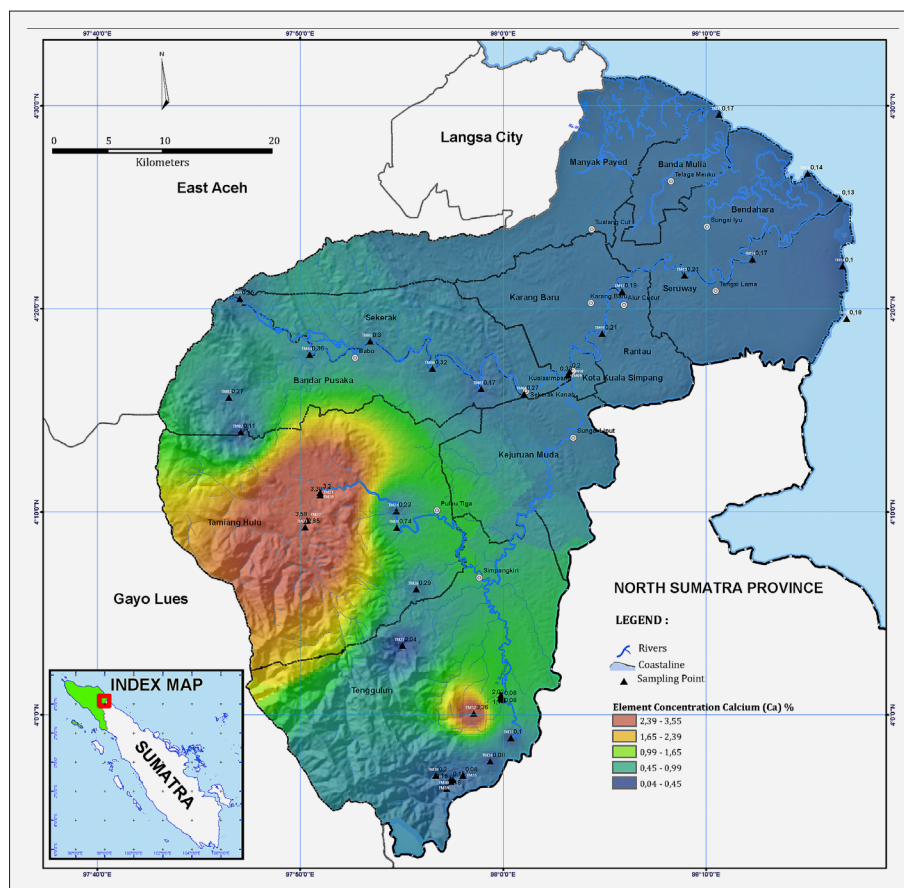


Figure 7: Spatial distribution of calcium anomalies in the Tamiang area, Aceh, Indonesia

of Pb and As at specific sites is noteworthy due to their environmental significance and potential mobility under fluctuating redox conditions (Briseño-Bugarín et al., 2024; Coşac et al., 2024; Faz et al., 2025; Tan et al., 2018). However, no mineralogical evidence currently supports active hydrothermal alteration or anthropogenic influence; thus, these enrichments are interpreted as lithologically derived rather than contamination-related. Zinc (Zn) occurs in concentrations ranging from 36 to 152 ppm (average ≈ 130 ppm), with the highest values found in Bandar Pusaka and Tenggulun (see Figure 6). The elevated Zn values likely reflect natural background variation associated with sulfide-bearing lithologies or secondary geochemical redistribution (Moghimi et al., 2024; Yaisamut et al., 2023).

4.2.3. REE and HFSE elements (Sc, Y, La, Li, Zr, Ti)

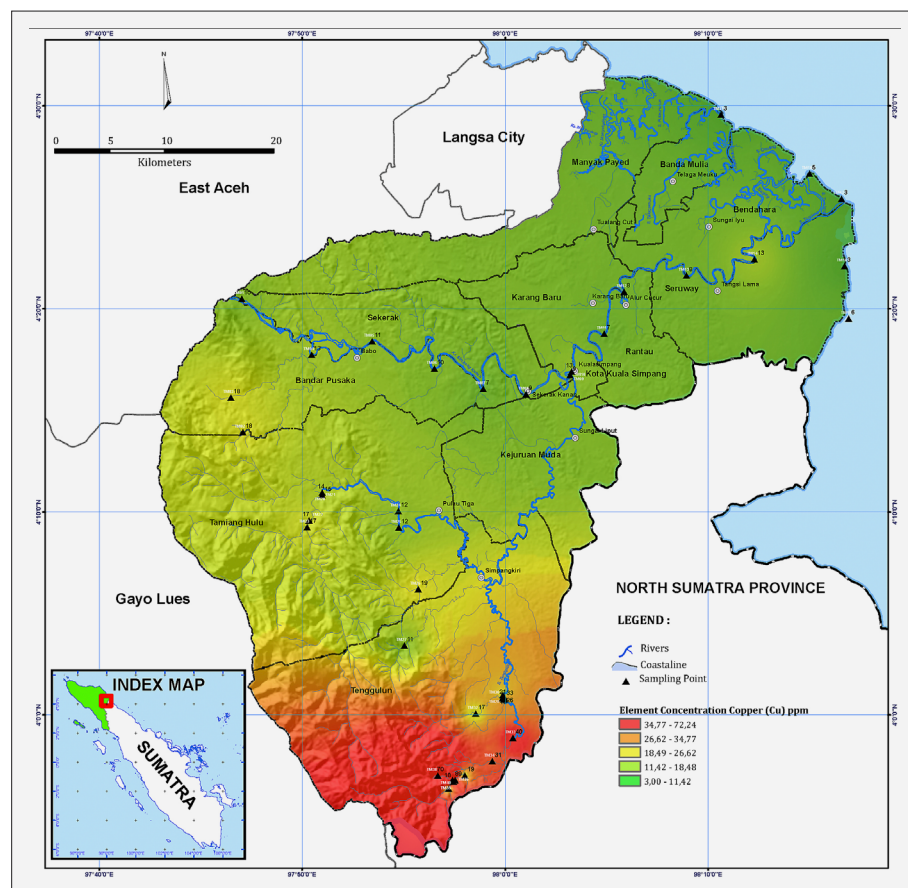
REE and HFSE elements reflect source rock composition as well as magmatic and weathering processes. These elements (Sc, Y, La, Li, Zr, Ti) show relatively uniform spatial distributions, indicating strong lithological control and minimal secondary mobility (see Figures 3–5). Ti (see Figure 3), although previously classified among the major and lithogenic elements, is discussed here owing to its dual geochemical behaviour.

Scandium (Sc) and yttrium (Y) exhibit similar upstream enrichment patterns, with maximum values of 9

ppm and 13 ppm, respectively. Their concentrations are highest in the Tamiang Hulu and Tenggulun areas (see Figure 4), suggesting that the upstream zones serve as primary sources of REE-bearing sediments. This trend reflects the influence of local lithology and weathering processes on elemental distribution. The co-occurrence of Sc and Y likely indicates their association with residual mineral phases such as goethite, hematite, and clay minerals enriched during lateritic weathering (Aida et al., 2025; Chassé et al., 2017; Halkoaho et al., 2020; Zhou et al., 2022). The spatial distribution of lanthanum (La), lithium (Li), and zirconium (Zr) is shown in Figure 5. Lanthanum (La) exhibits localized enrichment at Sekerak (TM05, 44 ppm), possibly associated with heavy minerals such as monazite or xenotime (Fakolade et al., 2024). The identified spatial associations among La, Y, and Sc suggest that REE enrichment is primarily controlled by residual mineral phases in weathered lithologies rather than by hydrothermal processes (Chassé et al., 2017; Halkoaho et al., 2020; Zhou et al., 2022).

In the Bandar Pusaka area, Li and Zr show elevated concentrations (42 ppm and 43 ppm at TM02–TM03, respectively). Lithium enrichment at these sites likely reflects inputs from clay-rich sediments or pegmatitic sources (Cameron et al., 2007; Rohiman et al., 2024). Zirconium enrichment corresponds to detrital zircon grains within resistant lithologies, indicating limited transport and high mineral stability under tropical weath-

Figure 8: Spatial distribution of copper anomalies in the Tamiang area, Aceh, Indonesia



ering conditions (Ali et al., 2022; Celis et al., 2022; Cořac et al., 2024). Overall, the distribution of REE and HFSE elements in the Tamiang Basin highlights the dominance of lithological and weathering controls, with minimal evidence for hydrothermal remobilization.

4.2.4. Miscellaneous or ambiguous elements (Ba, Mn, Sr, V)

Miscellaneous or ambiguous elements may have mixed lithological or secondary origins. As shown in **Figure 6**, elements such as Ba, Mn, Sr, and V exhibit distinct spatial patterns that reflect combined lithological and secondary geochemical influences.

Barium (Ba) shows the highest concentrations in the Bandar Pusaka–Rantau sector, ranging from 207 ppm to 673 ppm (average = 578 ppm). Anomalies at TM01 and TM11 are likely related to detrital barite or Ba-bearing feldspar minerals (Yaisamut et al., 2023). These occurrences suggest that Ba is primarily derived from geogenic sources, possibly transported through fluvial or sedimentary processes (Celis et al., 2022; Yaisamut et al., 2023).

Manganese (Mn) is particularly enriched in the Tenggulun area, with concentrations between 160 ppm and 1350 ppm (average $\approx$ 1008 ppm). Such enrichment is characteristic of weathering of Mn-bearing rocks and secondary oxide deposition under fluctuating redox conditions typical of tropical environments (Tonggiroh,

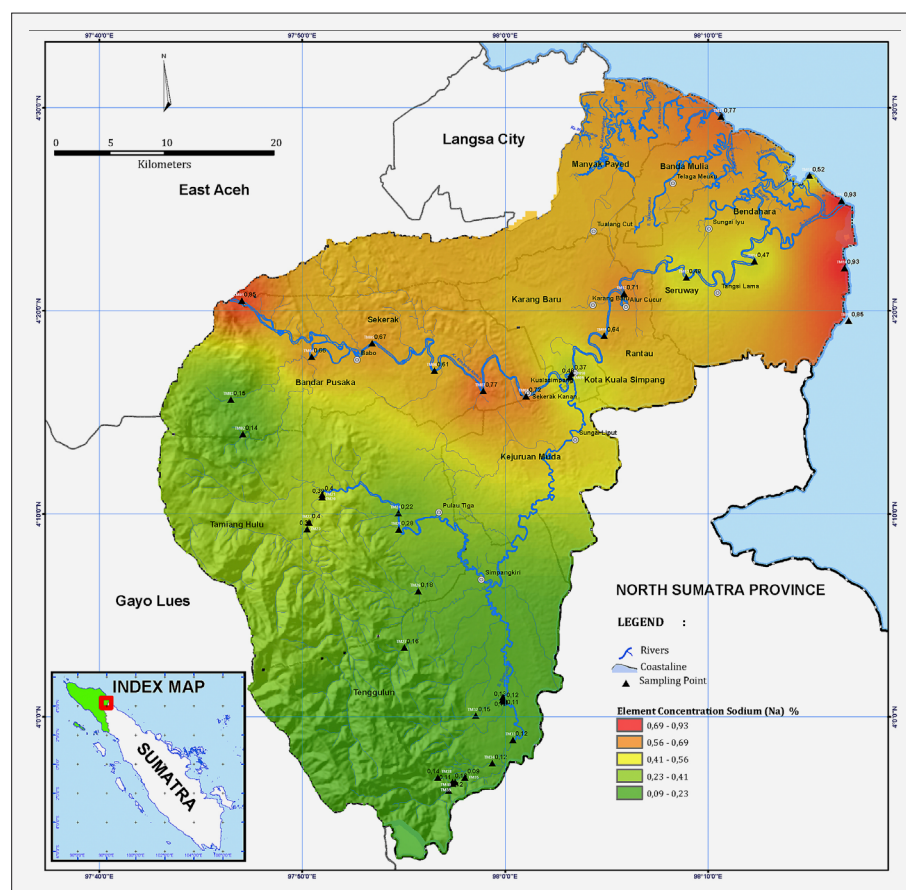
2020). The observed Mn distribution highlights zones of enhanced geochemical mobility influenced by hydrological and geomorphological factors.

Strontium (Sr) exhibits elevated levels in the Tenggulun and Tamiang Hulu areas (TM21–TM32), with concentrations ranging from 12 ppm to 144 ppm (average = 119 ppm). Its occurrence is consistent with carbonate-bearing lithologies and celestite–barite mineral assemblages (Akintola AI et al., 2013; Li et al., 2020; Smith et al., 2009; Wang, 2025). Elevated Sr values often correspond to celestite and barite formation, the main natural sources of Sr (Lyons et al., 2002). The concurrent enrichment of Ba and Sr likely indicates localized barite–celestite mineralization, while high Mn concentrations support the presence of manganese-rich lateritic or sedimentary deposits (Lyons et al., 2002; Tonggiroh, 2020).

Vanadium (V) concentrations range from 22 ppm to 101 ppm (average = 89 ppm), with the highest values recorded in Bandar Pusaka. Its spatial distribution appears controlled by local geological substrates containing V-bearing minerals (Irzon, 2018; Pourret & Dia, 2016). The occurrence of V suggests additional metallogenic potential in the region and warrants further petrological and geochemical investigation (Irzon, 2018; Moghimi et al., 2024; Pourret & Dia, 2016; Yaisamut et al., 2023).

Overall, Ba, Mn, Sr, and V display distinct spatial clustering patterns, predominantly in upstream regions

Figure 10: Spatial distribution of sodium anomalies in the Tamiang area, Aceh, Indonesia



local lithology and mineralization processes that have shaped the geochemical landscape of Tenggulun (Ayuso et al., 2010; Cooke et al., 2020; Müller et al., 2025).

Figure 9 illustrates that lithium (Li) exhibits elevated concentrations in the Bandar Pusaka area, where red contours indicate values exceeding 34 ppm. The observed lithium enrichment is interpreted to be associated with source rocks closely related to the Lokop Granite (Til), Tampur Limestone Formation (Totl), and Bruksah Formation (Tob) (Cameron et al., 2007). In contrast to copper, which demonstrates a strong affinity with mineralized intrusive bodies in Tenggulun, and calcium, which reflects carbonate weathering in Tamiang Hulu, the lithium distribution in Bandar Pusaka underscores the geochemical influence of granitic intrusions interacting with adjacent carbonate sequences. This pattern suggests that the interplay between granitoid sources and carbonate host rocks exerts a major control on lithium enrichment within this part of the study area (Cardoso-Fernandes et al., 2022).

Figure 10 illustrates the distribution of sodium (Na), which displays elevated concentrations along the main course of the Sungai Besar, extending from the inland areas around Rantau to the river mouth near Seruway, where red contours indicate values exceeding 0.69%. The relatively widespread occurrence of sodium within this fluvial system is interpreted as the result of weathering processes affecting igneous rocks, siliciclastic for-

mations, and feldspar-bearing minerals (Kirkwood et al., 2016). In the upstream regions, the Lokop Granite (Til) serves as a potential source, while the river also traverses several sedimentary formations, including the Baong Formation (Tmb), Keutapang Formation (Tuk), Seuleula Formation (Tps), Idi Formation (Qpi), and Quaternary alluvial deposits (Qh) (Cameron et al., 2007). These lithological units likely contribute feldspar fragments that account for the sodium enrichment observed in the sediments and waters of the Sungai Besar system.

The elements emphasized in the graphical presentation were selected for their distinct geochemical anomalies and geological relevance. The elevated levels of Cu, Co, Zn, and Pb in Tenggulun are consistent with geochemical patterns seen in skarn-related mineralization; however, mineralogical and structural data are needed to verify this association (Freitas et al., 2024; Pirajno, 2010; Xie et al., 2022). The enrichment of Ca and Sr in Tamiang Hulu corresponds to carbonate lithologies and fluid-rock interactions (Cooke et al., 2020; Nyakairu & Koeberl, 2001; Taylor & McLennan, 1985). In Sekerak and Bandar Pusaka, the presence of La and Li, together with relatively immobile elements such as Ti, V, and Zr, reflects felsic or alkali-rich source rocks (Kirkwood et al., 2016; McClenaghan et al., 2021; Müller et al., 2025; Zhao et al., 2025). Conversely, anomalies of Na and K in Rantau and Seruway are consistent with

tropical silicate weathering and leaching processes (Kirkwood et al., 2016; Xu et al., 2025). Collectively, these element-specific anomalies emphasize the strong lithological and geochemical controls governing metal distribution and mineralization potential across the Tamiang region. The observed geochemical signatures thus provide an essential foundation for guiding future exploration efforts and for understanding the geological evolution of this part of Aceh, Indonesia.

5. Conclusions

This reconnaissance geochemical survey provides the first comprehensive dataset of a) major and lithogenic; b) ore-related (chalcophile); c) REE and HFSE; and d) miscellaneous or ambiguous elements in the Tamiang region, Aceh, Indonesia. The results reveal distinct spatial variations that are primarily governed by lithological composition, geomorphological setting, and surface weathering processes. Major and lithogenic elements (Ca, K, Na, Fe, Al, Ti, Sr, Zr) display widespread enrichment patterns, reflecting their lithology, mineral composition, and weathering intensity. Elevated Ca and Sr contents in Tamiang Hulu indicate contributions from carbonate-bearing and feldspar-rich lithologies. In contrast, enrichment in Na and K occurs in Seruwai, Ti and Zr in Banda Pusaka, and Fe in Tenggulun. Ore-related elements (Cu, Pb, Zn, As, Co, Ni, and Cr) exhibit localized enrichments, particularly in Tenggulun and Bandar Pusaka, suggesting potential geochemical anomalies related to volcanic and intrusive lithologies rather than active mineralization. The REE and HFSE element anomalies (Sc, Y, La, Li, Zr, Ti) in Bandar Pusaka exhibit relatively uniform distributions, indicating a predominant lithological control with minimal secondary alteration, and reflecting the composition of the source rocks as well as the influence of primary magmatic and weathering processes. Their enrichment in upstream areas supports the interpretation of lateritic weathering over felsic to intermediate parent rocks. Miscellaneous or ambiguous elements (Ba, Mn, Sr, V) display significant spatial clustering, with elevated Ba–Sr values linked to barite–celestite mineral assemblages, while Mn and V enrichment likely reflects redox-driven accumulation in tropical soils. These patterns suggest mixed lithological and secondary origins, with elevated Ba and V observed in Banda Pusaka, and Mn and Sr in Tenggulun.

The most pronounced anomalies, namely Cu, Ca, Li, and Na, highlight distinct geochemical zones corresponding to lithological transitions and hydrological boundaries within the Tamiang Basin. Conversely, three elements Al, Sc, and Y exhibit the lowest concentrations and show no significant anomalies. These patterns collectively indicate that the geochemical variability of the basin is primarily controlled by lithology, surface processes, and sediment provenance, rather than by anthropogenic or hydrothermal inputs. Overall, these geo-

chemical patterns suggest localized metal enrichment rather than confirmed mineralization or deposit types. The results emphasize the importance of regional geological control on metal distribution and highlight zones of interest that warrant further detailed investigation. However, given the reconnaissance scale of this study, the limited sampling density, and the absence of mineralogical or structural verification, interpretations should be considered preliminary. Despite these limitations, this work establishes a valuable baseline geochemical dataset for the Tamiang region. The findings provide an initial framework for understanding regional geochemical variability and serve as a foundation for future, more detailed geological, mineralogical, and geophysical studies aimed at assessing the area's resource potential in a sustainable and scientifically robust manner.

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SAŽETAK

Preliminarno geokemijsko istraživanje u regiji Tamiang, Aceh, Indonezija

Regija Tamiang, u pokrajni Aceh, Indonezija, geološki je složena i nedovoljno istražena, s dostupnim samo osnovnim geokemijskim podacima. Ova studija predstavlja preliminarno geokemijsko istraživanje za procjenu prostornih razlika u koncentracijama metala i njihove geološke kontrolirajuće faktore. Analizirano je četrdeset uzoraka potočnih sedimenata iz različitih drenažnih sustava na području regije. U uzorcima je mjerena koncentracija 22 kemijska elementa (Al, As, Ba, Ca, Co, Cr, Cu, Fe, K, La, Li, Mn, Na, Ni, Pb, Sc, Sr, Ti, V, Y, Zn, Zr) metodom ICP-OES. Devetnaest elemenata pokazuje anomalne koncentracijske vrijednosti, a najvišim anomalijama ističu se Cu, Ca, Li, i Na. Koncentracije Al, Sc, i Y ostale su u granicama pozadinskih vrijednosti. Temeljem njihova geokemijskog ponašanja kemijski elementi mogu se grupirati u glavne litogene elemente, kao što su Al, Fe, Ca, K, Na, Ti, Sr, i Zr, koji upućuju na litologiju i intenzitet trošenja, te na rudne kemijske elemente, koji uključuju Cu, Pb, Zn, As, Co, Ni, i Cr, koji mogu označavati lokalizirana obogaćenja metalima. Elementi rijetkih zemalja i elementi visokoga naboja, kao što su La, Y, Sc, Li, Zr, i Ti pružaju uvid u sastav izvorišnih stijena te magmatske procese i procese trošenja, dok ostali elementi koji uključuju Mn, Ba, i Sr imaju miješano litološki i sekundarno porijeklo. Prostorni raspored ovih anomalija može upućivati na lokalno metalno obogaćenje povezano sa specifičnim litološkim zonama. Unatoč preliminarnom mjerilu i ograničenoj gustoći uzorkovanja ovi rezultati pružaju temeljni geokemijski okvir Tamian regije te čine osnovu za buduća geološka i geokemijska istraživanja i doprinose pouzdanim znanstvenim procjenama područja.

Ključne riječi:

preliminarna geokemija, potočni sediment, mineraloška prospekcija, geokemijsko kartiranje, Aceh, Indonezija

Author's contribution

Gartika Setiya Nugraha (Dr): conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, resources, software, supervision, validation, visualization, writing – original draft and writing – review & editing, investigation, data collection, and investigation. **Ibnu Rusydy** (MSc): project administration, data curation, and supervision. **Hamzah Nailan Edward** (MSc): software, editing article, formal analysis, and visualization. **Muhammad Taufiq** (B.Eng.): data collection, software, and formal analysis.

All authors have read and agreed to the published version of the manuscript.



Numerical Simulation and Regression-Based Prediction of Rotary Disc Cutter Forces in TBM Rock Cutting

Ebrahim Farrokh^{1*}, Hamid Rokhy², Davood Lotfi²

¹ Amirkabir University of Technology (Tehran Polytechnic), Tehran, Iran.

² R&D division of Tunnel Saz Machine Co., Tehran, Iran.

Abstract

This study introduces a computational framework for estimating disc cutter forces during rotary cutting in Tunnel Boring Machines (TBMs), combining LS-DYNA with a Smoothed Particle Galerkin (SPG) approach and the Riedel–Hiermaier–Thoma (RHT) material model. A total of 58 simulations were performed to examine how cutter forces vary with radial installation position, rock strength, contact area, and cutter spacing. The results demonstrate that normal, rolling, and side forces increase with rock compressive strength and contact interface size, but decrease as the cutter's installation radius grows. Regression analysis based on natural logarithmic transformations yielded predictive equations with high accuracy ($R^2 = 0.80\text{--}0.91$). Each fitted parameter is reported with its standard error and 95% confidence interval, ensuring transparency, reproducibility, and statistical robustness.

Keywords:

Rotary disc cutting; SPG; RHT; Cutter force prediction; Regression-based modelling

1. Introduction

Tunnel Boring Machines (TBMs) play a critical role in contemporary underground construction, especially in hard rock environments where accurate prediction of cutter forces is vital for optimizing machine performance and cutterhead design. The forces acting on disc cutters – normal, rolling, and side – vary significantly across the cutterhead zones (centre, face, and gage), and their precise estimation directly impacts operational efficiency. Predicting TBM performance and advance rates in hard rock conditions remains a significant challenge in tunnelling engineering. Recent empirical and machine-learning approaches have focused on developing models for TBM advance rate prediction and geotechnical risk assessment using field data and geological parameters (Arbabsiar et al., 2020a, 2020b). While these models provide valuable insight into overall TBM performance metrics, they do not address the fundamental mechanics of individual cutter forces at specific radial positions on the cutterhead – a critical gap for detailed cutterhead design optimization.

Traditionally, key design parameters such as cutter spacing and penetration rate have been derived from large-scale linear cutting tests, which are instrumental in

elucidating rock cutting dynamics. These tests offer valuable insight into the interaction between rock and cutting tools, enabling performance optimisation across diverse geological conditions (Entacher & Lassnig, 2012; Farrokh et al., 2015; Thyagarajan & Rostami, 2024; Pan et al., 2021). However, linear tests fail to replicate the rotary motion of actual TBM cutterheads, where circular trajectories influence chip formation and force distribution – introducing limitations when extrapolating linear test results to rotary cutting scenarios.

Although rotary cutting experiments have been conducted, they remain limited and often differ markedly from field conditions. For instance, the continuous rotary cutting tests by Geng et al. (2017, 2024) differ fundamentally from real-world operations. Recent studies (Deng et al., 2024; Huang et al., 2024; Zhang et al., 2024; Palassi et al., 2025) confirm that cutter forces vary with rotation radius, yet comprehensive predictive models that account for radial position remain underdeveloped.

Given the high cost and complexity of physical testing, numerical modelling has emerged as a powerful tool for investigating rock-cutter interactions. The Finite Element Method (FEM) is particularly favored for its ability to accommodate material heterogeneity, nonlinearity, and complex boundary conditions (Jaime, 2011; Yu, 2005). Advanced three-dimensional FEM models have successfully simulated complete cutting processes, including crack initiation, propagation, and chip forma-

* Corresponding author: Ebrahim Farrokh

e-mail address: e.farrokh@aut.ac.ir

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tion, with cutting force deviations as low as 7–11% compared to laboratory results (Jaime, 2011; Khosravi et al., 2021). Understanding rock fracture mechanisms under dynamic loading is crucial for accurate cutting simulations, with recent discrete element modelling demonstrating the importance of discontinuities and micro-parameters in controlling fracture patterns and strength properties (Hajibagherpour et al., 2020; Aftabi & Ahangari, 2023). These models facilitate parametric studies on factors such as cutting speed, bit geometry, confining stress, and pore pressure (Yu, 2005; Tulu, 2009), offering valuable insight for improving drilling performance and equipment design while minimizing reliance on costly experiments. Nonetheless, many existing approaches simplify the cutting problem into two-dimensional indentation models or fail to capture the full dynamics of three-dimensional rotary cutting. One note to consider is that in underground excavation environments, in-situ stress conditions significantly affect rock failure behaviour (Moomivand et al., 2022), though the present study focuses specifically on intact rock cutting under controlled conditions to establish fundamental force relationships.

Recent advancements in 3D dynamic simulations have further enhanced TBM disc cutting analysis. Wang et al. (2010) utilized ANSYS/LS-DYNA to simulate dual disc cutters cutting soft rock, examining phase angle effects and stress field distributions. These specialized platforms enable detailed modelling of fracture propagation and material failure under dynamic loading. Xu et al. (2022) validated discrete element models against full-scale linear cutting tests, demonstrating effective estimation of specific energy. Tan et al. (2013) contributed by developing 3D FEM models in Abaqus to simulate cutter kinematics during wear, incorporating failure mechanisms and achieving experimental verification.

Mesh-free methods, particularly Smoothed Particle Hydrodynamics (SPH), have shown promise in modelling large deformations during cutting. Jeong et al. (2013) applied SPH in AUTODYN-3D to simulate TBM disc cutter rock interaction, achieving cutting force predictions within 10% of experimental values and accurately determining optimal cutter spacing. Traditional Lagrangian methods often suffer from element distortion and reliance on erosion-based approaches, which compromise accuracy under large deformation. Mesh-free algorithms like SPH and Smoothed Particle Galerkin (SPG) improve stability and realism by avoiding erosion dependence. Discrete element methods, such as particle flow code, have also been effective in simulating rock fragmentation, with validation against linear cutting tests on Colorado red granite showing strong correlation in cutting coefficients and specific energy estimates (Xu et al., 2022).

Despite these advances, no existing numerical framework provides force estimation formulas that incorpo-

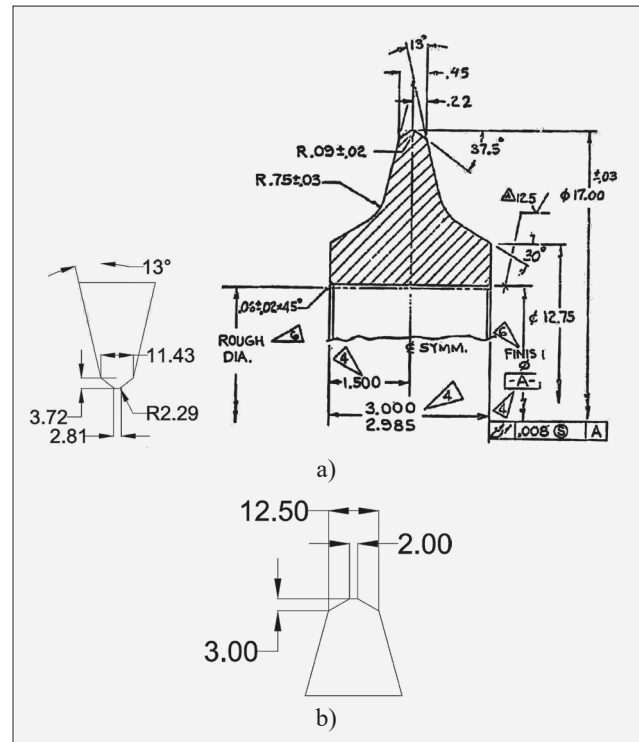


Figure 1: Cross-sectional geometries of the disc cutters used in the simulations: (a) 17-inch disc profile based on Colorado red granite cutting tests (Rostami, 1997); (b) 12-inch disc tip design from Tunnel Saz Machine Co. All dimensions are presented in millimetres.

rate radial cutter position across all cutterhead zones. Industry models such as the CSM model (Schlicke et al., 2024; Ko et al., 2014; Rostami, 1997) and field-based approaches (Farrokh, 2022; Salimi et al., 2022; Armaghani et al., 2021) continue to rely on linear cutting data, overlooking the complexities of rotary cutting.

To address this gap, Tunnel Saz Machine Co. initiated the development of a rotary cutting simulation framework using LS-DYNA, integrating the SPG mesh-free algorithm with the RHT material model. This hybrid approach applies SPG to the disc-rock interaction zone and Lagrangian elements to the bulk rock volume, balancing computational efficiency with modelling accuracy. Focusing on intact rock, the study aims to derive regression-based formulas for predicting normal, rolling, and side forces as functions of radial position, contact area, and rock strength. Unlike existing empirical models that focus primarily on advance rate prediction and overall TBM performance assessment (Arbabsiar et al., 2020a; Zhou et al., 2023), this research provides detailed force predictions for individual cutters at specific radial locations, enabling more precise cutterhead design optimisation and cutter layout planning. These findings offer a novel pathway for enhancing TBM cutterhead design and performance forecasting in rotary cutting environments. It is important to note that the simulation framework adopted here – including the SPG domain configuration, RHT material parameters, and

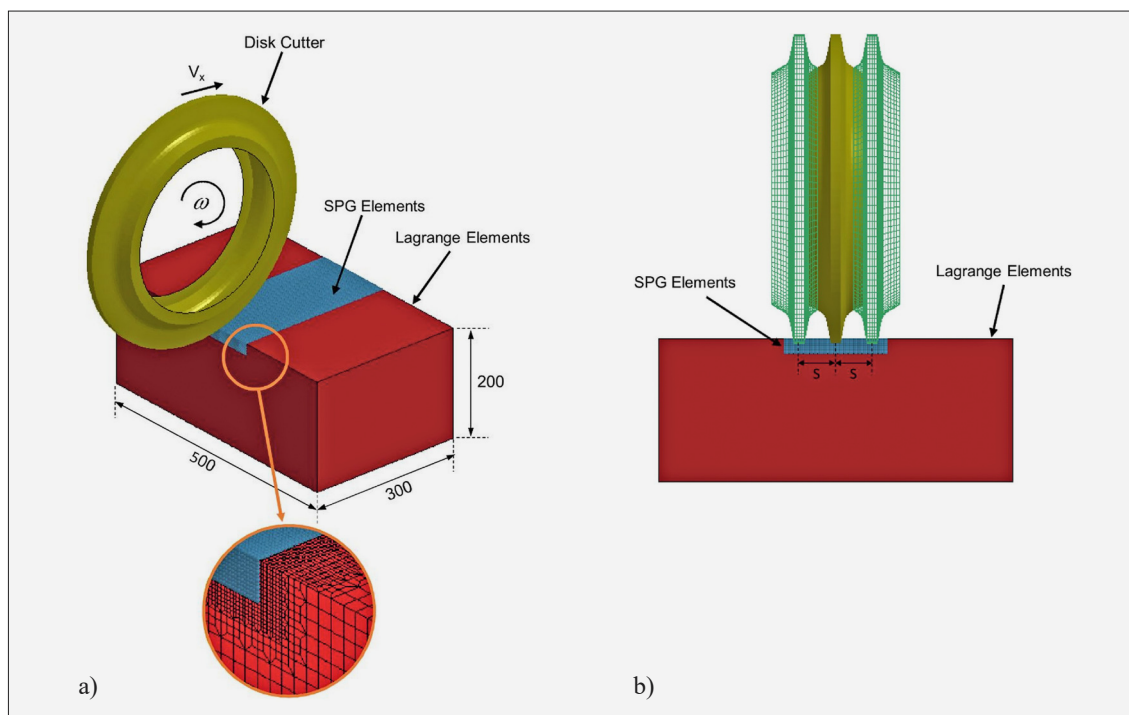


Figure 2: Configuration of the LS-DYNA rotary cutting simulation model: (a) three-dimensional view showing the cutter disc and rock block with dimensions in millimetres; (b) front view illustrating the targeted application of the SPG algorithm in the disc-rock interaction zone.

LS-DYNA strategy – builds directly upon the validated modelling approach presented by **Farrokh et al. (2024a, 2024b)**, which demonstrated strong agreement with experimental cutting tests on Colorado red granite. As such, the current study extends a previously benchmarked setup to a broader parametric space, ensuring the reliability and applicability of the presented regression models.

2. Numerical modelling

2.1. Disc profiles

The numerical analyses incorporated two distinct disc cutter geometries to reflect real-world cutting conditions. The first profile corresponds to a 17-inch disc (model A30581), previously utilized in linear cutting experiments on Colorado red granite at the Colorado School of Mines (**Rostami, 1997**). The second profile represents the tip geometry of a 12-inch disc developed by Tunnel Saz Machine Co., designed for rotary cutting applications. The cross-sectional geometries of both discs, with dimensions given in millimetres, are shown in **Figure 1**. These geometries were selected to capture the influence of cutter size and tip configuration on force generation during rotary interaction with rock.

2.2. Computational method

The LS-DYNA platform offers several computational strategies for simulating dynamic interactions, including

the Lagrange method, Smoothed Particle Hydrodynamics (SPH), and Smoothed Particle Galerkin (SPG). Each approach has distinct advantages depending on the deformation scale and complexity of the modelled process.

- The Lagrangian method, while widely used in finite element analysis, can yield inaccurate results in high-deformation scenarios due to its reliance on erosion-based element deletion. This limitation affects the fidelity of rock-cutting simulations, where material failure and fragmentation are critical.
- SPH, introduced in the late 1970s, replaces traditional mesh structures with discrete particles, enabling effective modelling of large deformations and irregular geometries. However, SPH demands substantial computational resources and poses challenges in defining boundary conditions.
- SPG builds upon SPH by incorporating Galerkin formulations, enhancing numerical stability – particularly under tensile loading – and improving accuracy in simulating brittle material behaviour. Recent applications of SPH and SPG in rock mechanics have demonstrated their effectiveness in capturing complex fracture processes (**Jeong et al., 2020; Wicaksana et al., 2021**).

Farrokh et al. (2024b) showed that mesh-free methods like SPH and SPG outperform erosion-dependent Lagrangian models in simulating rock cutting. Their study revealed a 100% variation in cutting force predictions when the erosion threshold was adjusted from 0.1 to 0.15 in Lagrange-based simulations of Colorado red granite.

Considering these factors, the SPG algorithm was selected for modelling the disc–rock interaction zone, where accurate force prediction is essential. To balance precision with computational efficiency, a hybrid configuration was adopted: Lagrange elements were used for the bulk rock volume, while SPG particles were applied to the region directly influenced by the cutter – defined as three times the penetration depth and three times the cutter spacing in width.

The final simulation setup, highlighting the targeted use of SPG in critical zones to enhance modelling accuracy without incurring excessive computational cost, is shown in **Figure 2**.

2.3. Constitutive material model

To simulate the mechanical behaviour of rock under dynamic cutting conditions, the Riedel-Hiermaier-Thoma (RHT) model was selected within LS-DYNA. This advanced plasticity-based damage model is specifically designed for brittle materials such as concrete and rock (Riedel et al., 2009). It incorporates three distinct strength surfaces – yield, failure, and residual – that collectively describe the material's response from initial loading through complete degradation.

- **Yield Surface:** Marks the onset of plastic deformation, constrained by a cap to ensure volumetric consistency.
- **Failure Surface:** Defines the threshold at which damage begins to accumulate.
- **Residual Surface:** Represents the fully degraded state, where strength is governed by residual parameters.

The model also accounts for strain rate sensitivity, enabling accurate simulation of dynamic loading scenarios (Tu and Lu, 2009). The elastic limit surface is scaled from the failure surface using a pressure-dependent factor and a parabolic cap function, as shown in **Figure 3** (Tu and Lu, 2009; Riedel et al., 2009). The post-failure behaviour is modelled using a damage factor D , which interpolates between the failure and residual surfaces (Chen, 1982).

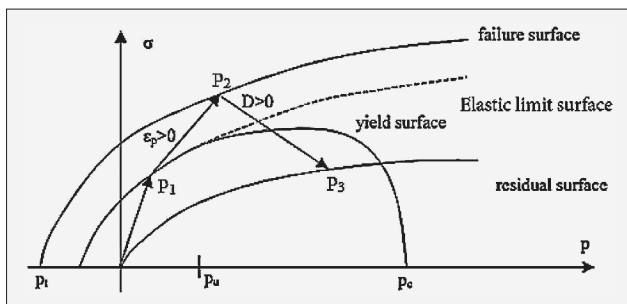


Figure 3: Representation of the RHT model's strength surfaces – yield, failure, and residual – illustrating the material's progressive response under loading and damage accumulation (adapted from Tu and Lu, 2009).

Table 1: Input parameters for the Riedel-Hiermaier-Thoma (RHT) material model used to simulate Colorado red granite behaviour in LS-DYNA, adapted from Xie et al. (2017)

Parameter	Value	Parameter	Value
Density (kg/m ³)	2660	NP	3.0
ALPHA	0	EOC	3E-5
PEL (MPa)	125	EOT	3E-6
PCO (GPa)	6.0	EC	3E+25
A ₁ (GPa)	25.7	ET	3E+25
A ₂ (GPa)	37.84	BETAC*	0.026
A ₃ (GPa)	21.29	BETAT**	0.007
B ₀	1.22	PTF	0.001
B ₁	1.22	GC*	0.53
T ₁ (GPa)	25.7	GT*	0.7
T ₂	0.0	EPSF	2.0
SHEAR (GPa)	21.9	XI	0.5
FC (MPa)	158	D ₁	0.04
FT	0.04	D ₂	1.0
FS	0.21	EPM	0.015
A	2.44	AF	0.25
N	0.76	AN	0.62
Q0	0.68	GAMMA	0.0
B	0.05		

* Exponent for compressive strain rate sensitivity

** Exponent for tensile strain rate sensitivity

For this study, material parameters for Colorado red granite were adopted from Xie et al. (2017), as summarized in **Table 1**. These values enable accurate representation of the rock's strength and deformation characteristics under rotary cutting loads.

3. Numerical analysis plan for the rotary cutting tests

To investigate the mechanical response of disc cutters under rotary cutting conditions, a comprehensive simulation matrix was developed. The analyses focused on key parameters known to influence cutter forces, including rock strength, cutter geometry, penetration depth, spacing, and radial installation position.

The rock's uniaxial compressive strength (UCS) was varied across four representative values: 50, 70, 115, and 158 MPa. Two disc diameters – 17 inches and 12 inches – were selected based on industry-standard configurations (see **Figure 1**). Cutter tip widths of 12.5 mm and 20 mm were included to assess contact mechanics. Penetration depths ranged from 4 to 12 mm, while cutter spacing was set at 25, 51, and 76 mm. Radial positions on the cutterhead were modelled at 250, 500, and 1000 mm to capture zone-specific force variations.

The simulations computed three primary force components acting on the disc cutter: normal force (F_n), roll-

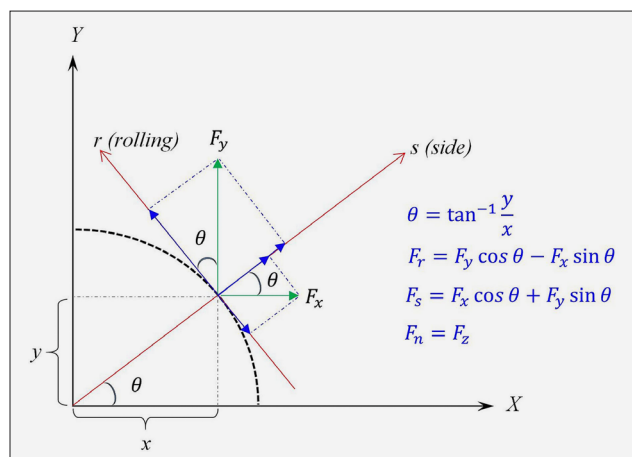


Figure 4: Force component calculation in rotary cutting simulations: transformation between the global coordinate system (X, Y, Z) and the disc-attached local system (r, s, n), with the dashed curve representing the cutter's rotational path

ing force (F_r), and side force (F_s). These were derived by resolving the interaction forces between the disc and rock within two coordinate systems: a fixed global frame (X, Y, Z) and a rotating local frame attached to the disc (r, s, n). The transformation between these systems, with the dashed curve representing the cutter's trajectory and the Z/n axes oriented perpendicular to the cutting plane, is shown in **Figure 4**.

3.1. Results of numerical analyses

The rotary cutting simulations produced detailed force data across a wide range of input conditions. Each analysis yielded values for normal force (F_n), rolling force (F_r), and side force (F_s), corresponding to specific combinations of cutter geometry, penetration depth, spacing, radial position, and rock strength.

To quantify the contact interface between the disc and rock, the contact area (A_{con}) was calculated using a graphical method. This involved analysing cutter inden-

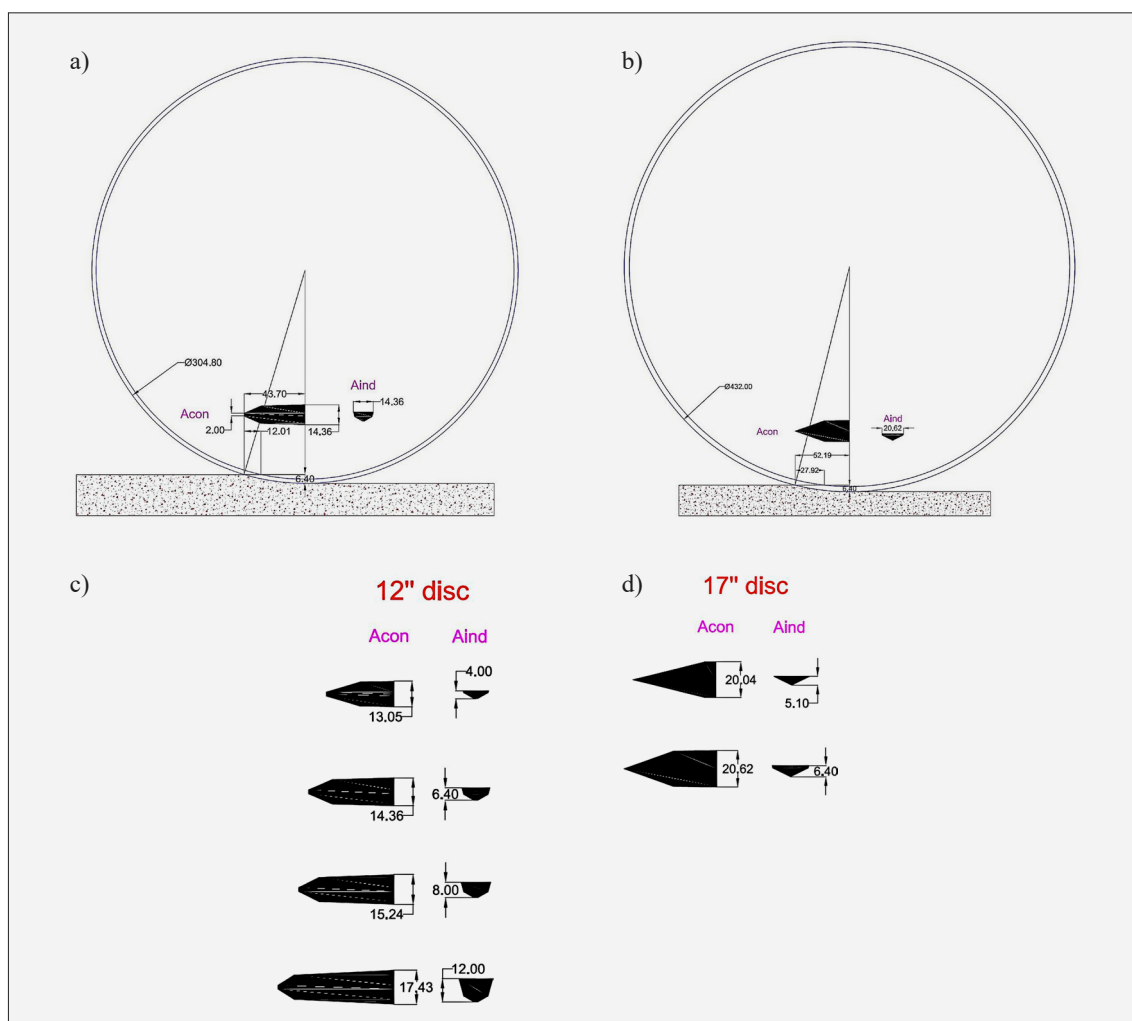


Figure 5: Variation in contact and indentation areas for 12-inch and 17-inch disc cutters at different penetration depths, used to determine cutter-rock interface geometry: (a) example of contact and indentation areas for the 12-inch disc; (b) example of contact and indentation areas for the 17-inch disc; (c) variation of contact and indentation areas for the 12-inch disc; (d) variation of contact and indentation areas for the 17-inch disc

Table 2: Summary of rotary cutting simulation results: input parameters and corresponding normal (Fn), rolling (Fr), and side (Fs) forces, along with calculated contact area (Acon) for each test case

Numerical analysis No.	UCS (MPa)	Cutter diameter (mm)	Spacing (mm)	Penetration (mm)	Radial position (mm)	Fn (kN)	Fr (kN)	Fs (kN)	Acon (mm ²)
1	158	305	25	6.4	1000	106.9	12.3	6.6	513
2	158	305	51	6.4	1000	135.5	14	8	513
3	158	305	76	6.4	1000	154.8	20.9	10.2	513
4	158	305	25	6.4	500	100.6	20.1	10.9	513
5	158	305	51	6.4	500	120.9	22.7	11.6	513
6	158	305	76	6.4	500	128.3	25.3	15.6	513
7	158	305	25	6.4	250	94.9	21.4	14	513
8	158	305	51	6.4	250	110.7	25.2	18.3	513
9	158	305	76	6.4	250	115.1	26.6	21.5	513
10	158	432	25	6.4	1000	143.1	16.1	8.1	772
11	158	432	51	6.4	1000	154.3	18.7	9.6	772
12	158	432	76	6.4	3000	160.9	19.8	1.9	772
13	158	432	25	6.4	500	115.2	17.7	12	772
14	158	432	51	6.4	500	121.6	19.6	14.4	772
15	158	432	76	6.4	500	148.3	25.6	17.5	772
16	158	432	25	6.4	250	105	22.3	19.9	772
17	158	432	51	6.4	250	117.7	25.1	22.3	772
18	158	432	76	6.4	250	136.2	27.3	26.1	772
19	158	432	25	5.1	1000	110	13.6	6.6	532
20	158	432	51	5.1	1000	139.5	15.1	8.3	532
21	158	432	76	5.1	1000	159.4	16.9	9.9	532
22	158	432	25	5.1	500	98	15	11.5	532
23	158	432	51	5.1	500	100.5	16.6	13.1	532
24	158	432	76	5.1	500	118.4	18.3	13.3	532
25	158	432	25	5.1	250	90.7	17.5	17.6	532
26	158	432	51	5.1	250	91.8	20.4	18	532
27	158	432	76	5.1	250	107.3	23.1	23.6	532
28	70	305	25	6.4	1000	47.35	8.9	5.1	513
29	70	305	51	6.4	1000	60.05	11.5	6	513
30	70	305	76	6.4	1000	68.59	13	6.8	513
31	70	305	25	6.4	500	46.2	11.3	7.2	513
32	70	305	51	6.4	500	55	14.8	9.3	513
33	70	305	76	6.4	500	59.7	15.7	10.1	513
34	70	305	25	6.4	250	39.6	15	11	513
35	70	305	51	6.4	250	45.5	16.3	12.4	513
36	70	305	76	6.4	250	49.6	17.5	14.6	513
37	70	432	25	6.4	1000	52.5	10	4.5	772
38	70	432	51	6.4	1000	66.59	11.3	5.6	772
39	70	432	76	6.4	1000	76.06	13.1	7	772
40	70	432	25	6.4	500	50.1	10.8	6.9	772
41	70	432	51	6.4	500	55.9	14.9	9.4	772
42	70	432	76	6.4	500	67.3	18	10.5	772
43	50	305	76	4	1000	42.02	10.9	5.8	347
44	50	305	76	12	1000	59.97	20.6	10	702
45	115	305	76	4	1000	96.64	15.9	8.4	347
46	115	305	76	8	1000	121.1	22.6	11.9	607
47	90	305	25	4	1000	52.8	9.5	4.9	347
48	90	305	51	4	500	61.2	12.7	6.8	347
49	130	305	76	4	250	88.4	19.2	11.5	347
50	130	305	25	8	500	108.6	21.5	13.2	607
51	90	305	76	8	3000	72.5	12	1.1	607
52	130	305	76	8	3000	95.8	15.5	1.5	607
53	90	432	25	4	1000	68.4	11.2	6	328
54	90	432	51	4	500	77.9	14.6	8.1	328
55	130	432	76	4	250	110.2	20.8	12.9	328
56	130	432	25	5.1	500	120.7	18.2	11.4	532
57	90	432	76	5.1	3000	98.6	13.5	1.2	532
58	130	432	76	5.1	3000	125.4	17	1.6	532

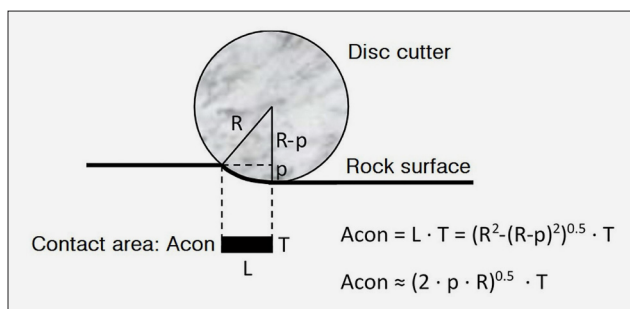


Figure 6: Simplified geometric method for estimating disc-rock contact area (A_{con}), based on cutter tip width, radius, and penetration depth

tation profiles in AutoCAD, accounting for penetration depth and disc diameter. The variation in contact and indentation areas for both 17-inch and 12-inch discs under different penetration scenarios is shown in **Figure 5**.

The outcomes of 58 rotary cutting simulations are summarised in **Table 2**. Each entry reports the input parameters and resulting force components, together with the computed contact area. The results reveal consistent trends: greater UCS and larger contact areas generally lead to increased cutting forces. Conversely, forces tend to decrease as the cutter's radial position increases, owing to reduced curvature-induced resistance.

A simplified geometric approach for estimating the contact area, as expressed in **Equation 1**, is presented in **Figure 6**.

$$A_{con} = T \cdot L = T \cdot (2 \cdot R \cdot p)^{0.5} \quad (1)$$

Where:

- A_{con} – disc contact area (mm^2),
- T – cutter tip width (mm),
- L – horizontal contact area length (mm),
- R – cutter radius (mm),
- p – cutter penetration (mm).

This formulation provides a practical tool for estimating contact area in future parametric studies.

3.2. Simple regression analysis

To explore the influence of individual parameters on disc cutter forces, a series of simple regression analysis were performed. These analyses focused on identifying direct relationships between input variables – such as rock compressive strength, cutter spacing, radial position, and contact area – and the resulting force components: normal (F_n), rolling (F_r), and side (F_s).

The results indicate a strong positive correlation between UCS and normal force, consistent across both 12-inch and 17-inch disc configurations, as shown in **Figure 7**. The coefficient of determination (R^2) was greater than 0.70, confirming the predictive strength of this relationship. This trend aligns with findings from previous cutting studies (Snowdon et al., 1982; Jeong et al., 2023).

Cutter spacing also showed a direct influence on all three force components. As spacing increased, the magnitude of F_n , F_r , and F_s rose accordingly. This pattern was observed for both disc sizes and across different rock strengths, as shown in **Figures 8** through **13**.

The effect of radial installation position on normal force was more complex. Initially, F_n increased with radial distance, peaking around 1000 mm, before declining beyond that point. This behaviour is attributed to the curvature of the cutting path – greater curvature near the centre enhances rolling and side forces, thereby reducing the normal force required for rock breakage, as shown in **Figure 14**.

Contact area (A_{con}) exhibited a modest correlation with normal force, as shown in **Figure 15**. While larger contact areas generally led to higher F_n values, the relationship was weaker than that observed for UCS. No significant correlation was found between A_{con} and the rolling or side forces.

In summary, UCS emerged as the most influential factor in predicting cutter forces, followed by spacing and contact area. Radial position introduced nonlinear effects due to geometric curvature, underscoring the need for multi-variable modelling in rotary cutting simulations.

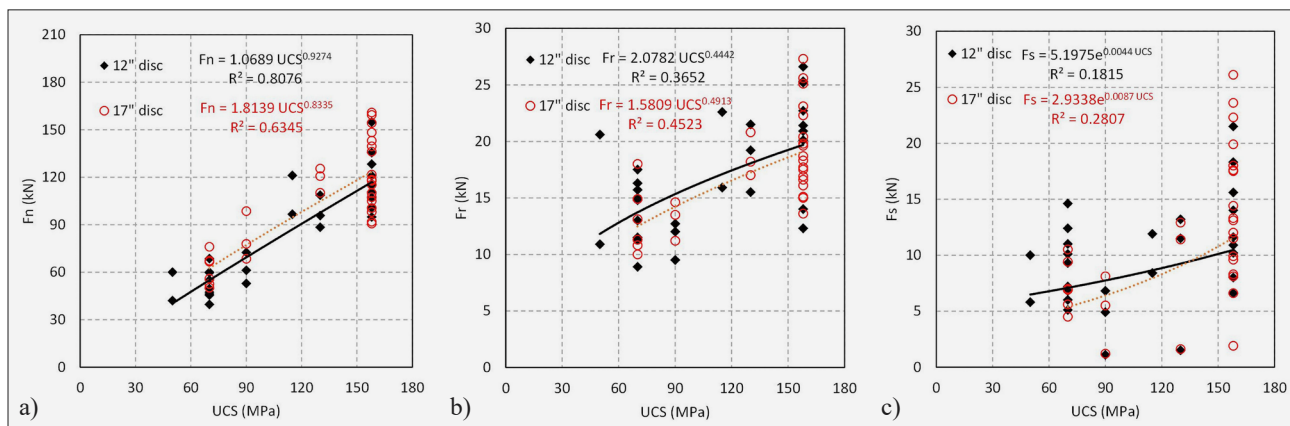


Figure 7: Influence of UCS on disc cutter forces – (a) normal force (F_n), (b) rolling force (F_r), and (c) side force (F_s) – for both 12-inch and 17-inch discs, showing a strong positive correlation

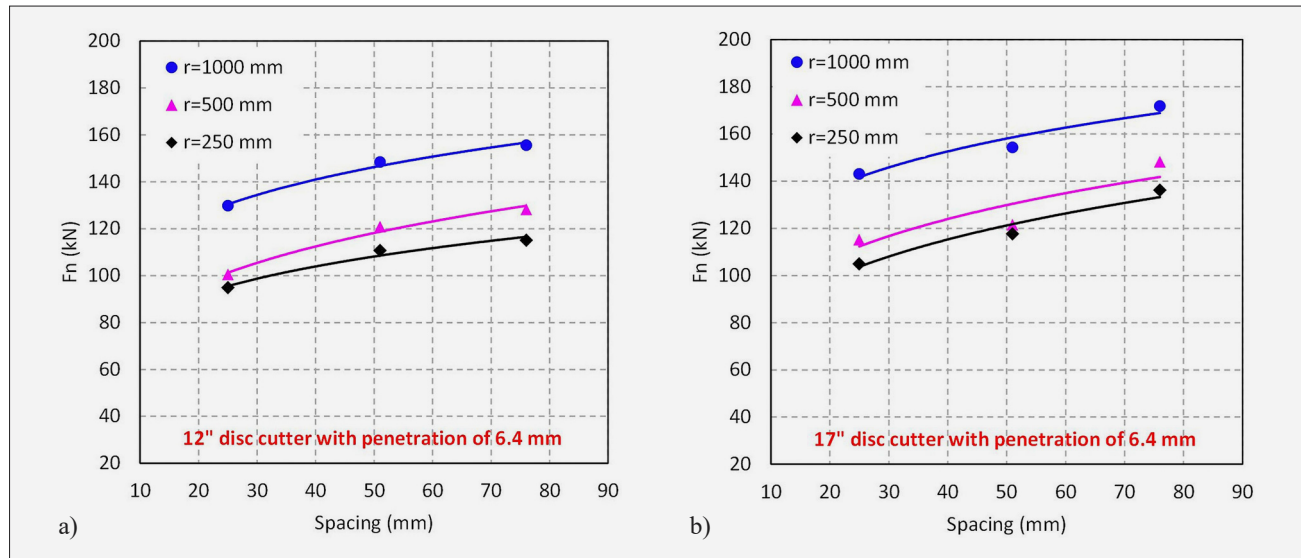


Figure 8: Variation in normal force with cutter spacing and radial position for simulations conducted on rock with a UCS of 158 MPa using (a) 12-inch and (b) 17-inch disc cutters.

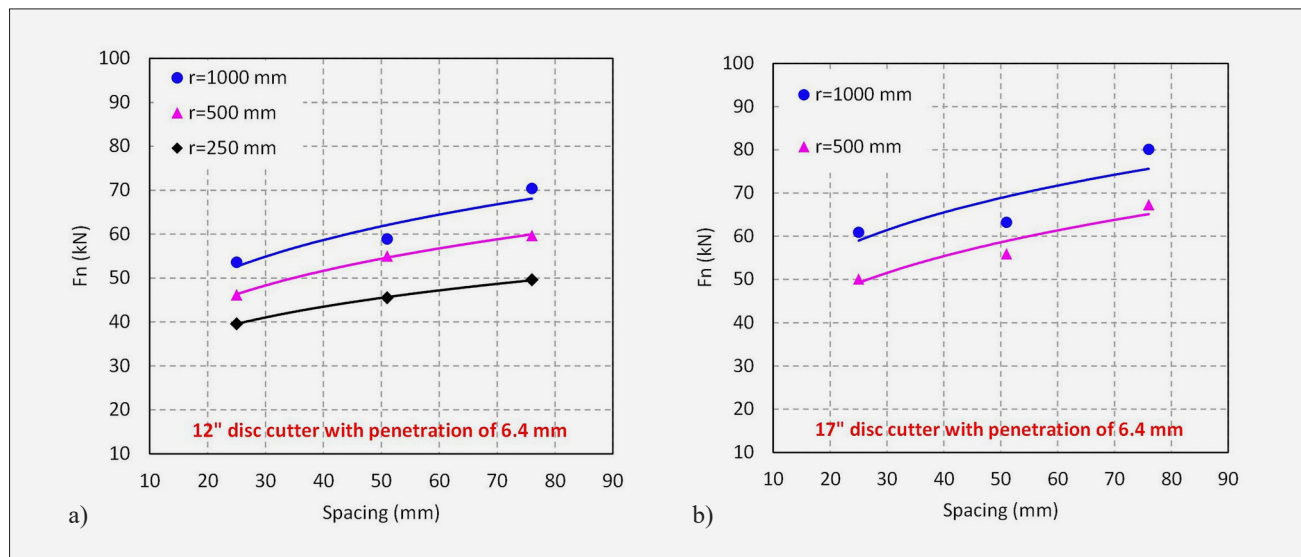


Figure 9: Relationship between cutter spacing, radial position, and normal force for simulations conducted on rock with a UCS of 70 MPa using (a) 12-inch and (b) 17-inch disc cutters.

3.3. Multiple regression analysis

To establish predictive relationships for disc cutter forces under rotary cutting conditions, multiple regression analysis was performed using the dataset generated from 58 validated LS-DYNA simulations. These simulations encompassed a wide range of input parameters, including UCS, cutter–rock contact area (A_{con}), and radial installation position (R), each of which had demonstrated statistical relevance in the preceding single-variable analyses. The objective was to formulate empirical equations for estimating the three primary force components – normal force (F_n), rolling force (F_r), and side force (F_s) – based on these influential variables. This approach enables a more comprehensive understanding

of how geological and geometric factors interact to affect cutter performance in rotary TBM operations.

To strengthen the statistical robustness of the regression models and to meet the assumption of normally distributed residuals, a natural logarithmic transformation was applied to all variables prior to analysis. Linear regression was then performed on the log-transformed data. Although the statistical fitting procedure itself is linear in the transformed space, the back-transformed equations are non-linear in their original form. This approach stabilizes variance, improves the normality of residuals, and linearizes multiplicative relationships during estimation, while ultimately yielding non-linear predictive equations that better capture the complex interactions between geological and mechanical parameters.

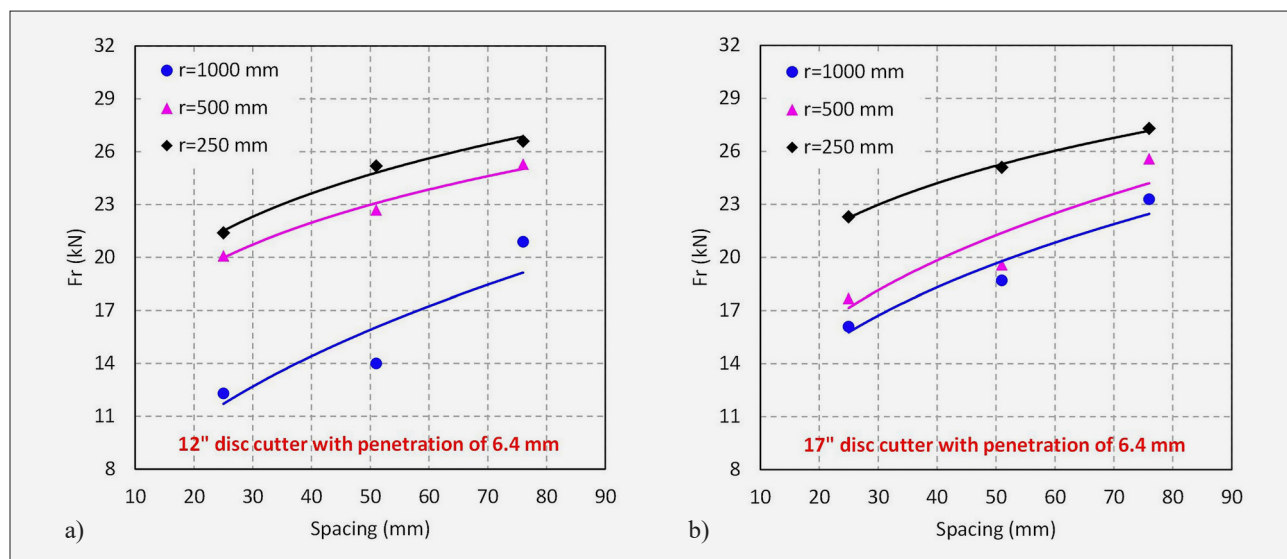


Figure 10: Rolling force trends as a function of cutter spacing and radial position for rock with 158 MPa compressive strength using (a) 12-inch and (b) 17-inch disc cutters

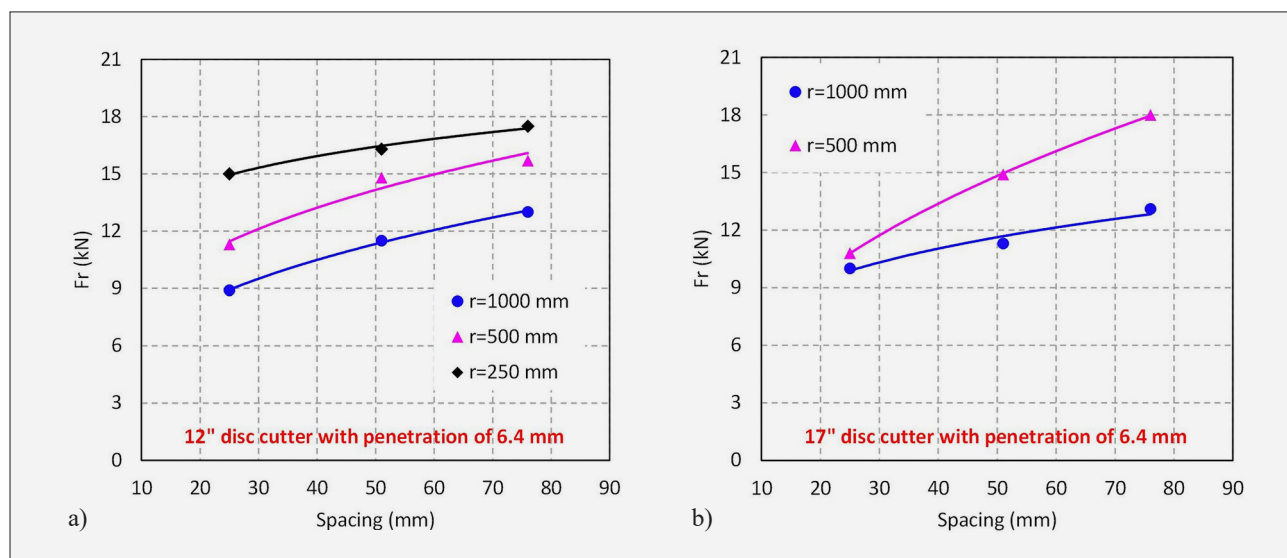


Figure 11: Rolling force variation with spacing and radial location for rock with 70 MPa compressive strength using (a) 12-inch and (b) 17-inch disc cutters

ters. The use of logarithmic transformation followed by linear regression is consistent with established practice in TBM performance modelling, including the development of the Colorado School of Mines (CSM) model (Rostami, 1997).

During the multiple regression process, each input variable was assessed for inclusion based on two statistical thresholds. First, a p-value less than 0.05 was required to confirm a meaningful relationship between the predictor and the corresponding force component, ensuring that the variable contributed significantly to the model. Second, the variance inflation factor (VIF) for each parameter had to remain below 10, which indicates low multicollinearity and confirms that the predictors are not excessively correlated with one another. These

criteria ensured that the final equations were both statistically valid and structurally stable, minimizing distortion from redundant or non-informative variables.

The optimised regression formulas for three key outputs – cutter normal force (F_n), rolling force coefficient (k_r), and side force coefficient (k_s) – are presented in Table 3. These models were developed using the natural logarithms of the target variables – $\ln(F_n)$, $\ln(k_r)$, and $\ln(k_s)$ – to enhance linearity and normalize error distributions. Predictor variables were also log-transformed to maintain consistency and improve model fit. The regression procedure employed both step-forward selection and best-subset evaluation to identify the most statistically robust combinations of predictors for each force component. All coefficients are reported as esti-

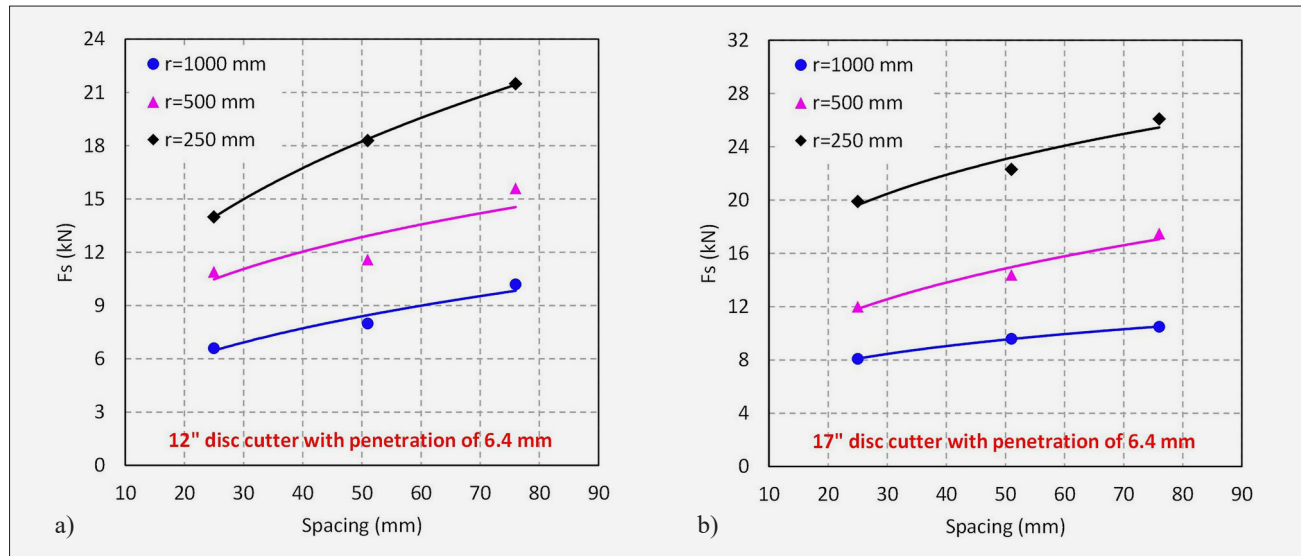


Figure 12: Side force behaviour across different cutter spacings and radial positions for rock with 158 MPa compressive strength using (a) 12-inch and (b) 17-inch disc cutters

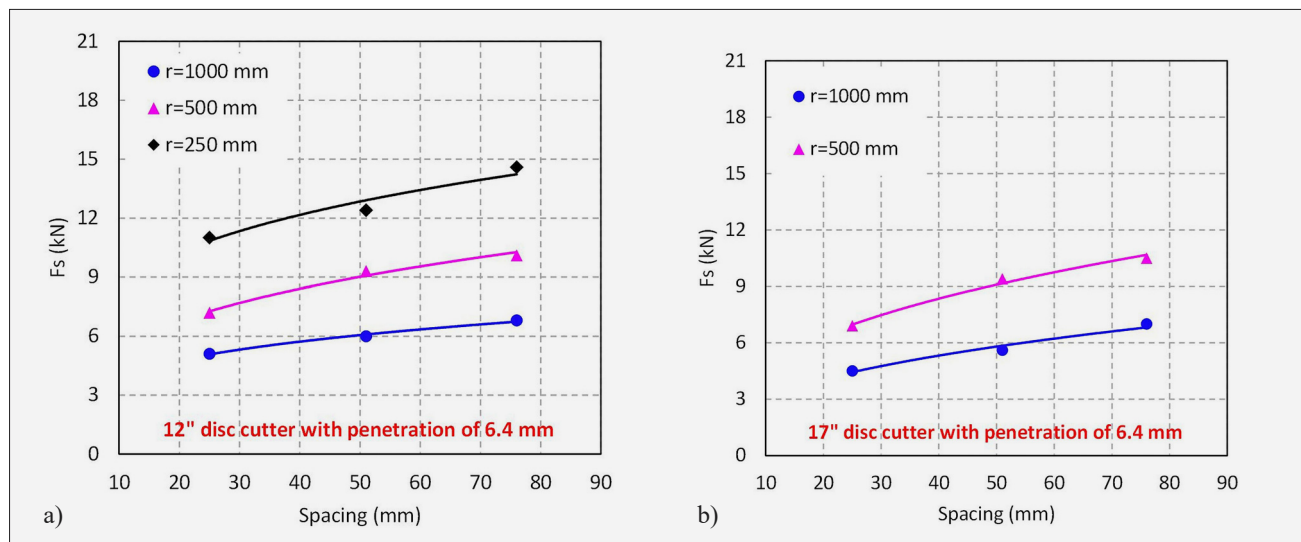


Figure 13: Side force response to spacing and radial placement for rock with 70 MPa compressive strength using (a) 12-inch and (b) 17-inch disc cutters

mates with their standard errors and 95% confidence intervals.

The coefficient of determination (R^2) is calculated by the software using the formula of $R^2 = (TSS - RSS) / TSS$, where TSS denotes the total sum of squares, representing the cumulative squared deviation of observed values from their mean, and RSS is the residual sum of squares, quantifying the squared differences between observed and predicted values. This metric reflects the proportion of variance in the dependent variable explained by the model.

Additionally, the term $(1 - \exp(-0.00872r))$, which appears in the final F_n formula, was extracted from the simple regression analysis of radial position effects, as illustrated in **Figure 14**. This exponential term captures the nonlinear influence of cutter radius on normal force, particularly in the outer zones of the cutterhead.

A direct comparison between the predicted cutting forces – calculated using the regression formulas in **Table 3** – and the actual values obtained from the LS-DYNA simulations is shown in **Figure 16**. The data points align closely with the 1:1 reference line, indicating strong agreement between modeled and observed results. To quantify this agreement, model accuracy was assessed using root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). For normal force (F_n), the regression model achieved RMSE = 17.70 kN, MAE = 13.56 kN, and MAPE = 12.16%; for rolling force (F_r), RMSE = 2.39 kN, MAE = 1.82 kN, and MAPE = 10.73%; and for side force (F_s), RMSE = 1.68 kN, MAE = 1.15 kN, and MAPE = 18.34%. These quantitative results, together with the visual validation in **Figure 16**, confirm the reli-

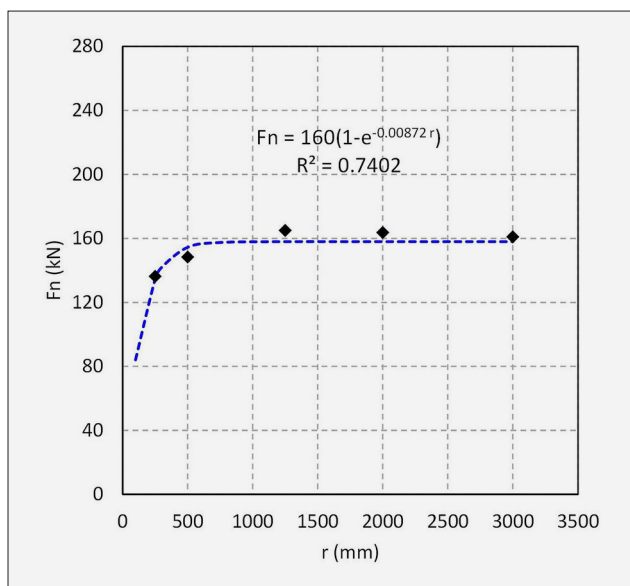


Figure 14: Nonlinear relationship between cutter installation radius and normal force for a 17-inch disc operating in rock with 158 MPa compressive strength

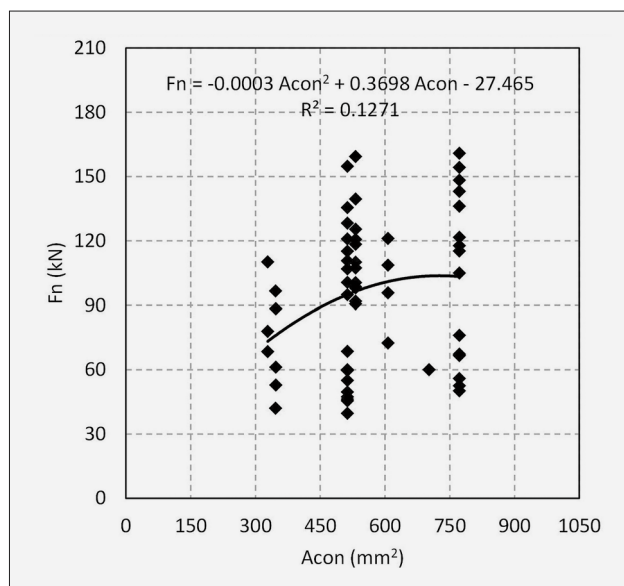


Figure 15: Correlation between disc-rock contact area and normal force, indicating a weaker but positive trend compared to other parameters

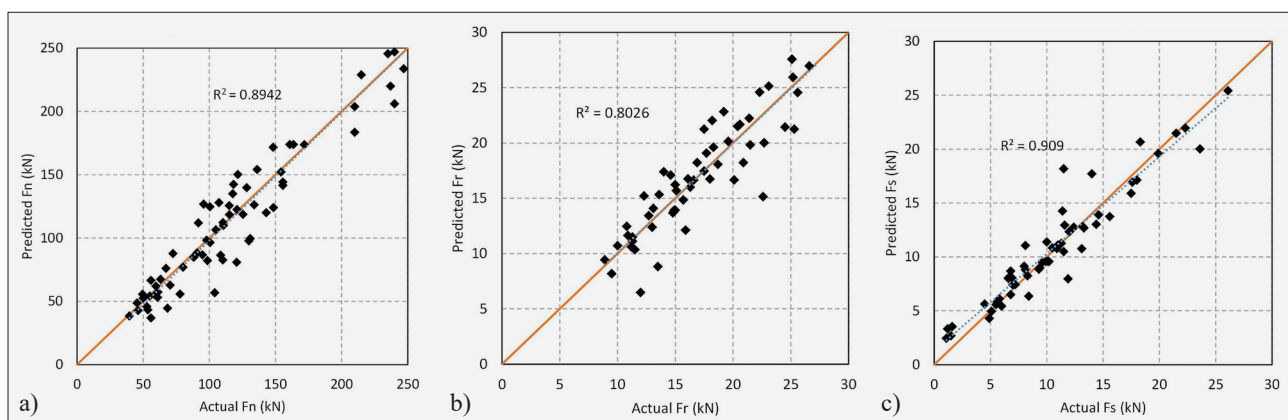


Figure 16: Comparison between predicted cutter forces versus calculated ones using regression formulas – and actual values from LS-DYNA simulations for (a) F_n , (b) F_r , and (c) F_s , showing strong alignment along the 1:1 reference lines.

Table 3: Final regression equations for estimating cutter normal force (F_n), rolling force coefficient (k_r), and side force coefficient (k_s), derived using natural log-transformed variables and stepwise selection methods

No.	Regression formula*	R ²	Parameter Estimates (with SE and 95% CI)
1	$\ln(F_n) = b_0 + b_1 \ln(UCS) + b_2 \ln(A_{con}) + b_3 \ln(S) + b_4 \ln(1 - \exp(-0.00872r))$	0.8942	b_0 : -4.6725 (SE = 0.0119, 95% CI [-4.697, -4.649]) b_1 : 0.9997 (SE = 0.0038, 95% CI [0.992, 1.007]) b_2 : 0.4996 (SE = 0.0030, 95% CI [0.494, 0.506]) b_3 : 0.3316 (SE = 0.0048, 95% CI [0.322, 0.341]) b_4 : 1.0082 (SE = 0.0674, 95% CI [0.892, 1.162])
2	$\ln(k_r) = b_0 + b_1 \ln(UCS) + b_2 \ln(r)$	0.8026	b_0 : 3.8410 (SE = 0.0248, 95% CI [3.791, 3.890]) b_1 : -0.5008 (SE = 0.0072, 95% CI [-0.515, -0.486]) b_2 : -0.4994 (SE = 0.0088, 95% CI [-0.517, -0.482])
3	$\ln(k_s) = b_0 + b_1 \ln(UCS) + b_2 \ln(r)$	0.9090	b_0 : 5.2701 (SE = 0.0365, 95% CI [5.196, 5.342]) b_1 : -0.5002 (SE = 0.0077, 95% CI [-0.516, -0.485]) b_2 : -0.8004 (SE = 0.0054, 95% CI [-0.811, -0.789])

* In these formulas, F_n is cutter normal force in kN, F_r is cutter rolling force in kN, UCS is uniaxial compressive strength of the rock in MPa, A_{con} is the contact area of the disc with the rock in mm², S is cutter spacing in mm, r is the radial position of the cutter in mm, k_r is the cutter coefficient for the rolling force, and k_s is the cutter coefficient for the side force.

Table 4: Measured cutter forces from RCM tests on Korean granite (Shin et al., 2024) and predicted values from regression equations developed in this study.

Penetration (mm)	Radial position (mm)	Fn (RCM) (kN)	Fn predicted (kN)	Fr (RCM) (kN)	Fr predicted (kN)	Fs (RCM) (kN)	Fs predicted (kN)
4	200	235.0	224.90	66	70.35	63.0	59.92
5	200	241.0	239.94	69	72.15	66.0	61.45
4	300	243.0	246.72	67	59.40	43.0	44.80
5	300	248.0	262.20	55	60.62	48.0	45.72
4	600	255.0	256.90	50	44.08	24.3	27.00
5	600	273.4	271.64	45	47.26	22.0	28.95

Table 5: Aggregate error metrics for comparison of predicted and measured forces in RCM tests on Korean granite

Force component	RMSE (kN)	MAE (kN)	MAPE (%)
Fn	6.24	5.33	2.17
Fr	7.84	6.56	10.79
Fs	3.00	2.57	7.03

ability of the regression equations and their applicability for estimating cutter forces under varying geological and geometric conditions.

The formulas presented in **Table 3** are in natural logarithmic format. The power format of these formulas are presented in **Equations 2 to 4**.

$$F_n = 0.009349 UCS A_{con}^{\frac{1}{2}} S^{\frac{1}{3}} (1 - \exp(-0.00872 r)) \quad (2)$$

$$k_r = \frac{F_r}{F_n} = \frac{46.6}{UCS^{\frac{1}{2}} r^{\frac{1}{2}}} \quad (3)$$

$$k_s = \frac{F_s}{F_n} = \frac{194.4}{UCS^{\frac{1}{2}} r^{\frac{4}{5}}} \quad (4)$$

3.4. Validation against RCM tests on Korean granite

To further assess the generality and predictive capability of the proposed regression equations, an additional validation was performed using the full-scale rotary cutting machine (RCM) tests reported by Shin et al. (2024). These experiments were conducted on Hwandeung granite with a uniaxial compressive strength of 205 MPa using a 17-inch disc cutter with a 21 mm tip width, a cutter spacing of 100 mm, and penetration depths of 4 mm and 5 mm. The RCM platform recorded the triaxial cutter forces during rotary cutting at radial positions of 200, 300, and 600 mm, providing an independent dataset for evaluating the performance of the developed force-prediction equations.

The measured normal, rolling, and side forces from the RCM tests together with the corresponding predicted values obtained from **Equations 2 to 4** are reported in **Table 4**. As shown in **Table 4**, the predicted normal forces close-

ly match the experimental values across all radii and penetration depths, with deviations typically below 3%. The rolling force predictions also follow the experimental trend, although slightly higher deviations are observed at larger radii, which is consistent with the higher variability of Fr reported in rotary cutting studies. The predicted side forces reproduce both the magnitude and the decreasing trend with increasing radius, demonstrating that the model captures the radial dependence of lateral loading.

To quantify predictive accuracy, the root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) were computed for each force component using the paired experimental and predicted values reported in **Table 4**. The values presented in **Table 5** represent aggregate statistics calculated across all penetration depths (4 and 5 mm) and radial positions (200, 300, and 600 mm), thereby providing an overall measure of model performance rather than case-by-case results. For the normal force, the RMSE and MAE were 6.24 kN and 5.33 kN, respectively, with a MAPE of only 2.17%, confirming the high reliability of the proposed formulation for Fn. The rolling force yielded RMSE and MAE values of 7.84 kN and 6.56 kN, with a MAPE of 10.79%, which is acceptable given the inherent variability of Fr observed in rotary cutting tests. The side force showed similarly strong agreement, with RMSE and MAE values of 3.00 kN and 2.57 kN and a MAPE of 7.03%, demonstrating that the model reproduces both the magnitude and radial trend of Fs with satisfactory accuracy.

The close agreement between the measured and predicted forces, combined with the consistently low error metrics, confirms that the proposed regression equations are capable of reproducing both the magnitudes and the radial trends of cutter forces observed in full-scale rotary cutting tests. This validation provides strong evidence that the equations can be reliably applied in practice for cutterhead layout optimization, accurate force estimation, and performance prediction in hard-rock TBM tunnelling.

4. Discussion

The results of the rotary cutting simulations and regression analyses provide valuable insight into the me-

chanical behaviour of disc cutters under varying geological and geometric conditions. By adopting an ln-linear regression framework, the present study ensures that the power-law relationships of influential parameters and cutter forces are captured transparently. The narrow confidence intervals observed for most coefficients confirm the stability of the ln-linear models, while wider intervals for radial effects highlight areas requiring further data expansion. The empirical models demonstrate that UCS is the most influential parameter across all force components, particularly for normal force (F_n), where its contribution is both statistically and physically dominant. This finding is consistent with established cutting theories and prior experimental studies (Snowdon et al., 1982; Rostami, 1997; Jeong et al., 2023). In the dataset, F_n values increased from 42 kN at UCS = 50 MPa to over 160 kN at UCS = 158 MPa, confirming the strong positive correlation observed in Figure 7.

The inclusion of contact area (A_{con}) and radial installation position (r) in the regression models enhances predictive capability. While A_{con} contributes positively to all force components, its effect is secondary compared to UCS. For example, increasing penetration from 4 mm to 12 mm expanded A_{con} from 347 mm² to 702 mm², raising F_n from 42 kN to nearly 60 kN (Table 2, analyses 43–44). The influence of radial position is more nuanced: F_n decreases as the cutter's installation radius decreases, whereas F_r and F_s increase owing to the reduced radius of curvature. This behaviour is captured effectively by the exponential term ($1 - \exp(-0.00872R)$), which reflects the nonlinear relationship between cutter radius and normal force (see Figure 14). The use of logarithmic transformation in the regression process further stabilised variance and improved model fit, producing equations that offer practical tools for estimating cutter forces in rotary TBM operations. Their accuracy was validated through comparison with simulation outputs, as shown in Figure 16, where predicted values closely matched actual results.

The regression-based force prediction formulas demonstrate strong agreement with recent full-scale rotary cutting tests. Huang et al. (2024) and Deng et al. (2024) reported that normal forces increase with cutting radius in granite, while side forces exhibit more complex behaviour. The simulations presented here captured the transition of side forces from higher values near the centre to reduced magnitudes at larger radii, consistent with those observations. The incorporation of radial position as a primary variable distinguishes this work from previous CSM-based models. Zhang et al. (2024) proposed modifications to the CSM model incorporating installation radius and synergistic effect factors using MatDEM simulations, but their calibration relied primarily on linear cutting data. In contrast, the SPG-based rotary cutting simulations presented here provide a direct representation of the circular trajectories experienced by disc cutters during TBM operation, producing validated regression formulas across 58 scenarios.

This study also advances numerical modelling approaches by applying the SPG mesh-free method to large-radius rotary cutting. Previous FEM-SPH studies (Geng et al., 2022; Xiao et al., 2017) primarily focused on dual-cutter interaction or small-radius rotary cutting. The validated SPG framework successfully simulated single-cutter rotary cutting at radii up to 3000 mm, bridging the gap between laboratory linear cutting tests and full-scale TBM cutterhead operation. Unlike previous models that primarily emphasize normal and rolling forces, the regression equations developed in this study predict all three force components – normal, rolling, and side – individually for both the center and face zones. This comprehensive formulation provides the complete force state required for cutterhead structural analysis and cutter bearing selection. The force components associated with the gauge area are inherently more complex and have been addressed in detail by Farrokh et al. (2024a).

The importance of proper material model calibration is well documented in rock mechanics. Hajibagherpour et al. (2020) demonstrated that discontinuities significantly affect fracture patterns around blastholes, while Aftabi and Ahangari (2023) showed that micro-parameters in particle flow code models critically influence predicted strength properties. The use of the RHT material model with parameters validated against Colorado red granite cutting tests (Xie et al., 2017; Farrokh et al., 2024b) ensured that the material response – including tensile cracking, compressive crushing, and strain-rate effects – was accurately represented in the rotary cutting simulations.

Several recent studies have addressed disc cutter wear prediction, highlighting that wear increases contact area and alters force distribution (Sabri & Goshtasbi, 2024; Wang et al., 2024). The force prediction formulas developed in this study were derived for sharp (unworn) cutters operating in intact rock, thereby establishing a baseline against which force variations induced by cutter wear can be quantitatively assessed. Future extensions could incorporate contact area growth due to wear, building upon the fundamental relationships established in this study. These findings have direct implications for cutterhead design and performance forecasting. By quantifying the influence of UCS, contact geometry, and cutter placement, cutter layout can be optimised to balance force distribution, reduce wear, and improve excavation efficiency. Moreover, the regression models can serve as input for higher-level TBM performance simulations, integrating geological variability with mechanical response.

It is important to recognize that field TBM cutting occurs under in-situ stress conditions that influence rock fracture behavior. Moomivand et al. (2022) demonstrated that the prevailing stress state has a significant impact on excavation stability. The present focus on intact rock under unconfined conditions establishes funda-

mental force relationships that serve as a baseline for future investigations incorporating confining stress effects. The modular structure of the regression formulas further facilitates extensions to include in-situ stress as an additional variable. Beyond stress considerations, subsequent research may also address cutter tip geometry, rock anisotropy, and dynamic loading conditions. Machine learning approaches could be explored to capture nonlinear interactions that extend beyond the capabilities of traditional regression.

Overall, this study introduces the first regression-based force prediction formulas that explicitly integrate radial position, contact area, and rock strength across center and face cutterhead zones. The application of the SPG mesh-free method to large-radius rotary cutting enables accurate simulation of single-cutter trajectories up to 3000 mm, thereby bridging the gap between laboratory-scale linear cutting tests and full-scale TBM operation. The comprehensive prediction of normal, rolling, and side forces provides the complete force state required for cutterhead structural analysis and bearing design. These contributions extend beyond the limitations of linear cutting test data, directly supporting engineering tasks such as cutter layout optimization, torque and thrust estimation, and bearing capacity verification. The study thus establishes a robust foundation for data-driven cutter force estimation and cutterhead design in hard rock tunnelling.

5. Conclusions

This study has presented a systematic numerical investigation into the rotary cutting behaviour of disc cutters, combining LS-DYNA simulations with regression-based modelling. A total of 58 simulation cases were examined, encompassing variations in rock strength, cutter geometry, penetration depth, spacing, and radial installation position. The RHT constitutive model was employed to represent the mechanical response of Colorado red granite under dynamic loading, enabling a realistic depiction of rock fragmentation and force generation.

The findings confirm that UCS is the dominant factor influencing cutter forces, particularly the normal force (F_n). Contact area and radial installation position also exert significant effects, with radial variation introducing nonlinear behaviour attributable to changes in curvature and velocity gradients across the cutterhead. Multiple regression analyses produced predictive equations for F_n , F_r , and F_s , with coefficients of determination (R^2) exceeding 0.80, thereby demonstrating strong statistical reliability.

The final regression formulas, derived through natural logarithmic transformations and validated against simulation data. These models support cutterhead layout optimisation, performance forecasting, and parametric sensitivity studies in hard-rock tunnelling. Notably, the

exponential term introduced for radial influence improves the accuracy of F_n prediction by capturing geometric effects that are not addressed in conventional linear cutting models.

Future research should extend this framework by incorporating additional variables such as cutter tip shape, rock anisotropy, and dynamic tool-rock interactions. Integration with machine-learning techniques may further enhance predictive accuracy and adaptability across diverse geological conditions. Overall, the methodology and results contribute to advancing reproducible, data-driven approaches for cutterhead design and performance modelling in mechanised tunnelling.

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Data Availability

No data has been used or produced during the preparation of this manuscript.

Competing interests

The contact author has declared that none of the authors have any competing interests.

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SAŽETAK

Numerička simulacija i regresijska procjena sila na rotacijskim diskovima pri rezanju stijena TBM-om

U ovome radu predstavljen je računalni postupak za procjenu sila na reznim diskovima tijekom rotacijskoga rezanja pri radu strojeva za bušenje tunela (TBM). koji objedinjuje programski paket LS-DYNA s metodom zaglađenih čestičnih Galerkinovih funkcija (SPG) te materijalnim modelom Riedel–Hiermaier–Thoma (RHT). Provedeno je ukupno 58 numeričkih simulacija kako bi se ispitaio utjecaj radijalnoga položaja ugradnje rezača, čvrstoće stijene, dodirne površine i razmaka između rezača na intenzitet sila. Rezultati pokazuju da normalne, kotrljajuće i bočne sile rastu s porastom tlačne čvrstoće stijene i povećanjem kontaktne površine, dok se smanjuju s povećanjem radijusa ugradnje rezača. Regresijskom analizom temeljenom na prirodnim logaritamskim transformacijama dobivene su jednačbe za procjenu sila visoke točnosti ($R^2 = 0,80 - 0,91$). Za svaki prilagođeni parametar prikazana je standardna pogreška te interval pouzdanosti od 95 %, čime se osigurava transparentnost, ponovljivost i statistička utemeljenost rezultata.

Ključne riječi:

rezanje rotacijskim diskom, SPG, RHT, regresijska procjena sila rezača, regresijsko modeliranje

Author's contribution

Ebrahim Farrokh (Associate Professor): conceptualization, methodology, data analysis, writing, reviewing and editing. **Hamid Rokhy** (Research Engineer): methodology, numerical analysis, reviewing and editing. **Davood Lotfi** (R&D director): methodology, reviewing and editing. All authors have read and agreed to the published version of the manuscript.

Shear wave modelling from conventional well logs using integrated deep learning Integrated Convolutional Neural Network (I-CNN)

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Original scientific paper



Rahmat Catur Wibowo^{1*}✉, Ida Bagus Suananda Yogi²✉, Indra Arifianto³✉, Muh Sarkowi⁴✉

¹ Geological Engineering, Universitas Lampung, Sumantri Brojonegoro No.1, Lampung, 35145, Indonesia.

² Centre for subsurface Imaging, Universiti Teknologi Petronas, Seri Iskandar 32610, Perak, Malaysia.

³ Earth Resources Engineering Department, Faculty of Engineering, Kyushu University, Fukuoka, 819-0395, Japan.

⁴ Geophysical Engineering, Universitas Lampung, Sumantri Brojonegoro No.1, Lampung, 35145, Indonesia.

Abstract

Shear-wave velocity (V_s), together with compressional wave velocity, provides a crucial source of information for both geomechanical and geophysical studies. V_s data are often unavailable. Moreover, direct measurement of V_s remains relatively costly. Four machine learning algorithms were created to predict V_s from traditional well logs in order to get around these restrictions: Probability Neural Network (PNN), Multilayer Feed-Forward Neural Network (MLFFNN), Deep Feed-Forward Neural Network (DFFNN), one-dimensional Convolutional Neural Network (1D-CNN), and an Integrated Convolutional Neural Network (I-CNN). The dataset consists of two wells (19,121 data points were gathered) of authentic industrial wireline logs from two anonymized wells, provided with formal authorization from the data owner exclusively for academic research purposes, including model training, testing, and validation. There were three primary parts in the methodology: (1) pre-processing the data to get rid of noise and change it into the right format; (2) using domain knowledge to drive feature engineering and selection; and (3) training, testing, and optimizing the model. The results demonstrated that the I-CNN model in RCW-1 well achieved the best performance, with an R^2 value of 0.971. When applied to the blind well (RCW-2), the I-CNN model maintained strong generalization capability, achieving an average R^2 value of 0.956. These findings indicate that the I-CNN outperforms other methods in handling complex, non-linear relationships in V_s prediction. Overall, this study contributes to the growing body of literature on machine learning applications in petrophysical analysis by introducing an integrated deep learning framework that surpasses traditional approaches.

Keywords:

shear wave; machine learning; neural network; integrated CNN

1. Introduction

Shear-wave velocity (V_s) plays a vital role in subsurface characterization, reservoir evaluation, and seismic interpretation because it controls rock elastic moduli, Poisson's ratio, and lithological differentiation (Pickett, 1963; Castagna et al., 1985; Tonni and Simonini, 2013). Accurate V_s estimation is fundamental for applications such as seismic inversion, geomechanical modelling, and dynamic stability assessment of reservoirs. However, obtaining complete V_s logs through dipole sonic measurements is often infeasible due to borehole instability, tool malfunction, or economic constraints (Lin et al., 2023). Consequently, researchers have long sought to infer V_s indirectly from other well logs. Classical empirical relationships such as Gardner's velocity–

density relation (Gardner et al., 1974), Greenberg–Castagna's mudrock line (Greenberg and Castagna, 1992), and Faust's resistivity–sonic transform (Faust, 1953) provided valuable initial frameworks but are restricted by their dependence on local lithological conditions and inability to capture the nonlinear relationships among petrophysical parameters (Mahmoudian et al., 2022; Olutoki et al., 2024).

With the advancement of data-driven techniques, machine learning (ML) and deep learning (DL) approaches have revolutionized the estimation of missing logs and elastic parameters from routine well logs (Rajabi et al., 2023; Ghorbani et al., 2025). These methods have been employed to model the highly nonlinear and heterogeneous relationships between petrophysical features and V_s . Among classical ML methods, algorithms such as support vector machines, random forests, and gradient boosting have shown remarkable accuracy and stability when trained on large, curated datasets (Yang et al., 2023). Nevertheless, these techniques heavily rely on manually

* Corresponding author: Rahmat Catur Wibowo

e-mail address: rahmat.caturwibowo@eng.unila.ac.id

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engineered features and cannot learn hierarchical representations directly from the data, which limits their scalability to complex stratigraphic intervals (**Olutoki et al., 2024**).

In this context, neural network-based approaches have emerged as superior alternatives owing to their capability to approximate nonlinear functions with high fidelity (**Dolatshahi and Molladavoodi, 2024**). The Probabilistic Neural Network (PNN), a model derived from Bayesian decision theory and Parzen window density estimation, is among the earliest neural frameworks applied to geophysical data (**Specht, 1990**). PNN models estimate the probability density of each class or regression target and compute the conditional expectation, resulting in smooth and uncertainty-aware predictions (**Earp et al., 2020**). The probabilistic nature of PNNs makes them highly robust for noisy and limited datasets. Their kernel-based structure, however, leads to high computational costs and poor scalability to large datasets. Furthermore, the smoothing parameter (σ) critically affects model bias and variance, making parameter tuning essential (**Tang et al., 2011; Gu et al., 2018**). PNNs perform well in homogeneous formations, but tend to struggle in heterogeneous lithologies where spatial and sequential dependencies are dominant (**Al-Mudhafer, 2017**).

To overcome some of these limitations, the Multilayer Feedforward Neural Network (MLFFNN), also known as the classical backpropagation network, has been widely adopted for V_s prediction (**Silva et al., 2013**). MLFFNNs are capable of learning complex nonlinear relationship between input logs and V_s through multiple layers of neurons and nonlinear activation functions. The simplicity and flexibility of MLFFNN architecture make it an attractive choice for various geological applications. However, this model treats each depth sample independently, ignoring the sequential and spatial continuity inherent in well-log data. As a result, while it may achieve high accuracy during training, its performance can degrade when predicting V_s at depth intervals not included in the training dataset or in entirely different wells, particularly if appropriate regularization techniques are not applied (**Khan and Kirmani, 2024; Al-Mudhafar et al., 2022**). Overfitting remains a common challenge, particularly when the training dataset is small or unbalanced.

Advancements in computing and data availability have paved the way for the Deep Feedforward Neural Network (DFFNN), an extension of MLFFNN with greater depth and representation power (**Tolstaya et al., 2023; Zeng et al., 2022**). By stacking multiple hidden layers, DFFNNs are capable for hierarchical feature extraction, enabling the network to learn both low-level and abstract representations of lithological and petrophysical interactions (**Shi et al., 2025; Vázquez-Ayala et al., 2025**). DFFNNs outperform shallow architectures in capturing the complex nonlinearities inherent in well-log data, particularly when predicting V_s across different

stratigraphic units. However, the enhanced representational capability of the model comes with trade-offs, including greater computational demands, a higher susceptibility to overfitting, and the requirement for more extensive hyperparameter tuning and optimization (**Khan and Kirmani, 2024**). Moreover, DFFNNs still lack explicit mechanisms to handle depth continuity, as they operate on static samples rather than sequential depth information.

A further evolution of neural networks for geophysical applications is the Convolutional Neural Networks (CNNs), which processes well logs as one-dimensional sequences along depth (**Li et al., 2025; Chen et al., 2022**). CNNs use convolutional filters to capture local spatial dependencies between log measurements, effectively learning depth-invariant features. This ability allows CNNs to recognize stratigraphic transitions and subtle textural variations that conventional neural networks overlook (**Rajabi et al., 2023**). CNNs are also computationally efficient due to parameter sharing and local connectivity. However, conventional CNN architectures are typically designed as single-stack models with fixed kernel sizes, limiting their receptive field and ability to represent multi-scale geological phenomena. As a result, while CNNs excel at detecting fine-scale patterns such as thin beds or local facies transitions, they often fail to capture broader depositional trends or compaction effects that occur over larger depth intervals (**Olutoki et al., 2024; Wang et al., 2022**).

Despite these advancements, several persistent research gaps remain in the literature on V_s prediction. First, existing DL models, particularly single-stack CNNs and DFFNNs, inadequately integrate multi-scale spatial features, making it difficult to simultaneously model local and global geological trends (**Olutoki et al., 2024**). Second, generalization across lithologies and basins remains limited; models trained on a single field often exhibit performance degradation when applied to other regions due to differences in depositional environments, compaction history, and mineralogy. Third, while probabilistic models like PNN inherently quantify uncertainty, deep CNN-based approaches typically lack uncertainty estimation, hindering their applicability for risk-sensitive reservoir characterization (**Earp et al., 2020; Alqahtani et al., 2018**). Lastly, many field datasets contain missing or incomplete well logs, whereas most neural network architectures assume the availability of all input features. Consequently, limited research has addressed the development of robust multi-input or modality-specific CNN architectures capable of handling incomplete data through feature-fusion or data-integration strategies (**Wang et al., 2022**).

To address these gaps, this study introduces an Integrated CNN (I-CNN) architecture designed to integrate multi-scale spatial feature extraction, cross-log fusion, and uncertainty awareness for V_s prediction. The proposed architecture consists of parallel convolutional

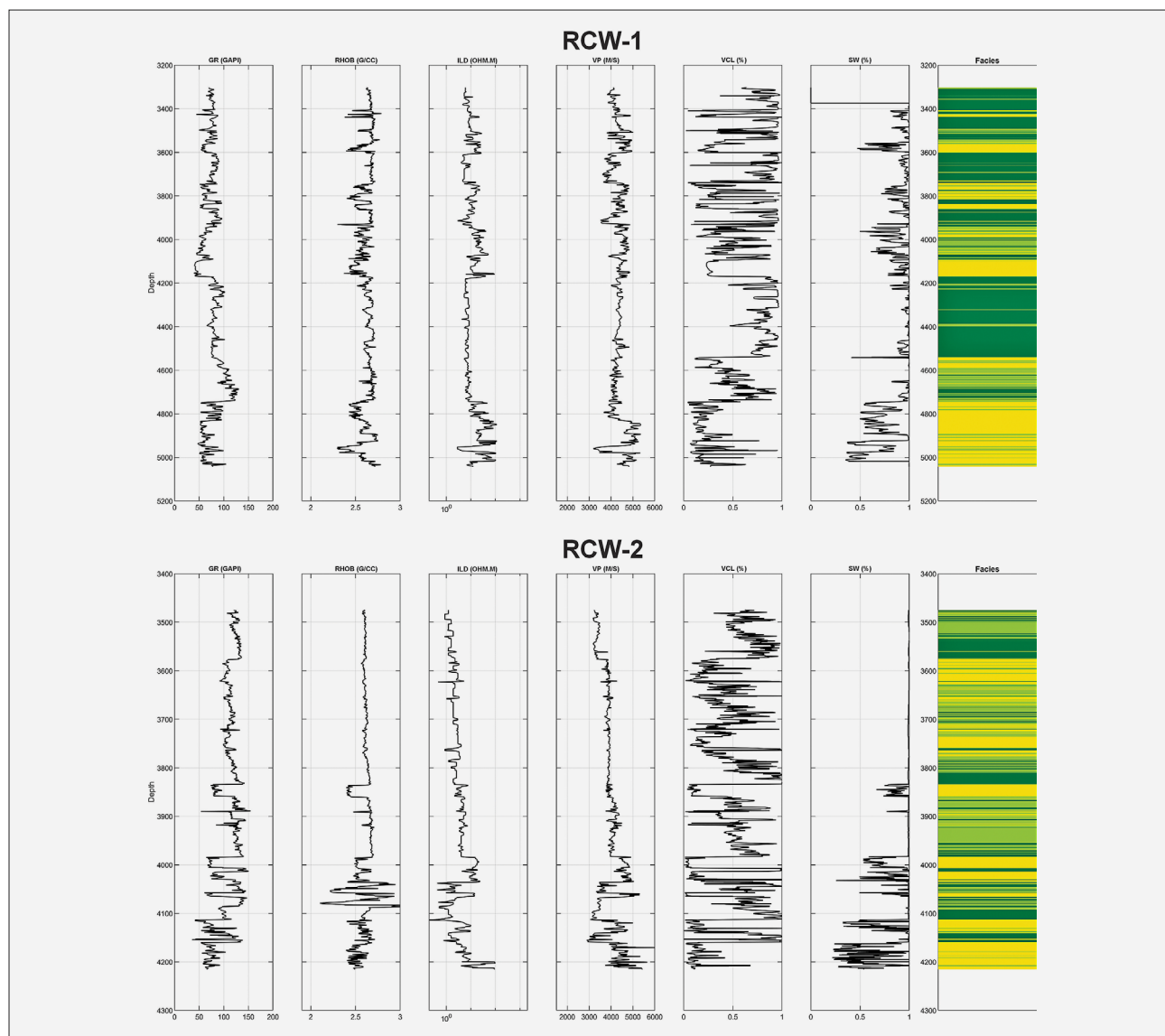


Figure 1: Composite well-log panels and facies interpretation for the RCW-1 (upper part) and RCW-2 (lower part) wells. Displayed from left to right are Gamma Ray (GR), Bulk Density (RHOB), Deep Resistivity (ILD), Compressional-wave velocity (V_p), Clay Volume (VCL), Water Saturation (SW), and the interpreted lithological facies (yellow indicates sandstone, light green indicates shaly sand, dark green indicates shale) plotted against depth.

branches with varying kernel sizes that capture fine to coarse depth patterns, followed by batch normalization, dropout layers for regularization, and feature-fusion dense layers for regression. By leveraging this structure, the model combines the local sensitivity of conventional CNNs with the broader context recognition of deep hierarchical networks. Through a comparative framework including PNN, MLFFNN, DFFNN, and single-stack CNNs, this study aims to demonstrate the superiority of the I-CNN in terms of accuracy, generalization, and robustness when predicting V_s from conventional well logs.

2. Geological condition in wells

The study is based on two anonymized wells, RCW-1 and RCW-2 (see **Figure 1**), which penetrate comparable

stratigraphic intervals within a rapidly subsiding siliciclastic sedimentary system typical of large Cenozoic marginal-sea basins. The stratigraphic succession is dominated by thick alternations of sandstone, siltstone, and shale, reflecting deposition in deltaic to shallow-marine environments under high sedimentation rates. Such depositional conditions commonly result in laterally variable facies distributions and pronounced vertical lithological heterogeneity. Sandstone units are generally characterized by lower gamma-ray responses, reduced clay volume (VCL), and higher elastic velocities, whereas shale-rich intervals exhibit elevated gamma-ray values, higher clay content, and reduced V_s .

Progressive burial and rapid subsidence lead to strong compaction effects and significant contrasts in elastic properties across the stratigraphic section. In shale-dom-

inated intervals, incomplete compaction and fluid-related effects may further reduce V_s , while sandstone intervals typically develop higher stiffness due to stronger grain frameworks and diagenetic modification. These lithological and stratigraphic characteristics provide a physically meaningful framework for interpreting variations in V_s predicted by machine-learning models.

Although the wells originate from the same anonymized dataset, differences in shale proportion, resistivity response, and depth coverage introduce sufficient stratigraphic variability to enable a robust evaluation of cross-well model generalization within this geological framework.

3. Methods

Deep neural networks (DNN) are being used in all engineering specialties (Blake et al., 2021; Spandonidis et al., 2022). Because of its comprehensive data, DNN is widely used in petroleum exploration and production, according to a review by Alkinani et al. (2019). The applications encompass the removal of wellbore damage (Kellogg et al., 2018), the integration of core and log data for permeability prediction (Babadagli and Al-Salmi, 2004; Eriavbe and Okene, 2019), forecasting hydrocarbon production in reservoirs subjected to water injection (Negash and Yaw, 2020), flow regime identification (Van Der Spek and Thomas, 1999), and the estimation of fluid rates across various phases and production simulation utilizing deep neural networks (Alakeely and Horne, 2020a). To identify the lithology from traditional well logs, a variety of models have been developed (Saikia et al., 2020). The following provides a detailed explanation and summary of the neural network-based V_s prediction approach using well logs.

3.1. Probability Neural Network (PNN)

As a non-linear method, the PNN approximation may successfully manage a variety of lithologies and differentiate between producing sands and shale intercalation (Khan et al., 2022; Durrani et al., 2020). A thorough description of PNN, a mathematical method for non-linear interpolation that trains input petrophysical logs, was given by Durrani et al. (2020).

The PNN is a theory of Bayes-Parzen classification, which is based on neural network principle (Mohebbali et al., 2020). It employs Gaussian weighting functions in fitting the input vector (x) to the chosen training samples (x_i). The mean of a normal Gaussian distribution is a representation of the training sample in which the algorithm can find the best control the width of the Gaussian parameter (σ_j) or standard deviation. The basic equation for the general PNN regression according to Todorov (2000) is given by the Equation 1:

$$y(x) = \frac{\sum_{i=1}^n y_i \exp(-D(x, x_i))}{\sum_{i=1}^n \exp(-D(x, x_i))} \quad (1)$$

where y_i represents the measured target log values, n represents total number of training samples, y is the new log value while $D(x, x_i)$ is expressed as Equation 2:

$$D(x, x_i) = \sum_{j=1}^p \left(\frac{x_i - x_{ij}}{\sigma_j} \right)^2 \quad (2)$$

The term $D(x, x_i)$ denotes the separation between each training point (x_i) and the input (x), and the total number of input is (p). The width of the Gaussian parameter (σ_j) differs in every input. After identifying the ideal set of smoothing parameters by cross-validation, which excludes some of the training data (Hampson et al., 2001), the conjugate gradient method is applied to reduce the validation error (Todorov, 2000).

3.2. Multi-layered Feed Forward Neural Network (MLFFNN)

Artificial Neural Networks (ANNs) employ a complex computational framework to predict target responses from input data. They consist of numerous parallel connections between nonlinear, parameterized, and bounded functions known as neurons. These neurons are organized according to the network architecture, typically following a multilayer perceptron (MLP) design in which neurons are arranged in successive layers. Within each layer of an MLP, all neurons receive the same set of input signals but operate independently, without direct interconnections among them.

Although the number of hidden layers and neurons in each layer can be chosen arbitrarily, an excessive number of neurons may lead to overfitting, where the model learns noise rather than meaningful patterns. Conversely, using too few neurons can result in underfitting and poor network performance. One of the key advantages of Artificial Neural Networks (ANNs) compared to traditional methods is their ability to efficiently process large and complex datasets, capturing nonlinear relationships that conventional approaches may overlook.

The output function of an Artificial Neural Network (ANN) denoted as $h_{\theta(x)}$, is calculated as Equation 3:

$$h_{\theta(x)} = a_1^3 = g(\theta_{10}^{(2)} a_0^{(2)} + \theta_{11}^{(2)} a_1^{(2)} + \theta_{12}^{(2)} a_2^{(2)} + \theta_{13}^{(2)} a_3^{(2)}) \quad (3)$$

where (g) represents the activation function, in this case a sigmoid function defined by Equation 4:

$$g(z) = \frac{1}{(1 + e^{-z})} \quad (4)$$

The activation function introduces nonlinearity into the model, allowing the network to capture complex relationships between input and output variables. For each neuron, the activation input z can be vectorized in matrix form, as follows:

$$\begin{cases} z_1^{(2)} = \theta_{10}^{(1)} I_0 + \theta_{11}^{(1)} I_1 + \theta_{12}^{(1)} I_2 + \theta_{13}^{(1)} I_3 \\ z_2^{(2)} = \theta_{20}^{(1)} I_0 + \theta_{21}^{(1)} I_1 + \theta_{22}^{(1)} I_2 + \theta_{23}^{(1)} I_3 \\ z_3^{(2)} = \theta_{30}^{(1)} I_0 + \theta_{31}^{(1)} I_1 + \theta_{32}^{(1)} I_2 + \theta_{33}^{(1)} I_3 \end{cases} \quad (5)$$

Here I_0, I_1, I_2 , and I_3 denote the input features (e.g. well-log parameters), while $\theta_{ij}^{(k)}$ are the weights connecting neuron j in layer $k - 1$ to neuron i in layer k . The vectorized form allows efficient computation across all neurons simultaneously.

The overall complexity of the neural network is contingent upon its architecture, specifically the quantity of hidden layers and the number of neurons in each layer. Nonetheless, as highlighted by **Sorosh et al. (2015)**, the network must be constructed with adequate complexity to discern data patterns while preventing overfitting.

An algorithm is employed to train the neuron network in order to reduce the error between the objective values and the network output values. This was accomplished through an iterative process that was aimed to determine the most optimal weights and biases. The Levenberg–Marquardt (LM) algorithm is the most well-known of the numerous algorithms that have been proposed in the literature for the purpose of training the network (**Wang et al., 2023**).

This study employed a MLFFNN architecture for the developed ANN model, trained using the gradient-based backpropagation algorithm to minimize prediction errors (**Brown et al., 2010**). The term backpropagation refers to the iterative process in which the network adjusts its internal weights to reduce the discrepancy between predicted and observed outputs. The error function of a specific input-output patterns is defined using the Root Mean Square Error (RMSE), as expressed in **Equation 6**:

$$RMSE(a, p) = \sqrt{\frac{1}{n} \sum_{i=0}^n (a_i - p_i)^2} \quad (6)$$

where a_i is the actual (measured) value for i^{th} sample, p_i is the predicted value produced by the network, and n is the total number of samples. The RMSE quantifies the model's prediction error, with lower values indicating higher accuracy and reliability. Model performance was further evaluated using multiple statistical metrics to ensure robustness across different magnitudes of data.

The backpropagation method, while popular for its simplicity and efficacy, possesses several shortcomings, including delayed convergence, incapacity to manage multiple targets, and a significant propensity to become ensnared in local minima during training. To overcome these issues, this study introduces an improved convergence approach by incorporating an acceleration factor, as formulated in **Equation 7**:

$$w(t + 1) = w(t)\beta[\Delta w(t)] + \alpha[w(t - 1)] \quad (7)$$

where w represents the connection weight, t is the iteration index (epoch), β is the learning constant, and α is the momentum (energy) constant. These constants, typically ranging between 0 and 1, are used to control the rate of learning and to smooth out abrupt gradient variations, thereby accelerating the convergence of the network while preventing oscillations during training.

3.3. Deep Feed Forward Neural Networks (DFFNN)

As a subset of machine learning, deep learning (DL) employs multiple layers of nonlinear transformations to construct hierarchical representations of data at increasing levels of abstraction. Through this multi-layered structure, deep learning models can automatically learn complex features and relationships directly from raw inputs, minimizing the need for prior domain knowledge, manual feature extraction, or heuristic coding rules (**Le-Cun et al., 2015**). In this study, a Deep Feed Forward Neural Network (DFFNN) was implemented and trained using the error backpropagation algorithm (**Rumelhart et al., 1986**) to optimize the weight matrices of each layer. The algorithm iteratively adjusts the model parameters by propagating the error, defined as the difference between the predicted and actual outputs from the output layer back through the hidden layers. During each iteration, the weight coefficients are updated to minimize this error, leading the network to converge toward an optimal set of parameters.

For each neuron in the (l^{th}) hidden layer, the forward propagation is expressed in **Equations 8** and **9**, as follows:

$$z^{(l)} = W^{(l)}a^{(l-1)} + b^{(l)} \quad (8)$$

$$a^{(l)} = f(z^{(l)}) \quad (9)$$

where:

$W^{(l)}$ = weight matrix at the l^{th} layer,

$b^{(l)}$ = bias vector at the l^{th} layer,

$a^{(l)}$ = activation output of the l^{th} layer,

$f(\cdot)$ = nonlinear activation function (e.g. ReLU, sigmoid, or tanh).

In the output layer, the predicted response $\hat{y}$ is given by **Equation 10**:

$$\hat{y} = f_{out}(W^{(L)}a^{(L-1)} + b^{(L)}) \quad (10)$$

Where L denotes the total number of layers in the network. For hidden Layers, the Rectified Linear Unit (ReLU) activation function was used, defined as **Equation 11**:

$$f(x) = \max(0, x) \quad (11)$$

ReLU introduces nonlinearity while mitigating vanishing gradient problems during training. For regression tasks, model performance was evaluated using the Root Mean Squared Error (RMSE) metric (**Equation 6**). The network weights were optimized via gradient-based learning, typically using Gradient Descent or its adaptive variants, such as Adam or RMSProp (**Raghavan et al., 2024**). The gradient of the loss function (∂L) with respect to the weight matrix (∂W) of the l^{th} layer is computed as **Equation 12**:

$$\frac{\partial L}{\partial W^{(l)}} = \delta^{(l)}(a^{(l-1)})^T \quad (12)$$

The weights are then updated iteratively using the learning rate η , as **Equation 13**:

$$W^{(l)} \leftarrow W^{(l)} - \eta \frac{\partial L}{\partial W^{(l)}} \quad (13)$$

where η controls the step size during optimization. The iterative process continues until convergence is achieved, yielding an optimal mapping between input features and target outputs.

3.4. Convolutional Neural Networks (CNNs)

One particular type of deep neural network is the Convolutional Neural Network (CNN), which uses convolutional operations to automatically identify, extract, and categorize characteristics from input data. CNNs have achieved remarkable success across a wide range of domains, particularly in image recognition, computer vision, and pattern classification (O'Shea and Nash, 2015; Li et al., 2021). Over time, numerous advanced architectures have been developed, including GoogLeNet, ResNet (Residual Network), and SENet (Squeeze-and-Excitation Network), each introducing novel strategies to enhance representational efficiency and mitigate training limitations.

The term convolution refers to a linear mathematical operation involving a dot product between a kernel (or filter) a small matrix of learnable parameters, and localized regions (slices) of the input data. The kernel slides systematically over the input feature map to compute weighted sums, resulting in a transformed output known as a feature map. This operation enables the network to capture local spatial patterns such as edges, textures, or gradients within the data (Li et al., 2021; Alakeely and Horne, 2020b).

A typical CNN architecture consists of several layers, including input, convolutional, pooling, and fully connected layers. Among these, the convolutional and pooling layers play a critical role in feature extraction and dimensionality reduction. In the convolutional layer, local features are extracted by applying convolutional kernels to the input feature map, while the pooling layer aggregates information by summarizing neighboring features, thus improving translation invariance and computational efficiency (Li et al., 2021).

Equation 14 below is the modified calculation algorithm for convolutional network features (Chen et al., 2020).

$$F_j^i = \sum_{i \in m_j} F_j^{t-1} * k_{ij}^l + b \quad (14)$$

The convolution process between the kernel k and input feature F is denoted by $(*)$, and bias b is introduced following each convolution mapping.

While increasing the number of layers can enhance the model's expressiveness, doing so introduces more parameters and may lead to overfitting or training instability (Guo et al., 2024). Advanced CNN architectures

address these challenges in different ways: (1) Inception Networks reduce dimensionality using parallel convolutions with kernels of size 1×1 , 3×3 , and 5×5 , concatenating their outputs into a single composite feature map. (2) ResNet model introduce skip connections, allowing gradients to flow directly across layers and effectively mitigating vanishing or exploding gradient issues in very deep networks (Alzubaidi et al., 2020).

The convolution operation uses a small kernel/filter that slides along the input data (**Equation 15**). A commonly used activation function is ReLU, (**Equation 11**), to make the network capable of modelling nonlinear relationships efficiently.

$$h_{i,j}^{(k)} = f \left(\sum_{m,n} x_{i+m,j+n} \cdot w_{m,n}^{(k)} + b^{(k)} \right) \quad (15)$$

where:

x = input data,

w = kernel (filter) weight,

b = bias term,

$h_{i,j}^{(k)}$ = output feature map, and

$f(\cdot)$ = activation function, typically the ReLU (see **Equation 11**).

The pooling operation reduces the spatial dimensionality of the feature maps while retaining the most relevant information. For instance, 2×2 max-pooling operation can be represented as **Equation 16**:

$$p_{i,j} = \max\{h_{2i+2j}, h_{2i+1,2j}, h_{2i,2j+1}, h_{2i+1,2j+1}\} \quad (16)$$

After convolution and pooling, the resulting feature maps are flattened and passed to one or more fully connected (dense) layers, similar in structure to those used in deep feed-forward networks (**Equation 17**). The CNN is then trained via the backpropagation algorithm and optimized using gradient-based methods such as Adam (**Equation 12**). The final output layer produces the target prediction (estimated V_s) using a linear function.

$$z^{(l)} = W^{(l)} a^{(l-1)} + b^{(l)}, \quad a^{(l)} = f(z^{(l)}) \quad (17)$$

3.5. Integrated Convolutional Neural Networks (I-CNNs)

An Integrated Convolutional Neural Network (I-CNN) – also referred to as a deep CNN – is an extension of the standard CNN in which multiple convolution–pooling blocks are stacked sequentially. This multi-stack configuration enables the network to extract hierarchical features at different levels of abstraction. In contrast to shallow CNNs, which primarily capture low-level local features (e.g. short-range variations in GR or RHOB logs), I-CNNs progressively learn higher-order representations such as lithological boundaries, facies transitions, and nonlinear relationships between petrophysical logs and the target V_s (LeCun et al., 2015; Goodfellow et al., 2016).

Each convolution layer performs a localized linear transformation followed by a nonlinear activation, expressed as **Equation 18**:

$$z_{i,j}^{(k)} = \sum_m \sum_n X_{i+m,j+n} \cdot w_{m,n}^{(k)} + b^{(k)} \quad (18)$$

where:

- X = local input patch,
- $w^{(k)}$ = kernel (filter) for the k^{th} feature map,
- $b^{(k)}$ = bias term, and
- $z_{i,j}^{(k)}$ = output activation before applying the nonlinearity.

The pooling layer then aggregates the maximum or mean value within a small neighborhood to reduce dimensionality while preserving the most informative spatial features. In the fully connected stage of the network, the standard linear operation is defined as **Equation 19**:

$$h = f(W_x + b) \quad (19)$$

where W and b are the weights and bias of the dense layer, and $f(\cdot)$ is the activation function ReLU (**Equation 11**). Mathematically, in an L -layer Integrated CNN (I-CNN), the output of the ℓ^{th} convolutional layer is represented as **Equation 20**:

$$z^{(\ell)} = f(\text{Conv}(a^{(\ell-1)}, W^{(\ell)}) + b^{(\ell)}) \quad (20)$$

where:

- $a^{(\ell-1)}$ = input feature map from the previous layer,
- $W^{(\ell)}$ = set of learnable kernels (filters),
- $b^{(\ell)}$ = bias vector term, and
- $f(\cdot)$ = non-linear activation function such as ReLU (**Equation 11**).

This operation allows the I-CNN to learn both spatially local and depth-wise dependencies among log attributes across multiple wells. Pooling layers are commonly inserted between convolutional layers to further reduce spatial dimensions and improve translation invariance. A typical Max-Pooling operation is expressed as **Equation 21**:

$$a^{(\ell)}(i, j) = \max_{(m,n) \in \Omega_{ij}} [z^{(\ell)}(m, n)] \quad (21)$$

where Ω_{ij} denotes the local receptive window around location (i, j) . After several convolution-pooling blocks, the feature maps are flattened and passed to one or more fully connected (dense) layers to integrate the learned representations **Equation 22**:

$$\hat{y} = W^{(FC)} a^{(L)} + b^{(FC)} \quad (22)$$

where $\hat{y}$ is the predicted target, such as V_s . To train the network, a loss function such as the Root Mean Squared Error (RMSE) (**Equation 6**) and backpropagation with gradient descent (or Adam optimizer) is used to update all convolutional and fully connected weights (**Equation 13**).

3.6. Workflow overview

The proposed workflow for shear wave prediction from conventional well logs is illustrated in **Figure 2**. This study adopts a systematic, comparative modelling framework integrating five machine learning algorithms: Probabilistic Neural Network (PNN), Multilayer Feedforward Neural Network (MLFFNN), Deep Feedforward Neural Network (DFFNN), single-stack one-dimensional Convolutional Neural Network (CNN), and a custom Integrated Convolutional Neural Network (I-CNN) architecture. The workflow encompasses model training, validation, and cross-well testing under a rigorous train/test/validation protocol to ensure robustness and reproducibility.

Training and testing were performed using data from RCW-1, which contains a comprehensive suite of conventional logs (gamma-ray, bulk density, resistivity, compressional sonic, clay volume and water saturation) along with dipole sonic-derived V_s . This configuration aligns with best practices in well-level supervised learning and model reproducibility (**Rajabi et al., 2023; Zeng et al., 2022**). To evaluate model generalization, an independent well (RCW-2) from a distinct stratigraphic interval was reserved exclusively for out-of-sample validation, enabling assessment of cross-well transferability critical for field-scale deployment (**Wang et al., 2022; Olutoki et al., 2024**).

Data preprocessing involved standard cleaning, outlier removal, depth alignment, and feature scaling (min-max and/or z-score normalization) to ensure numerical stability across algorithms and mitigate bias caused by inconsistent log units (**Rajabi et al., 2023; Ghorbani et al., 2025**).

The PNN model was implemented as a kernel-based Parzen window estimator generating probabilistic predictions, with its smoothing parameter (σ) optimized via nested cross-validation on RCW-1, following established geoscientific probabilistic regression procedures (**Earp et al., 2020; Alqahtani et al., 2018**). The MLFFNN baseline employed a single hidden layer trained via backpropagation with L2 regularization, representing local nonlinear mappings between log features and V_s while maintaining computational efficiency for moderate datasets (**Silva et al., 2013**). The DFFNN extended this architecture into multiple stacked dense layers with ReLU activations, batch normalization, and dropout regularization to capture hierarchical and compositional relationships. Hyperparameters (depth, width, learning rate, weight decay) were optimized through grid/random search with early stopping to minimize overfitting (**Tolstaya et al., 2023; Khan and Kirmani, 2024**).

The 1-D CNN treated depth-ordered logs as continuous one-dimensional signals, applying successive convolution and pooling operations to extract depth-invariant local features that enhance the detection of thin beds and transition zones (**Li et al., 2025; Chen et al., 2022**).

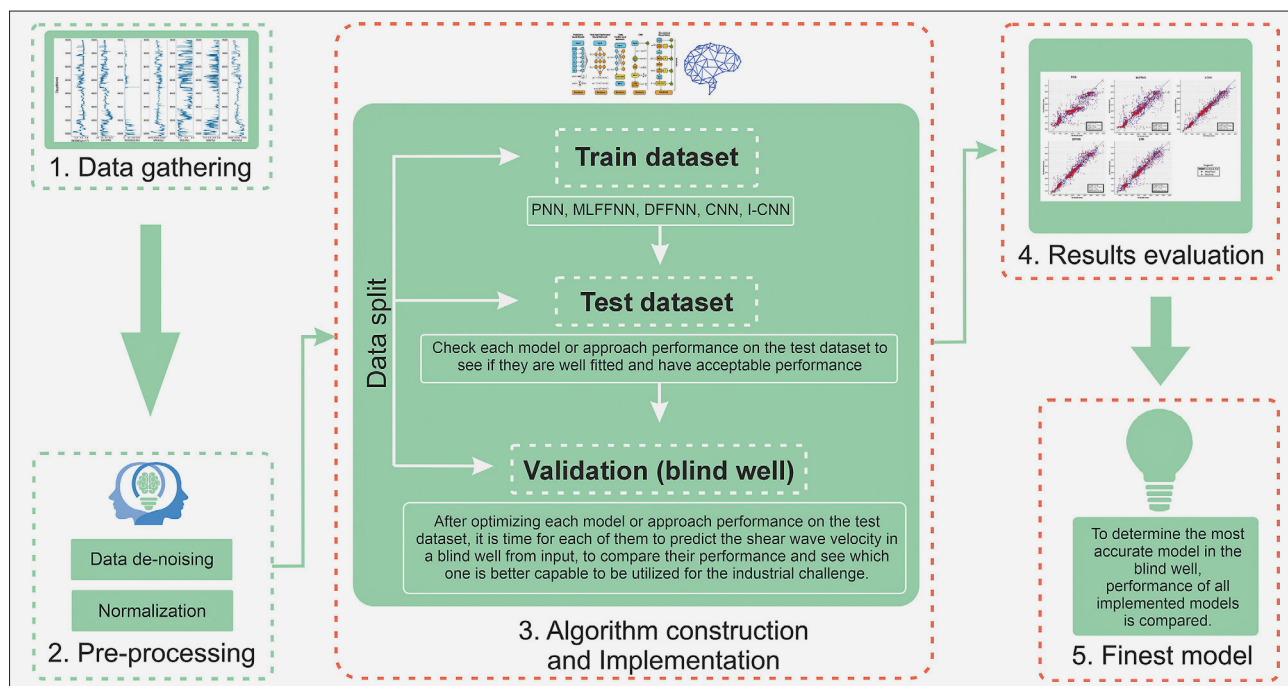


Figure 2: Procedure of the machine and deep learning workflow for V_s prediction

Building on this design, the I-CNN architecture incorporated three parallel convolutional streams with distinct kernel sizes – representing small, medium, and large receptive fields to simultaneously capture fine-scale, intermediate, and long-range depth patterns. Each stream consisted of Conv → BatchNorm → Activation → Dropout blocks, followed by the concatenation of feature maps and regression through fully connected layers (Rajabi et al., 2023; Olutoki et al., 2024). This multi-scale fusion strategy was devised to reconcile the competing requirements of resolving thin stratigraphic layers and modelling broader basin-scale variations, effectively addressing the single-scale limitation of conventional CNNs (Wang et al., 2022; Alqahtani et al., 2018).

All neural network models were trained using mean squared error (MSE) loss with adaptive optimizers (Adam or equivalent) and controlled via early stopping and validation patience to prevent overfitting. The PNN model employed MSE and likelihood-based criteria for optimal smoothing (σ) selection (Earp et al., 2020; Ghorbani et al., 2025).

To evaluate robustness and reproducibility, the RCW-1 dataset was split into randomized 70:30 train–test partitions and repeated for 150 independent random seeds, producing statistical distributions of performance metrics (R^2 , RMSE, MAE). This repeated-split approach mitigates endpoint selection bias and allows a fairer comparison of algorithmic stability (Rajabi et al., 2023). The best-performing models (selected based on validation R^2 and lowest RMSE) are then applied directly to RCW-2 without retraining for strict cross-well validation. The differences between in-sample and valida-

tion performance were analyzed to assess model transferability, lithological sensitivity, and resilience to variations in log distributions (Wang et al., 2022; Olutoki et al., 2024).

Comprehensive diagnostics and visualization tools, including scatter plots, residual histograms, multi-track depth logs, and feature-importance or standardized coefficient analyses were used to interpret results and identify depth intervals where model predictions diverge. These analyses enable transparent assessment of model behaviour and provide practical guidance for field implementation (Yang et al., 2023; Shi et al., 2025).

All models were implemented and evaluated in MATLAB (R2023b/2024a) using reproducible scripts. Fixed random seeds ensured deterministic results, while explicit seed sweeps supported robustness checks. Final deliverables included trained model files, standardized performance tables, and project-specific folders containing: Visualization figures (scatter, residuals, learning curves), Excel result sheets (depth, actual V_s , predicted V_s , residuals), and all code used for training and evaluation, thereby facilitating reproducibility and future independent validation (Rajabi et al., 2023; Ghorbani et al., 2025).

3.7. Data gathering and preparation

The dataset used in this study consists of conventional wireline logs acquired from two anonymized wells, referred to as RCW-1 and RCW-2, provided with formal authorization from the data owner exclusively for academic research purposes. Both wells penetrate comparable stratigraphic intervals within a siliciclastic sand-

stone–shale succession, ensuring geological consistency. At the same time, RCW-1 and RCW-2 exhibit differences in shale volume distribution, resistivity response, and depth coverage, which provide sufficient heterogeneity to evaluate cross-well generalization. Consequently, RCW-1 is used for model training and testing, while RCW-2 serves as a blind validation well, which is reserved exclusively for independent validation to evaluate the cross-well generalization capability of each predictive model. This partitioning strategy aligns with the best practices for supervised learning in geoscientific applications, minimizing information leakage and ensuring that model performance reflects true predictive capability rather than the memorization of site-specific patterns (Rajabi et al., 2023; Ghorbani et al., 2025; Wang et al., 2022). Each well includes conventional logging measurements acquired during open-hole conditions, as well as from well log analysis (e.g. clay volume and water saturation). The recorded logs comprise gamma ray (GR), bulk density (RHOB), deep resistivity (ILD), compressional sonic (V_p), clay volume (VCL), and water saturation (SW) (see **Table 1**). These parameters were selected as input features because they are standard in formation evaluation and provide complementary sensitivity to key petrophysical properties such as lithology, porosity, and fluid type (Gardner et al., 1974; Castagna et al., 1985; Chen et al., 2022). Feature selection was guided by both statistical assessment and geological reasoning (see **Figure 3**). Correlation analysis was used to evaluate potential redundancy among predictors; however, no geologically meaningful features were removed solely based on correlation thresholds. The objective was not aggressive dimensionality reduction, but the preservation of physically interpretable input variables. All retained features (GR, RHOB, ILD, V_p , VCL, and SW) have well-established petrophysical relevance to elastic properties, as demonstrated in previous studies, and therefore contribute complementary information to V_s prediction. The target variable, V_s , was derived from dipole sonic log measurements where available and treated as ground-truth calibration data for supervised learning. Prior to model training, V_s logs underwent quality control procedures, including the removal of isolated spikes associated with tool noise and mild smoothing using a short-window median filter. No anisotropy correction was applied due to the absence of cross-dipole measurements. These pre-processing steps ensure that V_s values represent reliable elastic properties suitable for model calibration and validation. Dipole sonic data are widely recognized as the most reliable source for V_s calibration, as they provide high-resolution information on the formation's elastic properties, an essential component for rock physics and geomechanical analysis (Tonni and Simonini, 2013).

The well logs were acquired under standard wireline logging practices using industry-grade sensors calibrated prior to field acquisition to ensure consistent response

curves and accurate depth calibration (Shi et al., 2025). Logging tools were operated under controlled borehole conditions to minimize measurement artifacts caused by mud invasion, washouts, or tool eccentricity. These conditions minimize non-geological influences on log responses and ensure that observed variations primarily reflect subsurface properties rather than acquisition artifacts. Each raw log was then subjected to initial quality control (QC) at the acquisition stage, where non-physical spikes, depth mismatches, and tool dropout zones were flagged for correction or removal. This QC step was necessary to reduce the risk of introducing spurious features that could mislead the learning algorithms (Zeng et al., 2022; Olutoki et al., 2024).

Following data acquisition, all log curves were depth-matched and resampled to a consistent vertical resolution of 0.15 m using linear interpolation to align measurements across logs with different sampling rates (Rajabi et al., 2023). Missing intervals, particularly in resistivity and sonic logs, were imputed using localized regression and median filtering where appropriate, while severely incomplete intervals were excluded from training to preserve data integrity (Geng and Wang, 2020). Outlier detection was performed using a combination of z-score analysis and interquartile range (IQR) thresholds to identify values exceeding three standard deviations from the mean. Detected anomalies were visually inspected against neighbouring depth intervals to distinguish between geological anomalies and measurement errors (Wang et al., 2022; Alqahtani et al., 2018).

To ensure comparability among features, all logs were normalized prior to modelling. Normalization was carried out using min–max scaling to a [0,1] range and z-score standardization for networks sensitive to scale differences, such as the DFFNN and CNN models (Tolstaya et al., 2023; Khan and Kirmani, 2024). This step prevents disproportionate weighting of high-magnitude logs (e.g. resistivity) and enhances convergence stability during training. For each well, normalization parameters were computed from the training data of RCW-1 and applied consistently to RCW-2 to simulate real-world deployment where models are calibrated on a reference RCW-1 and used for prediction on other wells within the same basin (Rajabi et al., 2023; Olutoki et al., 2024).

The lithological context of the wells was confirmed through the integration of well reports by the operating company, which identify alternating of sand–shale sequences typical of fluvial to shallow-marine depositional environments. This geological heterogeneity makes the dataset ideal for testing the adaptability of different neural network architectures in capturing nonlinear relationships between petrophysical properties and V_s (Li et al., 2025; Ali and Sheng-Chang, 2020). In total, RCW-1 contained approximately 3,000 valid data points after cleaning, while RCW-2 contained about 2,500 samples used solely for validation. The resulting dataset thus provides both sufficient volume for deep model training and

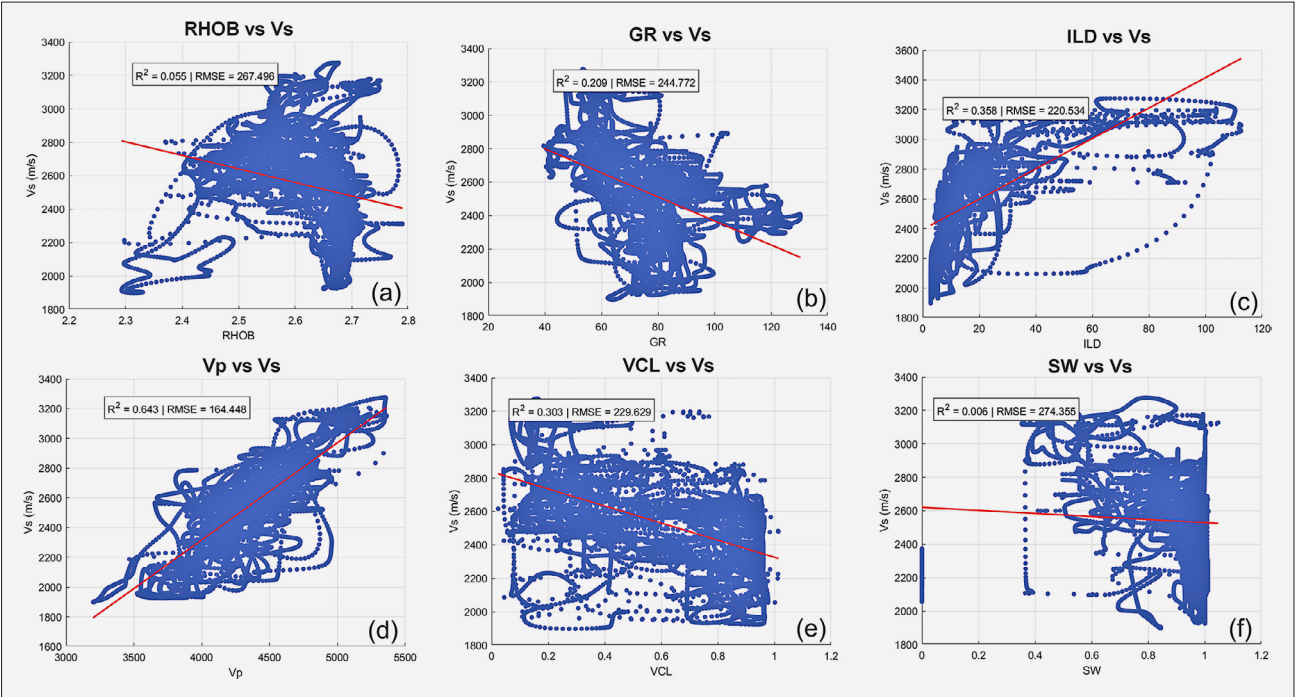


Figure 3: Scatter plots showing pairwise relationships among (a) gamma-ray (GR), (b) bulk density (RHOB), (c) deep resistivity (ILD), (d) compressional velocity (V_p), (e) clay volume (VCL), and (f) water saturation (SW) used as predictors for V_s . The proximity of data points to the 1:1 line indicates prediction accuracy, whereas systematic deviations reflect model bias or under- or over-estimation.

Table 1: Summary of petrophysical input parameters used for model training and validation

Well	Variables	Bulk Density	Gamma Ray	Deep Resistivity	Compressional Wave Velocity	Shear Wave Velocity	Clay Volume	Water Saturation
	Symbol (units)	RHOB (g/cc)	GR (GAPI)	ILD (ohms-m)	V_p (m/s)	V_s (m/s)	VCL (%)	SW (%)
RCW-1	Mean	2.62	75.92	14.52	4343.87	2541.89	0.57	0.86
	Std. Deviation	0.07	17.47	16.09	337.22	275.15	0.29	0.22
	Variance	-0.00	-305.30	-259.20	-113721.80	-75708.70	-0.08	-0.05
	Minimum	2.29	39.54	2.82	3199.07	1897.87	0.02	0.35
	Maximum	2.78	130.42	112.59	5362.23	3275.43	1.00	1.00
RCW-2	Mean	2.59	109.53	4.75	3912.50	2195.69	0.46	0.92
	Std. Deviation	0.09	21.76	8.99	443.79	336.21	0.28	0.15
	Variance	0.01	473.84	80.99	196949.99	113039.85	0.08	0.02
	Minimum	2.10	35.55	0.10	2892.55	1500.89	0.04	0.21
	Maximum	3.41	154.10	98.89	6154.53	3196.71	1.00	1.00

complexity to evaluate robustness under varying lithologic and stratigraphic conditions.

Figure 3 presents exploratory cross-plots between V_s and the selected input well logs using data from the RCW-1 well. This well was chosen for exploratory analysis because it provides the reference dataset for model training and testing. The blue dots represent smoothed data trends that reflect the dominant petrophysical relationships between V_s and each predictor, while the red

line show fitted regression trends used to assess the general behaviour of the data. The observed patterns confirm that V_s exhibits strong dependence on elastic and density-related parameters, particularly V_p and RHOB (see **Figure 3a** and **3d**), while GR, VCL, and SW primarily reflect lithological and fluid-related influences. These relationships provide physical justification for the inclusion of the selected features in subsequent machine-learning modelling.

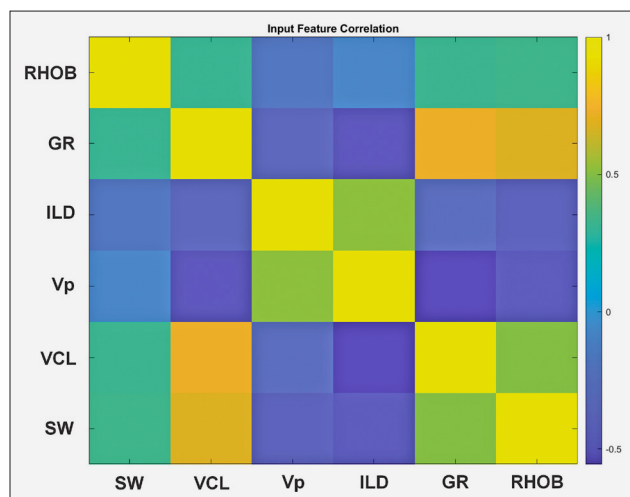


Figure 4: Correlation matrix of the input features used for V_s prediction, including RHOB, GR, ILD, Vp, VCL, and SW. Colours represent Pearson correlation coefficients, ranging from -1 (strong negative correlation, dark blue) to $+1$ (strong positive correlation, yellow), as indicated by the colour bar. The diagonal elements correspond to self-correlation.

The analysis of traditional well-logging data in this work uses two feature selection methods: non-relevant feature removal and heat-map correlation. Heatmap correlation identifies redundant or irrelevant elements by utilizing a correlation matrix to determine the relationships between them. The heatmap correlation matrix of every feature that is accessible is shown in **Figure 4**. That figure shows the correlation matrix of the input features used for V_s prediction. Several expected petrophysical relationships are observed, including a strong positive correlation between GR and VCL, reflecting their shared sensitivity to clay content. RHOB exhibits moderate correlation with GR and VCL, consistent with lithological and compaction effects. Compressional-wave velocity (V_p) shows moderate correlation with ILD, indicating coupled elastic and fluid-related influences, while negative correlations between V_p and GR–VCL highlight contrasts between sand-dominated and shale-rich intervals. As described in the methodology section, this correlation analysis was used to assess potential redundancy; however, no geologically meaningful features were removed solely based on correlation magnitude. All inputs were retained to preserve physical interpretability and complementary petrophysical information.

Finally, to ensure reproducibility and data governance, all preprocessed logs for both wells were stored in structured Excel files (.xlsx) with standardized naming conventions. Each file contains separate sheets for depth, log inputs, predicted outputs, and residuals, allowing direct interfacing with MATLAB workflow for model training, evaluation, and visualization. This standardized data management ensures full traceability from raw acquisition to final model output, supporting transparent scientific workflow practices as advocated in recent geo-

informatics research (Alqahtani et al., 2018; Rajabi et al., 2023).

3.8. Neural network implementation

3.8.1. Architecture

This study employs five distinct neural network architectures to evaluate their performance in predicting V_s from conventional well log inputs: Probabilistic Neural Network (PNN), Multi-Layer Feedforward Neural Network (MLFFNN), Deep Feedforward Neural Network (DFFNN), Convolutional Neural Network (CNN), and Integrated CNN (I-CNN). These models were selected to represent both shallow and deep learning paradigms with varying levels of complexity and learning capacity.

The PNN model is based on a statistical approach that uses kernel-based probability estimation and Bayes' decision theory for classification and regression tasks (Specht, 1990). In this implementation, the PNN receives six normalized log inputs: density (RHOB), gamma ray (GR), resistivity (ILD), compressional velocity (V_p), clay volume (VCL), and water saturation (SW), and propagates them through the radial basis function layer. The output layer integrates these probabilistic contributions to estimate the target V_s value. The model's fast training and strong generalization ability on smaller datasets make it attractive for geophysical applications where noise and non-linearity are present (Gu et al., 2018; Ali and Sheng-Chang, 2020).

The MLFFNN, a classical neural network, is structured with a single hidden layer containing 10 to 20 neurons, activated by a sigmoid or ReLU function. Inputs are fully connected to the hidden layer, which is then connected to a single linear output neuron representing V_s . This architecture is trained using backpropagation and stochastic gradient descent, minimizing the mean squared error between predicted and actual values. Although limited in representational capacity, MLFFNNs remain robust for many regression tasks and have been successfully applied in petrophysical property prediction (Silva et al., 2013).

To capture more complex, nonlinear relationships, the DFFNN extends the MLFFNN by incorporating two to four hidden layers with increasing neuron counts (e.g. 32–64–128). Each layer utilizes the ReLU activation function, and batch normalization is applied to stabilize learning and accelerate convergence. Dropout layers are also included to reduce overfitting. These enhancements allow the DFFNN to model deeper representations of the petrophysical log– V_s relationship, particularly in heterogeneous formations (Khan and Kirmani, 2024; Shi et al., 2025).

The CNN architecture leverages spatial locality in well logs by treating the input features as sequential data. A typical CNN in this study includes one-dimensional convolutional layers with kernel sizes of 2 or 3,

Table 2: Statistical summary of the input dataset for Wells RCW-1 (training & test) and RCW-2 (validation)

Statistical parameters	PNN	MLFFNN	DFNN	CNN	I-CNN
Training Set					
RMSE	113.21	114.56	57.42	63.18	46.21
R ²	0.83	0.83	0.96	0.95	0.97
Number of Data	9,234	9,234	9,234	9,234	9,234
Test Set					
RMSE	110.63	110.76	61.72	65.68	51.03
R ²	0.84	0.84	0.95	0.94	0.96
Number of Data	3,927	3,927	3,927	3,927	3,927
Validation Set					
RMSE	133.87	120.04	81.37	91.39	80.73
R ²	0.85	0.87	0.94	0.92	0.95
Number of Data	5,930	5,930	5,930	5,930	5,930

followed by max-pooling layers to reduce dimensionality. Convolutional filters automatically learn localized feature interactions among the log inputs, which is useful in capturing abrupt lithological transitions. The CNN is capped by fully connected layers to regress the V_s output. CNNs have proven effective in geophysical signal analysis and log data modelling, providing both robustness and interpretability (Chen et al., 2020).

Finally, the Integrated CNN (I-CNN) architecture enhances the standard CNN by introducing three consecutive convolution–batch normalization–dropout (Conv–BN–Dropout) blocks before the fully connected output stage. This stacked design increases the model’s ability to extract hierarchical features from the input logs, capturing both low-level and high-level signal characteristics. Each convolutional block contains multiple filters (e.g. 16–32–64), followed by 1D batch normalization and dropout with a rate of 0.25 to prevent overfitting. The stacking approach allows the model to exploit both local and global features for improved generalization across wells. This architecture is particularly suited for learning from noisy, stratigraphically variable logs common in real-world datasets (Alqahtani et al., 2018; Zeng et al., 2022).

Each model receives the same six input features, normalized consistently, and is trained on the RCW-1 dataset using 70% of the data for training and 30% for internal testing. The RCW-2 dataset is reserved for independent validation. Optimization is performed using the Adam optimizer with a learning rate tuned for each model. Loss is computed using root mean squared error (RMSE), and evaluation metrics include R² and RMSE on both test and validation sets. This standardized modelling framework enables a fair comparison of architecture performance while highlighting the strengths of deep convolutional designs for V_s estimation.

In addition to the network architecture, model training required the specification of several hyperparameters

to ensure stable convergence and reproducibility. Hyperparameter tuning was conducted using a Bayesian optimization strategy, which has been shown to be efficient for high-dimensional search spaces. For all neural network models, the learning rate was fixed at 1×10^{-3} , which provided a stable balance between convergence speed and training stability. Model training was performed using a mini-batch size of 64 samples, selected to optimize computational efficiency while maintaining gradient stability. Each network was trained for a maximum of 150 epochs, with an early-stopping criterion applied when the validation loss did not improve for 15 consecutive epochs, thereby preventing overfitting. Model convergence was monitored based on the stabilization of the RMSE loss function on the validation set. The final hyperparameter configuration was selected based on the minimum validation loss obtained during the optimization process. This procedure ensured that the reported model performance reflects optimized and reproducible training conditions rather than arbitrary parameter selection. The same hyperparameter tuning strategy and convergence criteria were applied consistently across all neural network architectures to ensure a fair comparison between models.

3.8.2. Training, test, and validation processes

The networks described above were trained using RMSE as the loss function. In order to help avoid overfitting of the networks, the early halting strategy was also applied in the final fitting. Following pre-processing, the validation data was fed into the model that ultimately performed the best across the train and test datasets. Each model’s output was stored for blind RCW-2 analysis and assessment.

Each model receives the same six input features, normalized consistently, and is trained on the RCW-1 dataset using 70% of the data for training and 30% for internal testing. The RCW-2 dataset is reserved for independent

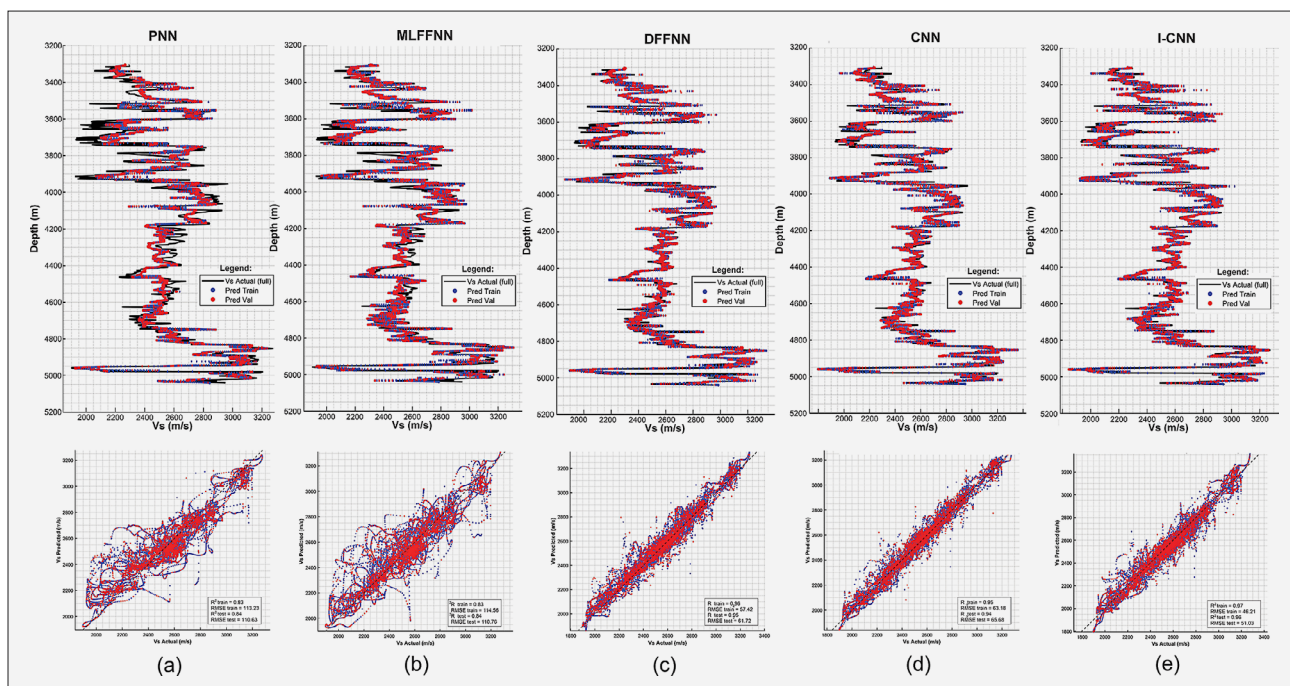


Figure 5: Comparison between measured V_s and predicted V_s obtained from five neural network architectures: (a) PNN, (b) MLFFNN, (c) DFFNN, (d) CNN, and (e) I-CNN in RCW-1 well. For each model, the upper panel shows depth-based V_s profiles, where the black curve represents measured V_s , blue markers denote training predictions, and red markers indicate test predictions. The lower panel presents cross-plots of predicted V_s versus measured V_s , where the dashed diagonal line corresponds to the ideal 1:1 relationship. Depth-wise comparison of measured and predicted V_s for training and testing phases, demonstrating that deep architectures (DFFNN, CNN, I-CNN) better capture stratigraphic variations than shallow networks (PNN, MLFFNN). The closer alignment of the I-CNN results to higher predictive accuracy and minimal bias across the training and testing datasets

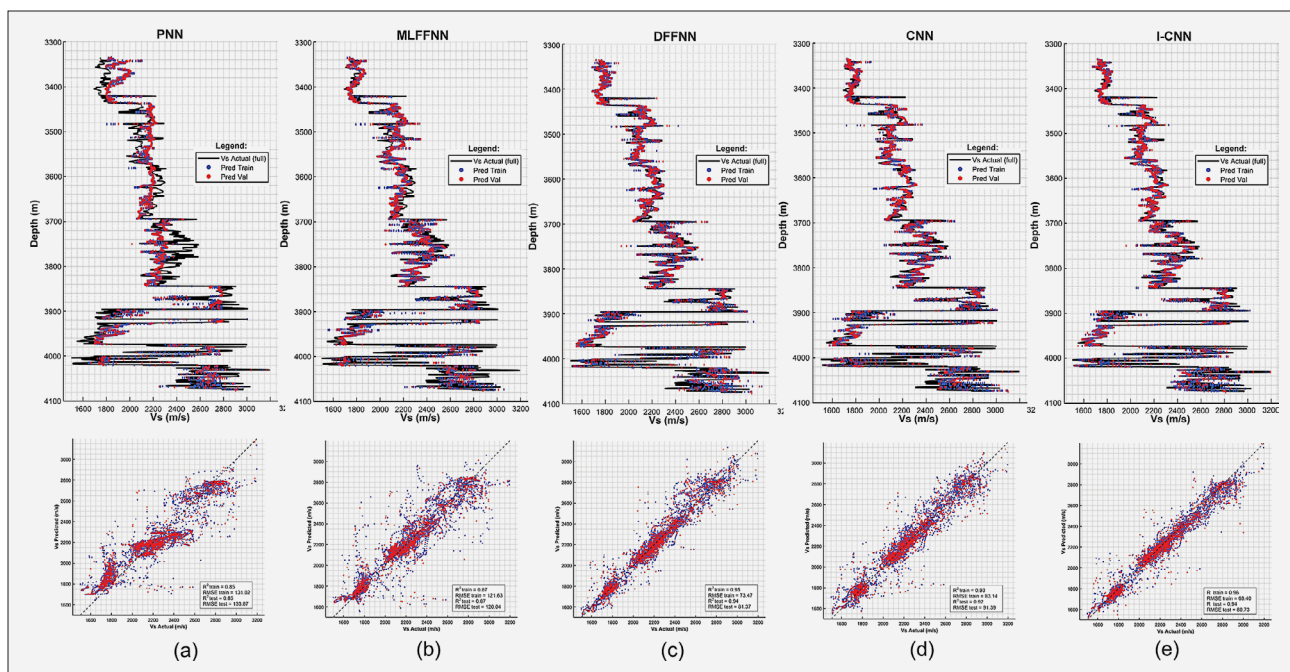


Figure 6: Validation well performance showing measured V_s alongside model predictions obtained from five neural network architectures: (a) PNN, (b) MLFFNN, (c) DFFNN, (d) CNN, and (e) I-CNN in RCW-2 well. The lower panel presents cross-plots of predicted V_s versus measured V_s , where the dashed diagonal line corresponds to the ideal 1:1 relationship.

The I-CNN maintains the most geologically consistent response, confirming strong cross-well generalization. Blind-well validation (RCW-2) cross-plot showing correlation between measured and predicted V_s values. The I-CNN displays the tightest clustering around the 1:1 line, reflecting robust transfer learning from Well RCW-1

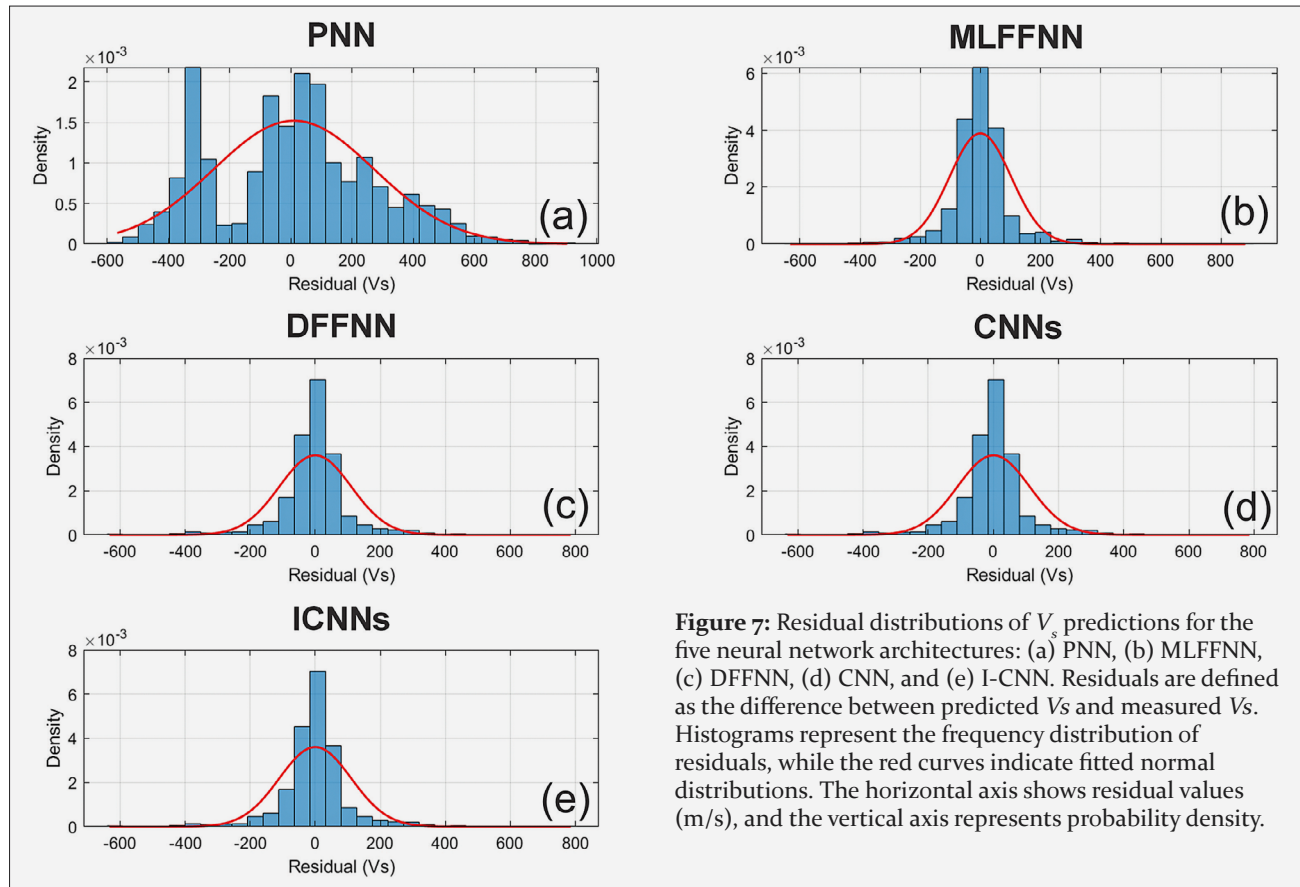


Figure 7: Residual distributions of V_s predictions for the five neural network architectures: (a) PNN, (b) MLFFNN, (c) DFFNN, (d) CNN, and (e) I-CNN. Residuals are defined as the difference between predicted V_s and measured V_s . Histograms represent the frequency distribution of residuals, while the red curves indicate fitted normal distributions. The horizontal axis shows residual values (m/s), and the vertical axis represents probability density.

ent validation. Optimization is performed using the Adam optimizer with a learning rate tuned for each model. Well RCW-2 was not involved in model training or hyperparameter optimization. It was used exclusively as an independent blind validation dataset to evaluate model generalization. Any validation metrics reported for RCW-2 reflect post-training model performance only. Loss is computed using RMSE, and evaluation metrics include R^2 and RMSE on both test and validation sets. This standardized modelling framework enables a fair comparison of architecture performance while highlighting the strengths of deep convolutional designs for V_s estimation.

3.9. Evaluation of models

The models' performances were evaluated using three metrics: R^2 as defined in Equation 23 and RMSE as outlined in Equation 6. R^2 quantifies the extent to which independent factors account for the variation in the dependent variable, while RMSE assesses the average squared deviation between anticipated and actual values. RMSE assesses the performance of regression models, with lower values indicating superior performance (see Table 2).

$$R^2(a, p) = \frac{\sum_{i=1}^n (a_i - p_i)^2}{\sum_{i=1}^n (a_i - \bar{a})^2} \quad (23)$$

4. Results

The statistical outcomes of the PNN, MLFFNN, DFFNN, CNNs, and I-CNNs on the training, testing, and validation datasets are presented in Table 2. Figure 5 presents a comparison of the applied models throughout the training, testing, and validation datasets, evaluated using R-squared and RMSE metrics.

Figure 5 illustrates the performance of five neural network architectures by comparing predicted and measured V_s values in both depth and cross-plot domains. Figures 5a and 5b show that the PNN and MLFFNN models reproduce the general V_s trend with depth; however, noticeable scatter and deviations from the measured profile are observed, particularly in intervals with rapid velocity variation. Figures 5c–e demonstrate improved agreement for the DFFNN, CNN, and I-CNN models. In these cases, predicted V_s profiles closely follow the measured V_s curve across most depth intervals, indicating enhanced capability to capture nonlinear elastic responses. This improvement is further confirmed in the corresponding cross-plots, where predictions cluster more tightly around the 1:1 line and exhibit reduced dispersion compared to simpler network architectures. Among all models, the CNN-based approaches show the most consistent performance for both training and blind validation datasets, suggesting superior generalization and reduced sensitivity to lithological heterogeneity. De-

viations observed at higher V_s values are minor and likely reflect local elastic contrasts rather than systematic model bias.

Figure 6 presents the blind cross-well validation results for RCW-2, providing a stringent test of model generalization beyond the training well. For clarity, training and validation labels shown for RCW-2 correspond to the evaluation of predictions generated by models trained on RCW-1 and do not indicate retraining or parameter updating using RCW-2 data. **Figures 6a** and **6b** show that the PNN and MLFFNN models reproduce the overall V_s trend but exhibit increased scatter and local mismatches, particularly in intervals with abrupt velocity changes. Improved agreement is observed for the DFFNN, CNN, and I-CNN models (see **Figures 6c–e**), where predicted V_s profiles closely follow the measured V_s curve across most depth intervals. This behaviour is corroborated by the corresponding cross-plots, which display tighter clustering around the 1:1 reference line and reduced dispersion relative to simpler architectures. Among the tested models, CNN-based approaches demonstrate the most consistent performance for RCW-2, indicating robust transferability of learned elastic–lithological relationships to an independent well. Minor deviations at higher V_s values are limited and likely reflect local stratigraphic or elastic contrasts rather than systematic model bias.

Figure 7 presents the residual distributions for all evaluated neural network models, providing a complementary assessment of prediction accuracy and bias. The PNN model (see **Figure 7a**) exhibits a relatively broad and asymmetric residual distribution, indicating higher variance and reduced stability. The MLFFNN model (see **Figure 7b**) shows a narrower distribution; however, minor skewness suggests residual bias in certain velocity ranges. In contrast, the DFFNN, CNN, and I-CNN models (see **Figures 7c–e**) display residual distributions that are more symmetric and tightly centered around zero. The reduced spread and near-Gaussian shape of these distributions indicate lower prediction error and improved robustness. Among these models, CNN-based architectures exhibit the most compact residual distributions, consistent with their superior performance observed in depth-based and cross-well validation results. The absence of pronounced skewness or multimodal behaviour in the residuals suggests that prediction errors are largely random rather than systematic, confirming that the models effectively capture the dominant elastic–lithological controls on V_s .

4. Discussion

The comparative results among the five neural network architectures: Probabilistic Neural Network (PNN), Multi-Layer Feedforward Neural Network (MLFFNN), Deep Feedforward Neural Network (DFFNN), Convolutional Neural Network (CNN), and Integrated I-CNNs, demon-

strate the progressive advantages of deep learning approaches in modelling the nonlinear behaviour between petrophysical logs and V_s . Quantitatively, the I-CNN consistently outperformed the other architectures, achieving an R^2 of 0.97 on the training data, 0.96 on the testing data, and 0.95 on the validation dataset, while maintaining the lowest RMSE range of 46–81 m/s. These metrics clearly indicate that the I-CNN captures both fine-grained and global patterns in the input data more effectively than shallower or single-stack architectures (**Rajabi et al., 2023; Olutoki et al., 2024; Ghorbani et al., 2025**).

From a qualitative perspective, the I-CNN model exhibited superior capability in replicating the detailed depth-dependent variations of V_s , especially across heterogeneous intervals characterized by interbedded sandstone and shale facies. The architecture's multiple convolutional blocks allowed for hierarchical feature extraction, learning local-scale variations at early convolutional layers and broader stratigraphic dependencies in deeper layers. Consequently, the I-CNN yielded smoother and more geologically consistent V_s profiles compared to the DFFNN and CNN, which tended to underfit abrupt velocity transitions. In contrast, the PNN and MLFFNN models displayed higher prediction variance and instability across the validation dataset, implying overfitting to localized data features, as similarly reported by **Gu et al. (2018)**.

Deeper insight into the model convergence process can be derived from **Figure 8**, which illustrates the evolution of Mean Squared Error (MSE) versus epoch for both training and validation phases. The learning-curve behaviour differs among the evaluated models due to their architectural characteristics and optimization mechanisms. For the PNN model, the observed increase in MSE after an initial decrease reflects its sensitivity to the smoothing parameter and kernel-based formulation, which can lead to reduced generalization when model complexity increases beyond an optimal range. This behaviour is consistent with over-smoothing effects commonly reported for probabilistic neural networks when applied to heterogeneous datasets. In contrast, the MLFFNN, DFFNN, CNN, and I-CNN models exhibit monotonically decreasing or stabilizing MSE values with increasing epochs. These architectures employ gradient-based optimization with adaptive weight updates, enabling progressive refinement of nonlinear relationships between input features and shear-wave velocity. For the deeper models (DFFNN, CNN, and I-CNN), the validation curves closely overlap with the training curves and are therefore visually indistinguishable at the plotting scale. This overlap indicates stable convergence and minimal generalization gap rather than the absence of validation results. Differences in the number of training epochs among models and wells arise from model-specific convergence behaviour and early-stopping criteria. Each architecture reaches convergence at a different rate depending on network depth, parameter count,

and data complexity, and training was terminated once the validation error stabilized. Consequently, the reported epoch ranges reflect optimal convergence rather than uniform iteration counts.

The I-CNN displayed a rapid decline in training loss during the first 50 epochs, followed by a gradual stabilization as the model approached optimal convergence. The validation loss curve maintained a close trajectory to the training loss, confirming the absence of significant overfitting and indicating efficient generalization (Alqahtani et al., 2018; Shi et al., 2025). By contrast, shallower models such as the MLFFNN and DFFNN exhibited slower convergence rates and larger oscillations in validation MSE, suggesting a less stable optimization process and limited capacity to generalize nonlinear dependencies in the data. The consistently low validation MSE in I-CNN implies that the model not only learned the intricate relationships between input logs and V_s but also effectively suppressed noise inherent to field-acquired log data. These convergence dynamics reinforce the robustness of deep convolutional architectures for petrophysical regression tasks, particularly when managing datasets with mixed lithological signatures and measurement uncertainties (Chen et al., 2022; Zeng et al., 2022).

The hierarchical learning structure of the I-CNN, composed of repeated convolution–batch normalization–dropout stacks, proved particularly advantageous for identifying latent correlations among input parameters such as RHOB, GR, ILD, and V_p . The multiple convolutional filters captured subtle relationships associated with lithologic composition, porosity, and fluid content, enabling improved prediction fidelity across depth intervals. This hierarchical extraction capability explains the reduced residuals observed in the validation well and the model's ability to maintain performance across varying stratigraphic conditions (Li et al., 2025; Ali and Sheng-Chang, 2020). Conversely, the DFFNN and MLFFNN architectures, while computationally simpler, lacked the feature locality mechanisms present in CNN-based models, leading to less sensitivity to spatial transitions within the log sequences.

The strong contribution of V_p and RHOB identified through feature-importance analysis is therefore geologically meaningful and consistent with elastic theory under conditions of rapid burial and compaction. The superior performance of nonlinear models, especially I-CNN, can be attributed to their ability to capture nonlinear elastic responses arising from stratigraphic heterogeneity, compaction disequilibrium, and lithological transitions. Linear models are inherently limited in representing these effects, which explains their reduced performance in mixed sandstone–shale successions. Residual analysis further supports this geological interpretation. Larger residuals at higher V_s values are likely associated with well-compacted sandstone intervals, where small variations in cementation, grain sorting, or diagenetic alteration can result in disproportionate changes in elastic response. Increased residual disper-

sion at lower V_s values corresponds to shale-dominated or transitional intervals, where clay content, fluid pressure, and mechanical anisotropy introduce additional heterogeneity. The absence of systematic depth-related bias suggests that the model captures intrinsic lithological and compaction-related controls rather than merely learning stratigraphic position.

Despite its strong performance, the I-CNN architecture is not without limitations. The model's depth and complexity increase training time and computational demand, which may constrain its applicability in field-scale deployment where computational resources are limited. Additionally, the reliance on large, high-quality datasets makes I-CNN performance vulnerable to data incompleteness or inconsistent acquisition conditions, a common challenge in subsurface datasets (Geng and Wang, 2020; Yang et al., 2023). While normalization and quality control procedures mitigated these issues, slight discrepancies between RCW-1 (training/testing) and RCW-2 (validation) still influenced prediction residuals, suggesting that model generalization remains partly dependent on inter-well similarity. The limited interpretability of deep learning models also poses a barrier for operational geoscience applications, as model outputs cannot be easily traced back to explicit geological reasoning (Alqahtani et al., 2018; Olutoki et al., 2024).

The successful blind validation across wells indicates that the trained model learns stratigraphically transferable elastic–lithological relationships, which is particularly important in thick Cenozoic clastic successions where lateral facies variations are common but governed by similar depositional and burial processes. This transferability implies that the proposed approach is applicable to neighbouring stratigraphic intervals within the same generalized basin framework, even when direct shear-wave measurements are unavailable.

From a geophysical perspective, the ability to predict V_s reliably within such stratigraphic systems has important implications for seismic-to-well calibration, elastic impedance analysis, and rock-physics modelling. In rapidly subsiding basins, accurate V_s estimation is especially valuable for characterizing mechanical stratigraphy, overpressure development, and elastic contrasts associated with sandstone–shale alternations. Although the geological description is intentionally generalized to comply with data-use restrictions, the integration of stratigraphic understanding with machine-learning analysis demonstrates that statistically robust models can yield geologically meaningful insights when guided by appropriate geological context.

Overall, the study confirms that deep convolutional frameworks, particularly Integrated CNN (I-CNNs), provide a significant advancement over conventional probabilistic and feedforward neural networks for V_s prediction. The improved convergence behaviour, lower generalization error, and enhanced representation of lithologic variation support the growing consensus that I-CNNs are currently the most powerful tool for petrophysical parameter

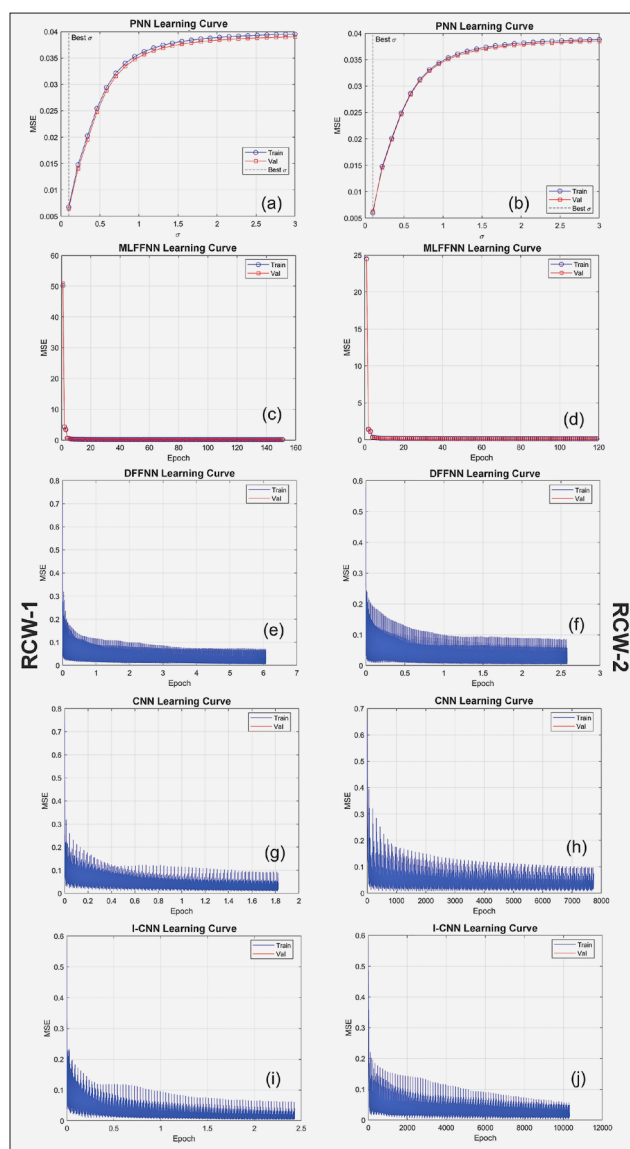


Figure 8: Learning curves showing the evolution of mean squared error (MSE) as a function of training epochs for the five neural network architectures evaluated in this study. Panels (a), (c), (e), (g), and (i) correspond to results obtained using the RCW-1 well (training and testing dataset), while panels (b), (d), (f), (h), and (j) show the corresponding results for the RCW-2 well (blind cross-well validation). The I-CNN converges rapidly within the first 50 epochs and stabilizes with minimal divergence between curves, confirming efficient generalization and absence of overfitting.

estimation in complex subsurface environments (Rajabi et al., 2023; Ghorbani et al., 2025).

5. Conclusions

This study demonstrates that among the five evaluated architectures: PNN, MLFFNN, DFFNN, CNN, and I-CNNs, the Integrated I-CNNs achieved the most accurate and geologically coherent shear wave velocity predictions from conventional well log data. Quantitative evaluation revealed that the I-CNNs consistently

achieved the highest R^2 (0.95–0.97) and lowest RMSE (46–81 m/s) across all phases, indicating superior precision and generalization ability. Qualitatively, the I-CNNs reproduced the fine-scale lithologic transitions and global velocity trends with minimal residuals, outperforming both traditional and single-stack networks. The results verify that multi-stack convolutional architectures can effectively capture multi-scale dependencies between petrophysical logs and elastic parameters, bridging the gap between empirical rock physics models and modern data-driven methods.

Nevertheless, this research identifies several limitations and opportunities for improvement. The computational demand associated with deep multi-stack training remains substantial, emphasizing the need for optimized architectures that balance model depth and computational efficiency. Furthermore, the dataset used – though representative – was limited to two wells within a single basin, which restricts the generalization potential to other geological settings. Variability in acquisition parameters and incomplete logs continue to pose challenges for real-world applications. Additionally, while normalization ensured input consistency, the study found that model performance decreased slightly when validated on stratigraphically distinct intervals, underscoring the importance of adaptive calibration across multiple wells.

Future research should aim to extend the model to a basin-scale application by incorporating a larger and more diverse set of wells that capture variations in depositional environments and diagenetic conditions. This expansion would allow for testing the robustness of I-CNNs models under broader geological heterogeneity. Incorporating hybrid modelling strategies that combine deep neural architectures with physics-informed constraints could further enhance model interpretability and physical realism. Additionally, implementing transfer learning and attention-based mechanisms may improve the adaptability of I-CNNs models when applied to new fields with limited data availability. The integration of explainable AI frameworks, such as SHAP or Grad-CAM visualization, could provide new insight into feature importance, bridging the gap between black-box predictions and geological reasoning. Finally, coupling the I-CNNs with seismic or core image data may open new opportunities for holistic elastic property prediction and real-time subsurface monitoring, establishing a pathway toward comprehensive data-driven reservoir characterization.

In conclusion, the I-CNNs presents a transformative approach for V_s prediction, combining computational intelligence with geophysical interpretability. Through continued refinement in data integration, model optimization, and interpretability, this framework has the potential to become an indispensable tool in the digital transformation of subsurface modelling and reservoir evaluation.

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Data Authorization and Ethical Compliance

All well-log data used in this study are authentic industrial datasets, provided with formal authorization from the data owner for exclusively academic research, including model training, testing, and validation. In accordance with the data-use agreement, geographical coordinates, field names, basin identifiers, and location-specific information are not disclosed. The data owner restricts the use of the dataset to methodological development and performance evaluation; therefore, the data are presented in an anonymized form, and only the derived results are reported. This limitation does not affect the scientific validity of the study, as the primary objective is to evaluate the methodological performance and generalization capability of machine-learning models rather than site-specific geological interpretation. The authors confirm full compliance with applicable data-use agreements and publication-ethics standards. No confidential, proprietary, or commercially sensitive information is disclosed, and no personal data is involved.

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SAŽETAK

Modeliranje posmičnih valova iz konvencionalnih karotažnih podataka korištenjem integrirane konvolucijske neuronske mreže dubokoga učenja (I-CNN)

Brzina posmičnoga vala, zajedno s brzinom kompresijskoga vala, pruža ključni izvor informacija za geomehanička i geofizička istraživanja. Dok se brzina kompresijskoga vala rutinski mjeri u većini bušotina, podatci o brzini posmičnoga vala često nisu dostupni, posebno u starijim bušotinama. To je uglavnom posljedica nedostatka odgovarajućih tehnologija prikupljanja podataka u to vrijeme i ograničenja trenutnih alata u zacičevljenim bušotinama. Uz to, izravno mjerenje brzine posmičnoga vala ostaje relativno skupo. Kako bi se zaobišla ta ograničenja, za predviđanje brzine posmičnoga vala iz tradicionalnih karotažnih mjerenja stvoreni su sljedeći algoritmi strojnoga učenja: vjerojatna neuronska mreža (PNN), višeslojna neuronska mreža s unaprijednim povratnim informacijama (MLFFNN), duboka neuronska mreža s unaprijednim povratnim informacijama (DFFNN), jednodimenzionalna konvolucijska neuronska mreža (1D-CNN) i integrirana konvolucijska neuronska mreža (I-CNN). Iz dviju bušotina prikupljen je 19 121 podatak. Metodologija se sastojala od triju glavnih dijelova: 1) predobrada podataka kako bi se uklonila buka i prilagodio odgovarajući format; 2) korištenje stručnoga znanja za pokretanje inženjeringa i odabira značajki; i 3) treniranje, testiranje i optimizacija modela. Rezultati su pokazali da je I-CNN model u bušotini RCW-1 postigao najbolje performanse, s R-kvadratnom vrijednošću od 0,971. Kada je primijenjen na drugu bušotinu (RCW-2), I-CNN model zadržao je snažnu sposobnost generalizacije, postižući prosječni koeficijent determinacije od 0,956. Ova zapažanja upućuju na to da I-CNN nadmašuje druge metode u rukovanju složenim, nelinearnim odnosima u predviđanju brzine posmičnih valova. Sveukupno, ova studija doprinosi rastućem opusu literature o primjeni strojnoga učenja u petrofizičkoj analizi uvođenjem integriranoga okvira dubokoga učenja koji nadilazi tradicionalne pristupe. Korištenje slijepe bušotine za testiranje dodatno potvrđuje robusnost i pouzdanost predloženoga I-CNN modela.

Ključne riječi:

posmični val, strojno učenje, neuronska mreža, integrirani CNN

Author's contribution

Rahmat Catur Wibowo: conceptualization, methodology, software, data curation, formal analysis, investigation, writing - original draft, visualization. **Ida Bagus Suananda Yogi:** data curation, writing - review & editing. **Indra Arifianto:** validation, data curation, formal analysis, writing - review & editing. **Muh Sarkowi:** methodology, supervision, project administration, resources, writing - review & editing. All authors have read and agreed to the published version of the manuscript.

Three-Dimensional Seepage Back Analysis of Dam Foundation and Abutments: a Case Study of the Karkheh Dam

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Mohammad Salehinik¹ , AliAsghar Mirghasemi^{2*} , Ahmadreza Tabibnejad³

^{1,2} School of Civil Engineering, College of Engineering, University of Tehran, Tehran, Iran.

³ Mahab Ghods Consulting Engineer, Takharestan St., Zafar St., Tehran, Iran.

Abstract

The foundation of the Karkheh Dam comprises a heterogeneous geological profile of highly permeable conglomerate layers interbedded with relatively impervious mudstones. Following the extreme flood events of March and April 2019, the reservoir first reached its normal water level (NWL) of 220 m above sea level and subsequently rose by approximately 5 m, peaking at 224.82 m on April 5. Although the dam crest is at 234 m, these conditions raised concerns regarding structural stability and potential seepage hazards, particularly during future floods. To mitigate these risks, strict operational measures were implemented to limit the hydraulic gradient within allowable design values, thereby reducing the likelihood of internal erosion and piping in the foundation and abutments. A three-dimensional seepage model of the foundation and abutment system was developed using FEFLOW 3D, incorporating six conglomerate layers at four reservoir levels. The model was calibrated against monitored seepage discharges by adjusting hydraulic conductivity coefficients and validated with piezometric data. The key results included the identification of the uplift pressure distribution beneath the spillway chute and pinpointing the location of maximum uplift pressure, which is critical for implementing new drainage wells. In addition, the analyses determined a threshold reservoir elevation above which the maximum average hydraulic gradient increases to levels that pose a heightened risk of internal erosion in the foundation and abutments. These findings, along with refined permeability parameters and hydraulic gradient distributions, provide deeper insight into the dam's hydro-geotechnical response under extreme hydrological loading and support targeted hydraulic safety management.

Keywords:

Seepage Analysis; Earth Dam; Hydraulic Gradient; Dam Monitoring; FEFLOW3D

1. Introduction

Seepage, defined as the gradual migration of water through soil or rock media, plays a pivotal role in the safety and long-term performance of embankment dams. Globally, earth dams remain susceptible to three principal modes of failure: external erosion from overtopping, internal erosion including piping and suffusion, and slope instability (Foster et al., 2000). Ensuring slope stability and controlling hydraulic behaviour within seepage-control elements are central to dam safety management. However, existing research reveals a noticeable gap in the systematic evaluation of embankment dam slope stability with respect to hydraulic control parameters, particularly under coupled seepage-stress conditions and fluctuating reservoir water levels (Zhou et al., 2023). Understanding the mechanisms by which internal erosion develops is essential for explaining how seep-

age-induced failure initiates and progresses in embankment dams. Important studies have advanced understanding of internal erosion mechanisms. Experimental relationships between limit curves and critical hydraulic gradients for piping in sandy gravels have been established (Skempton & Brogan, 1994). Similarly, experimental results on hydraulic gradients for various materials have been presented (Choe et al., 2022). Literature has addressed the need for an integrated definition of the critical hydraulic gradient that incorporates stress state effects. Experimental tests on a poorly graded mixture of washed Leighton Buzzard sand and decomposed granite, with a gap ratio indicative of internal stability, showed that the hydraulic gradient initiating erosion (i_{start}) increased from 0.7 to 1.77 as mean stress rose from 10 kPa to 200 kPa, due to reduced porosity (Chang & Zhang, 2013). Furthermore, microscopic observations of their study revealed that pore structure evolution strongly influences hydraulic gradients, with changes in connectivity affecting erosion potential. Loss of fine particles disrupts force chains, sharply increasing susceptibility to erosion. These effects mainly act during the linear

* Corresponding author: Ali Asghar Mirghasemi

e-mail address: aghasemi@ut.ac.ir

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compression phase of the soil's stress-strain response, indicating that the initial stress state is a key factor governing permeability (Zhang et al., 2022). For instance, a review of methods to determine conductivity in fractured rock masses noted that normal stress tends to reduce permeability, while shear stress may increase it (Shahbazi et al., 2020). While these physical processes are now better understood, predicting their occurrence in practice requires accounting for the natural variability and uncertainty of soil hydraulic properties.

Since seepage parameters are inherently non-deterministic, their treatment as random variables has been explored (Shahbazi et al., 2020; Zhang et al., 2022). Several studies have employed spatially variable random fields to account for heterogeneity in geotechnical parameters (Zhou et al., 2024). Seepage parameter inversion for earth-rockfill dams has been implemented using an Improved Chaos Sparrow Search Algorithm (ICSSA) combined with a radial basis function (RBF) neural network (Zhou et al., 2024). Seepage parameters can be calibrated using seepage monitoring data. Numerical simulations employing these calibrated parameters would produce more realistic and accurate results. Typical calibration methods for geotechnical parameters are detailed in literature (Xuefeng et al., 2019). Calibration against monitoring data, particularly from observation wells, enhances the realism of numerical simulations (Ganjalipour & Fatemi Aghda, 2019). Back-analysis methods, such as minimising the weighted sum of squared deviations between calculated and observed heads, are effective for optimizing permeability parameters (Ren et al., 2016). Building upon these uncertainty-based approaches, recent developments in numerical and artificial intelligence techniques have advanced the accuracy and scope of seepage analysis.

A variety of approaches exist for seepage analysis (Al-Janabi et al., 2025). In recent years, Artificial Intelligence techniques, such as feed forward neural networks, support vector regression, and adaptive neuro fuzzy inference systems have been increasingly applied to improve the predictive accuracy of piezometric head measurements, as demonstrated through seepage modelling of the Sattarkhan earth fill dam in northwestern Iran (Sharghi et al., 2018). More recently, Artificial Neural Networks have also been employed to assess the stability of rock slopes under steady state seepage conditions, highlighting the significant influence of pore water pressure on safety factors (Millán & Galindo, 2025). In addition, the use of genetic programming and conceptual modelling has been recommended as a promising approach to further enhance seepage prediction capabilities (Sharghi et al., 2018). Comparative analyses have shown that seepage lines and discharge rates obtained from physical, mathematical, and numerical models generally agree with those from Casagrande's equations and SEEP/W software. However, the SEEP/W model

performs poorly in accurately quantifying flow volume when the seepage line intersects the downstream slope (Al-Janabi et al., 2025). For earth-core rockfill dams, both two-dimensional (2D) and three-dimensional (3D) finite element seepage analyses are essential for accuracy. 3D analyses have demonstrated that the steady-state hydraulic gradient at the downstream toe can be nearly four times greater than the corresponding 2D value, and total discharge rates can be almost twice as high. Such differences are especially pronounced in narrow-valley settings, where reliance on 2D models alone may result in the underestimation of exit gradients and uplift forces (Ahmed & Bazaraa, 2009; Soleimanbeigi & Jafarzadeh, 2008). Among the many parameters influencing such analyses, hydraulic conductivity remains the most critical, directly controlling seepage quantity and pressure distribution.

Hydraulic conductivity, a critical parameter in all seepage studies, is typically assessed via Lugeon or pumping tests (Kaleris & Ziogas, 2020). Recent research on deep rock masses has also highlighted the significant impact of thermal conditions, revealing a non-linear positive correlation between hydraulic conductivity and water temperature; specifically, experimental results indicate that owing to changes in fluid kinematic viscosity, the hydraulic conductivity at 80°C is 2.31 times higher than at 30°C (Qiu et al., 2025). Anisotropic hydraulic conductivity can increase seepage rates and reduce slope stability, especially under rapid drawdown, where the stability coefficient initially falls sharply and then stabilises as permeability increases (Huang et al., 2017; Shuhaib & Khassa, 2024). Among advanced modelling tools, FEFLOW 3D has proven highly effective for simulating water flow through saturated, partially saturated, and unsaturated porous media under isotropic or anisotropic conditions, using finite element and finite volume schemes based on Darcy's and Richards' equations (Trefry & Muffels, 2007; Widomski et al., 2013a; Widomski et al. 2013b; Zhao et al., 2005). Such analyses are vital to ensure that hydraulic structures including gravity dams, diversion dams, and stilling basins are designed to resist uplift forces and high exit gradients (Salmasi et al., 2020). The application of these principles is exemplified by the Karkheh Dam case, where seepage control has been a decisive factor in ensuring long-term structural safety.

Despite extensive research on seepage analysis and dam safety, few studies have integrated three-dimensional numerical modelling calibrated with in-situ measurements to quantify both maximum average hydraulic gradient and uplift pressure for large earth-fill dams under extreme flood conditions in complex geological settings. This knowledge gap is particularly critical in the case of the Karkheh Dam, where the sheer scale of the structure, complex geological setting, and history of high seepage rates make it a prime candidate for such an integrated 3D, field-calibrated analysis.

The Karkheh Dam, located in Khuzestan Province, is a large earth-fill structure with a height of 127 m and a reservoir capacity of 5.9 billion m³ at normal water level. It incorporates a 400 MW hydroelectric plant and a 110 m-wide gated chute spillway (Heidarzadeh et al., 2019). Following initial impoundment, high seepage rates were recorded, prompting the design and staged construction of cut-off walls extending to impervious mudstones, with the aim of reducing maximum average hydraulic gradients. Since flow through the abutments and foundation can significantly affect stability and safety (Ahmed & Bazaraa, 2009), this study aims to determine the hydraulic conductivity of conglomerate layers and manage seepage flux and maximum average hydraulic gradient within allowable limits. FEFLOW models, developed to account for the dam's large scale and complex geometry, used a three-dimensional domain of approximately 4.2 × 3.5 km for each abutment to capture the variable longitudinal and vertical extents of the cut-off wall and the complex seepage dynamics through existing gullies.

The applicability of this three-dimensional model is substantiated by its successful calibration against monitored seepage discharges and its validation using observation well data, confirming its capability to accurately represent the complex heterogeneous geology of the foundation. Distinct from conventional studies that predominantly focus on internal erosion and seepage within the dam embankment, this research specifically addresses the seepage through the foundation and abutments. Beyond standard validation, the application of the model proves particularly critical during extreme flood events, such as the 2019 flood, when the water level rose approximately 5 m above the normal level. By identifying the precise locations of maximum uplift pressure, specifically beneath the spillway chute, and determining the reservoir elevation at which hydraulic gradients exceed safe limits, the model serves as an essential predictive tool. This capability not only facilitates the selection of appropriate new drainage well locations for spillway stability but also enables operators to implement targeted safety measures and proactively control internal erosion risks during future hydrological crises. Ultimately, this study provides a transferable methodological framework applicable to other large dams where seepage through the foundation and abutments poses a primary stability concern.

2. Theoretical background

The governing partial differential equation describing seepage through porous media is presented in Equation 1. This equation combines the continuity equation with Darcy's law, yielding Richards' equation for variably saturated flow conditions. It provides an accurate representation of flow within a homogeneous, anisotropic, saturated, and incompressible porous medium. This

equation was selected as it provides an accurate and standard framework for modelling steady-state seepage through saturated, anisotropic porous media, which are the representative hydrogeological conditions of the dam's foundation and abutments in our study. The finite element formulation, derived via the Galerkin method based on the principle of weighted residuals, is expressed in Equation 2 (Soleimanbeigi & Jafarzadeh, 2008).

$$\frac{\partial}{\partial x} \left(\rho k_x \frac{\partial h}{\partial x} \right) + \frac{\partial}{\partial y} \left(\rho k_y \frac{\partial h}{\partial y} \right) + \frac{\partial}{\partial z} \left(\rho k_z \frac{\partial h}{\partial z} \right) = 0 \quad (1)$$

Where:

- h – total hydraulic head (m),
- k_x, k_y and k_z – hydraulic conductivities in the x, y and z -directions (m/s),
- ρ – density of water (kg/m³).

$$\int_v ([B]^T [C] [B]) dV \{H\} = \int_A (q \langle N \rangle^T) dA \quad (2)$$

Where:

- $[B]$ – gradient matrix (1/m),
- $[C]$ – element hydraulic conductivity matrix (m/s),
- $\{H\}$ – vector of nodal hydraulic heads (m),
- A – area of the element face (m²),
- $\langle N \rangle$ – represents the vector of interpolation functions (dimensionless),
- q – unit flux across the element face (m/s).

3. Geological Characteristics and Investigations

The Karkheh Dam, completed on March 24, 2001, is founded on a geological sequence comprising conglomerate and mudstone strata. The conglomerate units display a wide range of textural characteristics, from loosely packed to densely cemented matrices. Interbedded horizontal mudstone layers act as hydraulic barriers, compartmentalizing the conglomerate into discrete aquifer units, each with distinct hydrogeological behaviour. Due to their very low hydraulic conductivity, these mudstones effectively restrict interlayer flow. As shown in Figure 1, the right abutment contains three mudstone horizons above the river level, designated Mud (+3), Mud (+2), and Mud (+1), and three below, designated Mud (−1), Mud (−2), and Mud (−3). Mud (+1) is considered hydraulically insignificant owing to its limited thickness and lateral discontinuity. On the left abutment, three mudstone horizons occur above the river level, numbered Mud (+2) to Mud (+4). The geological cross-section in Figure 1 illustrates the spatial variation and elevation of these horizons. Given their distinct hydro-mechanical properties, the conglomerate units bounded by each mudstone layer can be individually represented in the numerical seepage models for both the right and

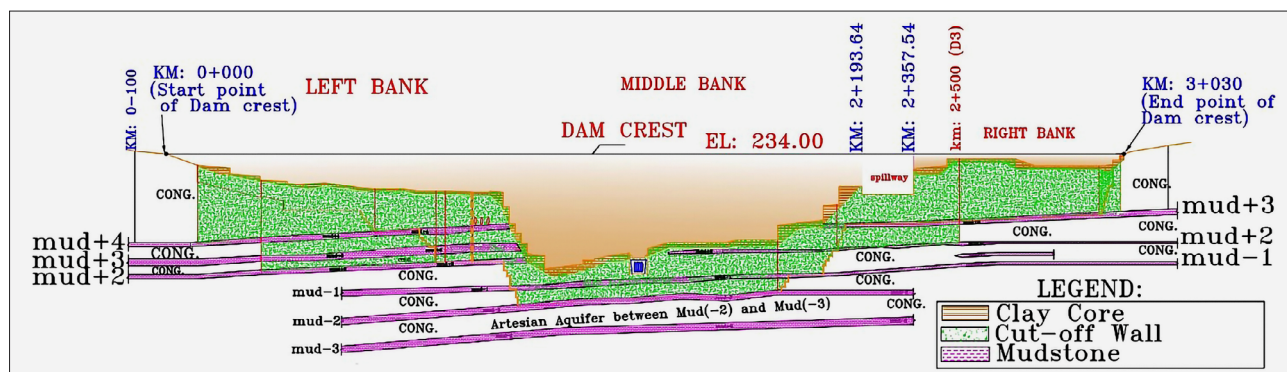


Figure 1: Longitudinal section of the Karkheh Dam foundation showing cut-off wall configuration and stratigraphic sequence across the left abutment, right abutment, and central core zones

left banks. The lateral boundaries of each model domain are defined by the mapped outcrops of the corresponding mudstone layer at the reservoir margin and on the downstream side as shown in **Figure 2** (labelled as Mud+3, Mud+2, etc.). Consequently, the respective conglomerate units receive reservoir recharge from different distances relative to the dam axis and from specific impounded areas.

It is worth noting that in **Figure 2**, the observation wells are indicated with the prefixes AW and NAW. The hydraulic heads from these wells are used to evaluate the model and compare it with real field data in subsequent sections.

Building on the identified stratigraphic configuration and its representation in the numerical seepage models, subsequent in-situ investigations were conducted to quantify the hydraulic conductivity parameters governing foundation and abutment seepage behaviour.

To determine the hydraulic conductivity of the dam foundation and abutments, a total of 823 Lugeon tests were conducted across various locations and geological strata within the foundation. These tests revealed a highly heterogeneous rock mass ranging from permeable to highly impermeable. ‘Open-framework’ conglomerates constitute 2–3% of the highly permeable zones. Approximately 20% of the rock mass consists of conglomerate with a sandy matrix and weak cementation with Lugeon values greater than 60, extending to a depth of 30 m. Another 7% comprises conglomerate with a sandy matrix and weak-to-moderate cementation (Lugeon values of ~60). About 28% of the rock mass exhibits average Lugeon values of 30, consisting of conglomerates with either good cementation or silty-sandy matrices. Furthermore, 28% of the rock mass is composed of conglomerate with a silty matrix and weak cementation, showing an average Lugeon value of 10. Additionally, pumping tests performed in two conglomerate aquifers beneath the riverbed, specifically between mudstone layers Mud (–1) and Mud (–2) as well as Mud (–2) and Mud (–3), were used as reference values for the initial hydraulic conductivity in the seepage calibration. Pumping test results indicated hydraulic conductivity values

ranging from 3.95×10^{-4} to 7.32×10^{-4} m/s. These values are approximately two orders of magnitude higher than the equivalent hydraulic conductivity estimated from Lugeon tests. This significant discrepancy is attributed to the scale effect; while Lugeon tests measure localised hydraulic conductivity, pumping tests capture the macro-permeability of the interconnected open-framework gravels and interconnected voids, which act as preferential flow paths. The hydraulic conductivity values derived from the back-analysis of the dewatering process for the hydropower excavation were consistent with those obtained from other deterministic approaches. Based on these investigations, the average hydraulic conductivity of the conglomerate was assessed as $(4-9) \times 10^{-4}$ m/s (Mirghasemi & Pakzad, 2005). This relatively high hydraulic conductivity is attributed to the presence of discontinuity zones and open-framework gravels within the conglomerate strata, allowing for turbulent flow. The hydraulic conductivity of the horizontally bedded mudstone layers ranged from 10^{-7} to 10^{-10} m/s, while the hydraulic conductivity of the Karkheh Dam cut-off wall was approximately 5×10^{-10} m/s (Mirghasemi et al., 2005).

Building upon the quantified hydraulic conductivity characteristics of the Karkheh Dam foundation and abutments, the ensuing evaluation incorporated hydraulic-gradient considerations to establish the critical threshold for internal erosion control and to inform the design length of the cut-off wall.

Experimental tests were conducted on Rhine River conglomerates, which exhibited a texture similar to that of the conglomerates in the Karkheh River. According to a technical meeting memorandum in Germany, the maximum average allowable hydraulic gradient for mitigating erosion risk in the Karkheh Dam foundation and abutments was determined to be 0.075 (Heidarzadeh et al., 2019). The design length of the cut-off wall was based on this critical hydraulic gradient. Following the establishment of this criterion, supplementary embankment earth fill was strategically placed in Zones 1 to 5 (see **Figure 2**) on the upstream side, as well as within the downstream gullies along the right bank. In addition

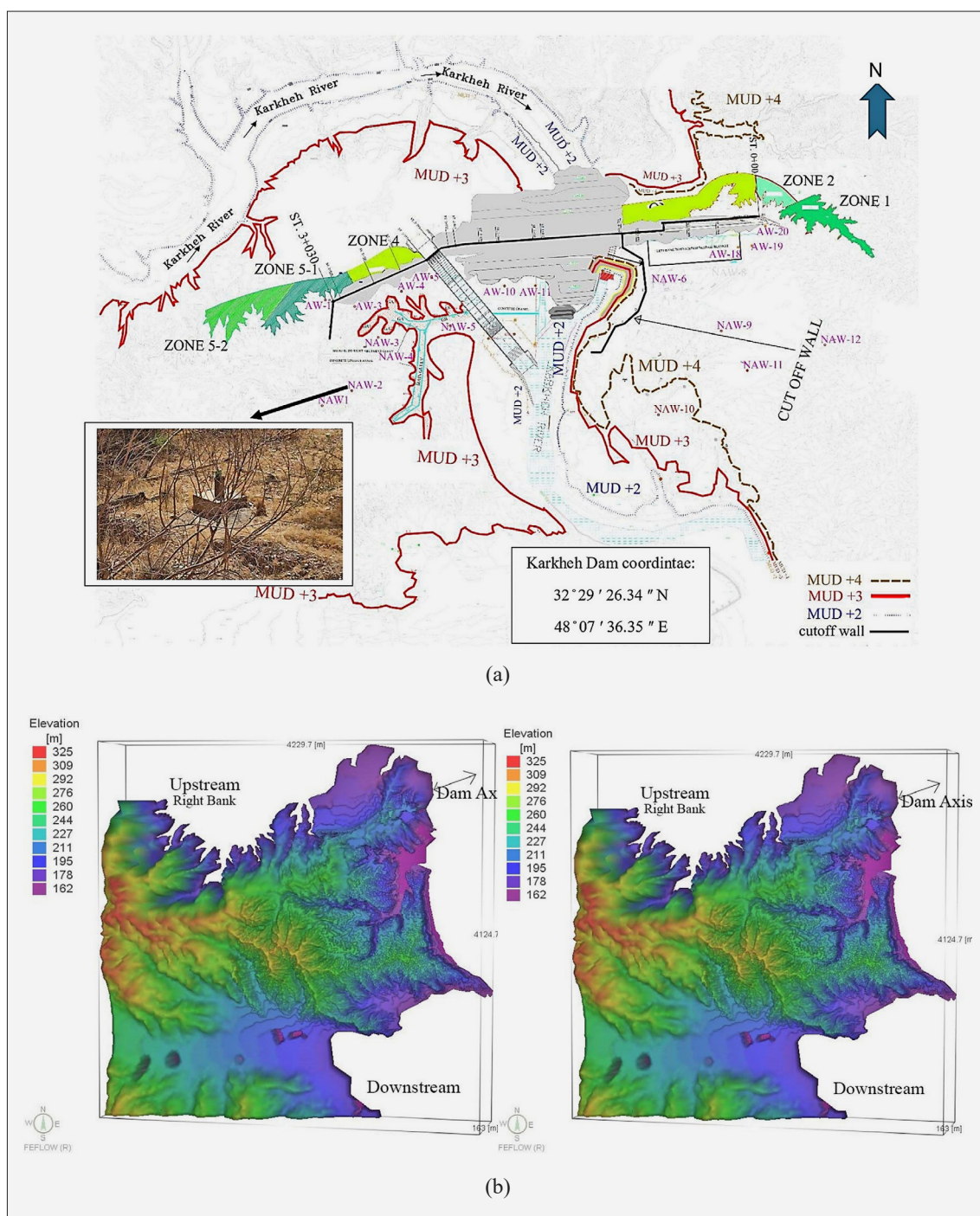


Figure 2: (a) General layout of Karkheh Dam indicating mudstone layer distributions, earthfill zones, and observation well locations. (b) Ground surface elevations (m.a.s.l.) from the FEFLOW model.

to increasing the seepage path length, these measures prevented shoreline erosion caused by wave action. During the early years of reservoir impoundment, fluctuations in water level, combined with the weak cementation of the Karkheh conglomerate, led to severe shoreline erosion (see **Figure 3a**). To address this, upstream embankments were constructed and the reservoir banks were armoured with riprap to ensure long-term erosion protection (see **Figure 3b**). Furthermore, a localised embankment was constructed to prevent water infiltration

into the gully adjacent to the left abutment and to reduce seepage in Zone 1.

4. Methodology

As previously noted, the large geometry of the structure, the complex geotechnical conditions (including the longitudinal and vertical extents of the cut-off wall in the dam design, as well as seepage dynamics through existing gullies), and the relatively high hydraulic conductiv-



Figure 3: (a) shoreline erosion caused by wave action; (b) soil-cement and supplementary embankment earth fill

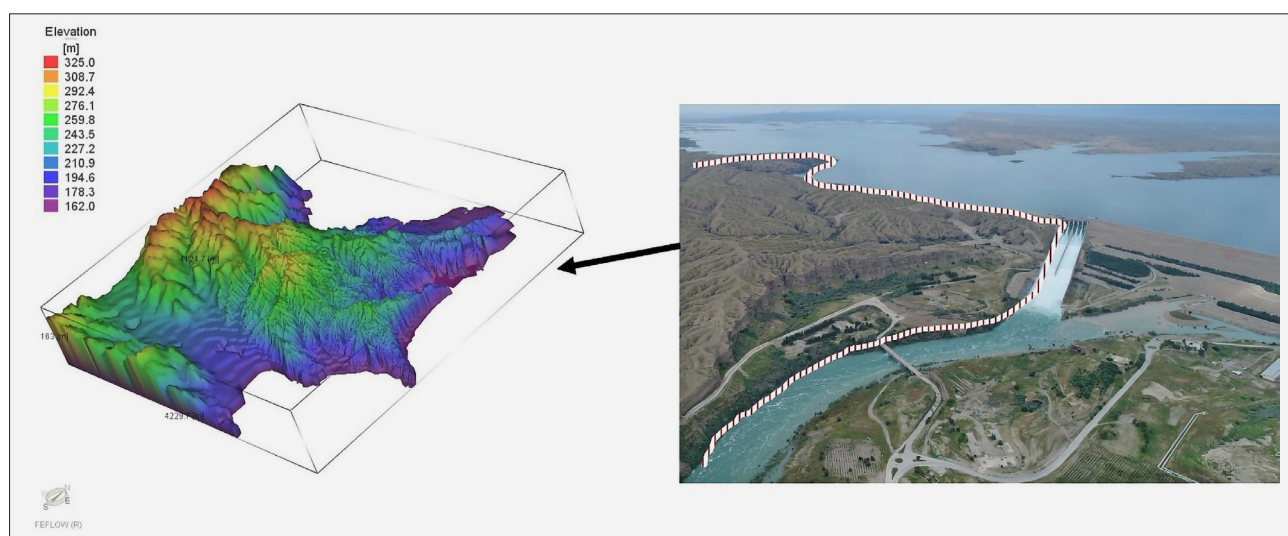


Figure 4: (a) numerical model geometry and (b) actual extent of the conglomerate above mudstone (+3) layer on the right abutment of the Karkheh Dam

ity of the foundation and abutments of the Karkheh Dam collectively necessitate a comprehensive three-dimensional seepage analysis. Given the necessity for three-dimensional analyses in such cases, FEFLOW is particularly well suited owing to its ability to model large-scale geometries, its computational efficiency, and its effectiveness in representing complex configurations. As an example of this modelling, **Figure 4a** presents the geometry of the numerical model for the conglomerate layer located above Mud (+3) on the right abutment, while **Figure 4b** illustrates the Karkheh Dam during the March 2019 flood and indicates the approximate extent of this layer.

4.1. Numerical Simulation

Considering the characteristics of the Karkheh Dam, together with the respective capabilities and limitations of state-of-the-art modelling tools, FEFLOW 3D was identified as the optimal choice for simulating seepage in geometrically complex configurations such as those present in the Karkheh Dam.

The software integrates a graphical user interface essential for the precise definition of the model geometry, with accurate delineation of boundaries being a critical step. To establish the three-dimensional model geometry, the locations of mudstone layer outcrops and the extents of the cut-off walls were initially mapped in plan view. The identification of these mudstone outcrops was achieved through the analysis of geological maps compiled during the construction phase and feasibility studies, as illustrated in **Figure 2**. By mapping the spatial distribution of each mudstone outcrop, a definitive boundary for the modelling domain was established. Earth-fill zones 1 to 5, in accordance with **Figure 2**, were also modelled. Appropriate boundary conditions were then applied to the surface topography and domain boundaries.

To ensure an accurate representation of field conditions, the thickness of conglomerate layers interbedded between mudstone strata was explicitly defined. Topographic survey data were utilized to incorporate elevation points relevant to the upper model layers. Following

planar domain definition, zones with differing hydraulic conductivity characteristics (such as cut-off walls and grout curtains) were represented using triangular prismatic three-dimensional elements. Within the inter-mudstone zones, conglomerate thickness was defined from the upper surface of the lower mudstone stratum to the base of the overlying mudstone layer.

Surface layers were modelled extending from the basal elevation of the uppermost mudstone to the specific elevations identified in the topographic survey. To finalise the three-dimensional construction, the conglomerate layer profiles, initially defined in two dimensions, were extruded to ensure volumetric continuity. The initial hydraulic conductivity parameters for these conglomerate layers were derived from the pumping test results detailed in Section 3.

It is worth noting that geologically, the dam body rests upon the upper conglomerate layers, specifically above the Mud (+3) layer in the right abutment and the Mud (+4) layer in the left abutment. However, since the primary objective of this study was to investigate seepage specifically through the foundation and abutments, the dam body itself was excluded from the simulation. Consequently, all numerical models consist solely of the foundation, abutments, and the cut-off wall, and therefore defining material properties for the earth dam body was not required.

4.2. Boundary Conditions

The upstream boundary condition was defined by the reservoir hydraulic head, applied to nodes situated below the reservoir water surface elevation. Conversely, the downstream boundary conditions were derived from comprehensive field inspections conducted during the 2019 flood events, corroborated by analyses of aerial footage and dam operational monitoring data. In fact, seepage exit elevations were determined based on site observations specific to this event. For scenarios where reservoir water levels fell below the normal operating level of 220 metres above sea level (m a.s.l.), the discharge points were adjusted proportionally to reflect these varying hydraulic conditions.

4.3. Calibration-Verification Approach and Performance Results

The model calibration process involved iterative adjustments to exit elevations and hydraulic conductivity values until the simulated seepage closely matched empirical field measurements. Hydraulic conductivity values were systematically adjusted across a range of reservoir water levels to align with site-measured discharge rates. The field monitoring program was designed to quantify seepage between individual mudstone pairs and to distinguish flow contributions from the left and right abutments through precise seepage measurements. The locations used for measuring seepage from the founda-



Figure 5: Location of the seepage measurement stations at the Karkheh Dam, monitoring discharge from the foundation and abutments.

tion and abutments are presented in **Figure 5**. The coloured regions delineate distinct seepage measurement zones, while the labels within the white circles correspond to the on-site identification codes for each zone. To keep the paper concise, the UTM coordinates and names of these points have been omitted.

Although the calibration methodology relied on a trial and error approach, which may limit precision compared with optimisation algorithms, it nevertheless provided a validated and practical framework for engineering applications. To ensure rigorous validation, hydraulic heads simulated at observation well locations were compared against field measurements from the dam abutments. Hydraulic gradients were calculated based on the differential between the reservoir water surface elevation and the hydraulic heads at the downstream exit points. Flow path lengths were determined via numerical analysis, enabling the comparison of calculated gradients with the allowable design limits. Consequently, the potential for internal erosion was evaluated across a range of reservoir water surface elevations. Furthermore, a representative average hydraulic conductivity was determined to support the estimation of total seepage discharge through the foundation and abutments. Finally, a sensitivity analysis was conducted to assess the influence of hydraulic conductivity anisotropy on the simulation results.

5. Results and Discussion

As described in the previous section, a three-dimensional (3D) seepage analysis was performed on six distinct geometries incorporating varying mudstone layers. These models were precisely matched to the actual site topography to ensure high accuracy and reliability. The hydrogeological domains were represented as representative homogeneous media, a standard simplification in deterministic seepage modelling. Although advanced probabilistic methods can account for spatial variability

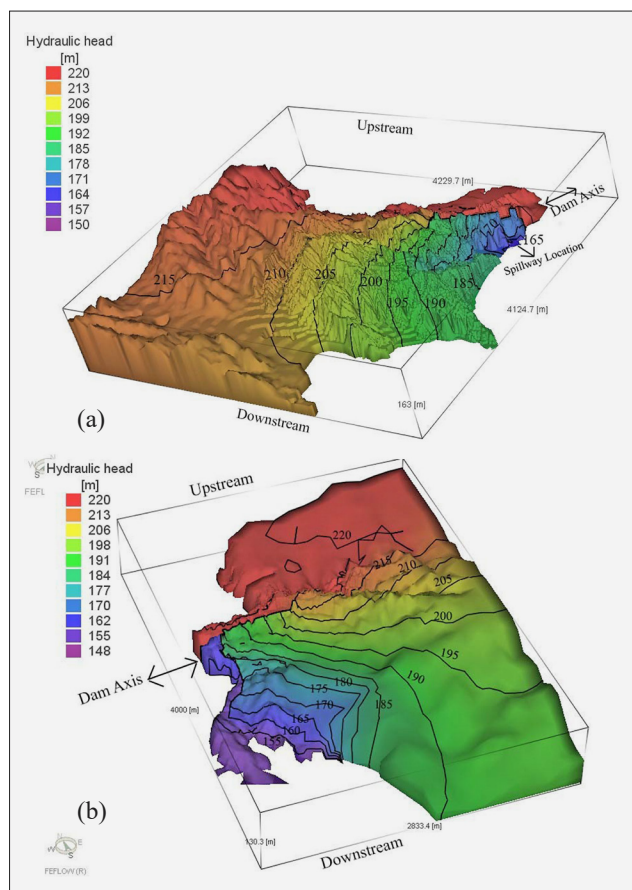


Figure 6. Three-dimensional seepage model showing equipotential lines from the numerical analysis of conglomerate layers at the normal reservoir water level: (a) Right abutment above Mudstone (+3); (b) Left abutment above Mudstone (+4).

to assess internal erosion risks in greater detail (Chi et al., 2025), future research could yield more precise outcomes by conducting extensive in-situ permeability tests to capture the heterogeneity of different zones within the foundation and abutments, as well as by extending the analysis to include transient seepage modelling. The 3D models developed for the different conglomerate units, together with the associated equipotential line distributions, are presented in **Figure 6-8**. Given that the dam body was not modelled, the dam axis is shown in these figures solely to represent the schematic location of the dam and the underlying cut-off wall. The numerical simulations were calibrated for reservoir water levels of 205, 210, 220 (NWL), and 225 m above sea level. Model validation was carried out by comparing the computed hydraulic heads at the observation wells with the corresponding field measurements at the dam site. The results of this comparison for the observation wells under normal water level conditions are provided in **Table 1**.

The quantitative comparison between the numerically computed hydraulic heads and the in-situ field measurements yields a Root Mean Square Error (RMSE) of 9 m. While this value indicates some numerical discrepan-

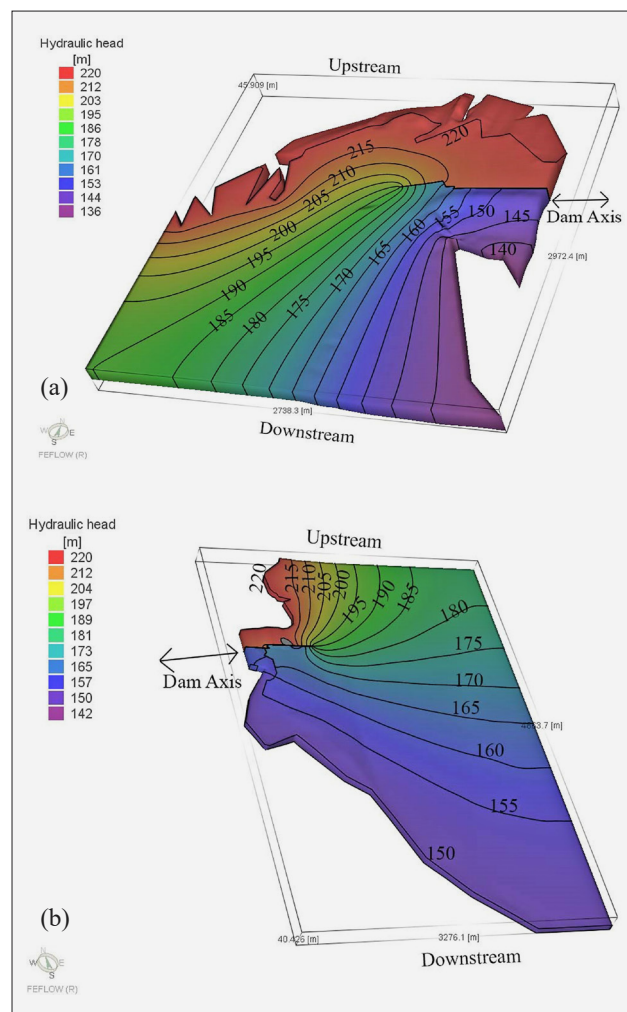


Figure 7: Three-dimensional seepage model showing equipotential lines within conglomerate layers at normal reservoir water level: (a) right abutment between mudstones (+2) and (+3); (b) left abutment between mudstones (+3) and (+4).

cies, it is widely considered an acceptable level of accuracy for validating the model's performance in complex hydrogeological studies. This conclusion is particularly valid when viewed relative to the significant total hydraulic head drop across the structure, where the error represents a relatively minor fraction of the overall hydraulic gradient. The observed discrepancies can be comprehensively attributed to three primary factors. First, a temporal mismatch existed during the monitoring period; the hydraulic head measurements did not always coincide precisely with the specific dates when the reservoir attained the simulation water levels. A typical time lag of approximately two to three days occurred before or after the target date. Moreover, the hydraulic response time of observation wells at different locations varies; not all observation points react simultaneously to a specific change in the reservoir head. Second, inherent heterogeneity within the rock mass is undoubtedly present in both horizontal and vertical profiles, creating a complex anisotropic system. Considering the extensive

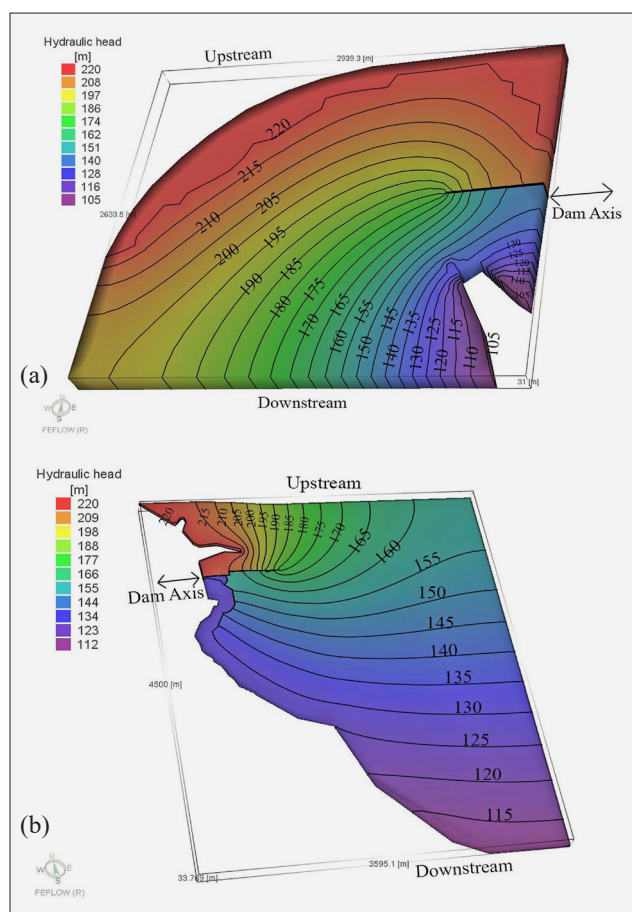


Figure 8: Three-dimensional seepage model showing equipotential lines within conglomerate layers at normal reservoir water level: (a) right abutment between mudstones (-1) and (+2); (b) left abutment between mudstones (+2) and (+3).

spatial scale of the modelled domain (spanning approximately 4 km), the necessary simplification of assuming homogeneity across such a vast domain naturally contributes to the observed deviations between the uniform numerical simulations and the spatially variable in-situ measurements. Third, and fundamentally, the numerical simulation utilizes an Equivalent Porous Media (EPM) approach to represent the fractured rock mass. Recent research highlights that the orientation of high-permeability discontinuities fundamentally dictates the flow regime, acting as the main channels for fluid movement which creates concentrated flow paths distinct from the surrounding matrix (Namdari et al., 2021). Since the actual groundwater flow occurs through discrete fracture networks and specific conductive features, local channelling effects can cause point-specific measurements to differ from the volume-averaged hydraulic heads calculated by the continuum model.

The Karkheh Dam spillway has a total length of 995 m, extending from the ogee to the end of the stilling basin. At the right bank, it intersects mudstone layers -1, +2, and +3 at various elevations. Numerical analysis results illustrate the variation in uplift pressure beneath the concrete slab specifically from the ogee crest to the inlet of the stilling basin (see Figure 9). Uplift pressure is highest at the right bank section, particularly within the conglomerate units between mudstone layers -1 and +2, and above layer +3, where it reaches up to 65 kPa. This increase in uplift pressure, exceeding values recorded during initial operation, is attributed to the clogging of drainage wells located beneath the spillway chute slab. Mitigation involves rehabilitating existing drainage wells and installing additional drainage boreholes where

Table 1: Comparison of measured and numerically simulated total hydraulic heads in observation wells at normal reservoir water level

Observation well Locating at right bank	Water Total Head (m)		Observation well Locating at left bank	Water Total Head (m)	
	Measured	Numerical Analysis		Measured	Numerical Analysis
AW6-2	216.34	215.06	AW16-1	186.48	182.6
AW3-2	184.31	188.36	AW17-1	193	188.39
AW4-2	176.89	176.81	AW18-2	200.63	194.36
AW5-2	161.76	161.55	AW19-1	205.35	200.85
NAW5-1	145.16	149.75	AW20-1	211.96	205.08
AW1-1	215.00	217.12	NAW7-1	175.38	167.47
AW3-1	186.52	177.38	NAW11-1	176	174.02
AW6-1	211.08	192.84	AW16-2	171.68	171.93
NAW2-1	189.41	186.47	AW17-2	174.94	171.21
NAW17-1	170.17	162.92	AW18-1	181.36	198
AW3-3	183.35	170.84	AW19-2	182	170.09
AW10-2	146.67	131.02	AW20-0	186.36	205
NAW16-2	139.14	141.4	NAW14-3	151.75	162.7
NAW17-2	172.56	155.31	NAW8-2	151.99	163.7
NAW5-2	151.54	145.93	NAW7-3	149.16	144.85

*Note: The Root Mean Square Error (RMSE) between the measured and numerical analysis values is 9 m.

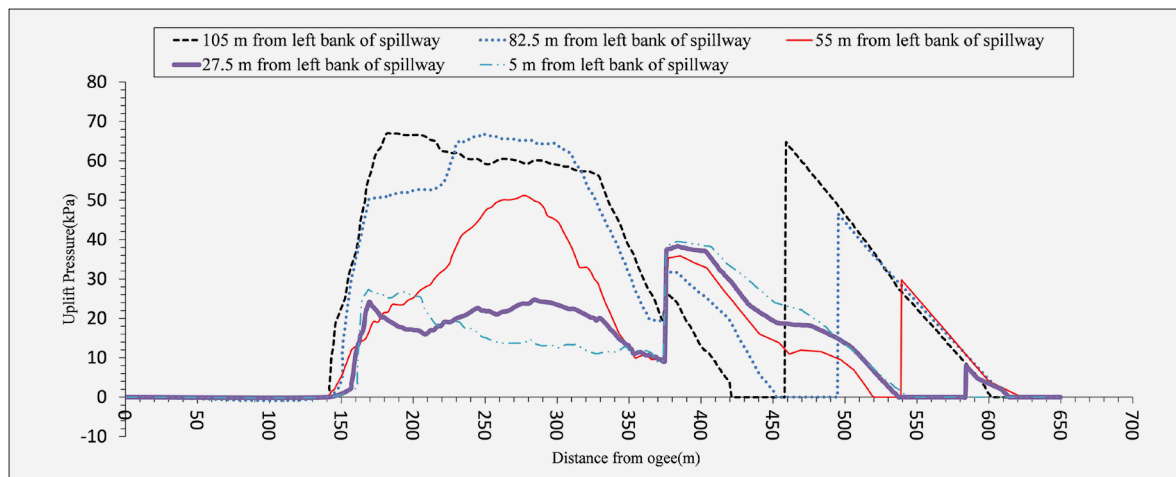


Figure 9: Evolution of uplift pressure beneath the spillway concrete slab with distance from the ogee crest at normal water level, based on five longitudinal cross-sections across the 118 m wide spillway

Table 2: Maximum average hydraulic gradients in conglomerate layers at different reservoir water levels, based on numerical analyses

Location of Conglomerate Layer	Reservoir Water Level (m.a.s.l)			
	205	210	220 (NWL)	225
Between mud (-1,+2) at the right bank	0.054	0.061	0.066	0.071
Between mud (+2,+3) at the right bank	0.056	0.066	0.069	0.076
Above mud (+3) at the right bank	0.030	0.034	0.044	0.052
Between mud (+2,+3) at the left bank	0.052	0.056	0.060	0.063
Between mud (+3,+4) at the left bank	0.030	0.032	0.036	0.040
Above mud (+4) at the left bank	0.034	0.047	0.062	0.069

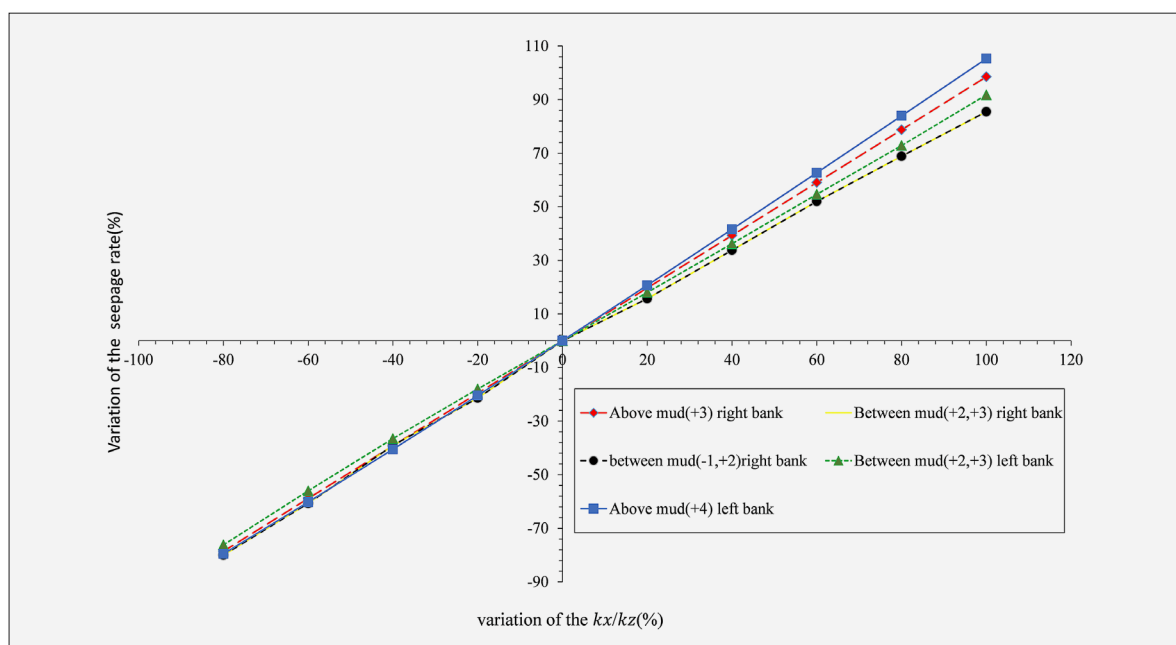


Figure 10: Sensitivity analysis of horizontal-to-vertical hydraulic conductivity ratios on seepage discharge through the Karkheh Dam abutments

uplift pressures exceed allowable limits. These works are currently in progress, with borehole locations selected based on the results of this numerical modelling. The

observed reduction in uplift pressures shown in **Figure 9** is associated with the presence of intersecting low-hydraulic conductivity mudstone layers.

The average maximum hydraulic gradient, defined as the gradient along the shortest seepage streamline, for various conglomerate layers at different reservoir water levels is presented in **Table 2**, and is based on numerical analyses. The locations of maximum gradient occur within the conglomerates situated between mudstone layers +2 and +3 on the right bank, and above mudstone layer +4 on the left bank. In all examined conglomerate layers, the maximum hydraulic gradient remains below the allowable limit of 0.075, indicating that under normal reservoir conditions the gradient operates within safe limits. However, at a reservoir elevation of 225 m above sea level (m.a.s.l.), the hydraulic gradient approaches the allowable limit of 0.075. Since reservoir elevations exceeding the normal operating level correspond to flood conditions where maintaining safety margins is critical (**Jain et al., 2023**), operators may temporarily store and regulate floodwater for potential use in dry periods only if strict limits are observed. Therefore, it is recommended that the reservoir level not be maintained at or above 225 m.a.s.l. to avoid establishing a steady-state seepage regime and to reduce the risk of initiating erosion in the foundation rock mass.

Following the calibration of 24 numerical analyses, an average hydraulic conductivity of 3.2×10^{-4} m/s was determined for the conglomerate layers forming the dam foundation and abutments. Using this average hydraulic conductivity in seepage calculations resulted in less than a 10 percent difference between the measured and computed seepage discharges.

During model calibration, the horizontal hydraulic conductivity was set to be ten times greater than the vertical hydraulic conductivity to achieve closer agreement with observations from well measurements. This anisotropy ratio represents a common assumption in most seepage analyses (**Bakker & Bot, 2025**). A subsequent sensitivity analysis was carried out to assess the influence of this anisotropic ratio on the dam seepage rate while keeping the horizontal hydraulic conductivity constant. In **Figure 10**, a horizontal-to-vertical permeability ratio of 5 serves as the benchmark (set as the origin at 0%, 0%), with the vertical and horizontal axes showing the percentage variations in seepage rate and anisotropy ratio, respectively. It is observed that the model sensitivity is notably higher for horizontal-to-vertical permeability ratios greater than 5. As shown in this figure, the influence of anisotropy is more pronounced in the upper conglomerate layers, where the vertical seepage component is markedly greater than in the lower layers. This vertical component is particularly significant within the outcrop zones. The results in **Figure 10** indicate that the effect of the vertical hydraulic conductivity is more pronounced in the conglomerate layers overlying the +4 mudstone layer on the left bank compared with the other cases. This aligns with recent findings indicating that the anisotropy ratio directly governs the depth of hydraulic influence; specifically, variations in

pore water pressure are primarily concentrated in near-surface layers when the vertical-to-horizontal permeability ratio is low, whereas higher vertical ratios allow these pressure changes to propagate significantly into deeper zones (**Zhang et al., 2025**). Such observations underscore the critical role of vertical flow components in heterogeneous formations, consistent with reported enhancements in downward fluid migration through vertical preferential pathways (**Tafti et al., 2021**).

6. Conclusions

To examine the seepage characteristics of the Karkheh Dam foundation and its abutments, a comprehensive analysis was conducted using the Finite Element Method (FEM) in FEFLOW 3D. Three-dimensional models were developed and calibrated against empirical monitoring data, resulting in 24 distinct simulations. The study encompassed six geometrical configurations and four reservoir water levels.

The principal findings are as follows:

- The applicability of this three-dimensional model is substantiated by its successful calibration against monitored seepage discharges and its validation using piezometric data, confirming its capability to accurately represent the complex heterogeneous geology of the foundation. The application of the model is particularly critical during extreme flood events, such as the 2019 flood. By identifying the precise locations of maximum uplift pressure, specifically beneath the spillway chute, and determining the reservoir elevation at which hydraulic gradients exceed safe limits, the model serves as an essential predictive tool. This capability enables operators to implement targeted safety measures and proactively control internal erosion risks during future hydrological crises.
- The cut-off wall played a critical role in reducing the hydraulic gradient and mitigating uplift pressure. However, given the substantial cost associated with extending the wall into deeper strata, the most effective solution for controlling uplift pressure beneath the spillway slab was the installation of new drainage boreholes. Their locations, determined through three-dimensional analyses, were selected to target zones with predicted peak uplift pressures.
- The three-dimensional seepage analysis revealed that the location of maximum uplift pressure could differ from that predicted by conventional two-dimensional analysis. This finding underscores the importance of using three-dimensional modelling to accurately represent hydraulic behaviour and pressure distribution within the dam foundation and abutments, and appurtenant structures such as the spillway.

- The proposed extension of the cut-off walls was adequate for conditions corresponding to the normal reservoir water level; however, during flood seasons, water levels could exceed this threshold. Such exceedance raises concerns about the prolonged retention of surplus water for use during arid periods. The results indicate that maintaining water levels above a specified margin higher than the normal reservoir elevation for durations exceeding the time required to reach steady-state seepage presents a high risk of initiating internal erosion within the foundation rock mass.
- Sensitivity analysis of anisotropic hydraulic conductivity indicated that the best agreement with observation well data was achieved when horizontal hydraulic conductivity was one order of magnitude greater than vertical hydraulic conductivity. It is observed that the model sensitivity is notably higher for horizontal-to-vertical permeability ratios greater than 5. The impact of hydraulic conductivity anisotropy was most evident in the upper conglomerate strata, where vertical seepage components were more prominent, particularly at locations identified as potential seepage surfaces.

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SAŽETAK

Trodimenzijska analiza procjeđivanja kroz temeljne naslage brane: studija slučaja brane Karkheh

Temeljne naslage brane Karkheh sastoje se od heterogenoga geološkog profila koji čine jako propusni konglomerati isprepleteni s relativno nepropusnim muljnjacima. Nakon ekstremnih poplava u ožujku i travnju 2019. godine akumulacija je prvo dosegla svoju normalnu razinu vode od 220 m nadmorske visine, a zatim se podigla za otprilike 5 m dosegnuvi vrhunac od 224,82 m 5. travnja 2019. godine. Iako se kruna brane nalazi na 234 m nadmorske visine, navedeni uvjeti izazvali su zabrinutost u vezi sa stabilnošću konstrukcije i potencijalnim opasnostima od procjeđivanja, osobito tijekom budućih poplava. Kako bi se umanjili ovi rizici, provedene su stroge operativne mjere radi ograničavanja hidrauličkoga gradijenta unutar dopuštenih projektnih vrijednosti, čime se smanjuje vjerojatnost unutarnje erozije i pojave procjednih kanala. Trodimenzijski model procjeđivanja kroz temeljne naslage brane razvijen je pomoću softvera FEFLOW3D, pri čemu je obuhvaćeno šest slojeva konglomerata na četirima različitim razinama akumulacije. Model je kalibriran u odnosu na izmjereno procjeđivanje uz prilagodbu hidrauličke vodljivosti te razvijen na temelju podataka o razinama podzemne vode u piezometrima. Ključni rezultati uključivali su identifikaciju raspodjele uzgona i određivanje lokacija maksimalnoga uzgona, što je bilo ključno za planiranje novih drenažnih zdenaca. Osim toga, analizama je definirana granična nadmorska visina akumulacije iznad koje maksimalni prosječni hidraulički gradijent raste do razina koje predstavljaju povećani rizik od unutarnje erozije u temeljnim naslagama brane. Ovi rezultati, zajedno s redefiniranim parametrima propusnosti i detaljnom raspodjelom hidrauličkih gradijenata, pružaju detaljan uvid u hidrogeotehničko ponašanje brane pod ekstremnim hidrološkim opterećenjem te omogućuju ciljano upravljanje sigurnošću hidrauličkoga sustava.

Ključne riječi:

analiza procjeđivanja, brana, hidraulički gradijent, nadzor brane, FEFLOW3D

Author's contribution

Mohammad Salehinik (Ph.D. Candidate): conceptualization, visualization, writing – original draft and writing, investigation, formal analysis and software. **Ali Asghar Mirghasemi** (Professor): conceptualization, methodology, supervision, resources, validation and review & editing. **Ahmadreza Tabibnejad** (Manager of Soil/Rock Mechanics & Earth Dams Department): conceptualization, data curation, project administration, supervision, resources and validation. All authors have read and agreed to the published version of the manuscript.

Modelling the effects of lateral loading on a bent strike-slip fault system: A case study from the Palu-koro and Matano faults, Indonesia

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Original scientific paper



Dian Kusumawati^{1,6}✉, David P. Sahara²✉, Nanang T. Puspito^{2*}✉, Mudrik R. Daryono³✉, Andri D. Nugraha²✉, Andrean V. H. Simanjuntak^{4,5}✉, Maulidia Ain Bening²✉, Faiz Muttaqy⁶✉

¹ Geophysical Engineering, Faculty of Mining and Petroleum Engineering, Institut Teknologi Bandung, Bandung 40132, Indonesia.

² Global Geophysics Research Group, Faculty of Mining and Petroleum Engineering, Institut Teknologi Bandung, Bandung 40132, Indonesia.

³ Earthquake Research Group, National Research and Innovation Agency (BRIN), Bandung 40135, Indonesia.

⁴ Indonesia Agency for Meteorology, Climatology and Geophysics (BMKG), Jakarta 10720, Indonesia.

⁵ Department of Geophysical Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia.

⁶ Research Center for Geological Disaster, National Research and Innovation Agency (BRIN), Bandung 40135, Indonesia.

Abstract

The Palu-koro and Matano faults form a major bent strike-slip fault system in central Sulawesi, Indonesia, accommodating significant crustal deformation associated with regional plate interactions. In this study, we investigate the mechanical response of this fault system using three-dimensional numerical modelling to evaluate how different lateral loading configurations influence fault slip and stress patterns. Dirichlet (displacement-rate) boundary conditions, inferred from regional plate velocities, are applied to the model domain at the x-face, y-face, and in combined x- and y-face configurations. Models with pure x-face or y-face loading generate lateral slip patterns that are mechanically compatible with idealized Riedel shear kinematics; however, the resulting slip sense differs from the present day tectonic motion of the Palu-koro and Matano faults. In contrast, models with combined boundary conditions reproduce first-order characteristics of the observed fault behaviour. In particular, scenarios with dominant lateral loading at the x-face (e.g. 70% x-face and 30% y-face) produce predominantly sinistral slip along both faults and higher slip concentrations along the Palu-koro Fault, consistent with tectonic and geodetic observations. The combined loading models also exhibit a subtle rotation of the maximum principal stress orientation from WNW-ESE along the Palu-koro Fault to NE-SW along the Matano Fault, which is qualitatively consistent with stress orientations inferred from focal mechanism inversions. Overall, the results suggest that combined regional lateral loading, with a dominant north-south lateral movement, provides a plausible mechanical framework for understanding deformation localization and stress rotation within the Palu-koro-Matano fault system.

Keywords:

bent strike-slip; fault lateral slip; fault tensile slip; Matano Fault; numerical modelling; Palu-koro Fault; Riedel shear

1. Introduction

Several conceptual models have been developed by structural geologists to explain rock deformation. One such model is the simple shear model, in which parallel planes slide past one another laterally, transforming an initially square material element into a rhombus (Harding, 1973). This parallel lateral loading causes the material to undergo both shear and rotation, such that one diagonal experiences shortening while the other undergoes extension. The maximum principal stress axis is aligned with the compressional (shortening) diagonal, whereas the minimum principal stress axis is aligned

with the extensional diagonal (Davis and Reynolds, 1996; Ragan, 1973). Within such a simple shear system, internal faulting patterns known as Riedel structures develop, consisting of synthetic and antithetic strike-slip shear fractures (Kavyani-Sadr et al., 2022; Riedel, 1929) (see Figure 1).

The Palu-koro and Matano faults are located on the island of Sulawesi in eastern Indonesia, where the tectonic setting is complex due to the collision of four plates: the Eurasian/ Sunda, Australian, Philippine sea, and Pacific plates (Hall, 2012; Hamilton, 1979; Silver et al., 1983) (see Figure 2). The Australian Plate moves north-northeastwardly, while the Philippine Sea and Pacific plates move northwestwardly relative to the Eurasian/Sunda Plate (DeMets et al., 2010), generating both north-south and east-west components of regional lateral tectonic loading.

* Corresponding author: Nanang T. Puspito

e-mail address: nanangpuspito@gmail.com

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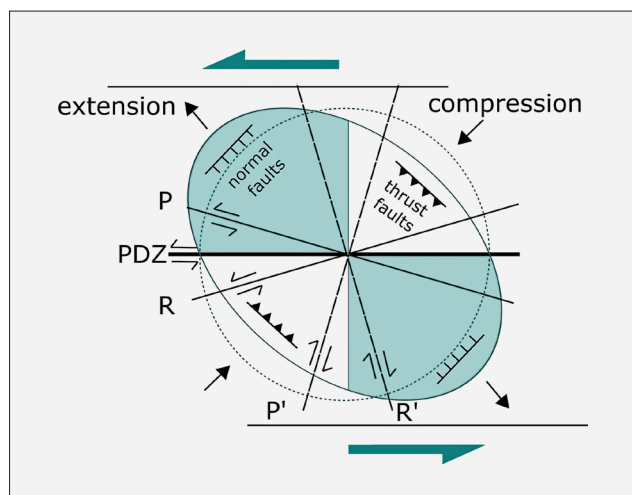


Figure 1: Schematic diagram of a sinistral Riedel shear zone developed under simple shear deformation. PDZ denotes the principal displacement zone. R represents the Riedel shear and P represents the synthetic secondary shear. R' and P' are the conjugate Riedel shear and the conjugate secondary shear, both exhibiting antithetic motion relative to the PDZ. The green shaded areas indicate tensile quadrants, whereas the white areas represent compressional quadrants. The dashed circle is the undeformed model. Modified after Riedel (1929), Yu et al. (2022), and Roy et al. (2021).

Stress inversion has been used to study the deformation of Sulawesi. **Beaudouin et al. (2003)** divided the island of Sulawesi into several zones and performed stress inversion using focal mechanism data to obtain σ_H orientations. They observed areas of contraction and extension in Sulawesi. In the following studies, stress orientation in the Palu-koro and Matano faults, have been inverted using focal mechanism data. Northwest-southeast (NW-SE) stress orientation in the Palu-koro Fault and northeast-southwest (NE-SW) stress orientation in the Matano Fault are observed (**Kusumawati et al. 2025; Othav et al., 2025**) (see **Figure 2**). These rotating stress orientations provide important evidence for evaluating the mechanical response of bent strike-slip faults to regional lateral tectonic loading.

Numerical modelling is common for studying geodynamics, where direct observation is limited. It can be used to study the dynamics of the Earth by solving and simulating the physical processes (**Gerya, 2019; Zelst et al., 2021**). Several studies have applied numerical modelling and explained the deformation surrounding the faults. **Wang et al. (2017)** applied numerical modelling to simple stepovers and bends using a 3-D finite element code to study the stress perturbation, strain partitioning, and fault evolution. Their model predicts the stress and strain distribution around stepovers and bends, and explains the key differences between these configurations in the Dead Sea trough, Death Valley, and along the San Andreas Fault. **Bening et al. (2022)** study the fault deformation during strain buildup and release in a strike-slip fault with a brittle elastic-viscoelastic materi-

al. The modelling results explained the pattern of seismicity observed on the Great Sumatran Fault.

Utilizing numerical modelling to analyze continuum crustal deformation, we investigate how regional lateral loading, represented by a simple shear framework, influences deformation within a bent strike-slip fault system. The Palu-koro and Matano faults, subjected to regional tectonic loading from both east-west and north-south directions, serve as natural examples for our analysis. The rotating stress orientations observed along these faults serve as qualitative reference patterns for exploring the mechanical response of bent strike-slip systems to lateral loading. Accordingly, we apply several lateral loading scenarios to examine deformation localization at the faults, as expressed by fault slip distributions, and the resulting stress orientation. We then further compared them to the present-day conditions of the faults. The results indicate that combined lateral loading, dominated by a north-south direction, provides the consistent explanation for observed fault slip distributions and stress orientations, offering a mechanical explanation for the higher slip rate and shorter recurrence behaviour of the Palu-koro Fault relative to the Matano Fault.

2. Tectonic setting

The Palu-koro and Matano faults in Indonesia are located within the Sunda Plate, at the western termination of a major sinistral strike-slip fault system in eastern Indonesia that extends from Papua to Sulawesi. The major sinistral strike-slip fault system consist of the Yapen and Sorong faults in Papua, the Sula-Sorong fault zone in North Molucca, the Matano and Palu-koro faults in Sulawesi, that further terminates at the Sulawesi subduction trench in the north (**Silver et al., 1983; Hamilton, 1979**) (see **Figure 2**). The sinistral strike-slip fault system developed in response to the oblique convergence of the Australian, Philippine Sea, and Pacific plates relative to the Eurasian/Sunda Plate (**Hall, 2012; Hamilton, 1979; Silver et al., 1983**). The Australian Plate moves north-northeastward at a rate of 76 mm/year, whereas the Philippine Sea and Pacific plates move northwestward at rates of 106 mm/year and 101 mm/year (**DeMets et al., 2010**), respectively. The complex plate interaction strongly influences the kinematics of the Palu-koro and Matano faults, as demonstrated by microblock rotation model that explain the observed geodetic velocity field in Sulawesi (**Socquet et al., 2006**).

The development of the Palu-koro and Matano faults consisted of two main periods of tectonic activity: (1) the Mesozoic-Paleogene and (2) the Neogene (**Baillie and Decker, 2022; Hall and Wilson, 2000**). During the Mesozoic-Paleogene, the main tectonic blocks that later formed Sulawesi were formed (**Hall, 2012**). In the Neogene, these blocks moved, rotated, and interacted through complex geological processes, leading to the development of the present day K-shaped Sulawesi

(Hall and Wilson, 2000; Socquet et al., 2006). Within this framework, the Palu-koro and Matano faults developed in association with the present configuration of the tectonic blocks, while the oblique convergence at the regional scale may have contributed to the observed left-lateral slip motion along the faults.

3. Methodology

3.1. Data

In this study, we formed a block model of the Palu-koro and Matano faults to run the numerical modelling. The block was built with a size of 3.5° length and 3.75° width over the area of central Sulawesi, with the Palu-koro and Matano faults located at the center of the block. We created an elastic half-space model for the block with 80 km thickness of elastic layer to simplify the model. For the depth of the fault, we set it from 0 to 30 km depth, considering the average Moho discontinuity depth in Sulawesi from CRUST1.0 (Laske et al., 2013). The material properties were also referred from CRUST1.0: the density, P- and S-wave velocity of 2780 kg/m³, 6385 m/s, and 3663 m/s for 0 to 30 km depth; and 3113 kg/m³, 7437 m/s, and 4177.3 m/s for 30 to 50 km depth, respectively.

We considered ten segments of the Palu-koro and Matano faults in the model: Donggala, Palu, Saluki, Moa, Meloi, Kuleana, Pewusai, Matano, Pamsoa, and Ballawai segments. The segments were referred from the National Center for Earthquake Studies of Indonesia (PUSGEN) (2017), Natawidjaja et al. (2021), and Daryono (2016), as shown in Figure 2. The observation target is the regional deformations of the faults, thus we modelled a simplified version of the faults by excluding the fault details in some segments, such as the fault's branching in the Palu segment and the fault stepover in Matano Lake. We modelled these parts as continuous segments.

The block is divided into a hexahedral mesh consisting of 6834 cells and 8304 nodes. Due to the non-planar geometry of the fault, the mesh size adapts to the curvature of the fault while maintaining the hexahedral shape of the cell. The size of the cells near the bend of the fault is smaller than the cells at the planar part of the fault. The maximum, minimum, and average cell edge lengths are 21.51 km, 6.44 km, and 12.71 km, respectively. The average size of the cell edge is still smaller than the length of the fault segment, 18.8 km to 66.5 km (PUSGEN, 2017), thus still considered as a reliable resolution for the modelling. The mesh in this study was created using Coreform Cubit 2021.11 (Coreform, Orem, UT, USA). Coreform Cubit is software for creating high-quality finite element analysis meshes.

3.2. Method

We used the finite element method for the numerical modelling, implemented in Pylith software. Pylith is a finite element software for simulating dynamic and qua-

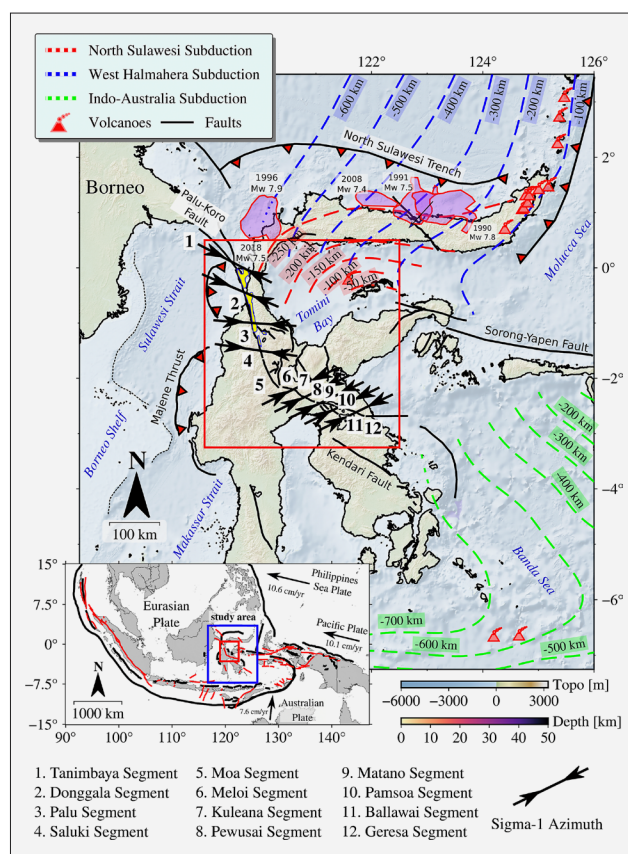


Figure 2: Tectonic setting of Sulawesi and surrounding regions. The historical earthquake slip models (purple) from Zheng et al. (2023) highlight major events ($M_w > 7$), including the 2018 M_w 7.5 Palu earthquake (yellow). The dashed lines denote major subduction systems: North Sulawesi (red), West Halmahera (blue), and Indo-Australian (green) (Hayes et al., 2018). Maximum principal stress (σ_1) azimuths along the Palu-koro and Matano faults are shown after Kusumawati et al. (2025) and Octav et al. (2025). The red square outlines the numerical modelling domain. The bathymetry profile were downloaded from BATNAS-BIG (<https://sibatnas.big.go.id/>), fault line from PUSGEN (2017), Natawidjaja et al. (2021), and Daryono (2016).

si-static deformation of the crust, including simulating the deformation due to fault slip (Aagaard et al., 2017, 2013). The software uses the domain decomposition approach in the fault slip implementation and the Krylov subspace method to solve the linear equation.

Based on the regional tectonic setting of Palu-koro and Matano faults, the oblique convergence of the Australian, Philippine Sea, and Pacific plates relative to the Eurasian/Sunda Plate produces an average relative plate motion vector of 97 mm/year directed northwestward. This displacement rate magnitude was used to define three lateral loading scenarios, representing the regional tectonic loading. We imposed the lateral loading by prescribing Dirichlet (displacement) boundary conditions on the lateral faces of the model domain. The coordinate system was defined such that the east, north, and upward directions correspond to the positive x-, y-, and z-axes, respectively.

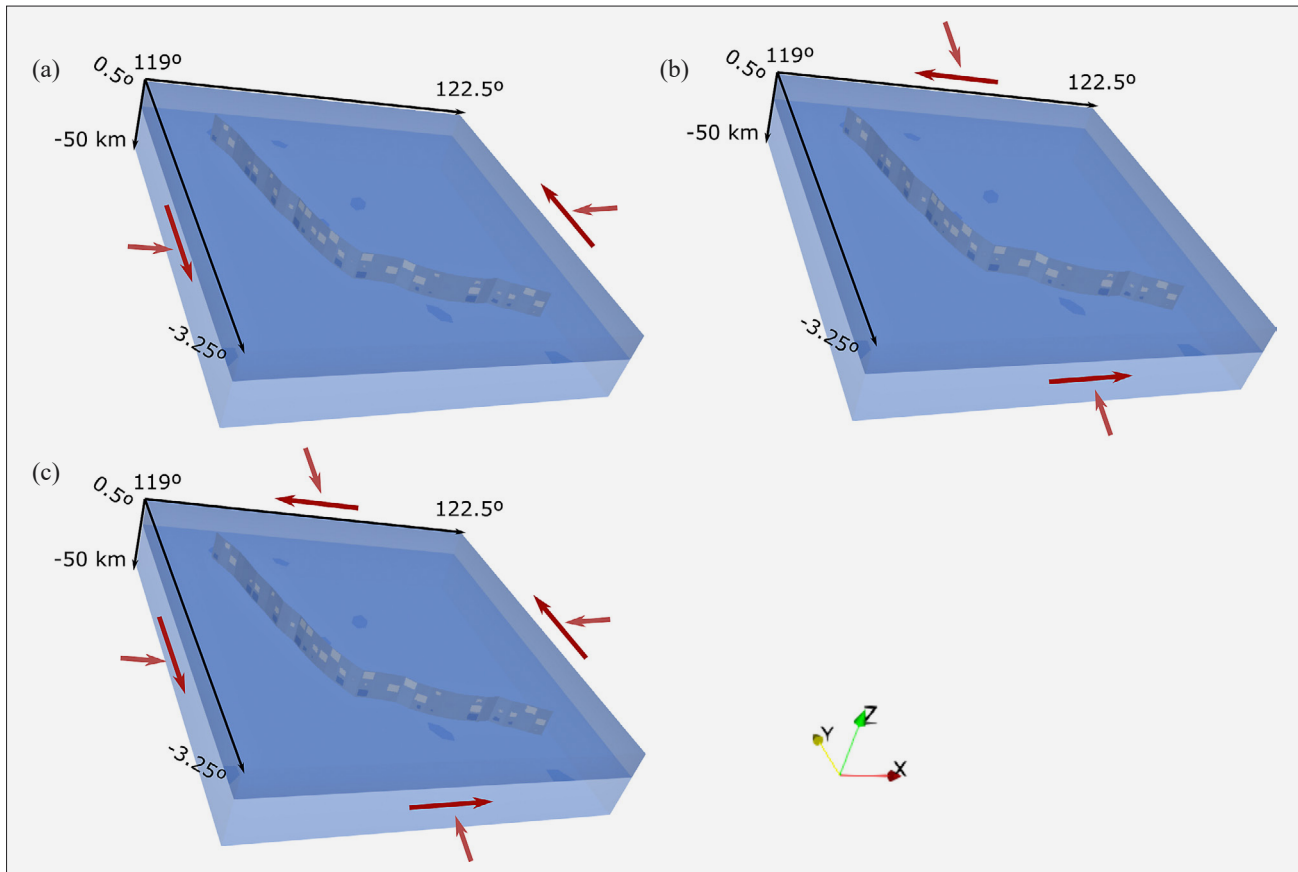


Figure 3: Model set up and boundary condition: (a) the x-face boundary condition, (b) the y-face boundary condition, (c) the combine x- and y-faces boundary conditions. The x- y- and z-axis are showing the east, north and up directions.

Tabel 1: Combine x- and y-faces boundary conditions, displacement rate magnitude propotion at the x- and y-faces: 10%:90%, 30%:70%, 50%:50%, 70%:30%, and 90%:10%.

Proportion (x- and y-faces) 10%:90%			Proportion (x- and y-faces) 50%:50%			Proportion (x- and y-faces) 90%:10%		
Faces	Disp. rate x (mm/year)	Disp. rate y (mm/year)	Faces	Disp. rate x (mm/year)	Disp. rate y (mm/year)	Faces	Disp. rate x (mm/year)	Disp. rate y (mm/year)
xpos	-5	10	xpos	-5	49	xpos	-5	87
xneg	5	-10	xneg	5	-49	xneg	5	-87
ypos	-87	-5	ypos	-49	-5	ypos	-10	-5
yneg	87	5	yneg	49	5	yneg	10	5
Proportion (x- and y-faces) 30%:70%			Proportion (x- and y-faces) 70%:30%					
Faces	Disp. rate x (mm/year)	Disp. rate y (mm/year)	Faces	Disp. rate x (mm/year)	Disp. rate y (mm/year)			
xpos	-5	29	xpos	-5	68			
xneg	5	-29	xneg	5	-68			
ypos	-68	-5	ypos	-29	-5			
yneg	68	5	yneg	29	5			

- The x-face boundary condition

In the first scenario, we applied shear displacement rate of 97 mm/year on the x-faces of the model domain, as shown in **Figure 3a**, generating north-south lateral movement with a left lateral or sinistral sense of motion. An axial displacement of ap-

proximately 5% of the imposed shear rate (≈ 5 mm/year), was applied to the x-faces together with the shear displacement to maintain compressive normal traction on the fault (Aagaard et al., 2017). This configuration is hereafter referred to as the *x-face boundary condition*.

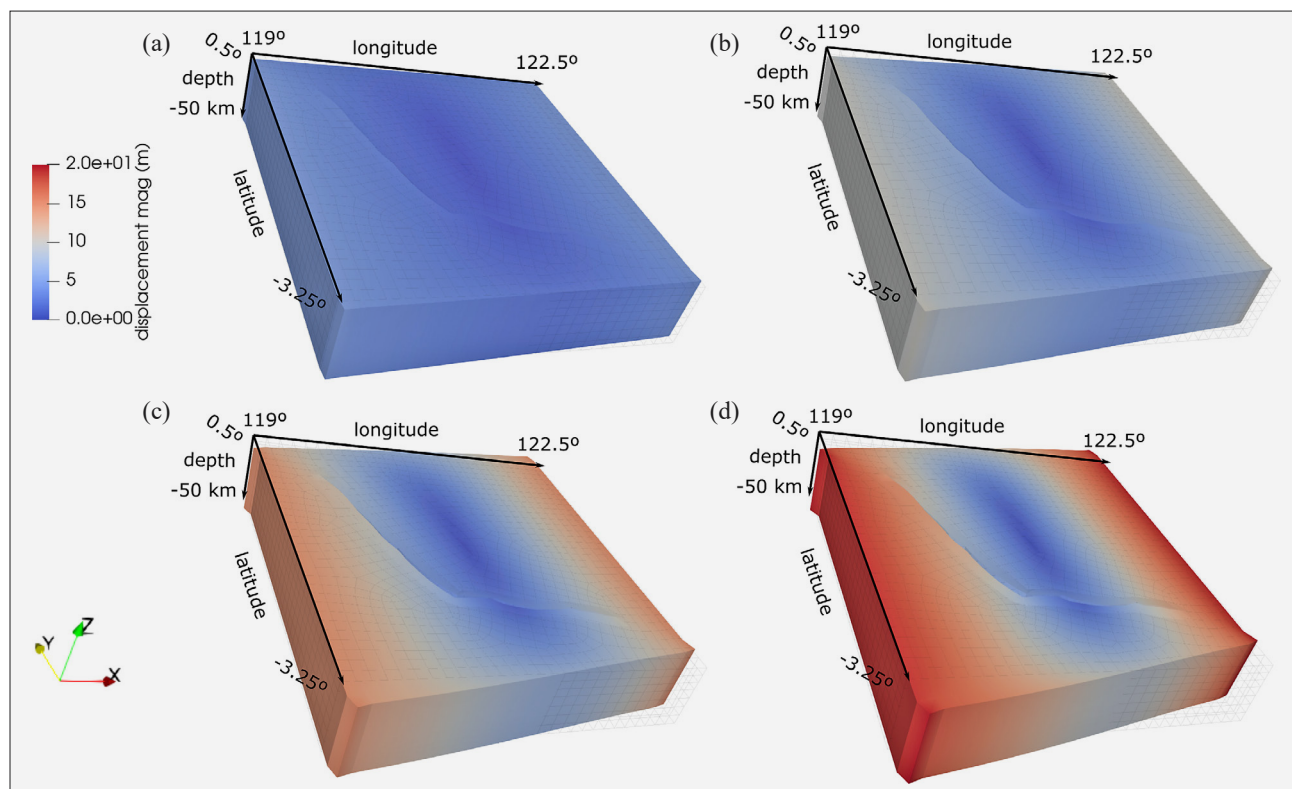


Figure 4: The displacement magnitude (m) of block deformation for the x-face boundary condition, at: (a) year 50, (b) year 100, (c) year 150, and (d) year 200. The figure is exaggerated by a factor of 2000. The gray mesh is the original undeformed form of the block. The x- y- and z-axis are showing the east, north and up directions.

- The y-face boundary condition

In the second scenario, we applied shear and axial displacement rates of 97 mm/year and ≈ 5 mm/year, at the y-faces of the model domain as shown in **Figure 3b**. The boundary condition creates west-east lateral movement on the y-faces with a left lateral or sinistral sense of motion. This configuration is hereafter referred to as the *y-face boundary condition*.

- The combine x- and y-faces boundary conditions

We combined the x-face and y-face boundary conditions for the third scenario, to approximate natural tectonic loading involving both north–south and west-east components. The relative contribution of shear displacement rate applied to the x- and y-faces was varied in proportions of 10%:90%, 30%:70%, 50%:50%, 70%:30%, and 90%:10%, respectively (**Figure 3c**; **Table 1**). The axial displacement rate was kept constant across all combined-loading cases. This configuration is hereafter referred to as the *combine x- and y-faces boundary conditions*.

The load due to displacement at the boundary condition will generate shear and normal stresses on the fault surface. A slip on the fault will occur when the stresses overcome the fault constitutive model. In this study, fault behaviour is governed by static friction constitutive law, in which the fault will slip when the shear stress (τ) is equal to or greater than the failure resistance component. The failure resistance consists of fault cohesive

strength (C) and fault static friction (μ_s) multiplied by the effective normal stress (σ'), which is the normal stress subtracted by fluid pore pressure (**Oppenheimer et al., 1988**; **Sibson, 1974**), following the Coulomb failure criterion (**Equation 1**).

$$\tau = C + \mu_s \sigma' \quad (1)$$

A cohesion value of 0 MPa was assigned to account for the pre-existing fault with negligible cohesive strength. A static friction of 0.5 was adopted, corresponding to a moderately strong fault and lying slightly below the lower bound of Byerlee friction ($0.6 < \mu_s < 0.8$) (**Colletini et al., 2019**). A simulation was performed over a duration of 200 years. Since the objective of this study is to investigate the mechanical response of bent strike-slip faults to regional lateral tectonic loading – rather than the coseismic processes – the use of a static friction formulation within an elastic half-space framework is sufficient and computationally efficient. Model results were visualized using Paraview (**Ahrens et al., 2014, 2005**).

The imposed boundary conditions produce a deformation of the model block, expressed as displacement magnitudes (m) in the x-, y-, and z-directions at mesh nodes. These boundary conditions also drive fault motion, quantified in terms of fault slip (m), including both lateral and tensile slips components. In addition, the applied loading generates stresses throughout the model

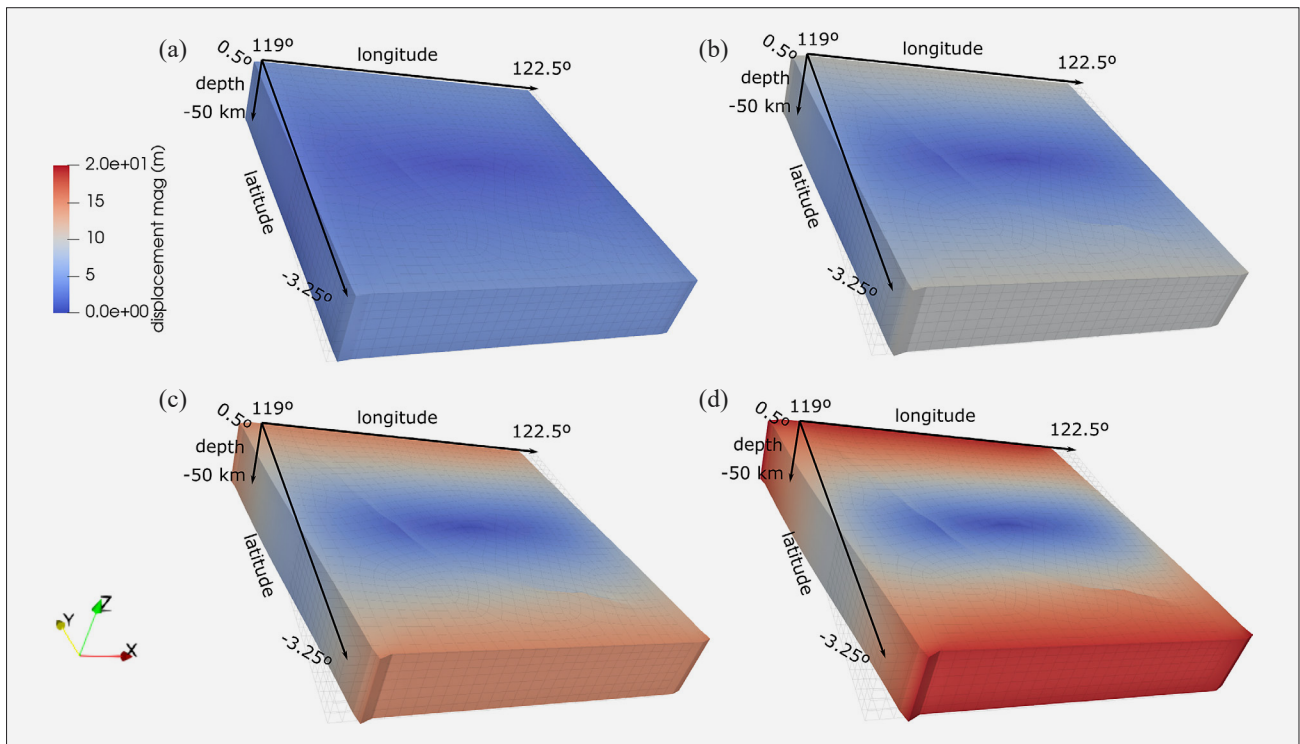


Figure 5: The displacement magnitude (m) of block deformation for the y-face boundary condition, at: (a) year 50, (b) year 100, (c) year 150, and (d) year 200. The figure is exaggerated by a factor of 2000. The gray mesh is the original undeformed form of the block. The x- y- and z-axis are showing the east, north and up directions.

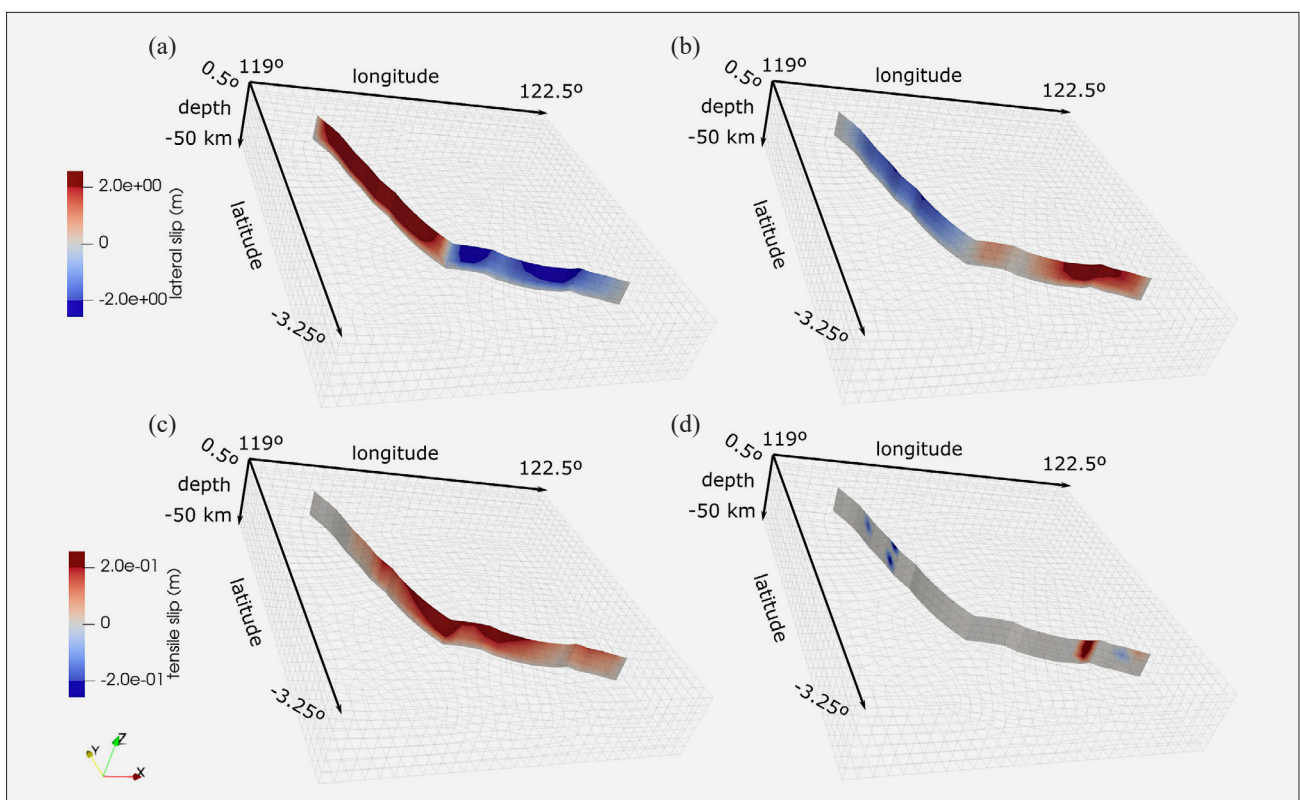


Figure 6: The fault slip, represented by the lateral and tensile slip (m), on the Palu-koro and Matano faults at year 200 for: (a) the x-face boundary condition lateral slip (m), (b) the y-face boundary condition lateral slip (m), (c) the x-face boundary condition tensile slip (m), (d) the y-face boundary condition tensile slip (m). The gray mesh is the original undeformed form of the block. The x- y- and z-axis are showing the east, north and up directions. Positive lateral slip represents a left lateral motion, while positive tensile slip represents an opening.

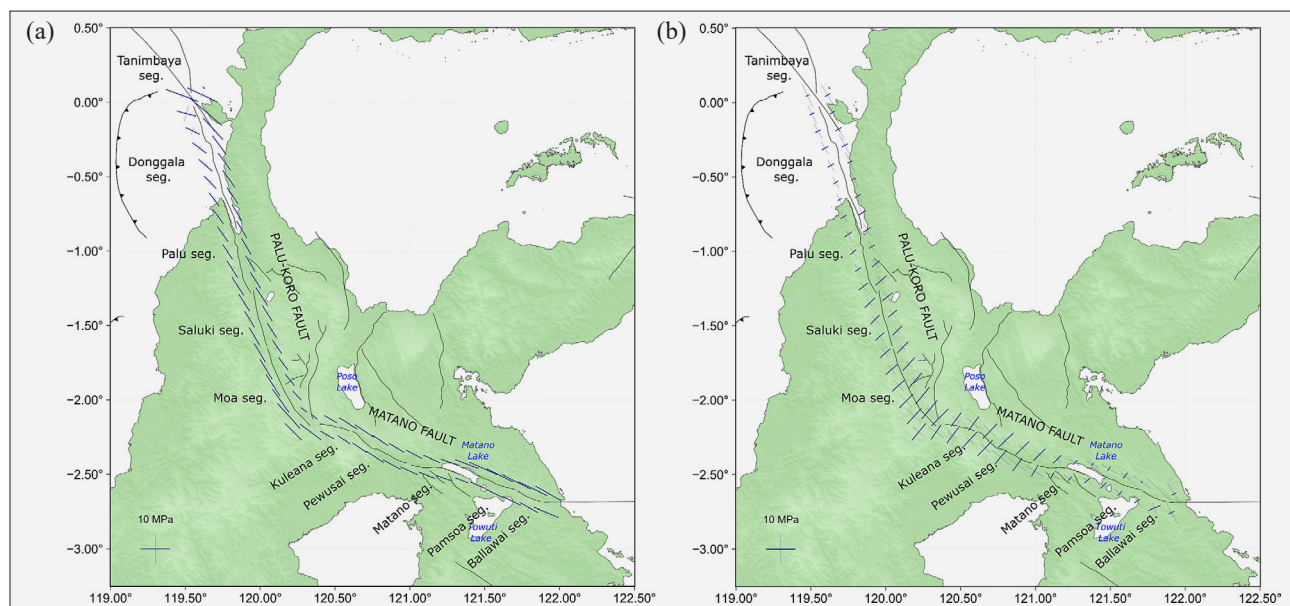


Figure 7: Maximum principal stress (bold dark blue line) along the Palu-koro and Matano faults for: (a) the x-face boundary condition, (b) the y-face boundary condition. The principal stress was estimated from the deformation at year 200.

domain, represented by the stress tensor computed at mesh cells. From the stress tensor, we estimated the principal stress magnitudes and azimuths to characterize the resulting stress orientation within the model.

4. Results

4.1. The x-face boundary condition

As the simulation time increases from 50 to 200 years, the displacement magnitude in the x-face boundary condition model progressively increases from the positive and negative x-boundaries toward the center of the domain, producing a vertically oriented zone of relatively low displacement at the model center (see **Figure 4**). The resulting fault slip pattern shows positive lateral slip (left-lateral motion) up to 2 m, along the Palu–koro Fault and negative lateral slip (right-lateral motion) along the Matano Fault (see **Figure 6a**). The left-lateral slip along the Palu–koro Fault is interpreted to result from its orientation, which is nearly parallel to the imposed x-face boundary loading. Under this configuration, the Palu–koro Fault accommodates shear in the same sense as the applied lateral motion, analogous to a Riedel shear (R) motion in a simple-shear system. In contrast, the Matano Fault trends WNW–ESE and is oriented nearly perpendicular to the x-face boundary, resulting in antithetic motion relative to the imposed shear, and this behaviour is consistent with the kinematics of a conjugate secondary shear (P') within a simple-shear framework (see **Figure 1**).

Positive tensile slip (fault opening) is observed from the southern segment of the Palu–koro Fault, near the bending, toward the Matano Fault (see **Figure 6c**). In particular, the opening is highly concentrated near the fault bend and along the western segment of the Matano

Fault, which is interpreted to result from the combined effects of fault geometry and the WNW–ESE orientation of the Matano Fault relative to the imposed lateral loading. The estimated maximum principal stress direction shows a broadly uniform northwest–southeast orientation from the Palu–Koro Fault to the Matano Fault (see **Figure 7a**). This stress pattern is likely influenced by the imposed north–south lateral movement at the x-face boundary condition and is broadly consistent with the orientation of the compressional axis expected under simple-shear deformation.

4.2. The y-face boundary condition

In the y-face boundary-condition model, the displacement magnitude is highest, up to 20 m, along the y-faces and gradually decreases toward the center of the domain, forming a zone of relatively low displacement with an orientation parallel to the y-faces (see **Figure 5**). The resulting fault-slip pattern differs from that observed in the x-face boundary condition scenario. Positive lateral slip (left-lateral motion) is concentrated along the Matano Fault, whereas negative lateral slip (right-lateral motion) occurs along the Palu–Koro Fault (see **Figure 6b**). The left-lateral slip along the Matano Fault is compatible with the kinematics of a synthetic secondary shear (P) that accommodates deformation in the same sense as the imposed lateral motion. In contrast, the right-lateral slip along the Palu–Koro Fault is consistent with the behaviour of a conjugate Riedel shear (R'), exhibiting antithetic motion relative to the applied lateral loading (see **Figure 1**).

Tensile slip in the y-face boundary-condition model exhibits fewer and more limited opening areas compared to the x-face boundary condition scenario. Localized

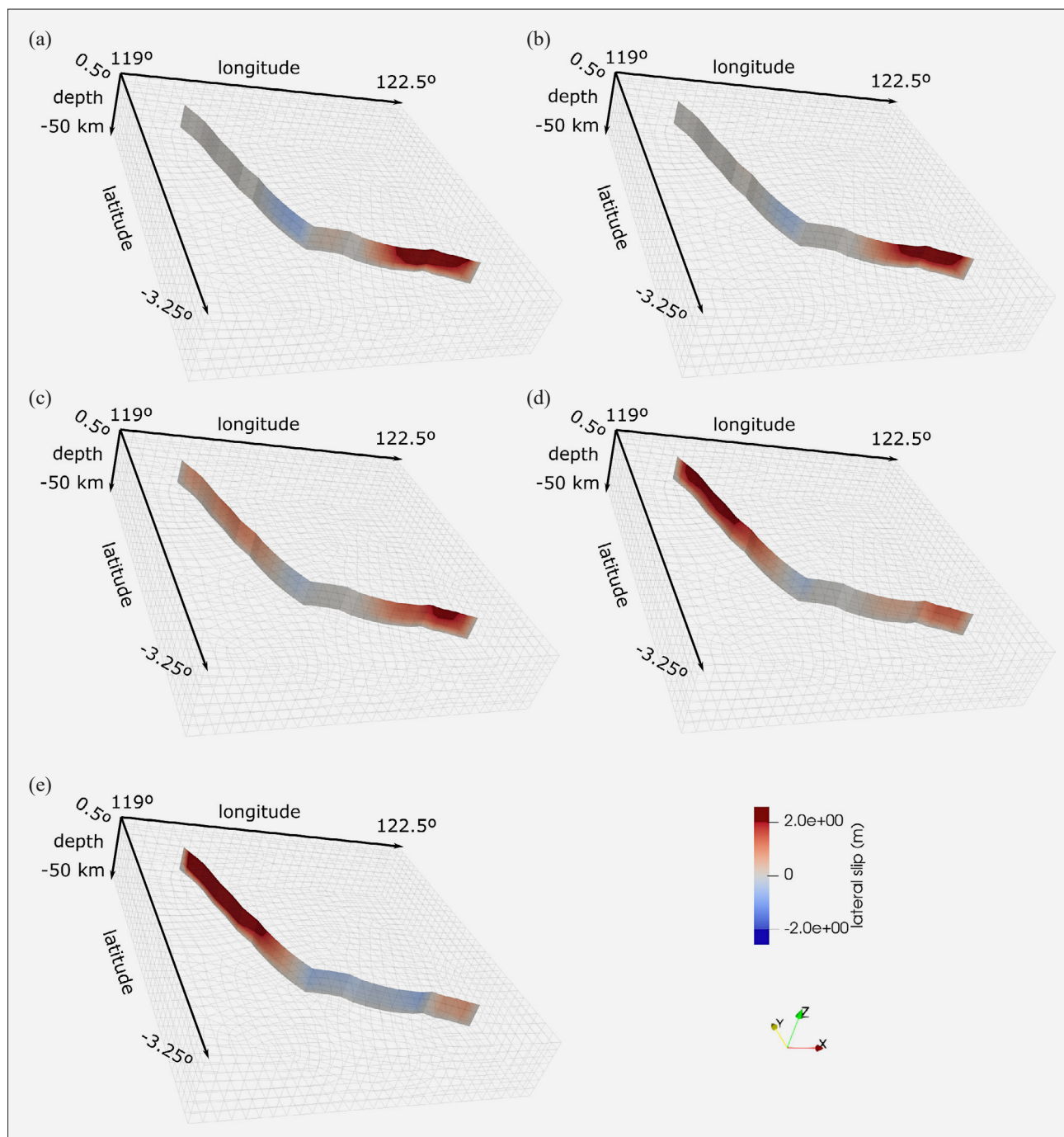


Figure 8: The fault slip, represented by the lateral slip (m), on the Palu-koro and Matano faults at year 200 for the combined x- and y-faces boundary conditions, with x- and y-faces percentage proportion: (a) 10%:90%, (b) 30%:70%, (c) 50%:50%, (d) 70%:30%, (e) 90%:10%. The x- y- and z-axis are showing the east, north and up directions. Positive lateral slip represents a left lateral motion.

positive tensile slip (opening) is mainly observed along the eastern segment of the Matano Fault, which may be related to local fault geometry (see **Figure 6d**). The maximum principal stress orientation in the y-face boundary-condition model shows a relatively uniform northeast–southwest trend (see **Figure 7b**). This stress orientation is largely perpendicular to the fault strike, which may contribute to the generally limited development of opening along the fault.

4.3. The combine x- and y-faces boundary conditions

The modelling results for the combined x- and y-face boundary-condition scenarios are illustrated by the lateral slip (see **Figure 8**) and tensile slip (see **Figure 9**). For scenarios with a small displacement-rate contribution on the x-faces (see **Figure 8a**), the fault slip pattern closely resembles that of the y-face boundary condition model, with

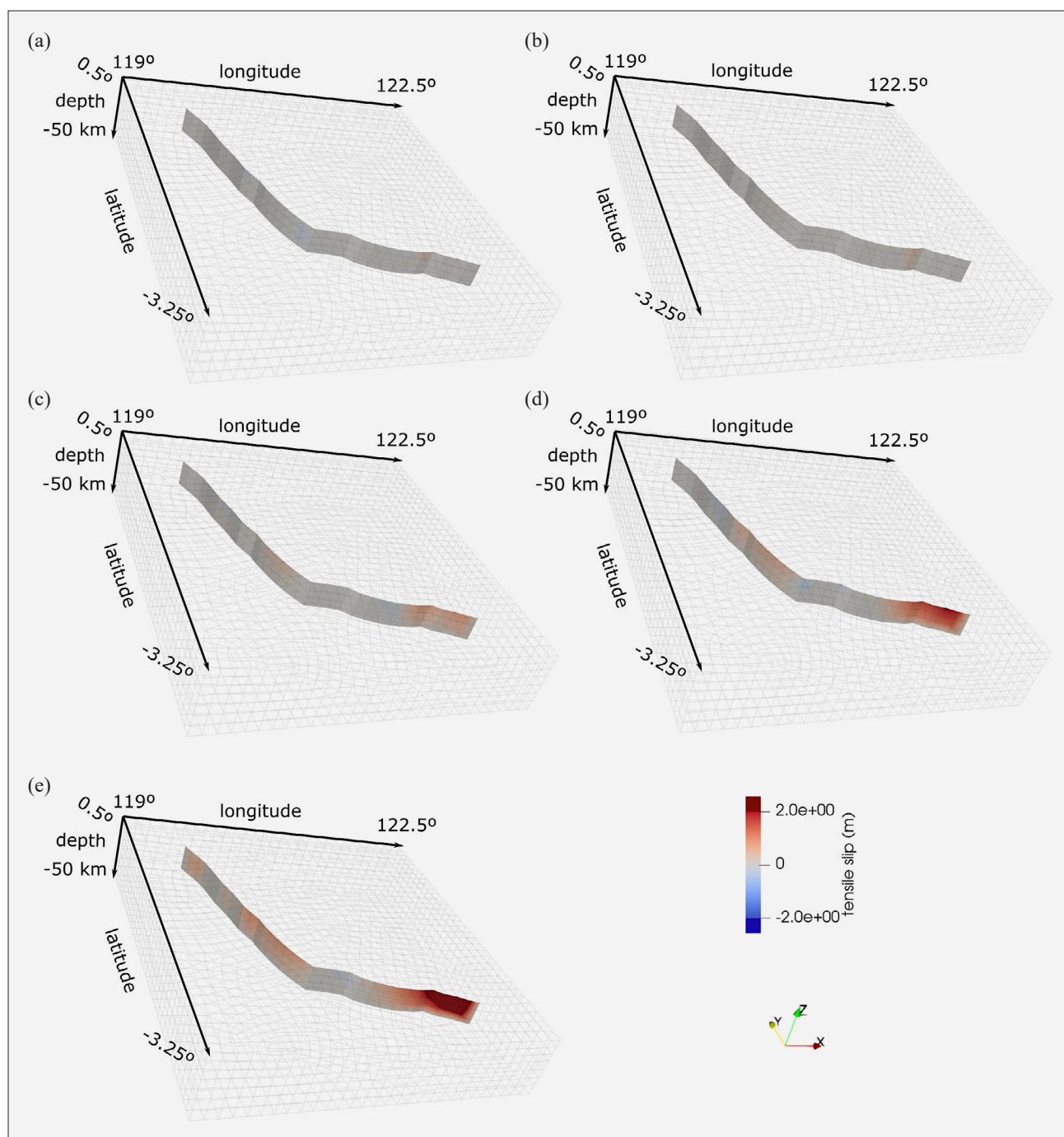


Figure 9: The fault slip, represented by the tensile slip (m), on the Palu-koro and Matano faults at year 200 for the combined x- and y-faces boundary conditions, with x- and y-faces percentage proportion: (a) 10%:90%, (b) 30%:70%, (c) 50%:50%, (d) 70%:30%, (e) 90%:10%. The x- y- and z-axis are showing the east, north and up directions. Positive tensile slip represents an opening.

positive lateral slip concentrated along the Matano Fault. In contrast, scenarios with a large displacement rate contribution on the x-faces (see **Figure 8e**) produce slip distributions similar to those of the x-face boundary condition scenario, with dominant positive slip along the Palu-koro Fault. In general, as the proportion of displacement applied on the x-faces increases from 10% to 90%, the magnitude of positive lateral slip along the Matano Fault progressively decreases, while slip becomes increasingly dis-

tributed along the Palu-koro Fault (see **Figure 8a–e**). For the tensile slip, positive tensile slip (opening) is distributed at the Matano Fault as the proportion of displacement rate increases on the x-faces (see **Figure 9a–e**). However, the concentration of the opening is located at the easternmost part of the Matano Fault, in contrast with the x-face boundary condition scenario (see **Figure 6c**).

In general, the maximum principal stress orientations produced by the combined boundary condition models

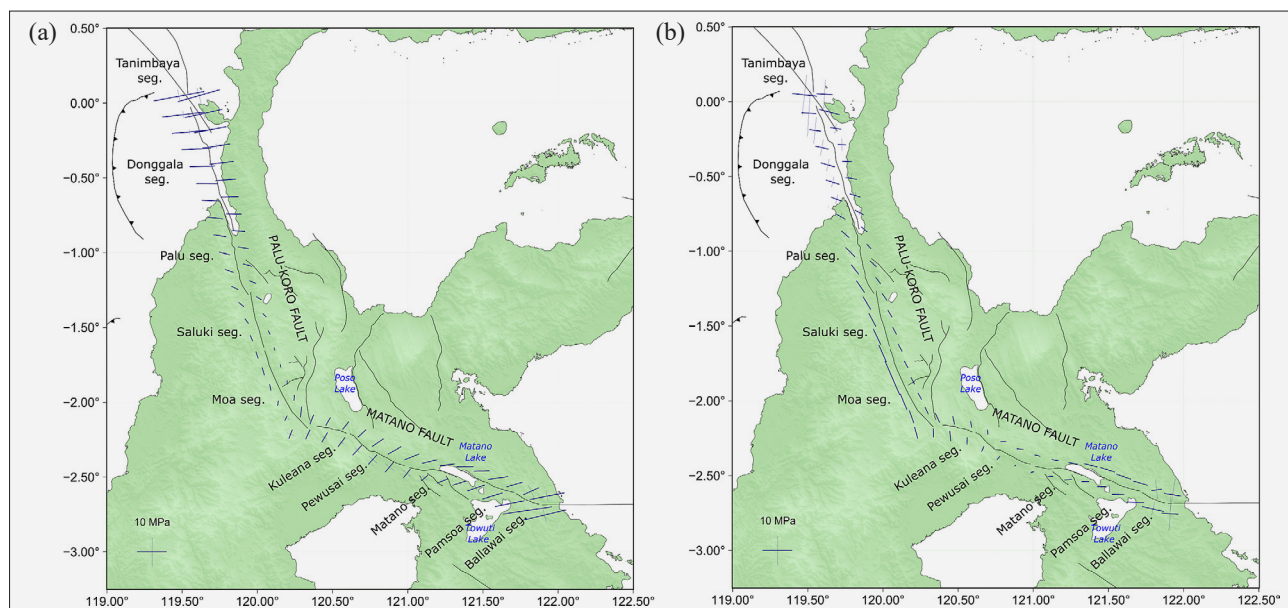


Figure 10: Maximum principal stress (bold dark blue line) along the Palu-koro and Matano faults for the combined x- and y-faces boundary conditions, with x- and y-faces percentage: (a) 30%:70%, (b) 70%:30%. The principal stress was estimated from the deformation at year 200.

exhibit spatially non-uniform azimuths, with its orientation influence by the dominant displacement rate component. Representative results are shown for the 30%:70% (x-face 30%) scenario (see **Figure 10a**) and the 70%:30% (x-face 70%) scenario (see **Figure 10b**). For the x-face 30% scenario, the maximum principal stress along the Palu-koro Fault is oriented predominantly E–W to WNW–ESE. In contrast, the x-face 70% scenario yields a stress orientation along the Palu-koro Fault that is rotated toward a more NW–SE trend. Along the Matano Fault, the maximum principal stress shows a consistent NE–SW orientation throughout the fault for the x-face 30% scenario. For the x-face 70% scenario, a NE–SW orientation is maintained primarily between Lake Matano and Lake Towuti, while stress orientations outside this area become more parallel with the fault strike.

5. Discussion

The fault-slip motions produced by the pure x-face and y-face boundary-condition models are mechanically consistent with the classical Riedel shear system (see **Figure 6**), suggesting that Riedel shear kinematics may be applicable to bent strike-slip systems for describing idealized slip patterns. However, this consistency does not imply that the Palu-Koro and Matano faults formed as Riedel fractures generated by simple shear deformation.

In comparison with the present-day tectonic behaviour of the Palu-koro and Matano faults, the pure x-face and y-face boundary-condition models do not adequately reproduce the observed fault motions. Observations indicate that both faults accommodate predominantly sinistral motion, driven by the westward motion of the

Philippine Sea and Pacific plates relative to the Eurasian/Sunda Plate, within which Sulawesi is located. Geodetic velocity measurements in the Palu-koro region reveal a rotation of velocity vectors from NW–SE to NNW–SSE, which has been successfully explained by microblock rotation models (**Socquet et al., 2006**). This rotation facilitates the transfer and continuity of left-lateral motion from the Matano Fault to the Palu-koro Fault.

Among the modelled scenarios, the combined x-face and y-face boundary conditions with a dominant x-face rate – particularly the x-face 70% configuration – most closely reproduce this tectonic behaviour. This scenario yields sinistral slip along both the Palu-koro and Matano faults, with a higher concentration of slip localized on the Palu-koro Fault (see **Figure 8d**). The high concentration slip at the Palu-koro Fault, is consistent with reported geodetic and geological estimates indicating a higher fault slip rate along the Palu-koro ($\approx 35\text{--}40$ mm/year) compared to the Matano Fault ($\approx 20\text{--}21$ mm/year) (**Bellier et al., 2001; Patria et al., 2023; Socquet et al., 2006**). The dominance of north–south lateral loading in the preferred configuration of this study is also broadly compatible with northward microblock rotation inferred from geodetic observations (**Socquet et al., 2006**).

Although subtle, rotation of the maximum principal stress orientation is observed in the combined x-face and y-face boundary condition models (see **Figure 10**). In the x-face 30% configuration, the maximum principal stress orientation transitions from WNW–ESE along the Palu-koro Fault to NE–SW along the Matano Fault. A similar spatial variation is observed in the x-face 70% configuration, with orientations changing from NW–SE

at the Palu–koro Fault to NE–SW at the Matano Fault. This pattern likely reflects the superposition of lateral loading applied at the x-face and y-face boundaries, where x-face loading favors NW–SE-oriented stresses and y-face loading favors NE–SW-oriented stresses (see **Figure 7**).

In general, the numerical models with combined boundary condition configurations with a dominant north–south lateral loading applied at the x-face, reproduce fault slip distributions that are broadly consistent with the present day kinematics of the Palu–koro and Matano faults. The modelled sinistral motion, higher slip concentration along the Palu–koro Fault, and rotation in stress orientation are qualitatively compatible with geological and geodetic observations. However, the imposed proportions of north–south and east–west lateral loading at the x-face and y-face represent simplified approximations of the regional tectonic loading. Future studies should consider observed geodetic velocity fields in Sulawesi to better constrain boundary condition rates and improve the numerical modelling results.

6. Conclusions

We investigated the mechanical response of a bent strike-slip fault system, represented by the Palu–koro and Matano faults, using numerical modelling with Dirichlet (displacement rate) boundary conditions applied at the x-face, y-face, and combined x- and y-faces of the model domain, with rate value inferred from the regional plate velocity. The conclusions are described as follows.

1. Models with pure x-face or y-face loading produce lateral slip patterns that are compatible with idealized Riedel shear kinematics; however, these patterns differ from the present-day tectonic motion of the fault system.
2. Combined boundary condition models reproduce first-order characteristics of the observed fault behaviour, including spatial variations in stress orientation along the Palu–koro and Matano faults.
3. Particularly, the model with a dominant lateral loading at the x-face, e.g. 70% x-face and 30% y-face (dominantly north–south lateral movement) produces a predominantly sinistral slip along both faults and a higher slip concentration along the Palu–koro Fault, consistent with tectonic observations.
4. A rotation in maximum principal stress orientation from WNW–ESE along the Palu–koro Fault to NE–SW along the Matano Fault is also observed, which is qualitatively consistent with stress orientations inferred from focal mechanism inversions.

The combined regional lateral loading with a dominant north–south component provides a plausible mechanical framework for understanding deformation localization and stress rotation within the Palu–Koro–Matano fault system. Although this study does not explicitly

address long-term geodynamic evolution, the results offer mechanical insight into how present-day regional lateral loading interacts with the existing Palu–Koro–Matano fault geometry and caused the slip accumulation as well as stress rotation along the faults.

7. Nomenclature

Symbol/ term	Description
xpos	boundary condition plane at $x = 122.5^\circ$
xneg	boundary condition plane at $x = 119^\circ$
ypos	boundary condition plane at $y = 0.5^\circ$
yneg	boundary condition plane at $y = -3.25^\circ$
x-face	xpos and xneg boundary condition
y-face	ypos and yneg boundary condition
x-face 30%	boundary condition with proportion 30% of shear displacement rate applied at the x-face and 70% of shear displacement rate applied at the y-face
x-face 70%	boundary condition with proportion 70% of shear displacement rate applied at the x-face and 30% of shear displacement rate applied at the y-face

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SAŽETAK

Modeliranje utjecaja lateralnog opterećenja na povijesne “strike-slip” sustave rasjeda: primjer iz Palu-koro Matano rasjeda, Indonezija

Rasjedi Palu-koro i Matano tvore glavni povijeni “strike-slip” sustav rasjeda u središnjem dijelu Sulawesi, Indonezija, te prihvaćaju značajne deformacije kore povezane s regionalnim pokretima tektonskih ploča. U ovoj studiji istražen je mehanički odgovor ovog rasjednog sustava koristeći trodimenzionalno numeričko modeliranje kako bi se procijenili utjecaji različitih lateralnih opterećenja na pomak rasjeda i raspodjelu naprezanja. Dirichletovi (brzina pomaka) granični uvjeti, izvedeni iz regionalnih brzina kretanja tektonskih ploča, primijenjeni su na model na x-lice, y-lice, te u kombiniranim konfiguracijama x- i y-lica. Modeli s čistim opterećenjima na x-licu ili y-licu stvaraju lateralne obrasce klizanja koji su mehanički kompatibilni s idealiziranom kinematikom Riedelovih smičnih zona; međutim, smjer klizanja razlikuje se od današnjeg tektonskog kretanja Palu-koro i Matano rasjeda. Suprotno tome, modeli u kombiniranim graničnim uvjetima reproduciraju karakteristike prvog reda promatranog ponašanja rasjeda. Konkretno, slučajevi s dominantno lateralnim opterećenjem na x-licu (npr. 70% x-lice i 30% y-lice) proizvode pretežito lijeve pomake duž oba rasjeda i više koncentracije klizanja duž Palu-koro rasjeda, što je u skladu s tektonskim i geodetskim opažanjima. Kombinirani model opterećenja također pokazuje suptilnu rotaciju orijentacije maksimalnog glavnog naprezanja od ZNZ-IJI duž Palu-koro rasjeda do SI-JZ duž Matano rasjeda, što kvalitativno odgovara orijentacijama naprezanja izvedenim iz fokalnih mehanizama inverzije. Općenito, rezultati ukazuju da kombinirano regionalno lateralno opterećenje, s dominantnim sjever-jug lateralnim pomakom, pruža prihvatljiv mehanički okvir za razumijevanje lokaliziranih deformacija i rotacije osi naprezanja unutar Palu-koro-Matano rasjednog sustava.

Ključne riječi:

povijeni “strike-slip”, rasjedno lateralno klizanje, rastezno lateralno klizanje, Matano rasjed, numeričko modeliranje, Palu-koro rasjed, Riedelovo smicanje

Author's contribution

Dian Kusumawati (Dr., expertise in seismology and numerical modelling): performed and conceived the study, conceptualization, wrote the original draft. **David P. Sahara** (Dr. rer. nat., expertise in seismology and geomechanics): performed supervision and formal analysis, review and editing the draft, project administration. **Nanang T. Puspito** (Dr., seismology Professor): performed supervision, formal analysis, funding acquisition, and reviewed the draft. **Mudrik R. Daryono** (Dr., expertise in geology): performed supervision, formal analysis, and reviewed the draft. **Andri D. Nugraha** (Dr., seismology Professor): data curation. **Andrean V. H. Simanjuntak** (Dr., expertise in seismology): performed visualization and reviewed the draft. **Maulidia Ain Bening** (Meng., expertise in numerical modelling): performed software methodology. **Faiz Muttaqy** (Dr., expertise in seismology and tomography): performed supervision and reviewed the draft.

All authors have read and agreed to the published version of the manuscript.

Hybrid Luus–Jaakola and Levenberg–Marquardt inversion for magnetic anomalies over 2D fault-like structures

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Mojtaba Babaei^{1*} , Mohammad Rezaie² 

¹ Department of Geophysics, Ha.C., Islamic Azad University, Hamedan, Iran.

² Department of Mining Engineering, Faculty of Engineering, Malayer University, Malayer, Iran.

Abstract

This study presents a shortened summary focusing on the hybrid Luus–Jaakola–Levenberg–Marquardt inversion and its superior performance on both synthetic and Perth Basin data.

In this study, a hybrid approach is introduced and evaluated for estimating the geometric and physical parameters of 2D fault structures from magnetic data. This method integrates the global search capability of the Luus–Jaakola (LJ) algorithm with the rapid convergence of the Levenberg–Marquardt (LM) algorithm, enhanced by two components: a multi-start strategy and a controlled perturbation scheme. This combination overcomes the limitations of initial value dependency and the instability of certain parameters, particularly the effective inclination angle (α). The performance of the proposed method was assessed using both synthetic and real-world data. The results demonstrate that the hybrid approach provides higher accuracy and stability in parameter estimation compared to each individual algorithm, especially under noisy conditions. Perturbation experiments and sensitivity analysis revealed a clear parameter hierarchy: depth parameters exhibit the strongest amplitude influence (approximately 200–267% variation), followed by the amplitude coefficient (approximately 85%) and the effective magnetization angle (approximately 63%), while the fault dip angle shows minimal amplitude sensitivity (approximately 5%). The analysis of the effective magnetization angle demonstrated its critical role in identifying optimal starting regions for stable estimations, with the location of these regions contingent on the state of other parameters. In the real-data application, the hybrid method yielded parameters consistent with plausible geological models of the area. The findings of this study offer a practical framework for improving magnetic data inversion, particularly in noise-contaminated environments.

In this study, a hybrid approach combining the Luus–Jaakola (LJ) and Levenberg–Marquardt (LM) algorithms is introduced for estimating the geometric and physical parameters of 2D fault structures from magnetic data. The method leverages the global search capability of LJ and the rapid convergence of LM, while incorporating a multi-start strategy and controlled perturbation to overcome initial value dependency and instability in critical parameters such as the effective inclination angle (α). The performance was assessed using both synthetic and real-world data. For synthetic data with 15% noise, the hybrid method achieved an RMS of 4.45 nT, significantly outperforming standalone LJ (17.44 nT) and LM (4.60 nT), while reducing the estimation error of α from 25.40% to 9.39% through controlled perturbation. When applied to real magnetic data from the Perth Basin, Australia, the hybrid approach yielded an RMS of 1.33 nT compared to 2.16 nT (LJ) and 10.61 nT (LM), producing parameters consistent with the plausible geological model of the area. These findings demonstrate that the hybrid framework offers superior accuracy and stability for magnetic data inversion, particularly under noisy conditions.

Keywords:

magnetic inversion; fault; Luus–Jaakola algorithm; Levenberg–Marquardt algorithm; hybrid Luus–Jaakola–Levenberg algorithm

1. Introduction

Magnetometry, a sub-discipline of exploration geophysics, enables the identification and modelling of subsurface structures by measuring variations in the Earth's magnetic field. These variations, known as “magnetic anomalies,” arise from differences in the intensity and

direction of magnetization in rocks and minerals. Magnetic bodies such as dikes, faults, or mineralized lenses disturb the ambient field, creating patterns with distinct amplitudes and shapes on the Earth's surface (Sharma, 1987; Biswas and Acharya, 2016; Ekwok et al., 2023).

Faults are fractures or shear zones within the Earth's crust along which significant displacement has occurred. This displacement alters the lithology and magnetic properties on either side of the fault, giving rise to a detectable magnetic anomaly. The primary objective of this research is to develop and apply an optimal method

* Corresponding author: Mojtaba Babaei

e-mail address: m_babaei@iau.ac.ir

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for estimating the geometric and physical parameters of a fault, including the amplitude coefficient, dip angle, effective magnetization angle, the depths to the top and bottom of the fault scarp, and the origin location, based on the analysis of these anomalies. The accurate interpretation of these parameters plays a crucial role in reconstructing the subsurface model, understanding tectonic processes, and exploration applications (Grant and West, 1965).

Numerous methods have been proposed for the interpretation of magnetic anomalies. These include least-squares methods (Abdelrahman et al., 2009; Tlas and Asfahani, 2011), Euler deconvolution (Reid et al., 1990; Salem and Ravat, 2003; Dewangan et al., 2007), Werner deconvolution (Stagg et al., 1989; Hansen, 2005; Usman et al., 2014), gradient methods (Abdelrahman et al., 2007; Essa and Elhussein, 2017), the analytic signal (Nabighian, 1972; Salem, 2005; Aydin, 2008), the tilt angle (Miller and Singh, 1994; Essa et al., 2018; Pham et al., 2019; Elhussein and Shokry, 2020), and the Fourier transform (Gudmundsson, 1966; Gupta, 1988; Olurin et al., 2017). Although these methods are simple and fast, they suffer from two fundamental limitations: high sensitivity to noise and dependency on initial information.

Gradient-based methods, such as the Levenberg–Marquardt (LM) algorithm (Marquardt, 1963), utilize the derivative of the objective function with respect to the parameters. Consequently, they exhibit rapid convergence and high precision near an optimal solution and require less computational memory. However, they are sensitive to the starting point, can face challenges with derivative computation in complex models, and are prone to becoming trapped in local minima, in addition to being sensitive to noise. In contrast, global search derivative-free methods, such as the Luus–Jaakola (LJ) algorithm (Luus and Jaakola, 1973), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), Ant Colony Optimization (ACO), and Bat Algorithm (BA) (Biswas and Acharya, 2016; Ekinci et al., 2019; Di Maio et al., 2020; Essa and Abo-Ezz, 2021; Essa, 2021; Singh and Biswas, 2021; Biswas et al., 2022; Ai et al., 2023; Babaei and Hosseini Pilangorgi, 2024; Babaei and Hosseini Pilangorgi, 2025), are capable of exploring the entire parameter space and bypassing local minima. They are applicable even to complex nonlinear models without requiring derivatives. Nevertheless, compared to gradient-based methods, they suffer from slower convergence rates, the need for meticulous parameter tuning, and higher computational costs, while sensitivity to noise may persist under certain conditions.

The shared limitations of both classes of methods necessitate the development of a hybrid approach. Such a method would leverage the global search capability to eliminate dependency on the initial guess and avoid local minima, while simultaneously benefiting from the

speed and accuracy of gradient-based techniques near the optimal solution. To this end, this study proposes a hybridization of the Luus–Jaakola global search algorithm with the Levenberg–Marquardt local optimization method. This combination is enhanced with two key components: a multi-start strategy and a controlled random perturbation scheme, aiming to improve the stability and accuracy of fault parameter estimation, particularly with noisy data. The results from applying this approach to both synthetic and real-world data indicate that the proposed hybrid method can recover all geological model parameters with high precision and completely eliminate the dependency on initial values. The remainder of this paper presents the mathematical framework and detailed implementation of the developed hybrid algorithm, the datasets and experimental conditions, the inversion results under various scenarios, and a comparative analysis with other conventional methods.

2. Materials and Methods

2.1. Luus–Jaakola Algorithm (LJ)

The Luus–Jaakola (LJ) algorithm is a derivative-free, stochastic direct search method employed for solving nonlinear optimization problems, particularly those involving complex or non-differentiable objective functions. Its core idea is to initiate a global search across the parameter space and then progressively shrink the search region to converge toward an optimal solution (Luus and Jaakola, 1973). In the context of parameter estimation, the objective function is defined as the Sum of Squared Errors (SSE), which is minimized:

$$S(X) = \min_X \sum_{i=1}^m (d_i^{\text{obs}} - d_i^{\text{calc}}(X))^2 \quad (1)$$

where $\mathbf{X} = [x_1, x_2, \dots, x_p]$ is the vector of p unknown model parameters, d_i^{obs} represents the i^{th} observed data point (from a total of m points), and d_i^{calc} is the corresponding model-calculated value for the parameter vector $\mathbf{X}$.

The algorithm commences by selecting initial values for the parameters, $\mathbf{X}^{(0)}$, an initial search radius, $\mathbf{r}^{(0)}$, for each parameter, and a shrinkage factor, ε . The shrinkage factor is a key component in the LJ method, controlling the size of the search domain. Initially, the search is performed over a large region of the parameter space. After each iteration, the dimensions of this region are reduced using the shrinkage factor. This contraction facilitates the gradual convergence of the search toward an optimal point. The value of ε is typically chosen between 0.85 and 0.95 to ensure a balance between reducing the search space and preventing a premature loss of sample diversity.

In each iteration j , a set of N candidate solutions is generated by perturbing the current best solution, $\mathbf{X}^{(j)}$.

For each parameter x_i in the vector, a random number u_i is drawn from a uniform distribution over $[-1, 1]$, and a new potential parameter value is calculated as:

$$x_{i,\text{candidate}}^{(j)} = x_i^{(j)} + u_i \cdot r_i^{(j)} \quad (2)$$

The objective function $S(\mathbf{X})$ is then evaluated for each of the N new candidate vectors. The candidate vector that yields the lowest objective function value becomes the new best solution for the next iteration, $\mathbf{X}^{(j+1)}$. Subsequently, the search radius is systematically reduced according to the rule:

$$r_i^{(j+1)} = \varepsilon \cdot r_i^{(j)} \quad (3)$$

This gradual reduction transitions the algorithm from a global exploration phase to a focused local exploitation phase. The process continues until a predefined maximum number of iterations, $j^{\max}$, is reached, or until the change in the objective function value falls below a convergence threshold. The defining features of the LJ algorithm are its ability to search a broad parameter space, its robustness against local minima, and its independence from derivative or Jacobian matrix computations.

2.2. Levenberg–Marquardt (LM) Algorithm

The Levenberg–Marquardt (LM) algorithm is a local nonlinear optimization method based on nonlinear least squares. It synergistically combines the advantages of the Gauss–Newton method and the gradient descent method. This algorithm is particularly effective for problems where the objective function has a complex curvature and high precision is required in the vicinity of the minimum (Marquardt, 1963). The LM objective function is also defined to minimize the sum of squared residuals between observed and calculated magnetic data. At each step, the LM algorithm provides an improved estimate of the required parameter adjustments by computing the gradient and the Jacobian matrix, $\mathbf{J}$. The parameter update rule is given by (Marquardt, 1963):

$$\mathbf{X}^{(k+1)} = \mathbf{X}^{(k)} - (\mathbf{J}^T \mathbf{J} + \lambda \mathbf{I})^{-1} \mathbf{J}^T \mathbf{r} \quad (4)$$

where $\mathbf{X}^{(k)}$ is the parameter vector at iteration k , $\mathbf{J}$ is the Jacobian matrix of model sensitivities with respect to the parameters, $\mathbf{r}$ is the vector of residuals ($\phi^{\text{obs}} - \phi^{\text{calc}}$), $\mathbf{I}$ is the identity matrix, and λ is the damping factor. The damping factor interpolates between the Gauss–Newton method (as $\lambda \rightarrow 0$) and the gradient descent method (as $\lambda \rightarrow \infty$).

2.3. The Proposed Hybrid LJ–LM Method

The primary goal of this research is to estimate the model parameters including the amplitude coefficient (K), dip angle (θ), effective magnetization angle (α), depths to the top and bottom of the fault scarp (z_1 and z_2), and horizontal location (w) – by minimizing the misfit

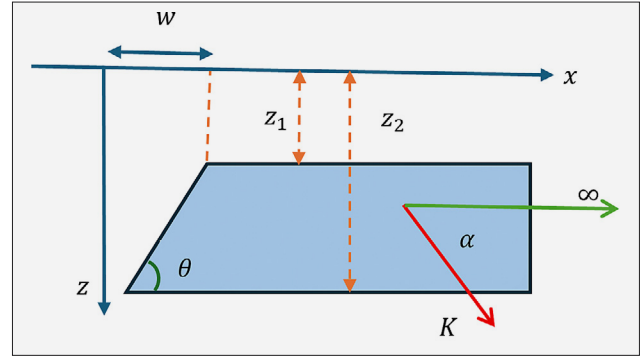


Figure 1: Inclined fault model

between the calculated magnetic data (T^{calc}) and the observed data (T^{obs}) as defined in Equation 1. To achieve this, we first implement the Luus–Jaakola (LJ) algorithm using a multi-start and perturbation strategy. This initial step is designed to generate multiple high-quality starting points for the subsequent local optimization.

The Levenberg–Marquardt (LM) algorithm is then employed to refine the solutions obtained from the LJ phase. The key advantage of using LM in this context is its ability to converge rapidly to a precise solution when initiated near the global minimum. By seeding the LM algorithm with the high-quality initial guesses provided by the robust global search of LJ, the overall accuracy and stability of the inversion process for the studied magnetic anomalies are significantly enhanced.

3. Forward Model

In the forward modelling of a 2D fault, the total magnetic field anomaly, T_0 , measured at a point x_i along a profile is considered to be composed of two components: a regional field, $Z(x_i)$, and the residual anomaly, $T(x_i)$ caused by the fault structure:

$$T_0(x_i) = T(x_i) + Z(x_i) \quad (5)$$

In this study, the residual anomaly is generated by a dipping fault model. The calculation of this anomaly is performed using the following forward model expression (Aydin, 2008):

$$T(x_i) = K \left\{ \cos(\theta + \alpha) \left[\tan^{-1} \left(\frac{(x_i - w) - (z_2 - z_1) \cot \alpha}{z_2} \right) - \tan^{-1} \left(\frac{(x_i - w)}{z_1} \right) \right] + \sin(\theta + \alpha) \ln \left(\frac{((x_i - w) - (z_2 - z_1) \cot \alpha)^2 + z_2^2}{(x_i - w)^2 + z_1^2} \right)^{1/2} \right\} \quad (6)$$

In this model, the parameters are defined as follows (see also Figure 1):

- K is the amplitude coefficient (in nanoTeslas, nT),
- θ is the dip angle of the fault,

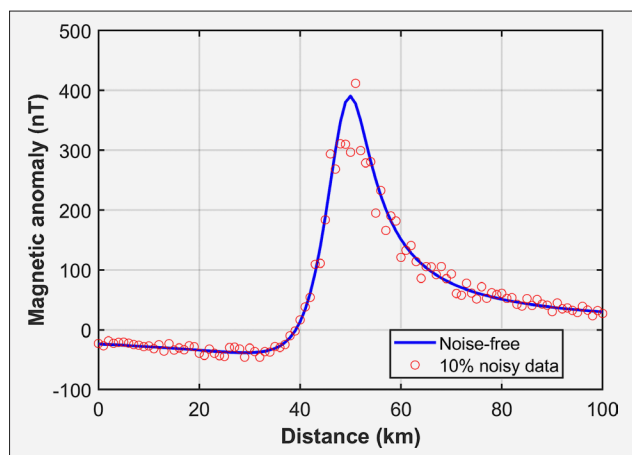


Figure 2: Synthetic magnetic anomaly calculated from the forward model (Equation 6) using true parameters $K=400$ nT, $\theta=35^\circ$, $\alpha=30^\circ$, $z_1=4$ km, $z_2=7$ km, $w=50$ km. Red line: noise-free model response; black circles: data with 10% random noise added according to Equation 7.

- α is the effective angle of magnetization,
- z_1 is the depth to the top edge of the fault,
- z_2 is the depth to the bottom edge of the fault,
- w is the horizontal location of the fault's origin along the profile.

The variable x_i represents the horizontal position of the observation point.

This equation describes the magnetic response of a 2D fault at any given observation point. It forms the basis for the comparison between modeled data and observed data during the inversion process.

4. Modelling (Synthetic Data)

To evaluate the proposed hybrid method, a synthetic magnetic anomaly dataset was generated based on the analytical model of a 2D dipping fault using Equation 7. First, the forward model response was calculated using the true parameters: . Subsequently, to simulate realistic conditions, 10% random noise from a uniform distribution was added to the data according to Equation 7:

$$T^{\text{Noisy}}(x_i) = T^{\text{True}}(x_i) \times [1 + \lambda \cdot (r_i - 0.5)] \quad (7)$$

To examine the effect of noise, Figure 2 displays the synthetic magnetic anomaly calculated from the forward model both with and without noise.

To analyze the results of the sensitivity analysis, the plots in Figure 3 illustrate the changes in the model response due to a relative change in each parameter at three levels: 70%, 100% (the reference curve or base value), and 130% of the base value.

In these plots, the reference curve (100%) represents the original model state, against which the other curves are compared. A detailed interpretation of the sensitivity analysis is as follows:

- **Depth Parameters (z_1 and z_2):** z_1 (see Figure 3c): Shows the classical burial depth effect. Shallower faults (70% = 2.8 km) produce stronger anomalies (~600 nT peak), while deeper faults (130% = 5.2 km) yield weaker signals (~200 nT peak). This behaviour reflects the well-known inverse relationship between source depth and anomaly amplitude. z_2 (see Figure 3d): Exhibits a seemingly counterintuitive pattern where increasing z_2 from 70% (4.9 km) to 130% (9.1 km) increases amplitude from ~150 nT to ~550 nT. This occurs because z_1 is held fixed ($z_1 = 4$ km) during the OAT analysis. Consequently, varying z_2 effectively changes the fault thickness ($z_2 - z_1$) from 0.9 km (at 70%) to 5.1 km (at 130%), with thicker faults naturally producing larger anomalies. This behaviour highlights an important distinction: while z_1 tests burial depth sensitivity (source-to-observer distance), z_2 in an One-At-a-Time (OAT) framework tests thickness sensitivity when z_1 is fixed. This is consistent with the standard practice of treating z_1 and z_2 as independent parameters during inversion, as both must be estimated separately to define the fault geometry completely. Both depth parameters significantly influence anomaly amplitude, with z_2 showing the highest overall sensitivity (267% amplitude variation) among all tested parameters.
- **Angular Parameters (θ and α):** The dip angle (θ) exhibits the expected inverse relationship with amplitude: steeper faults (larger θ) produce weaker anomalies due to reduced effective cross-sectional area. Over the tested range (24.5° to 45.5°), amplitude varies by approximately 5% ($410 \rightarrow 390$ nT), indicating low amplitude sensitivity. The primary effect of θ is on anomaly shape and horizontal positioning rather than magnitude. The magnetization direction (α) predominantly controls the dipole asymmetry pattern but also moderately influences amplitude (~63% variation over $\pm 30\%$ parameter change) due to its trigonometric coupling in Equation 6, where it modulates both horizontal and vertical magnetic field components. While both angular parameters primarily affect anomaly shape, α shows notably higher amplitude sensitivity than θ .
- **Amplitude and Location Parameters (K and w):** Changes in the amplitude coefficient K produce significant amplitude variations (~85% over $\pm 30\%$ parameter change: $280 \rightarrow 520$ nT), demonstrating considerable model sensitivity. The horizontal location parameter w does not affect amplitude but controls the spatial positioning of the anomaly, its variation causes lateral displacement of the entire curve, which is a geometric translation rather than a sensitivity to anomaly intensity.

In summary, the OAT sensitivity analysis reveals a clear hierarchy: depth parameters (z_1 , z_2) exhibit the strongest amplitude influence (~200–267% variation),

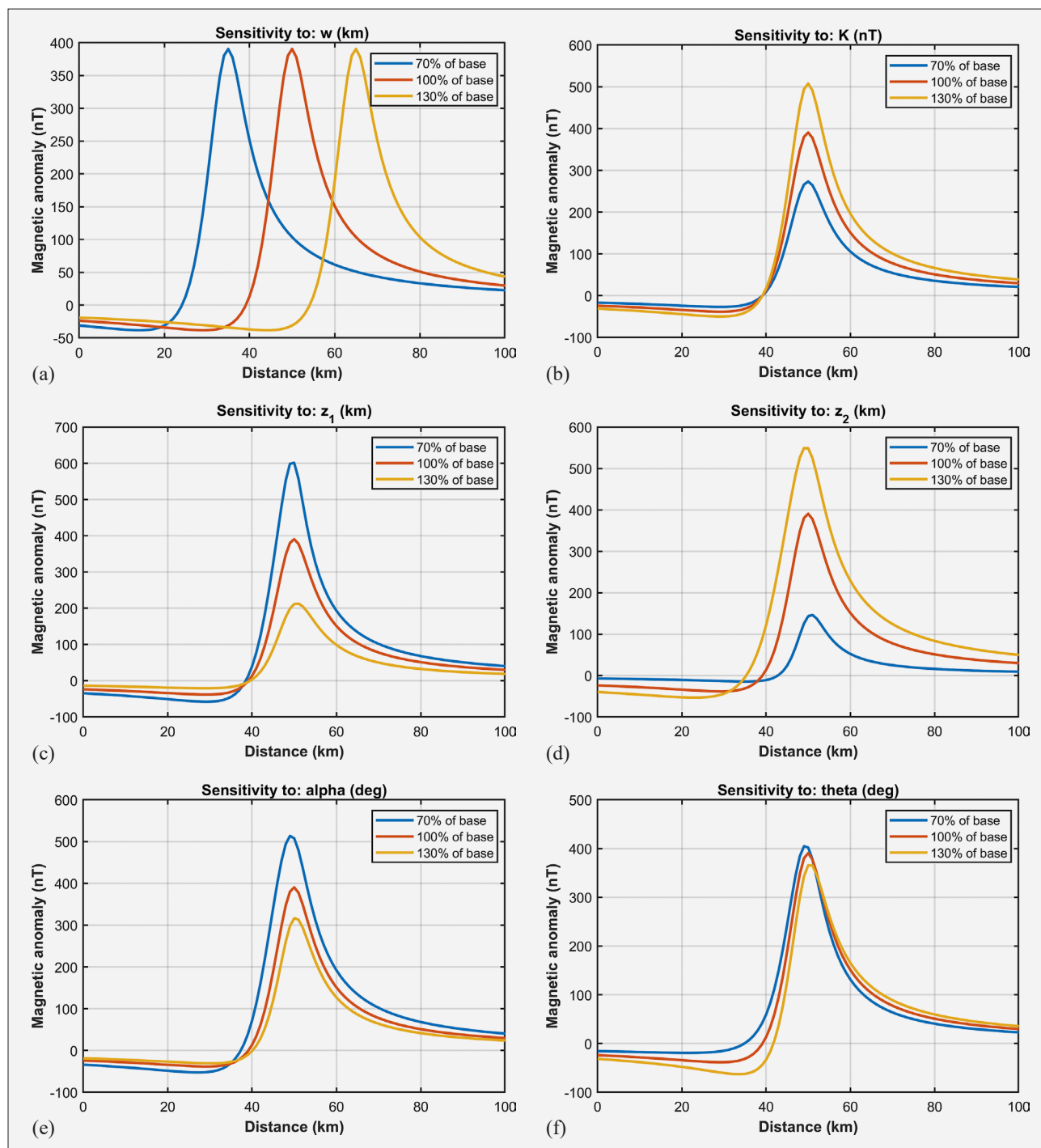


Figure 3: Sensitivity analysis showing changes in model response due to relative parameter variations at three levels: 70%, 100% (reference/base value), and 130% of base values. Panels show sensitivity to: (a) horizontal location w , (b) amplitude coefficient K , (c) depth to top edge z_1 , (d) depth to bottom edge z_2 , (e) effective magnetization angle α , and (f) fault dip angle θ . Results indicate K and θ have the most substantial impact on model response, while α exhibits the lowest sensitivity.”

followed by K (~85%) and α (~63%), while θ shows minimal amplitude sensitivity (~5%). This ranking has direct implications for inversion: the high sensitivity of z_1 , z_2 , and K ensures robust parameter recovery, whereas the low amplitude sensitivity of θ – coupled with its strong shape influence – necessitates careful initialization, making it a critical focus for the hybrid LJ-LM approach.

5. Inversion of Synthetic Data

To assess the accuracy, stability, and efficiency of the inversion algorithms, a controlled synthetic dataset was initially employed. This approach facilitates the evaluation of the methods under ideal and reproducible conditions, where confounding factors such as measurement

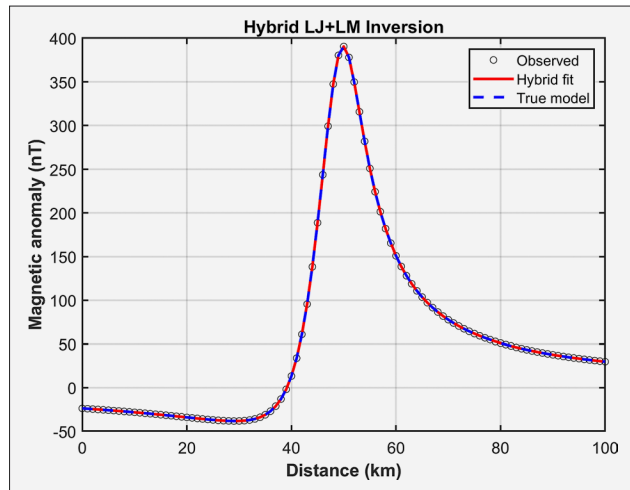


Figure 4: Comparison of observed magnetic anomaly (black circles) with hybrid LJ→LM inversion results (red line) for noise-free synthetic data. Dashed blue line: true model response. The hybrid method achieved perfect parameter recovery with RMS = 0.00 nT (see Table 1).

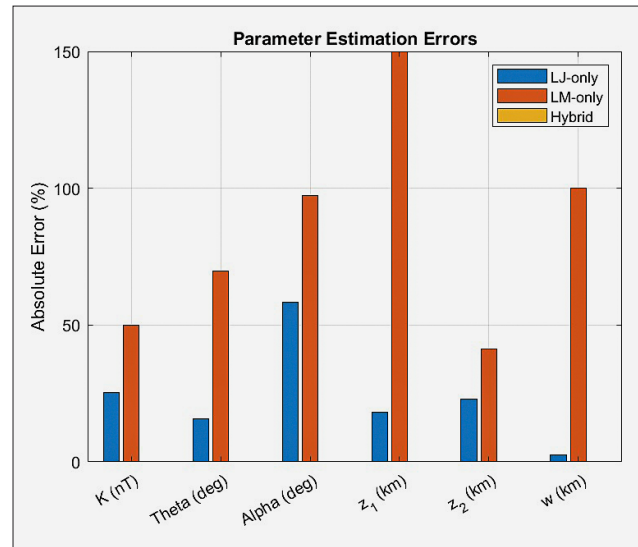


Figure 5: Comparison of the absolute percentage error in parameter estimation for the three inversion methods on noise-free data.

Table 1: True model parameter values and the estimated values from the three inversion methods for noise-free data, along with the percentage error and the Root Mean Square (RMS) error for each method.

Parameter	TRUE	LJ-only	%Err-LJ	LM-only	%Err-LM	Hybrid	%Err-HY
K (nT)	400.00	501.43	25.36	599.38	49.85	400.00	0.00
θ (°)	35.00	40.54	15.84	59.38	69.66	35.00	0.00
α (°)	30.00	47.54	58.45	0.81	97.29	30.00	0.00
z_1 (km)	4.00	4.73	18.27	10.00	150.00	4.00	0.00
z_2 (km)	7.00	8.60	22.87	9.90	41.38	7.00	0.00
RMS (nT)	—	11.23	—	105.24	—	0.00	—

noise or geological instabilities are eliminated. Consequently, the intrinsic capability of the algorithms to retrieve the true model parameters can be rigorously tested. The use of synthetic data also enables an objective comparison between different methods and allows for a detailed analysis of the model's sensitivity to initial parameter estimates and perturbations. In this section, the inversion results for noise-free data are first presented and compared. Subsequently, the same analyses are repeated using data contaminated with 10% peak-to-peak random noise to investigate the performance of the methods under conditions that more closely approximate real-world data.

5.1. Inversion Setup and Parameterization

To evaluate the performance of the algorithms, a synthetic magnetic anomaly dataset was generated using the true model parameters: $[K, \theta, \alpha, z_1, z_2, w] = [400 \text{ nT}, 35^\circ, 30^\circ, 4 \text{ km}, 7 \text{ km}, 50 \text{ km}]$. To robustly test the efficacy of the proposed hybrid method, the initial search bounds for the parameters were deliberately set to be wide. This was designed to challenge the standalone Levenberg–Marquardt algorithm, which is likely to face convergence issues under such conditions, thereby highlighting

the ability of the hybrid method to overcome this challenge. The initial search ranges for the parameters were defined as follows:

- $K \in [200, 600] \text{ nT}$
- $\theta \in [1^\circ, 90^\circ]$
- $\alpha \in [1^\circ, 90^\circ]$
- $z_1 \in [1, 10] \text{ km}$
- $z_2 \in [1, 100] \text{ km}$
- $w \in [10, 150] \text{ km}$

Three distinct approaches were employed for parameter estimation:

1. **Luus–Jaakola (LJ) Method:** A global search configured with a maximum of 1000 iterations, an initial population of 50 candidates, and a shrinkage factor of 0.85.
2. **Levenberg–Marquardt (LM) Method:** A local optimization initiated with a random starting point selected from within the defined parameter bounds.
3. **Hybrid (LJ-LM) Method:** Execution of the LJ algorithm first, followed by using its best-fit output as the starting point for the LM algorithm to refine the solution.

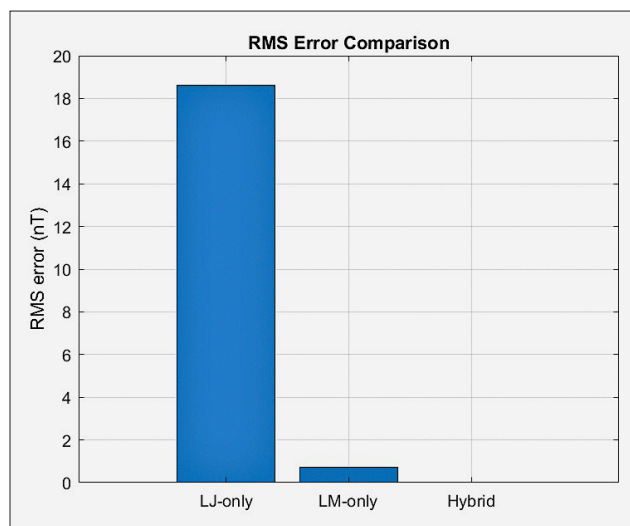


Figure 6: Comparison of the RMS error obtained from the three inversion methods for noise-free synthetic data.

5.2. Initial Inversion Results (Noise-Free Data)

To evaluate the performance of the proposed hybrid approach, which combines the Luus–Jaakola (LJ) global search algorithm with Levenberg–Marquardt (LM) local optimization, the synthetic data generated from the reference model were first inverted without the addition of measurement noise. **Figure 4** compares the observed data from the model, the fit produced by the hybrid method, and the response of the true model. As illustrated, the hybrid method successfully reproduced the observed anomaly curve completely, achieving a perfect match with the true model.

Table 1 presents the true parameter values alongside the values estimated by the standalone LJ algorithm, the standalone LM algorithm (initiated from the same random starting model), and the hybrid method. The table also includes the percentage error for each method.

As observed, the hybrid method was able to retrieve all parameters with perfect accuracy (zero error) and reduce the RMS error to zero (to two decimal places). In contrast, the standalone LM method, due to its high sensitivity to initial conditions, exhibited significant deviations, particularly for the parameter α and the depth parameters, resulting in a very high RMS error (over 105 nT). The LJ method performed better than LM but still demonstrated lower accuracy compared to the hybrid approach, particularly for parameters with lower sensitivity such as θ and α , which are more prone to convergence issues in standalone methods. This test demonstrates that even in the absence of noise, using the LM algorithm alone with an inadequate initial model leads to a severe divergence of the results. In contrast, the combination of a global search and a local optimization is capable of overcoming the dependency on the initial guess to recover the exact solution. **Figure 5** visually represents the percentage error for each parameter across the different methods.

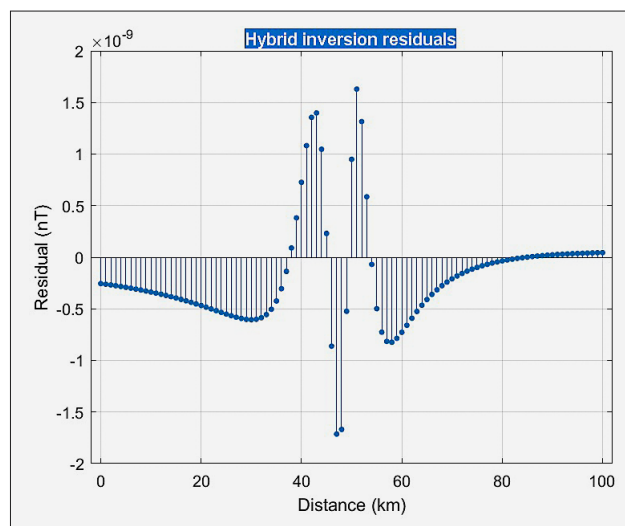


Figure 7: Residuals from the hybrid LJ→LM inversion for noise-free data.

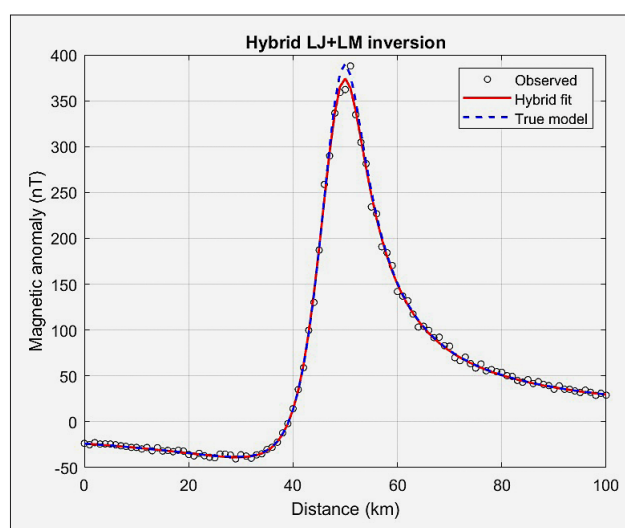


Figure 8: Comparison of 15% noisy synthetic magnetic data (black circles) with true model response (dashed blue line) and fit from hybrid LJ→LM method (solid red line). The hybrid method achieved RMS = 4.45 nT with parameter errors: K (1.96%), θ (1.29%), α (25.40%), z_1 (9.29%), z_2 (4.73%) as shown in **Table 2**.

As shown in **Figure 6**, the standalone LJ method recorded a notable RMS error (approximately 11.23 nT, as per **Table 1**). Although the standalone LM method achieved a much higher RMS (105.24 nT), the hybrid (LJ→LM) method successfully reduced the RMS error to virtually zero, indicating a complete reproduction of the model response and precise convergence in the absence of noise.

Figure 7 displays the residuals from the hybrid inversion, which have reached a magnitude on the order of 10^{-9} nT. This demonstrates a perfect fit between the model response and the observed data. The symmetrical distribution and extremely small amplitude of these residuals signify complete convergence and the high precision of the hybrid method in data reconstruction.

Table 2: Comparison of true and estimated model parameter values, percentage error, and RMS error for the 15% noisy data using the LJ, LM, and hybrid approaches.

Parameter	TRUE	LJ	%Err-LJ	LM	%Err-LM	Hybrid	%Err-HY
K (nT)	400.00	497.00	24.25	521.04	30.26	392.15	1.96
θ (°)	35.00	45.95	31.28	34.99	0.02	35.45	1.29
α (°)	30.00	47.20	57.34	21.71	27.62	22.38	25.40
z_1 (km)	4.00	4.94	23.48	4.82	20.56	4.37	9.29
z_2 (km)	7.00	8.81	25.92	6.51	6.96	6.67	4.73
RMS (nT)	---	17.44	---	4.60	---	4.45	---

5.3. Inversion Results for Noisy Data

To evaluate the stability of the algorithms against a higher level of noise, the synthetic data from the reference model were contaminated with 15% peak-to-peak random noise (relative to the signal's amplitude) and then inverted. All other conditions, including the parameter search ranges and the configuration of the three methods, remained identical to the previous sections. **Figure 8** illustrates the fit of the hybrid model to the 15% noisy data. The increased noise level led to greater dispersion in the observed data points and a reduction in the clarity of the signal's peak, creating more challenging conditions for achieving precise parameter convergence. Despite the evident scatter of the data points, the resulting fit still effectively reconstructs the overall signal trend and provides a suitable overlay, even in regions with high gradients.

Table 2 displays the true, estimated, and percentage error values for the parameters for each of the three methods under the 15% noise condition. As expected, the percentage errors have increased compared to the noise-free case. The parameter α exhibits the highest sensitivity to noise, with the errors for the standalone LJ and LM methods reaching approximately 57% and 28%, respectively. Nevertheless, the hybrid method successfully reduces the errors for all parameters and achieves the lowest RMS error (approximately 4.45 nT).

While the difference in RMS error between the standalone LM method (4.60 nT) and the hybrid LJ→LM approach (4.45 nT) may appear modest – only approximately 3% – the hybrid method demonstrates a substantially superior performance in parameter accuracy, particularly for the angular parameters. As shown in **Table 2** and **Figure 9**, the hybrid method achieves significantly lower percentage errors for nearly all parameters compared to both standalone methods. Most notably, for the critical parameter α (effective magnetization angle), the hybrid method reduces the error to 25.40%, compared to 27.62% for LM and 57.34% for LJ. Similarly, for the amplitude coefficient K and the dip angle θ , the hybrid method attains errors below 2%, whereas the standalone LJ method exhibits errors exceeding 24% and 31%, respectively. This demonstrates that the hybrid approach provides not only a slightly better data fit (lower RMS) but, more importantly, a more accurate and geologically meaningful parameter

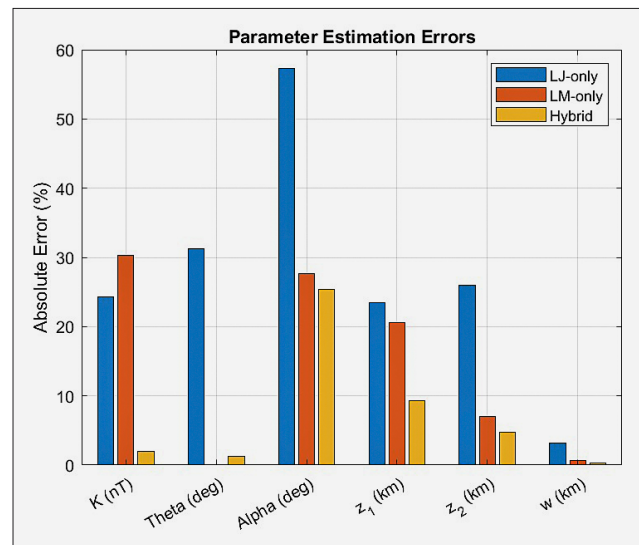


Figure 9: Absolute percentage error in parameter estimation for three inversion methods on 15% noisy synthetic data. LJ method shows highest errors ($\alpha > 57\%$), LM method shows improvement but still high error for α ($\approx 28\%$), while hybrid method achieves lowest errors for nearly all parameters ($< 3\%$ for K and θ), demonstrating superior accuracy and stability under high-noise conditions.

estimation, which is the ultimate goal of geophysical inversion. The error distribution across parameters reflects the sensitivity hierarchy established in Section 4. The high-sensitivity parameters (z_1 , z_2 , K) converge more reliably even under noise, with the hybrid method achieving errors of 9.29% for z_1 , 4.73% for z_2 , and 1.96% for K. In contrast, α – despite its moderate-to-high sensitivity ($\sim 63\%$) – shows significantly higher error (25.40%) due to its trigonometric coupling in the forward model, which amplifies noise effects. The parameter θ , while showing low amplitude sensitivity ($\sim 5\%$), exhibits very low error (1.29%) in the hybrid approach, confirming that its strong shape influence allows stable convergence despite weak amplitude response.

Figure 9 illustrates the trend of absolute parameter errors for the three inversion approaches on the 15% noisy data. As can be seen, the LJ method recorded the highest error for all parameters. This error exceeds 57% for α , indicating its high sensitivity to noise. The LM method shows a significant improvement over LJ, yet it still exhibits a relatively high error for the α parameter (approxi-

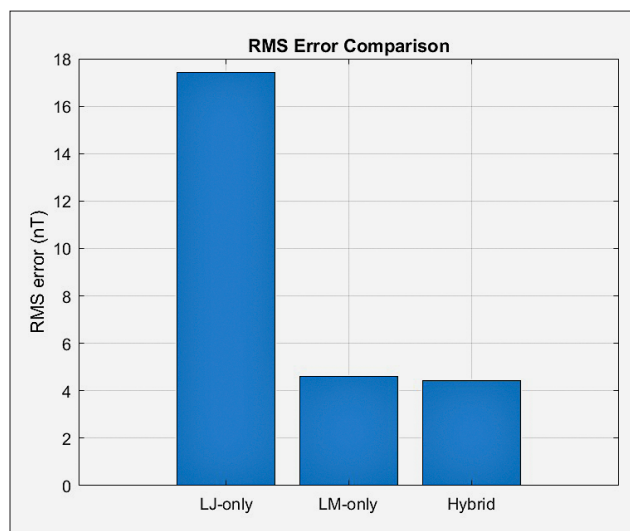


Figure 10: RMS error comparison for three inversion methods on 15% noisy synthetic data. Standalone LJ registered highest RMS (17.44 nT), indicating weaker convergence in noisy environment. Standalone LM and hybrid LJ→LM methods achieved considerably lower RMS values (4.60 nT and 4.45 nT respectively), demonstrating higher accuracy and greater robustness against noise.

mately 28%). In contrast, the hybrid method achieves the lowest error for nearly all parameters notably, less than 3% for K and θ which underscores its superior accuracy and stability even under high-noise conditions.

To better visualize the performance of the three inversion methods from an RMS error perspective, **Figure 10** presents a comparative bar chart of this metric for the 15% noisy data. As shown, the standalone LJ method registered the highest RMS value of 17.44 nT, indicating its weaker convergence in a noisy environment. The standalone LM and, particularly, the hybrid (LJ→LM) methods achieved considerably lower RMS values (4.60 nT and 4.45 nT, respectively), demonstrating their higher accuracy and greater robustness against noise.

Finally, **Figure 11** displays the residuals from the hybrid inversion. As can be observed, the majority of the residual values lie within the ± 5 nT range. Only a few positive or negative spikes with larger amplitudes (up to approximately +24 nT and -14 nT) are visible, which are a direct consequence of the noise perturbations. The overall symmetrical pattern around zero and the absence of any systematic trend indicate that the hybrid method was able to reproduce the model response with adequate fidelity, even in the presence of relatively high noise.

6. Analysis and Interpretation of Algorithm Performance on Angular Parameters (α and θ)

The angular parameters of the model, comprising the effective dip (α) and the fault slope (θ), play a decisive role in shaping the magnetic anomaly and are typically

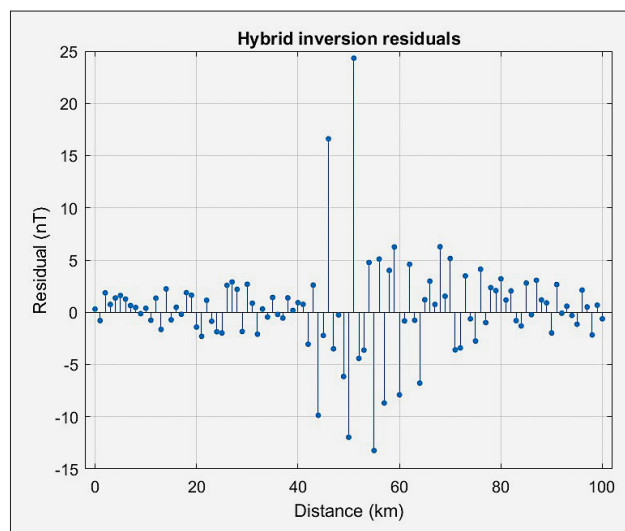


Figure 11: Residuals from hybrid LJ→LM inversion on 15% noisy synthetic data. The majority of residual values lie within ± 5 nT range. Positive and negative spikes (up to approximately +24 nT and -14 nT) are direct consequence of noise perturbations. Overall symmetrical pattern around zero and absence of systematic trend indicate hybrid method reproduced model response with adequate fidelity.

challenging in terms of stability during the inversion process. Due to the model's nonlinear response to these parameters, the lower accuracy of local optimization methods, and their relatively high correlation with each other, these two parameters can cause algorithms to become trapped in local minima or yield estimates far from the true values.

To more thoroughly evaluate the performance of the three approaches standalone LJ, standalone LM, and the hybrid LJ→LM in estimating these two parameters, the effect of a controlled initial perturbation in α was first investigated to determine how the algorithms react to a change in the starting point. Subsequently, a two-dimensional α - θ sensitivity analysis was conducted to map the error distribution in the joint parameter space and identify its optimal region. The combination of these two tests provides a comprehensive picture of the algorithms' strengths and weaknesses and highlights the advantage of the hybrid method in selecting suitable starting points and achieving stable convergence.

6.1. Effect of a Controlled Initial Perturbation in α on the Performance of the Hybrid Algorithm

The results presented in the preceding sections demonstrated that the hybrid (LJ→LM) method consistently registered significantly lower RMS values compared to the standalone LJ or LM methods, for both noise-free and 15% noisy data. However, a closer examination of the absolute parameter error comparison figures reveals that all methods, including the hybrid one, exhibit weaker performance in estimating the parameter α (effective

Table 3: Comparison of inversion results for synthetic data with 15% noise after applying a perturbation of $\Delta\alpha = +7^\circ$.

Parameter	TRUE	LJ-only	%Err-LJ	LM-only	%Err-LM	Hybrid	%Err-HY
K (nT)	400.00	417.26	4.32	200.00	50.00	360.55	9.86
θ (°)	35.00	45.67	30.49	31.04	11.32	35.73	2.10
α (°)	30.00	47.99	59.96	11.21	62.63	27.18	9.39
z_1 (km)	4.00	4.93	23.23	10.00	150.00	4.28	6.94
z_2 (km)	7.00	8.82	26.06	1.25	82.08	6.76	3.40
RMS (nT)	---	13.94	---	84.58	---	4.44	---

dip) compared to other parameters. The model's nonlinear nature with respect to α , its high correlation with other angular parameters (especially θ), and its strong dependency on the starting point all contribute to local algorithms like LM easily becoming trapped in local minima or converging to inaccurate estimates.

Applying a controlled perturbation to the initial value of α can steer the search path toward more stable regions and increase the probability of escaping local minima. In this study, only the parameter α was displaced from its true value by an amount $\Delta\alpha$, such that $\alpha_{init} = \alpha_{true} + \Delta\alpha$. All other parameters were kept at their true values to isolate and purely evaluate the effect of the perturbation on α . The model response was then calculated with this new α value, and 15% peak-to-peak uniform random noise was added to the data. The inversion process was executed using all three algorithms: LJ, LM, and the hybrid LJ→LM. **Table 3** presents the estimated parameter values and their corresponding relative percentage errors for the unperturbed and initially perturbed α cases.

A comparison of these results indicates that for the hybrid method, applying a controlled perturbation led to a dramatic reduction in the error of α , from 25.40% (in **Table 2**) to 9.39%. This significant improvement was accompanied by relatively small changes in the other parameters; for instance, the percentage error decreased for parameters like θ and z_2 , while it increased for others, including K . Another important observation is that the final RMS of the hybrid method remained nearly constant in both scenarios (4.45 nT → 4.44 nT), indicating that using a small, targeted perturbation preserved the overall quality of the fit without introducing negative side effects.

This finding, combined with the analysis of the figures showing the change in α error as a function of $\Delta\alpha$ (see **Figure 12**), suggests that a limited range for the initial perturbation (around 1 to 2 degrees) can be optimal, providing the greatest error reduction. In contrast, larger perturbations (over 7 degrees) lead to a noticeable decline in accuracy. In summary, a small and targeted initial perturbation in α can be considered a form of guided local optimization that, while maintaining the overall fit quality, effectively compensates for this parameter's inherent weakness in stability and sensitivity to the starting point.

Figure 13 shows the relationship between the initial value of α and the estimated α after running the hybrid

(LJ→LM) method on synthetic data with 15% noise. The horizontal axis represents the initial α value, obtained by adding the initial displacement $\Delta\alpha$ to the true value (30 degrees). The vertical axis displays the final estimated α after the inversion is complete. The black dashed line represents the initial value, the horizontal red line indicates the true value of α , and the colored points show the estimated values, with the color of each point corresponding to the final RMS value according to the color bar on the right. Points located above the red line indicate an overestimation, while proximity to it signifies higher accuracy. The plot demonstrates that for small perturbations, the estimated α remains close to the true value. However, as $\Delta\alpha$ increases, the estimates gradually deviate from the true value, with significant divergence occurring at larger perturbations (e.g. 8 to 10 degrees).

Although the plots in **Figures 12** and **13** were generated based on a specific scenario involving a 2D fault synthetic dataset with 15% noise and with other parameters held constant – and thus their results cannot be generalized as a universal rule for all models, noise conditions, or full inversion runs – their analysis provides several important insights for this particular problem. First, this sensitivity analysis shows that under controlled conditions, the minimum error for α occurs within a small initial perturbation range (approximately 1–2 degrees). Second, the curve in **Figure 12** reveals the existence of a “safe zone,” which could be useful for tuning the initial value of α in this specific model and test data. Third, the rapid increase in error for perturbations exceeding about 7 degrees serves as a warning, highlighting the risk associated with choosing initial values far from reality. Thus, this case study, in addition to monitoring the sensitivity and stability of α , is valuable as a reference for comparison and for designing adaptive experiments under different geometric and noise conditions, although it should not be directly used as a guide for selecting initial values in real-world scenarios.

6.2. Two-Dimensional α – θ Sensitivity Analysis and its Relation to the Hybrid Results

To assess the model's sensitivity to key parameters, an RMS contour map was plotted in the α – θ space, while keeping the other parameters fixed at the values from the best hybrid solution (see **Figure 14**). The results show

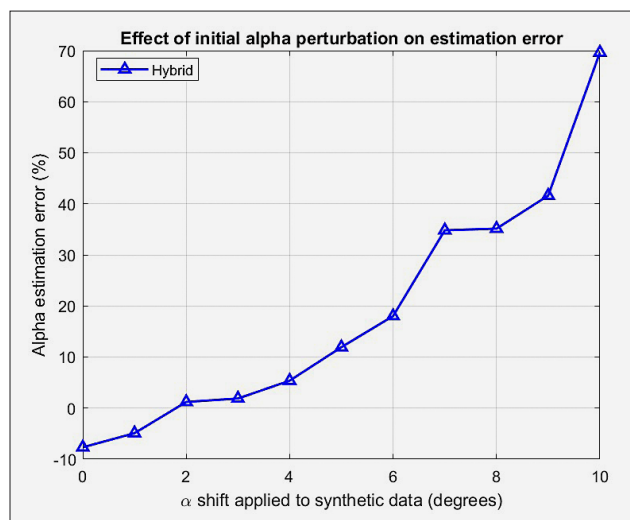


Figure 12: Variation of α estimation error in hybrid LJ→LM method as function of initial perturbation $\Delta\alpha$ for 15% noisy synthetic data. The analysis shows minimum error occurs within the small initial perturbation range (approximately 1–2 degrees). The rapid increase in error for perturbations exceeding about 7 degrees highlights the risk of choosing initial values far from reality.

that the region of minimum RMS is very narrow and is centered around $\alpha \approx 24^\circ$ and $\theta \approx 35^\circ$. This distribution indicates that small changes in these two parameters can cause significant variations in the model error. By comparing the values obtained from the hybrid method with the perturbed start ($\alpha = 27.18^\circ$, $\theta = 35.73^\circ$, $\text{RMS} = 4.44$ nT) with the location of the contour minimum, it is observed that the θ value almost perfectly matches the optimal center, and the α value differs by only about 3° . This proximity demonstrates that the hybrid algorithm successfully entered the optimal error region and overcame the challenge of local minima traps.

7. Real Data Application: The Perth Basin Case Study, Australia

To assess the practical efficacy of the proposed magnetic inversion methods – namely the standalone LJ, standalone LM, and the hybrid LJ+LM approach – a real-world dataset from a magnetic anomaly profile over a fault structure on the western margin of the Perth Basin, Australia, was utilized. These data were first reported by **Qureshi and Nalaye (1978)** and have since been employed in several reputable geological and geophysical studies, including those by **Biswas and Rao (2021)** and **Essa et al. (2023)**. The profile has a total length of 40 km and was sampled at 1 km intervals (see **Figure 15**). This case validates the applicability of the 2D assumption because the selected profile represents a laterally homogeneous section, as consistently utilized in previous Perth Basin inversion studies (**Biswas and Rao, 2021; Essa et al., 2023**).

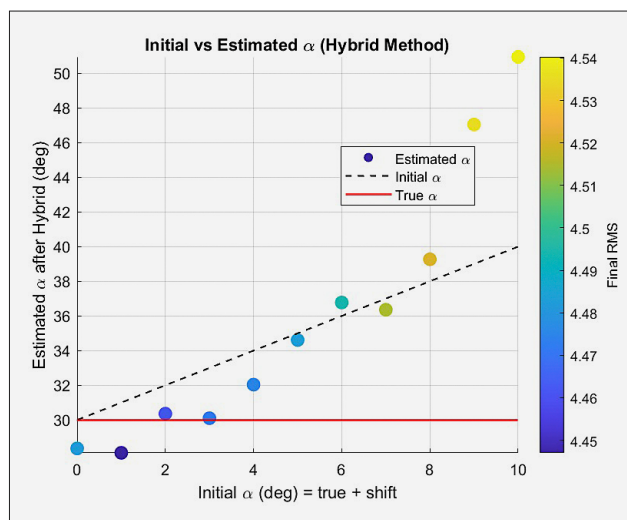


Figure 13: Estimated α from hybrid LJ→LM method versus initial α (true value of 30° plus $\Delta\alpha$) for 15% noisy synthetic data. Black dashed line: initial value; horizontal red line: true α value; colored points: estimated values with color corresponding to final RMS. For small perturbations, estimated α remains close to true value. As $\Delta\alpha$ increases, estimates gradually deviate with significant divergence at larger perturbations (8–10 degrees).

After digitizing the data, this profile served as the basis for the analysis and estimation of the fault model parameters in this study. The Perth Basin, located in Western Australia, has a north-south trend. It is considered the southern extension of the Carnarvon Basin and, with an area of approximately 100,000 km², is of significant geomorphological and economic importance. The presence of more than twenty commercial oil and gas fields underscores the region's significance in hydrocarbon exploration. The basin's formation resulted from an intracontinental rifting process that ultimately led to the separation of India from Australia, recording a thick succession of sediments from the Permian to the present day. Its tectonic and structural boundaries, particularly on the western side, host major fault systems and are considered prospective zones for mineral and energy resource exploration, making their study of considerable scientific and industrial value (**Olierook et al., 2015**).

In this research, the forward model (**Equation 6**) was used to simulate the magnetic response of the 2D fault, and the search bounds for the parameters were selected based on geological information and previous studies. First, the LJ algorithm was executed as a global search, followed by the LM algorithm for local refinement of the parameters. In the hybrid LJ+LM approach, to enhance the stability of the parameter α (effective dip), a small random perturbation ($\pm 1^\circ$) was added to its value after the LJ run. A wider search margin of 0.20 was then applied for α in the subsequent LM search, while other parameters were searched within a standard margin of 0.10. This hybrid cycle was repeated over 10 runs with internal multi-starts to secure the lowest possible RMS minimum.

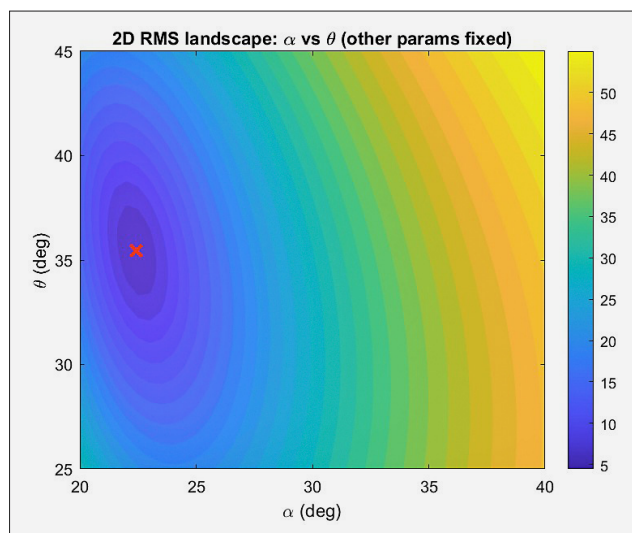


Figure 14: RMS contour map in α - θ parameter space with other parameters fixed at best hybrid solution values. The minimum RMS region is very narrow, centered around $\alpha \approx 24^\circ$ and $\theta \approx 35^\circ$. The hybrid method with perturbed start ($\alpha = 27.18^\circ$, $\theta = 35.73^\circ$, $\text{RMS} = 4.44$ nT) shows the θ value almost perfectly matches the optimal center, and α differs by only $\sim 3^\circ$, demonstrating successful entry into optimal error region while overcoming local minima traps.

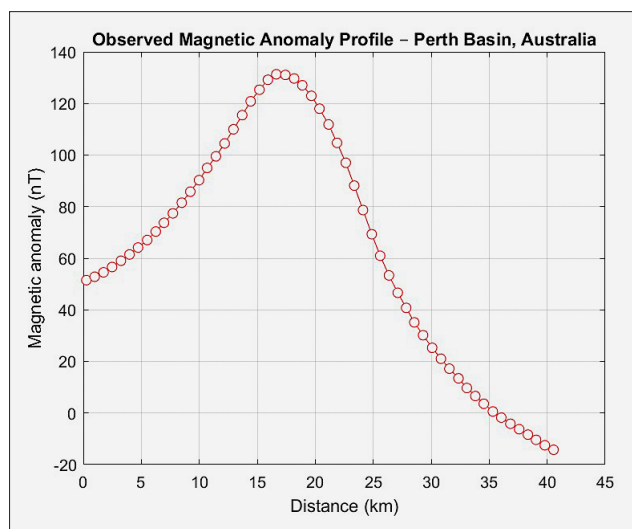


Figure 15: Observed magnetic anomaly profile over the western boundary of the Perth Basin, Australia.

To ensure the best possible outcome was achieved, a multi-run wrapper framework was also implemented. This framework executed the entire three-pronged process (LJ, LM, Hybrid) 50 times with different initial conditions, selecting and recording the best global result based on the lowest RMS achieved by the hybrid method.

Figure 16 illustrates the model fit to the real Perth Basin data. As can be observed, while the output of the LJ algorithm follows the general shape of the anomaly, it shows a significant discrepancy on the eastern flank of the curve (at distances greater than 30 km). The LM approach, initiated with random starts, provides a better local fit than

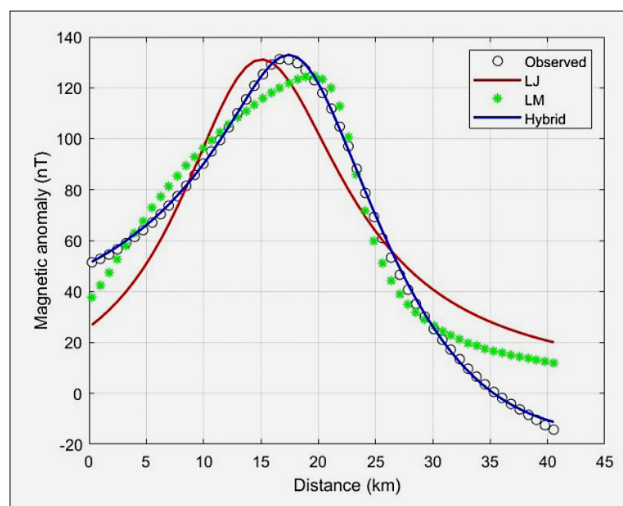


Figure 16: Perth Basin real magnetic anomaly data (Qureshi and Nalaye, 1978) inverted using three methods. Black circles: observed data (40 km profile, 1 km sampling); red line: LJ method ($\text{RMS} = 2.16$ nT); green stars: LM method ($\text{RMS} = 10.61$ nT); blue line: hybrid LJ+LM with α perturbation and multi-start ($\text{RMS} = 1.33$ nT). The hybrid method achieved lowest error, demonstrating superior performance on real fault structure data.

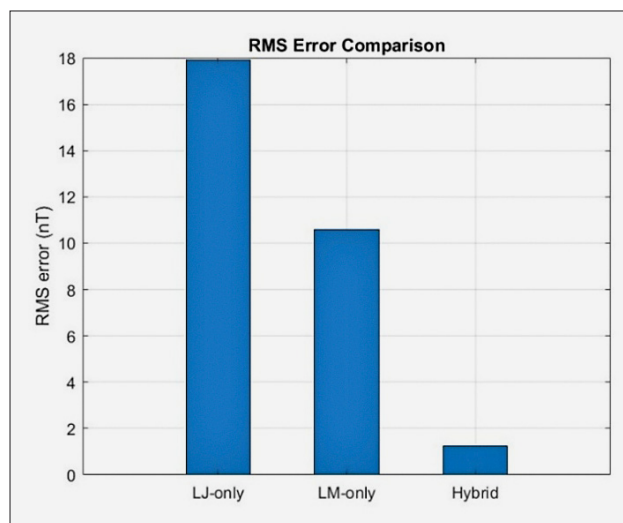


Figure 17: RMS error comparison for Perth Basin real data inversion. Hybrid LJ+LM method achieved lowest error (1.33 nT), performing significantly better than standalone LJ (2.16 nT) and LM (10.61 nT) methods, confirming practical efficacy of the proposed hybrid approach on real-world fault structures.

LJ but has limited accuracy around the anomaly's peak. In contrast, the hybrid LJ+LM method – implemented with an initial perturbation on α and a wider search margin for it – successfully reconstructed the curvature of the peak and the decay slope in the far-field regions, closely matching the observed data. It achieved the lowest RMS among the three approaches (see **Figure 17**). This result clearly demonstrates the superior agreement of the hybrid method with the real data and validates the choice of the stabilization settings for α in a real-world application.

Table 4: Estimated parameters for the 2D fault from real data using the hybrid (LJ→LM), standalone LJ, and standalone LM algorithms, compared with previous studies.

Parameter	LJ	LM	Hybrid	Essa (2023)	Qureshi & Nalaye (1978)	Rao & Babu (1983)	Tlas & Asfahani (2011)	Di Maio et al. (2020)
K (nT)	223.6	46.41	128	146.62	-	-	200.56	169.4
z_1 (km)	7.06	2.03	6.16	5.98	5.80–6.85	6.26	7.22	8.5
z_2 (km)	12.8	7.113	13.13	14.99	15.55–17	15.45	13.72	12
θ (°)	146.5	10	93.25	95.64	30	40	35.56	35.86
α (°)	-69.5	13.13	-21.45	-21.14	-	-	-	-
w (km)	19.79	22.79	17.9	18.05	-	-	-	-
RMS (nT)	2.163	10.61	1.33	7.18	-	-	-	-

Table 4 presents the quantitative results of the inversion process for the real Perth Basin data, alongside the findings from five key previous studies.

The consistency of our depth estimates with the range reported across multiple studies (z_1 : 5.80–8.50 km, z_2 : 12–17 km) and particularly close agreement with recent advanced methods (Essa et al., 2023) demonstrates the reliability of our hybrid approach. Moreover, our substantially lower RMS error (1.33 nT compared to 2.16–10.61 nT in other studies) indicates superior data fitting while maintaining geologically plausible parameters.

An analysis of the inversion results, as detailed in **Table 4**, highlights the superior performance of the proposed hybrid LJ-LM algorithm. The key findings are summarized as follows:

- 1. Superior Data Fit:** The hybrid method achieved the lowest Root Mean Square (RMS) error of 1.33 nT. This value indicates a significantly better fit to the observed data compared to both the standalone LJ (RMS = 2.163 nT) and the standalone LM (RMS = 10.61 nT) algorithms. Notably, our method's RMS is also considerably lower than the 7.18 nT reported in the recent study by **Essa et al. (2023)**.
- 2. Accurate Parameter Estimation:** The parameters estimated by the hybrid approach demonstrate strong geological consistency. The values for top depth ($z_1 = 6.16$ km), slope angle ($\theta = 93.25^\circ$), effective magnetization inclination ($\alpha = -21.45^\circ$), and horizontal position ($w = 17.9$ km) show excellent agreement with the findings of **Essa et al. (2023)**. Furthermore, the estimated top depth (z_1) falls precisely within the classic range of 5.80–6.85 km established by **Qureshi and Nalaye (1978)**.
- 3. Limitations of Standalone Methods:** The standalone algorithms showed significant drawbacks. Although the LJ method produced a moderate RMS, it yielded a geologically implausible slope angle ($\theta = 146.5^\circ$). Conversely, the LM method failed to converge to a meaningful solution, resulting in an extremely high RMS (10.61 nT) and inaccurate parameter estimates, which underscores its dependency on a good initial model.

In conclusion, the results from our hybrid model were compared with a wider range of studies (**Rao and Babu, 1983; Tlas and Asfahani, 2011; Di Maio et al., 2020**). This comparison shows that our model consistently aligns with established literature regarding the structure's key parameters, such as the amplitude factor (K) and depths (z_1, z_2).

While direct validation through gravity data or borehole information was not available for this study, the strong agreement of our results with six independent investigations using diverse optimization methods (see **Table 4**) provides compelling evidence for the accuracy of the estimated fault parameters. Future studies integrating multi-method geophysical data and detailed borehole information would further strengthen subsurface characterization in this region. Future Work: The methodology may be extended to 3D magnetic data and integrated airborne or geothermal exploration settings.

8. Conclusions

In this study, a hybrid approach was developed and evaluated for the inversion of magnetic anomalies caused by 2D fault structures. The method is based on the combination of the Luus–Jaakola (LJ) and Levenberg–Marquardt (LM) algorithms, enhanced with two key components: a multi-start strategy and a controlled perturbation technique. The primary objective was to overcome the limitation of initial model dependency and to improve the stability of estimating geometric and physical parameters, particularly the effective inclination angle, α .

The results from synthetic data demonstrated that the hybrid method achieves higher accuracy compared to standalone LJ and LM implementations. For instance, in the presence of 15% noise, our approach reduced the RMS error to 4.45 nT, a significant improvement over the values obtained from standalone LJ (17.44 nT) and LM (4.60 nT). Furthermore, by applying a suitable initial perturbation to α , its estimation error was successfully reduced from 25.40% to 9.39%. The one-dimensional analysis of $\Delta\alpha$ and the two-dimensional sensitivity analysis of the α - θ space confirmed that small perturba-

tion ranges can define “safe” starting regions for achieving more stable convergence, and that the optimal location of these regions depends on whether other parameters are fixed or free.

Importantly, these results reveal a critical distinction between data fit quality and parameter accuracy. While the standalone LM method achieved an RMS of 4.60 nT – close to the hybrid method’s 4.45 nT – the hybrid approach delivered dramatically superior parameter recovery. The percentage errors for K and θ were reduced to less than 2% with the hybrid method, compared to 24–31% with LJ. This highlights a crucial point often overlooked in inversion studies: a good data fit (low RMS) does not necessarily guarantee an accurate parameter estimation, especially in highly nonlinear problems. The hybrid method’s ability to combine global exploration with local refinement ensures both aspects are optimized simultaneously.

When applied to real data from the Perth Basin, Australia, the hybrid method again proved its superiority by achieving an RMS of 1.33 nT (compared to 2.16 nT for LJ and 10.61 nT for LM) and yielding parameters consistent with the plausible geological model of the area.

For the Perth Basin case study, the convergence of results from multiple optimization algorithms (see **Table 4**) effectively serves as indirect validation in the absence of direct ground-truth data. The estimated fault geometry, with depths of 6.16 km to 13.13 km and near-vertical dip (93.25°), is consistent with the tectonic setting of a rift basin margin. Collectively, the findings indicate that this hybrid approach provides an effective framework for enhancing the accuracy and stability of magnetic data inversion, especially under noisy conditions. It can therefore be employed as a practical and robust solution in similar geophysical investigations. The methodology shows particular promise for airborne magnetic surveys, mineral exploration in structurally complex areas, and geothermal fault detection.

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SAŽETAK

Hibridna Luus-Jaakolina i Levenberg-Marquardtova inverzija za magnetske anomalije nad 2D rasjednim strukturama

Ova studija predstavlja skraćeni sažetak usmjeren na hibridnu Luus-Jaakola-Levenberg-Marquardtovu inverziju i njezine iznimne performanse na sintetičkim podacima i podacima bazena Perth.

U ovoj studiji predstavljen je i evaluiran hibridni pristup za procjenu geometrijskih i fizičkih parametara 2D rasjednih struktura iz magnetskih podataka. Ova metoda integrira mogućnost globalnoga pretraživanja Luus-Jaakolina (LJ) algoritma s brzom konvergencijom Levenberg-Marquardtova (LM) algoritma, poboljšanu dvjema komponentama: strategijom višestrukoga pokretanja i shemom kontroliranih perturbacija. Ova kombinacija prevladava ograničenja ovisnosti početne vrijednosti i nestabilnosti određenih parametara, posebno efektivnoga kuta nagiba (α). Performanse predložene metode procijenjene su korištenjem sintetičkih i stvarnih podataka. Rezultati pokazuju da hibridni pristup pruža veću točnost i stabilnost u procjeni parametara u usporedbi sa svakim pojedinačnim algoritmom, posebno u uvjetima šuma. Eksperimenti perturbacije i analiza osjetljivosti otkrili su jasnu hijerarhiju parametara: parametri dubine pokazuju najjači utjecaj amplitude (otprilike 200 – 267 % varijacije), zatim slijede koeficijent amplitude (otprilike 85 %) i efektivni kut magnetizacije (otprilike 63 %), dok kut nagiba rasjeda pokazuje minimalnu osjetljivost amplitude (otprilike 5 %). Analiza efektivnoga kuta magnetizacije pokazala je njegovu ključnu ulogu u identificiranju optimalnih početnih područja za stabilne procjene, pri čemu lokacija tih područja ovisi o stanju drugih parametara. U primjeni stvarnih podataka hibridna metoda dala je parametre u skladu s vjerojatnim geološkim modelima područja. Rezultati ove studije nude praktičan okvir za poboljšanje inverzije magnetskih podataka, posebno u okruženjima kontaminiranim šumom. U ovoj studiji predstavljen je hibridni pristup koji kombinira Luus-Jaakolin (LJ) i Levenberg-Marquardtov (LM) algoritam za procjenu geometrijskih i fizičkih parametara 2D rasjednih struktura iz magnetnih podataka. Metoda iskorištava mogućnost globalnoga pretraživanja LJ-a i brzu konvergenciju LM-a, a istovremeno uključuje strategiju višestrukoga pokretanja i kontrolirane perturbacije kako bi se prevladala ovisnost o početnoj vrijednosti i nestabilnost kritičnih parametara kao što je efektivni kut nagiba (α). Performanse su procijenjene korištenjem sintetičkih i stvarnih podataka. Za sintetičke podatke s 15 % šuma hibridna metoda postigla je RMS od 4,45 nT, znatno nadmašujući samostalni LJ (17,44 nT) i LM (4,60 nT), a istovremeno je smanjila pogrešku procjene α s 25,40 % na 9,39 % kontroliranom perturbacijom. Kada se primijeni na stvarne magnetske podatke iz bazena Perth u Australiji, hibridni pristup dao je RMS od 1,33 nT u usporedbi s 2,16 nT (LJ) i 10,61 nT (LM), što rezultira parametrima u skladu s vjerojatnim geološkim modelom područja. Ti nalazi pokazuju da hibridni okvir nudi vrhunsku točnost i stabilnost za inverziju magnetskih podataka, posebno u uvjetima šuma.

Ključne riječi:

magnetska inverzija, rasjed, Luus-Jaakolin algoritam, Levenberg-Marquardtov algoritam, hibridni Luus-Jaakola-Levenbergov algoritam

Author's contribution

Mojtaba Babaei (Assistant Professor of Geophysics): conceptualisation, methodology, investigation, software, validation, writing – original draft, and writing – review and editing. **Mohammad Rezaie** (Assistant Professor of Geophysics): data curation, formal analysis, visualisation, and review and editing.

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Risk Management in the Construction of Metropolitan Running Tunnels Using Emulsion Explosives: Case Study

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Maksym Kononenko¹ , Oleh Khomenko² , Serhii Hapiev³ ,
Roman Tereshchuk³ , Roman Dychkovskyi^{2,4*}

¹ Dnipro University of Technology, Department of transport systems and energy-mechanical complexes, 19 Yavornytskoho Ave., 49-005, Dnipro, Ukraine.

² Dnipro University of Technology, Department of Mining Engineering and Education, 19 Yavornytskoho Ave., 49-005, Dnipro, Ukraine.

³ Dnipro University of Technology, Department of Construction, Geotechnics and Geomechanics, 19 Yavornytskoho Ave., 49-005, Dnipro, Ukraine.

⁴ AGH University of Krakow, Faculty of Management, Al. Mickiewicza 30, 30-059 Krakow, Poland.

Abstract

This study proposes a methodology for calculating the drilling-and-blasting parameters used in the construction of metropolitan running tunnels employing emulsion explosives within an integrated risk-management framework. Drilling-and-blasting operations in metropolitan tunnel construction require high precision in blast-hole design to ensure stable fragmentation and to minimize technical and operational risks. This study aims to develop a risk-oriented methodology for calculating drilling-and-blasting parameters for running tunnels based on the rational spatial arrangement of blast holes and controlled rock fragmentation. The proposed methodology is grounded in elasticity theory and quasi-static and wave-based hypotheses of rock failure under explosive loading. Blast holes are arranged in groups according to tunnel face areas using contour retreat principles. Straight cuts are designed based on the crushing zone radius, followed by calculations of the line of least resistance, explosive consumption, hole spacing, charge per hole, and total explosive expenditure. A power-law relationship is employed to define blast-hole geometry as a function of explosion pressure, hole diameter, uniaxial compressive strength, rock structure, jointing, and geostatic stress conditions. Numerical simulations confirmed the formation of stable inelastic deformation zones and uniform rock fragmentation, significantly reducing the occurrence of oversized blocks at the tunnel face. The study integrates analytical blast-design calculations with numerical stress-strain modelling within a unified risk-management framework for metropolitan tunnelling. Implementation of the proposed methodology improves blasting efficiency and safety, enables up to 14% savings in excavation resources, and reduces technical and operational risks associated with drilling-and-blasting works in urban underground construction.

Keywords:

drilling-and-blasting operations; emulsion explosives; stress-strain modelling; rock mass failure; tunnel excavation efficiency

1. Introduction

The rapid expansion of urban areas, accompanied by the construction of residential buildings, transport infrastructures, industrial facilities, and municipal structures, has intensified the competition for available land. In major metropolitan centers, the scarcity of free space has become a critical urban-planning challenge, limiting the establishment of new parks, pedestrian zones, and recreational areas. As cities continue to densify, the pressure on surface-level urban development increases, necessitating more efficient spatial planning strategies to ensure sustainable growth (Haiko et al., 2023).

To address these constraints, modern cities increasingly rely on the integrated use of both surface and sub-surface spaces as a means of optimizing limited urban territory. Vertical urban zoning enables an effective redistribution of transport and pedestrian flows, separating high-speed and regular traffic as well as public and private mobility systems (Pankratova et al., 2024a). Within this framework, underground construction plays a vital role, providing alternative corridors for transport and utilities while simultaneously relieving the overloaded surface environment (Pankratova et al., 2024a). Such development not only enhances transport efficiency but also contributes to reducing visual clutter and improving the aesthetic quality of urban landscapes (Pankratova et al., 2024a; Pankratova et al., 2024b; Cheberichko et al., 2023; Pankratova et al., 2024c). The rational development of underground space has therefore become a key direction in contemporary urban engineering, par-

* Corresponding author: Roman Dychkovskyi

e-mail address: dychkovskyi.r.o@nmu.one

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ticularly in high-density metropolitan areas (Haiko et al., 2023; Cheberiyachko et al., 2023; Pankratova et al., 2024c; Avanoğlu-Çetin & Öztürk, 2019). Consequently, strategic planning and technological innovation in subsurface construction are increasingly essential for ensuring sustainable and resilient urban growth.

Among underground transport systems, metropolitan railways represent one of the most efficient solutions for reducing emissions, decreasing traffic congestion, and improving overall mobility in densely populated cities. By shifting a significant portion of passenger and freight traffic below ground, metro systems help alleviate surface-level transport pressure and contribute to more sustainable urban development (Cheberiyachko et al., 2023; Avanoğlu-Çetin & Öztürk, 2019; Alkhdour et al., 2023). Their construction requires large-scale excavation of running tunnels, frequently conducted under complex geological and hydrogeological conditions that vary significantly between urban sites (Radkevych et al., 2022). These subsurface operations involve not only substantial engineering challenges but also strict requirements for environmental protection and structural stability (Petrenko et al., 2023). The use of drilling-and-blasting methods, while effective, introduces considerable technical, operational, and safety risks that must be carefully managed to prevent accidents and minimize adverse impacts (Haiko et al., 2023; Pankratova et al., 2024c; Alkhdour et al., 2023; Petrenko et al., 2020). Therefore, optimizing tunnel construction processes through advanced planning, risk assessment, and controlled blasting techniques is critical to the successful development of metropolitan railway infrastructure.

Given the growing demand for underground transport infrastructure and the increasing complexity of urban geological settings, there is a critical need for research aimed at improving the safety, predictability, and efficiency of blasting operations. The use of emulsion explosives in tunnel construction offers significant advantages but also requires advanced methodologies for blast-hole design, fragmentation control, and risk mitigation. Developing integrated risk-management approaches tailored to metropolitan running tunnels is therefore essential to ensure secure construction processes, minimize environmental and operational hazards, and enhance the overall sustainability of urban underground development.

Object of the Case Study. Currently, the city of Dnipro faces serious transport problems. Surface transport cannot cope with the passenger flow, leading to severe congestion in the city center. Residents of remote areas are forced to spend a significant amount of time travelling to the city center, not to mention the risks (Cheberiyachko et al., 2023; Zhang et al., 2024) they face while using overcrowded minibuses (Pankratova et al., 2024c, Lyashenko et al., 2018). Analysis of the city's development and the functioning of urban passenger transport show that, in the short term, surface trans-

port services will not be able to provide sufficient growth in passenger transportation, which confirms the need to develop an underground metro system. Therefore, considering the significant prospects for the development of Dnipro as one of the most important industrial, scientific, educational, cultural, financial, and business centers of Ukraine, further enhancing its international image and investment attractiveness, the completion of the metro construction is crucial for addressing the city's socio-economic development issues, improving transport infrastructure, increasing the quality of transport services, and achieving high operational efficiency and profitability. Another important factor highlighting the relevance of metro construction is the potential use of its underground infrastructure as a shelter, which has become particularly relevant due to Russian military aggression that has caused significant destruction to infrastructure in populated areas (Cheberiyachko et al., 2023; Myronova, 2016).

The construction of a metro line is an especially dangerous, technically complex, and unique project with a Level I responsibility. Currently, the first stage of the Dnipro city metro (Dnipro Metro) includes six stations, a branch to the depot, and the depot itself, with a total length of 7.076 km. The extension of the first stage from the "Vokzalna" station to the "Muzeina" station is designed to connect the existing line with the central part of the city. The route alignment in plan and profile was determined based on the placement of stations in the main passenger-generating hubs, taking into account the existing urban development and geological and hydrogeological conditions. The extended line passes under Dmytra Yavornytskoho Avenue, where the stations "Teatralna," "Tsentrlna," and "Muzeina" will be located (Avanoğlu-Çetin & Öztürk, 2019; Krysin et al., 2004). All stations are designed with island platforms long enough to accommodate five-car trains. Station vestibules are underground and connected to underpass crossings. Analysis of architectural and construction solutions for building vestibules (Alkhdour et al., 2023; Kholodenko et al., 2014), escalator passages (Radkevych et al., 2022; Petrenko et al., 2023; Myronova, 2015), and running tunnels (Petrenko et al., 2020; Kononenko et al., 2023) has shown that, to increase the efficiency of metro construction, technological solutions for intensifying tunnel excavation must be considered. One such solution is the use of rational blasting parameters (BPR), which improves work safety and leads to resource savings during construction (Zhang et al., 2024; Kononenko et al., 2011). Another improvement in blasting technology is not only enhancing the safety of explosive works (Lyashenko et al., 2018) but also reducing their environmental impact (Myronova, 2016) by replacing TNT-based explosives with domestically produced emulsion explosives (EEs) (Krysin et al., 2004), which are safe to transport and store (Kholodenko et al., 2014), cost-effective (Kholodenko et al.,

2015), and environmentally friendly (Myronova, 2015; Kononenko et al., 2021).

So, the aim of this study is to develop a new methodology for calculating blasting parameters for the excavation of metro running tunnels. This methodology takes into account key factors, such as the diameter of the blast holes, the pressure of the explosive products, and the compressive strength limits of the rock. In addition, it considers the structural composition of the rock, its fracturing, and the degree of compaction under in-situ stress, ensuring a more accurate and safe design of tunnel blasting operations.

2. Literature Review on Risk Factors and Management Approaches in the Construction of Metropolitan Running Tunnels Using Emulsion Explosives

The construction of metropolitan running tunnels represents one of the most technically demanding segments of underground infrastructure development. As cities expand and demand for efficient public transport increases, underground rail systems become essential elements of sustainable urban mobility (Petrenko et al., 2023; Bashynska et al., 2024; Pivnyak, 2025). However, tunnel construction in densely built urban areas is associated with severe geological, geotechnical, environmental, and technological challenges. The frequent necessity to work at significant depths, often in highly heterogeneous rock masses with variable water content, increases the complexity of ensuring structural stability and maintaining safe working conditions (Kononenko et al., 2011; Vladoiko et al., 2025). In this context, blasting remains one of the primary excavation methods in hard-rock environments, requiring a sophisticated understanding of both the rock mass response and explosive performance.

The adoption of emulsion explosives has significantly reshaped blasting technology for underground tunnelling. Compared to traditional TNT-based or ANFO explosives, EE offer enhanced detonation stability, improved water resistance, controllable energy output, and higher operational safety (Kholodenko et al., 2014; Kononenko et al., 2023; Listh, 1978). Their properties make them especially advantageous in metro construction, where geological unpredictability and proximity to surface structures demand precise control of explosive effects. Despite these advantages, improper selection of blast parameters or inadequate design of drilling-and-blasting patterns can still lead to overbreak, excessive vibrations, rock mass loosening, equipment damage, and safety hazards (Kononenko et al., 2023; Polyanska et al., 2024). Therefore, comprehensive research into optimal EE application and associated risk-management strategies is timely and essential.

The use of explosive energy in confined underground environments introduces a spectrum of interrelated risks

(Pankratova et al., 2024b; Polyanska et al., 2025). These include uncontrolled rock fracturing, excessive seismic vibrations, flyrock, gas contamination, unstable excavation walls, and unpredictable stress redistribution within the rock mass (Pankratova et al., 2024b; Brown & Hudyma, 2016). The magnitude and character of these risks depend not only on the physical and mechanical properties of the geological medium but also on drilling accuracy, explosive charging density, detonation velocity, and blast initiation timing. In metro construction, additional risks arise from the presence of nearby historical buildings, underground utilities, subway infrastructure, and sensitive architectural sites (Pankratova et al., 2024b; Brown & Hudyma, 2016; Sala & Richert, 2025). These factors elevate the consequences of blasting errors, making risk assessment and mitigation vital components of the construction process.

Although numerous national and international methodologies exist to guide drilling-and-blasting operations, many of them were developed using outdated explosive formulations and simplified assumptions about rock behaviour (Kononenko et al., 2023; Kononenko et al., 2011; Gu & Cao, 2023). A significant portion of these methodologies do not adequately account for the detonation characteristics of modern emulsion explosives, dynamic stress-wave interactions, or the complex mechanics of crack propagation in heterogeneous rock masses. Furthermore, available approaches often rely on empirical values with wide coefficient ranges, introducing uncertainty into the design of blast patterns (Kononenko et al., 2023; Gu & Cao 2023; Pyzalski et al., 2025). Thus, there is a clear scientific gap requiring updated analytical and computational tools that integrate modern explosive properties, advanced numerical modelling, and refined geological characterization.

The proposed methodology is clearly distinguished from existing analytical and empirical approaches by introducing several fundamentally new elements. These include an integrated risk-oriented framework that explicitly accounts for the formation of inelastic deformation zones and fragmentation predictability in metropolitan tunnelling. A physically justified blast-hole grouping strategy is implemented, linking tunnel face geometry with controlled contour retreat principles. In addition, a power-law relationship is proposed for determining the line of least resistance under urban tunnelling conditions using emulsion explosives, thereby enhancing the reliability and transferability of the design methodology.

The actuality of this research is driven by the rapid expansion of metropolitan transportation systems worldwide, accompanied by growing expectations for construction safety, environmental protection, and operational efficiency (Pankratova et al., 2024b; Shcherba et al., 2025). Authorities increasingly require evidence-based justification of blasting parameters to minimize ground vibrations, prevent structural damage, and ensure worker safety (Gu & Cao, 2023; Ma et al., 2019).

As projects grow in scale and societal importance, the economic consequences of blasting inefficiencies also intensify (Serdaliyev & Iskakov, 2022). Therefore, developing scientifically grounded, validated methodologies for evaluating risk factors and optimizing management strategies using emulsion explosives directly contributes to improving construction quality, reducing costs, and enhancing safety across the industry.

The current drilling-and-blasting design methods for metropolitan running tunnels are largely based on empirical rules, simplified deterministic formulas, or adaptations of mining-oriented practices that do not fully account for the specific constraints of urban tunnelling. The existing approaches typically treat blast-hole spacing, charge distribution, and explosive consumption as independent parameters, with limited consideration of their coupled influence on rock mass response, fragmentation uniformity, and operational risk. Moreover, most methodologies do not explicitly integrate risk-management principles, such as the control of oversized block formation, predictability of inelastic deformation zones, and variability in rock mass structure under geostatic stress. The use of emulsion explosives in metropolitan conditions further accentuates these limitations, as their energy release characteristics are often not adequately reflected in conventional blast design models.

The scientific novelty of this study lies in the development of an integrated, risk-oriented methodology that unifies analytical blast-parameter calculation, physically justified blast-hole grouping, and numerical stress-strain modelling within a single design framework. Unlike existing methods, the proposed approach establishes a power-law relationship between the line of least resistance and key geological, mechanical, and explosive parameters, enabling rational and predictable blast-hole layout design for tunnel faces. The methodology explicitly targets risk reduction by ensuring the formation of stable inelastic deformation zones and uniform fragmentation, thereby minimizing oversized blocks. This advances current knowledge by shifting drilling-and-blasting design from empirical tuning toward a physically grounded, predictive, and resource-efficient framework tailored to metropolitan tunnel construction using emulsion explosives.

This research provides an integrated understanding of risk factors associated with drilling-and-blasting operations in metro tunnel construction and outlines best-practice management approaches tailored to modern EE technologies. By combining field observations, analytical methods, and numerical modelling, it establishes a robust foundation for calculating rational blasting parameters and predicting rock mass behaviour. The outcomes may be used to refine construction guidelines, support decision-making for designers and engineers, and strengthen regulatory frameworks. Moreover, the findings help bridge the gap between traditional empirical methods and contemporary high-precision engineer-

ing practices, thereby contributing to the future development of safer, more efficient underground construction technologies.

3. Research Methodology, Methods & Materials

The choice of the technological scheme and the method of rock excavation during the construction of running tunnels is influenced by the engineering-geological conditions of the project area, the water saturation of the intersected rocks, rock pressure, and other factors (Morelli, 2015). Given the engineering-geological conditions of tunnel construction, the tunnels are located at a depth of 68 m in hard rock (granites) with a compressive strength of 49–123 MPa. Therefore, their construction will be carried out using a closed (underground) method with drilling-and-blasting operations (DBO). For the construction of the running tunnels from Shaft No. 16-bis to the “Muzeina” station, a full-face excavation scheme has been adopted (Radkevych et al., 2022). This technological scheme is applied for tunnelling in stable rocks with compressive strength $\sigma_c \geq 40$ MPa and in workings not exceeding 10 m in height and 20 m in width. These geometric limitations are linked to the capability of drilling and auxiliary equipment, as well as to the risk associated with opening an unsupported span of considerable height in a single cycle.

It is well known that DBO is a set of work processes associated with the detachment of rock from the massif through the action of explosive energy. The term “DBO” emphasizes the inseparable and interdependent nature of the processes of drilling, charging, and blasting (Kononenko et al., 2023; Gu & Cao 2023; Carlos et al., 2017). Depending on how rationally the parameters of DBO are determined, they may significantly affect the technical and economic indicators of underground excavation. Currently, numerous methodologies exist for calculating DBO parameters in underground mine workings (Kononenko et al., 2023; Mishra, 2012). These methodologies vary in the complexity of their algorithms and often yield substantially different results. Therefore, several existing methodologies proposed by leading researchers from different countries are considered herein.

The first class of methodologies focuses on determining the specific explosive consumption, which is defined based on practical data, empirical formulas, or tabulated reference information (Gu & Cao, 2023; Fedoreiko et al., 2025). Based on the specific explosive consumption, the number of blast holes is calculated, followed by the remaining DBO parameters (Bozic & Strelec, 2020). A significant drawback of this approach is that the coefficients used in calculations cover a very wide range of values, and their selection depends largely on the designer’s qualification (Gu & Cao, 2023; Bozic & Strelec, 2020). As a result, the DBO parameters are often defined using average values, which negatively af-

fect blasting efficiency and ultimately require additional trial blasts to refine rational DBO parameters (**Kononenko et al., 2023; Gheorghiosu & Becuț, 2024**). The authors of these methodologies include Protodiakonov M.M., Bogomolov V.I., Pokrovskiy M.M., Mindeli E.O., Sukhanov A.F., Ibraev Sh.I., Taranov P.Ya., Langefors U., Borisova S.S., Roginskiy V.M., Bokii B.I., Baron L.I., and others. Analysis of the most common methodologies that rely on preliminary determination of specific explosive consumption shows that rock strength and cross-sectional area of the excavation are the key factors in all these approaches (**Kononenko et al., 2011; Fedoreiko et al., 2019**). Less frequently, the formulas include explosive performance, charging density, and blast-hole depth. The formulas were developed during the 1920s–1960s and were later refined by subsequent researchers, while some remain in their original form. Their major limitation is that they were developed for TNT-based explosives and do not account for the detonation characteristics of modern emulsion explosives (EE) (**Kononenko et al., 2021**).

Methodologies belonging to the second class differ fundamentally. These methods involve determining the zones of crushing and fracturing around a blast hole, depending on the physical-mechanical properties of the rock mass and the detonation characteristics of the explosive. Based on these zones, the minimum burden between groups of blast holes and the spacing within rows are calculated, after which the holes are arranged in the tunnel face. Andriievskiy O.P. (**Andriievskii, 1993**) proposed a methodology for calculating and designing the DBO plan for underground mine workings, which includes determining the radii of the crushing and fracture zones, with the latter used to define the minimum burden. The blast holes are arranged according to a calculated grid. Perimeter holes are placed uniformly along the contour at a spacing not exceeding the radius of the fracture zone, and their spacing is calculated separately. Building upon Andriievskiy's method, Vokhmin S.A., Kurchin H.S., and Kirsanov O.K. proposed an improved version through the introduction of an empirical formula for determining the detonation velocity of ammonium-nitrate-based explosives as a function of charge diameter and charging density. They also developed a graphical-analytical procedure for designing DBO parameters.

Therefore, based on the combined action of quasi-static and shock-wave mechanisms of rock destruction (**Kosenko et al., 2025**), and integrating both previously described methodological approaches, it is necessary to develop a new methodology for determining DBO parameters for the construction of metro running tunnels that accounts for both the physical-mechanical properties of the rock mass and the detonation characteristics of modern explosives.

The development of a methodology for determining DBO parameters for metro running tunnels included the following stages:

- design and sequential calculation of cut holes based on the radius of the crushing zone;
- development of a methodology for determining DBO parameters based on the principle of arranging groups of blast holes according to the areas they occupy in the tunnel face and their placement along breakage contours;
- verification of the calculated parameters of DBO with EE under real-world conditions using numerical modelling of the stress–strain state of the rock mass in the tunnel face under explosive loading.

To develop the methodology for DBO parameter determination during metro tunnel construction, the generally known laws of elasticity theory and the main principles of the quasi-static–wave hypothesis of solid-medium destruction by explosion were applied. Numerical modelling of inelastic deformation zones caused by changes in the stress–strain state of the rock mass under explosive action was performed using the finite element method in the licensed engineering analysis software SolidWorks Simulation.

When constructing running tunnels underground using blasting with emulsion explosives (BPE), the most common cross-sectional shapes are oval or circular. Therefore, the methodology for calculating BPE parameters in the construction of running tunnels will be developed for these two excavation shapes.

The procedure for calculating BPE parameters according to the new methodology consists of the following main stages. The first stage includes the calculation and design of the initial cut (**Kononenko et al., 2023**), and the second stage involves the direct calculation of the number of boreholes, their placement in the excavation face, and the total explosive consumption per face (**Khomenko et al., 2019**).

According to the research presented in **Kononenko et al. (2023b)**, the spacing between boreholes in the initial cut equals the radius of the crushing zone and is determined by the formula:

$$R_{zm} = 0.5 \cdot d \cdot \sqrt{1 + \frac{\rho \cdot D^2 \cdot K_{dz}}{2 \cdot \sigma_{st} \cdot K_{sp} \cdot K_s \cdot K_u}}, \text{ m}; \quad (1)$$

where d – borehole diameter, m; ρ – density of explosives or emulsion explosives (**Kononenko et al., 2021**), kg/m³; D – detonation velocity of explosives, m/s; σ_{st} – compressive strength of rocks, Pa; K_{dz} – coefficient accounting for the change in pressure of explosive gases on the walls of the charge cavity depending on the charge diameter (**Kononenko et al., 2023b**); K_{sp} – rock structure coefficient, depending on rock mass properties (**Kononenko et al., 2023b**): for viscous, elastic, and porous rocks $K_{sp} = 2.0$; for dislocated rocks with variable bedding and fine fracturing $K_{sp} = 1.4$; for schistose rocks with variable strength and bedding perpendicular to the charge cavity $K_{sp} = 1.3$; for massive brittle rocks $K_{sp} = 1.1$; for monolithic rocks $K_{sp} = 1.0$; for fine-porous, loose

rocks $K_{sp} = 0.8$; K_s – coefficient of structural weakening of the rock mass, determined using one of the formulas in (Kosenko et al., 2025); K_u – empirical coefficient of rock compaction under mining pressure (Kosenko et al., 2025).

The minimum area of the initial cut is determined empirically as:

$$S_{vr} = 0.45 \cdot (l_{sh} \cdot \eta)^{0.91}, \text{ m}^2, \quad (2)$$

where l_{sh} – length of the borehole set, m; η – borehole utilization coefficient, 0.8–0.95.

The minimum number of boreholes in the cut, without accounting for compensatory (empty) holes:

$$N_{vr} = \frac{S_{vr}}{\pi \cdot R_{zm}^2}, \text{ pcs.} \quad (3)$$

According to the second stage, the following calculations are performed: borehole spacing, areas of borehole groups, number of boreholes, spacing between them, charge per borehole, specific and total explosive consumption for the tunnel face (Kononenko et al., 2024). The determination of explosive performance based on the degree of detonation velocity realization is carried out according to the methodology presented in Kononenko et al. (2023c). The calculated specific explosive consumption is determined by the most universal formula of Prof. M.M. Pokrovskiy (Kononenko et al., 2024):

$$q = 0.01 \cdot \sigma_{st} \cdot K_{sp} \cdot k_{zat} \cdot e, \text{ kg/m}^3, \quad (4)$$

where σ_{st} – compressive strength of rocks, MPa; k_{zat} – rock confinement coefficient, ranging 1.2–1.5; e – relative performance coefficient of explosives, calculated according to Kononenko et al. (2023c).

The volume of blasted rock in the mass is:

$$V = S_{pr} \cdot l_{sh}, \text{ m}^3, \quad (5)$$

where S_{pr} – tunnel area at the face:

$$S_{pr} = 0.25 \cdot \pi \cdot B_{pr} \cdot H_{pr}, \text{ m}^2, \quad (6)$$

with B_{pr} – tunnel width, m; H_{pr} – tunnel height, m.

The calculated explosive quantity per face:

$$Q = q \cdot V, \text{ kg.} \quad (7)$$

Considering the operating conditions of borehole charges, their placement relative to the open surface, and the need to crush the rock mass to pieces < 0.2 m, the calculation of borehole spacing is recommended based on the radius of the intensive crushing zone (Kononenko et al., 2023b).

Calculated borehole spacing:

$$W = R_{zm} \cdot \left(1 + \frac{\rho \cdot D^2 \cdot d \cdot K_{dz}}{8 \cdot R_{zm} \cdot \sigma_{st} \cdot K_{sp} \cdot K_s \cdot K_u} \right)^{0.5}, \text{ m.} \quad (8)$$

Contour borehole area:

$$S_k = S_{pr} - \pi \cdot \frac{B_{pr} - 2 \cdot (\Delta_o + W)}{2} \cdot \frac{H_{pr} - 2 \cdot (\Delta_o + W)}{2}, \text{ m}^2, \quad (9)$$

where Δ_o – distance from the excavation contour to the line of contour boreholes, equal to the radius of the crushing zone R_{zm} , typically 0.15–0.25 m based on practical experience.

Face area for production boreholes:

$$S_{vid} = S_{pr} - (S_{vr} + S_k), \text{ m}^2. \quad (10)$$

where S_{vr} – accepted cut area, m².

Number of production boreholes:

$$N_{r,v} = \frac{1.27 \cdot q \cdot S_{vid}}{\rho \cdot d_z^2 \cdot k_z}, \text{ pcs.}, \quad (11)$$

where k_z – borehole filling coefficient, 0.30–0.85, or calculated empirically (Kononenko et al., 2023a):

$$k_z = 0.225 \cdot \sigma_{st}^{0.25}, \quad (12)$$

where σ_{st} – compressive strength of rocks, MPa.

Area per production borehole:

$$S_{v,sh} = \frac{S_{vid}}{N_{r,v}}, \text{ m}^2. \quad (13)$$

Adjusted calculated borehole spacing:

$$W_{sr,v} = \sqrt{S_{v,sh}}, \text{ m.} \quad (14)$$

Distance between production boreholes in a row:

$$a_{r,v} = m \cdot W_{sr,v}, \text{ m,} \quad (15)$$

where m – charge convergence coefficient for production boreholes, 1.0–1.3.

Number of rows of production boreholes:

– across tunnel width:

$$n_{h,r,v} = \frac{0.5 \cdot B_{pr} - \Delta_o - 0.5 \cdot b_{vr}}{W_{sr,v}} - 1, \text{ pcs.}; \quad (16)$$

– along tunnel height:

$$n_{v,r,v} = \frac{0.5 \cdot H_{pr} - \Delta_o - 0.5 \cdot h_{vr}}{W_{sr,v}} - 1, \text{ pcs.}; \quad (17)$$

where b_{vr} and h_{vr} – width and height of the cut, m.

Actual distance between rows of production boreholes:

– across width:

$$W_{h,f} = \frac{0.5 \cdot B_{pr} - \Delta_o - 0.5 \cdot b_{vr}}{n_{h,r,v} + 1}, \text{ m;} \quad (18)$$

– along height:

$$W_{v,f} = \frac{0.5 \cdot H_{pr} - \Delta_o - 0.5 \cdot h_{vr}}{n_{v,r,v} + 1}, \text{ m.} \quad (19)$$

Optimal contour rows of production boreholes follow the tunnel cross-section shape.

Number of production boreholes in the i^{th} contour:

$$N_{v(i)} = \frac{2 \cdot \pi \cdot \sqrt{0.125 \cdot (b_i^2 + h_i^2)}}{a_{r,v}}, \text{ pcs.}, \quad (20)$$

where b_i and h_i – width and height of the i^{th} contour, m.

Actual spacing between boreholes in the i^{th} contour:

$$a_{f,v(i)} = \frac{2 \cdot \pi \cdot \sqrt{0.125 \cdot (b_i^2 + h_i^2)}}{N_{v(i)}}, \text{ m.} \quad (21)$$

Total number of production boreholes:

$$N_{vid} = \sum_{i=1}^n N_{v(i)}, \text{ pcs.} \quad (22)$$

Calculated distance between contour boreholes:

$$a_{r,k} = m \cdot W_{sr,v}, \text{ m.} \quad (23)$$

where m – charge convergence coefficient for contour boreholes, 0.75–0.95.

Number of contour boreholes:

$$N_k = \frac{2 \cdot \pi \cdot \sqrt{0.125 \cdot ((B_{pr} - 2 \cdot \Delta_o)^2 + (H_{pr} - 2 \cdot \Delta_o)^2)}}{a_{r,k}}, \text{ pcs.} \quad (24)$$

Actual distance between contour boreholes:

$$a_{f,k} = \frac{2 \cdot \pi \cdot \sqrt{0.125 \cdot ((B_{pr} - 2 \cdot \Delta_o)^2 + (H_{pr} - 2 \cdot \Delta_o)^2)}}{N_k}, \text{ m.} \quad (25)$$

Total number of boreholes in the tunnel face to be charged:

$$N = N_{vr} + N_{vid} + N_k, \text{ pcs.}, \quad (26)$$

where N_{vr} – number of charged cut boreholes, pcs.

Average charge per borehole:

$$Q_{sh} = \frac{Q}{N}, \text{ kg.} \quad (27)$$

Charge in a borehole according to its purpose:

$$Q_z = K_n \cdot Q_{sh}, \text{ kg.} \quad (28)$$

where K_n – coefficient accounting for increase or decrease of charge depending on borehole type: for cut borehole $K_n = 1.1$ – 1.2 , for production borehole – $K_n = 1.0$, for contour borehole on sides and roof $K_n = 0.9$ – 1.0 , for contour borehole on floor $K_n = 1.0$ – 1.2 .

Actual explosive consumption per face:

$$Q_f = N_{vr} \cdot Q_{vr} + N_{vid} \cdot Q_{vid} + N_{bp,k} \cdot Q_{bp,k} + N_{p,k} \cdot Q_{p,k}, \text{ kg.} \quad (29)$$

where Q_{vr} – charge in cut borehole, kg; Q_{vid} – charge in production borehole, kg; $Q_{bp,k}$ – charge in contour boreholes at sides and roof, kg; $Q_{p,k}$ – charge in floor contour boreholes, kg.

Actual specific explosive consumption:

$$q_f = \frac{Q_f}{V_f} = \frac{Q_f}{S_{pr} \cdot l_{sh} \cdot \eta}, \text{ kg/m}^3. \quad (30)$$

Length of boreholes filled with blasted material:

$$L_{zab} = l_{zab,vr} \cdot N_{vr} + l_{zab,vid} \cdot N_{vid} + l_{zab,bp,k} \cdot N_{bp,k} + l_{zab,p,k} \cdot N_{p,k}, \text{ m.} \quad (31)$$

where $l_{zab,vr}$, $l_{zab,vid}$, $l_{zab,bp,k}$ and $l_{zab,p,k}$ – lengths of cut, production, side and roof contour, and floor contour boreholes, m.

Mass of blasted material:

$$M = 0.25 \cdot \pi \cdot d^2 \cdot L_{zab} \cdot \rho_{zab}, \text{ kg.} \quad (32)$$

where ρ_{zab} – density of blasted material, kg/m³.

The presented methodology and mathematical framework provide a systematic approach for calculating blasting parameters in the construction of underground metro tunnels. It allows for accurate determination of borehole placement, charge distribution, and explosive consumption under practical field conditions. The approach is adaptable to both oval and circular tunnel cross-sections, enhancing operational efficiency and safety. Overall, this method offers a reliable tool for optimizing excavation processes in urban underground construction.

4. Results of Management Solutions for the Construction of Metro Running Tunnels Using Emulsion Explosives: Shaft No. 16-bis to “Muzeina” Station, Dnipro city

As an example, let us consider the calculation of blasting parameters for the construction of the running tunnel from Shaft No. 16-bis to the “Muzeina” station of the Dnipro city metro (Dnipro Metro). The calculation is based on the initial data provided in **Table 1**, which includes key parameters such as tunnel dimensions, rock properties, and explosive characteristics. This example demonstrates the practical application of the developed methodology for determining borehole placement, charge distribution, and overall explosive consumption. By using this data, it is possible to optimize the blasting design to ensure maximum efficiency and safety during excavation. The methodology is applicable to both oval and circular tunnel cross-sections, providing flexibility for real urban mining conditions. This case illustrates how the proposed approach can be effectively implemented in actual metro construction projects.

The results of the calculation of blasting parameters for the construction of the running tunnel from Shaft No. 16-bis to the “Muzeina” station of the Dnipro Metro, using the developed methodology, are presented in **Table 2**. The calculations include the determination of borehole placement, charge distribution, and the total amount

Table 1: Initial data for calculating blasting parameters for the construction of the running tunnel from Shaft No. 16-bis to the “Muzeina” station of the Dnipro city metro

Name	Unit of measurement	Value
Width of the running tunnel	m	6.0
Height of the running tunnel	m	6.2
Rock compressive strength	MPa	123
Rock density	kg/m ³	2660
Depth of the excavation	m	68
Rock fracturing	-	Highly fractured
Depth of cut (break) boreholes	m	1.8
Depth of blasting boreholes	m	1.6
Depth of contour boreholes	m	1.5
Borehole diameter	m	0.043
Cut type	-	Prismatic
Density of cartridge emulsion explosive Ukrainit-P-SA	kg/m ³	1150
Detonation velocity of cartridge explosive Ukrainit-P-SA	m/s	5050

of explosive required per tunnel face. Each parameter was derived based on the initial data, taking into account rock properties, tunnel dimensions, and the characteristics of the emulsion explosion. The results demonstrate how the methodology can be applied to optimize the excavation process for efficiency and safety. Both cut, production, and contour boreholes were considered in the analysis to ensure complete fragmentation of the rock mass. These results provide a practical example of implementing the proposed blasting design in real metro construction conditions.

Based on the results of the calculation of blasting parameters for the construction of the running tunnel, the layout of the boreholes at the tunnel face was determined. This layout ensures the optimal placement of cut, production, and contour boreholes to achieve efficient rock fragmentation. The arrangement was designed to account for the geometry of the tunnel, the properties of the rock mass, and the characteristics of the explosive used. The resulting borehole pattern is illustrated in **Figure 1**, providing a clear visual representation of the proposed design. This diagram serves as a practical guide for implementing the blasting plan in the field.

By comparing the developed blasting parameters passport with the current passport for the construction of the running tunnel from Shaft No. 16-bis to the “Muzeina” station of the Dnipro Metro, it was found that the calculated BPE parameters using the proposed methodology allow a 14% reduction in the number of boreholes at the tunnel face, from 108 to 93. This indicates that the proposed methodology for calculating blasting parameters

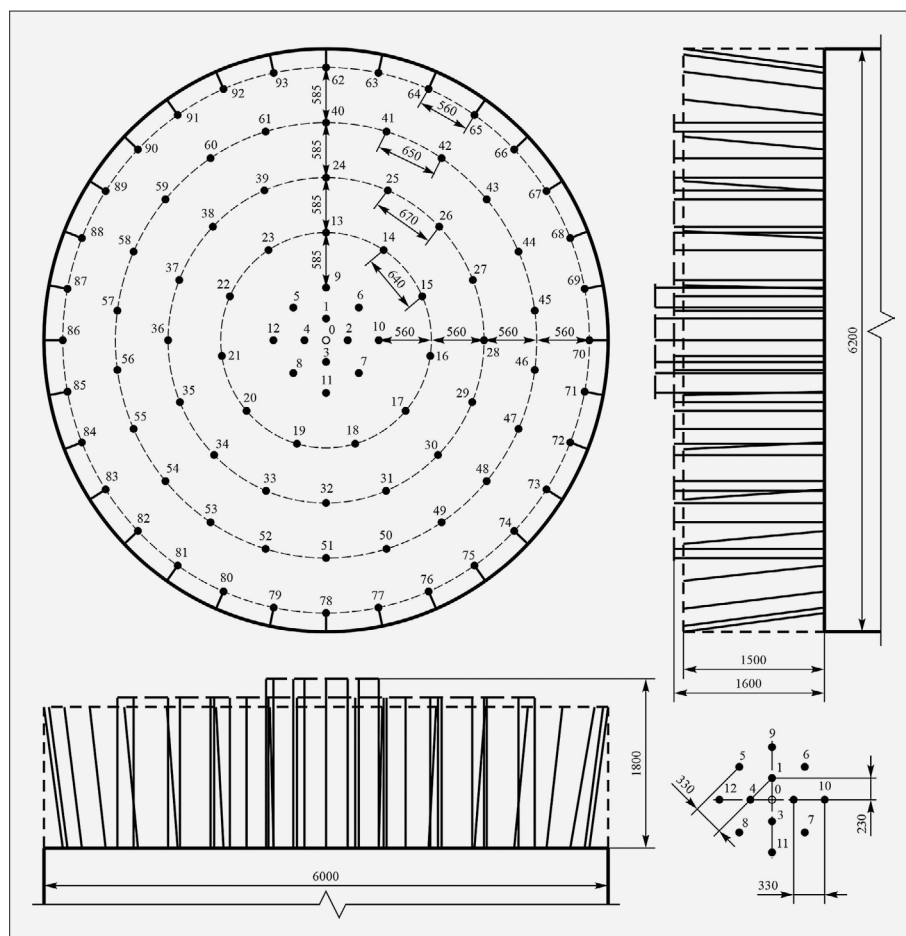
Table 2: Results of the calculation of blasting parameters for the construction of the running tunnel from Shaft No. 16-bis to the “Muzeina” station of the Dnipro city metro

Name	Unit	Value
Rock structure coefficient, K_{sp}	—	1.1
Structural weakening coefficient of the rock mass, K_s	—	0.4
Rock compaction coefficient, K_u	—	1.003
Calculated specific explosive consumption, q	kg/m ³	1.67
Calculated explosive quantity per face, Q	kg	78.0
Radius of the crushing zone, R_{zm}	m	0.23
Calculated borehole spacing, W	m	0.57
Number of cut (break) boreholes, N_{vr}	pcs	12
Number of production boreholes, N_{vid}	pcs	49
Number of contour boreholes, N_k	pcs	32
Total number of boreholes, N	pcs	93
Average charge per borehole, Q_{sh}	kg	0.84
Mass of cartridge emulsion explosive Ukrainit-P-SA	kg	0.25
Charge amount:		
— for cut borehole, Q_{vr}	kg	1.0
— for production borehole, Q_{vid}	kg	0.75
— for contour borehole, Q_k	kg	1.0
Actual explosive consumption per face, Q_f	kg	75
Charge length with cartridge explosive:		
— cut borehole, $l_{z,vr}$	m	1.12
— production borehole, $l_{z,vid}$	m	0.84
— contour borehole, $l_{z,k}$	m	1.12
Borehole utilization coefficient, η	—	0.95
Actual predicted specific explosive consumption, q_f	kg/m ³	1.71

optimizes borehole placement at the face by accounting for the physical and mechanical properties of the rock mass and the detonation characteristics of the explosives, resulting in more accurate outcomes.

To verify the parameters calculated with the new methodology, numerical modelling of the stress-strain state of the rock mass under explosive loading is required. One of the most promising approaches for studying the mechanism of explosive rock breakage is the use of numerical modelling based on the finite element method (FEM) (Babets et al., 2023). Today, FEM is one of the most advanced modelling techniques, providing a high degree of realism (Moldabayev et al., 2021). Numerical modelling allows for the investigation of processes and phenomena that are economically impractical or impossible to study in practice (Aitkazanova et al., 2022). Despite the sophistication of mathematical tools and computing technologies, there are relatively few validated software packages capable of accurately simulating the processes occurring during an explosion. In this field, SolidWorks (Petlovanyi

Figure 1: Layout of boreholes at the face of the running tunnel



et al., 2022) and ANSYS (Smoliński et al., 2021) are the leading software solutions. Both packages use FEM and are widely applied in mining for modelling the stress-strain state of rock masses under both mining pressure (Tereshchuk et al., 2018) and explosive loading (Kononenko et al., 2024).

According to the theory of material resistance (Kyrylenko et al., 2025; Kononenko et al., 2024), dynamic calculations can be approximated using static calculations with a dynamic coefficient. Therefore, to model the stress-strain state of the rock mass under explosive loading, the licensed SolidWorks Simulation software, available at the Dnipro University of Technology was used. Compared to ANSYS, SolidWorks Simulation reduces the time required for a single computational experiment when solving static problems. At the same time, it is much easier to work with SolidWorks Simulation than with the more complex ANSYS package, which requires a higher level of expertise for problem setup.

The purpose of numerical modelling of the stress-strain state of the rock mass under explosive loading is to verify the calculated blasting parameters for the metro tunnel. The FEM modelling methodology for explosive rock breakage using SolidWorks Simulation included the following stages: creation of the model geometry;

definition of the physical and mechanical properties of the model material; setting initial loads, constraints, and mesh; and analysis and processing of results.

During the first stage, the model geometry was created. Since the running tunnel has a width of 6 m and a height of 6.2 m, the model dimensions were set to 30 m in width, height, and depth to eliminate the influence of the model geometry on the simulation results.

The second stage of the modelling involved determining the physical and mechanical properties of the material in the model, including the elastic modulus, Poisson's ratio, shear modulus, density, and the tensile and compressive strength limits. Particular attention was given to accurately representing the real properties of the rock mass, as these parameters govern the propagation of stress waves generated by the explosion. Taking into account the structural composition of the rocks, their fracturing, and the degree of compaction under in-situ stress, the compressive strength of the isotropic model material is determined using a specific analytical expression:

$$\sigma_{st}^m = \sigma_{st} \cdot K_{sp} \cdot K_s \cdot K_u, \text{ MPa.} \quad (33)$$

This approach ensures a more realistic reproduction of the rock mass behavior under loading. In addition, refining these physical and mechanical parameters is es-

Table 3: Average values of the physical and mechanical properties of the model material

Name	Value
Elastic modulus, $\times 10^{10}$ Pa	5.4
Poisson's ratio	0.25
Shear modulus, $\times 10^{10}$ Pa	2.16
Density, kg/m^3	2660
Tensile strength, $\times 10^6$ Pa	5.4
Compressive strength, $\times 10^6$ Pa	54

sential for correctly defining boundary conditions and evaluating the response of the rock mass to explosive forces. Therefore, the second stage of the modelling process forms a critical foundation for obtaining reliable stress–strain calculations.

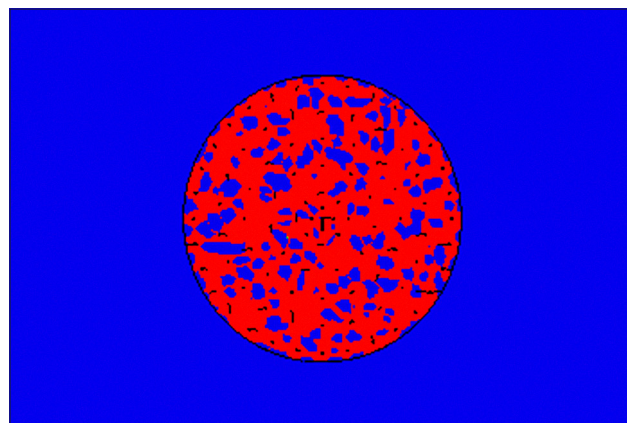
The adopted average values of the physical and mechanical properties of the model material are presented in **Table 3**. These parameters were determined based on the analysis of the geological characteristics of the rock mass and available experimental data, ensuring their consistency with real conditions. The use of average values simplifies the modelling process while maintaining sufficient calculation accuracy.

According to the next stage of the modelling process, the initial loads, boundary conditions, and the mesh of the model were established. The accuracy of the predicted rock mass failure depends significantly on how correctly these conditions are defined. Since an explosion can be represented as an initial impact followed by the action of explosion-product pressure (Persson et al., 2018), a pressure perpendicular to the walls and the tunnel face was applied in all blast holes to simulate this process, taking into account the dynamic coefficient (Torbica & Lapčević, 2015). The pressure of the explosion products inside the blast holes, considering the charge diameter, was calculated using the expression:

$$P_m = \frac{\rho \cdot D^2 \cdot K_{dz} \cdot K_d}{8}, \text{ Pa}, \quad (34)$$

where K_d – the dynamic coefficient.

The computational experiment for determining the change in the stress–strain state of the rock mass at the tunnel face was carried out in the following sequence. First, the geometric model was constructed according to the adopted parameters and the blast hole layout shown in **Figure 1**. Then, in the SolidWorks Simulation environment, a new static analysis was selected. Based on the data presented in **Table 3**, the physical and mechanical properties of the model material were assigned. The Coulomb–Mohr criterion, commonly used for brittle materials with different tensile and compressive properties, was applied as the failure criterion. The model geometry was then fixed, and the explosion-product pressure was applied along the entire length of the blast holes. To avoid the influence of undercharged blast holes on the results,

**Figure 2:** Zones of inelastic deformation formed in the rock mass at the face of the running tunnel under explosive loading

this factor was not considered. The model mesh was generated using curvature-based refinement with high density. Afterward, the computational procedure was launched, and upon completion, the results were refined in the parameter settings. The zones of inelastic deformation that formed in the rock mass at the tunnel face under explosive loading are shown in **Figure 2**.

The areas at the tunnel face where the model material exhibits a safety factor ≤ 1 delineate the zones of rock mass failure under explosive loading. In **Figure 2**, the red regions surrounding the blast holes represent zones of inelastic deformation in the rock mass resulting from the explosion. Analysis of the numerical modelling results of the stress–strain state of the model material at the tunnel face under explosive loading showed that the predicted granulometric composition of the rock after blasting will be less than 0.2 m. This indicates that the use of blasting parameters calculated according to the new methodology for metro tunnel excavation under the specified engineering and geological conditions will prevent the ejection of oversized rock fragments after blasting.

The proposed methodology for calculating blasting parameters in metro tunnel construction has been demonstrated to provide an effective and practical approach for optimizing borehole placement, charge distribution, and overall explosive consumption. Its application to the running tunnel from Shaft No. 16-bis to the “Muzeina” station of the Dnipro Metro allowed a 14% reduction in the number of boreholes while ensuring efficient rock fragmentation, illustrating the method’s capability to improve excavation efficiency without compromising safety. The methodology proves versatile, being applicable to both oval and circular tunnel cross-sections and adaptable to a variety of rock mass properties and explosive characteristics. Numerical modelling using the finite element method confirmed that the calculated parameters produce a controlled stress–strain response in the rock mass and result in a predictable granulometric composition of less than 0.2 m. These simulations demonstrate

that the approach effectively prevents oversized rock fragments from being ejected, enhancing operational safety and reliability. Overall, the combination of analytical calculation and numerical verification confirms that the proposed methodology is robust, reliable, and suitable for practical implementation in metro tunnel construction under complex engineering and geological conditions.

5. Discussion of Research Results

The proposed methodology for calculating blasting parameters in metro tunnel construction provides a structured and practical approach for optimizing excavation processes. By applying the methodology to the running tunnel from Shaft No. 16-bis to the “Muzeina” station of the Dnipro Metro, key parameters such as borehole placement, charge distribution, and total explosive consumption were determined in a way that ensures both efficiency and safety. The initial data, including tunnel dimensions, rock properties, and explosive characteristics, allowed for precise tailoring of the blasting design to the specific geological conditions of the site, demonstrating the methodology’s applicability in real-world urban mining projects.

Static FEM analysis with a dynamic coefficient provides only an approximate representation of explosive loading, as it cannot explicitly capture the transient nature of shock-wave propagation and high strain-rate effects associated with detonation. The approach assumes an equivalent quasi-static load, which neglects wave reflections, stress superposition, and time-dependent energy dissipation in the rock mass. Material behaviour is typically described using linear or simplified nonlinear constitutive models, limiting the accurate simulation of fracture initiation, crack propagation, and progressive damage under dynamic loading. In addition, the use of a dynamic coefficient requires prior assumptions or calibration, which introduces uncertainty and reduces generality across different geological conditions. Consequently, such modelling should be regarded as a verification and comparative tool for stress–strain trends and deformation zones, rather than a substitute for fully coupled dynamic or explicit blast simulations.

Comparison with the existing blasting passport revealed that the proposed approach reduces the total number of boreholes at the tunnel face by 14%, from 108 to 93, without compromising rock fragmentation. This reduction reflects the optimization achieved by accounting for the physical and mechanical properties of the rock mass as well as the detonation characteristics of the explosives. The methodology ensures that cut, production, and contour boreholes are arranged to maximize energy efficiency while maintaining safety standards, thereby reducing unnecessary drilling and explosive consumption.

Numerical modelling using the finite element method (FEM) in SolidWorks Simulation further verified the cal-

culated blasting parameters. The simulation allowed for a detailed analysis of the stress–strain state of the rock mass under explosive loading, taking into account boundary conditions, pressure distribution, and rock material properties (Babets et al., 2023; Brand, 2011). The results indicated controlled inelastic deformation zones and a predictable granulometric composition of fragmented rock, demonstrating that the proposed blasting design produces the desired breakage without ejecting oversized rock fragments. This validation highlights the methodology’s reliability and reinforces its practical utility.

The versatility of the methodology is evident in its applicability to different tunnel cross-sections, including both oval and circular profiles, and its adaptability to varying rock mass characteristics and explosive types. By integrating both analytical calculations and numerical verification, the approach provides a comprehensive framework for designing safe and efficient blasting operations (Pankratova et al., 2024b; Kononenko et al., 2023a; Gu & Cao, 2023). The combined use of precise calculation and simulation ensures that the excavation process is optimized for both energy efficiency and operational control.

The proposed adapted methodology for calculating the parameters of drilling and blasting operations for the construction of interstation tunnels has been tested under real operating conditions. The approbation was carried out during the development of underground mine workings at the mines of PJSC “Zaporizhzhia Iron Ore Combine” (Kononenko et al., 2023a). The methodology was applied to full-scale industrial blasting operations rather than laboratory or numerical simulations. This allowed the reliability and practical applicability of the proposed approach to be evaluated under complex geological and mining conditions. The obtained results confirm the feasibility of using the methodology in real tunnel construction and mining practice.

Overall, the results confirm that the proposed methodology is robust, reliable, and suitable for practical implementation in metro tunnel construction under complex engineering and geological conditions. The significant reduction in borehole numbers, the predictability of rock fragmentation, and the controlled stress–strain response achieved through numerical modelling all demonstrate that the approach enhances operational safety, reduces material and labor costs, and provides a reproducible framework for similar projects. This combination of analytical and computational methods establishes a strong foundation for improved planning and execution of urban tunneling operations.

6. Conclusions

The present study has proposed and validated a novel methodology for calculating blasting parameters in the construction of metro running tunnels, with application to the Dnipro Metro line from Shaft No. 16-bis to the “Muzeina” station. Analysis of existing approaches for under-

ground excavation highlighted that the most effective strategy combines the determination of specific explosive consumption with the assessment of deformation zones formed around each borehole (Pankratova et al., 2024b; Kononenko et al., 2023a). This integrated approach ensures a more accurate, safe, and resource-efficient design for blasting operations in complex urban mining conditions. The developed methodology introduces a fundamentally new framework for designing borehole placement and charge distribution in metro tunnels (Kononenko et al., 2023a; Gu & Cao, 2023). It is based on grouping boreholes according to their occupied area at the tunnel face and their arrangement along the contour (Ma et al., 2019; Yuan, 2011). Critical factors, including the radius of intensive rock fragmentation, borehole and charge diameters, explosive pressure, rock compressive strength, structural composition, fracturing, and compaction under overburden stress, are explicitly accounted for. Each borehole is assigned a precisely calculated charge, ensuring optimal rock fragmentation while minimizing unnecessary energy expenditure and reducing operational risks.

Validation through numerical modelling using the finite element method (FEM) confirmed the robustness of the methodology. Simulations of the stress–strain state of the rock mass under explosive loading demonstrated controlled the formation of inelastic deformation zones, with a predicted post-blast granulometric composition of less than 0.2 m. These results indicate that the proposed methodology effectively prevents the ejection of oversized rock fragments, enhances operational safety, and ensures predictable rock breakage. Implementation of the new parameters led to a rationalized layout of boreholes, achieving a 14% reduction in the total number of boreholes at the tunnel face compared to the existing blasting passport. This reduction demonstrates the methodology's potential for significant resource savings and operational efficiency without compromising the quality of rock fragmentation. The approach is versatile, applicable to both oval and circular tunnel cross-sections, and adaptable to varying rock mass properties and explosive types, making it suitable for a wide range of urban tunnelling projects.

Overall, the combination of analytical calculation, empirical consideration of rock properties, and numerical verification establishes a comprehensive, reliable, and practical framework for metro tunnel blasting design. The methodology provides an effective tool for optimizing excavation efficiency, reducing material and labor costs, and enhancing safety and predictability in underground construction projects. These findings offer a reproducible and scientifically grounded basis for the planning and execution of metro tunnelling operations under complex engineering and geological conditions.

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SAŽETAK

Upravljanje rizicima u izgradnji gradskih prometnih tunela primjenom emulzijskih eksploziva: studija slučaja

U ovome radu predlaže se metodologija za proračun parametara bušačko-minerskih radova u izgradnji gradskih prometnih tunela uporabom emulzijskih eksploziva u okviru integriranoga sustava upravljanja rizicima. Bušačko-minerski radovi u urbanim tunelima zahtijevaju visoku preciznost projektiranja minskih bušotina kako bi se osigurala stabilna fragmentacija stijenske mase i smanjili tehnički i operativni rizici. Cilj istraživanja jest razviti metodologiju temeljenu na upravljanju rizicima za proračun parametara bušačko-minerskih radova u tunelima temeljem racionalnoga prostornog rasporeda bušotina i kontrolirane fragmentacije stijena. Predložena metodologija zasniva se na teoriji elastičnosti te kvazistatičkim i valno-temeljenim hipotezama loma stijena pod djelovanjem eksplozivnoga naprezanja. Minske bušotine raspoređene su u grupe prema površinama čela tunela, primjenom načela konturiranoga povlačenja. Linije pravca loma projektirane su na temelju radijusa zone drobljenja, nakon čega slijede proračuni linije najmanjega otpora, potrošnje eksploziva, razmaka bušotina, količine punjenja po bušotini i ukupne potrošnje eksploziva. Geometrija minskih bušotina definirana je potencijalnim zakonom, koji povezuje tlak eksplozije, promjer bušotine, jednoosnu tlačnu čvrstoću stijene, strukturu i ispućalost stijenske mase te geostatičke uvjete naprezanja. Numeričke simulacije potvrdile su formiranje stabilnih zona neelastičnih deformacija i ujednačenu fragmentaciju stijenske mase, znatno smanjujući pojavu prevelikih blokova na čelu tunela. Metodologija integrira analitičke proračune miniranja s numeričkim modeliranjem stanja naprezanja i deformacija stijenske mase unutar jedinstvenoga okvira upravljanja rizicima u gradskim tunelima. Primjena predložene metodologije povećava učinkovitost i sigurnost miniranja, omogućuje do 14 % uštede u resursima iskopa te smanjuje tehničke i operativne rizike povezane s bušačko-minerskim radovima u urbanim podzemnim građevinskim zahvatima.

Ključne riječi:

bušačko-minerski radovi, emulzijski eksplozivi, modeliranje stanja naprezanja i deformacija, lom stijenske mase, učinkovitost tunelskoga iskopa

Author's contribution

Maksym Kononenko (Doctor of Engineering, Professor) - conceptualization, methodology, formal analysis, original draft; **Oleh Khomenko** (Doctor of Engineering, Professor) - supervision, data validation, review & editing; **Serhii Hapiev** (Doctor of Engineering, Professor) - data curation, software support, results visualization & investigation; simulation, technical validation; **Roman Tereshchuk** (Doctor of Engineering, Professor) - environmental assessment, editing and proofreading; **Roman Dychkovskyi** (Doctor of Engineering, Professor): - overall supervision, literature review, mechanical modeling, finite element.

Integrated Geoscience, and Geospatial Analysis for Hydrocarbon Exploration in the Khewari Block, Sindh, Pakistan

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Original scientific paper



Muhammad Junaid^{1,2*}, Muhammad Sajid², Taimoor Ahmad², Eko Kusratmoko¹, Reza Syahputra³, Shaukat Khan⁴, Adi Wibowo¹, Muhammad Kashif⁵

¹ Department of Geography Science, Universitas Indonesia, Depok, Indonesia.

² Department of Earth Sciences, Abbottabad University of Science and Technology, Pakistan.

³ Department of Geology, University of Indonesia, Depok, Indonesia.

⁴ Geological Engineering and Geomatics, Chang'an University, Xi'an, China.

⁵ Department of Earth Sciences, University of Sargodha, Pakistan.

Abstract

The Khewari Block, located in the structurally complex Lower Indus Basin of Sindh, Pakistan, occupies a tectonically favorable yet insufficiently explored sector of a Mesozoic–Cenozoic rifted basin known for its hydrocarbon prospectivity. This study employs an integrated geophysical geospatial workflow to confine subsurface architecture and assess reservoir potential. Extensive interpretation of 2D seismic profiles identifies a system of NE-SW-oriented normal faults, horsts, grabens, and local compressional structures, producing a wide range of trap geometries, including fault-bounded closures, rollover anticlines, and tilted fault blocks. Time and depth structure mapping refines horizon geometries and identifies structurally isolated blocks with enhanced trapping potential. Bouguer and residual gravity anomaly maps further resolve density differences associated with uplifted carbonate platforms and sediment-filled troughs, confirming segmentation of the structure based on seismic data. Surface dataset complements, such as DEM-based elevation, slope models, and land-use classification, offer further limitations on terrain accessibility, drainage systems, and operational capabilities. The integration of surface and subsurface datasets reduces the uncertainty in the interpretation process, improves the delineation of traps, and contributes to the most effective well-placement planning. The multidisciplinary approach illustrates the effectiveness of integrating seismic reflection, gravity modelling, and surface-based GIS analysis to create a coherent structural framework of frontier basins. The workflow is transferable to other data-limited regions and provides a robust foundation for evidence-based hydrocarbon exploration and decision-making.

Keywords:

Hydrocarbon Exploration; Seismic Interpretation; Gravity Anomalies; Geospatial Integration; Khewari Block

1. Introduction

The Khewari Block, located in the Lower Indus Basin of Sindh, Pakistan, is a structurally favorable yet under-explored region with considerable hydrocarbon potential, owing to its complex tectonic framework and the presence of thick Mesozoic–Cenozoic sedimentary successions (Jadoon et al., 2020). While the Lower Indus Basin has historically contributed significantly to Pakistan's energy sector, exploration within the Khewari Block itself has remained limited because of its geological complexity and restricted accessibility (Aftab et al., 2022). Although the nearby blocks, such as the Kadanwari and Sawan gas fields, have undergone extensive geophysical and drilling operations, the Khewari Block, located in the southeastern part of the Lower Indus Basin

between the Jacobabad High to the north and the Hyderabad Platform to the south, remains insufficiently characterized. Regionally, this area forms part of a rift-dominated structural regime associated with the breakup of Gondwanaland, which created a series of horsts, grabens, and tilted fault blocks that control hydrocarbon migration and entrapment (Khan et al., 2021). The proximity of the Khewari Block to productive reservoirs within the Lower Goru Formation in adjacent fields further highlights its exploration significance within the broader Indus Basin petroleum system. Unconsolidated Quaternary sediments also make geophysical images less clear, which makes it more difficult to define the structure of reservoirs with certainty (Khayitov et al., 2021; Sajid et al., 2021). The seismic reflection data have turned out to be essential in the detection of structural traps, especially fault-bounded closures that happened due to NE-SW trending normal faults related to the regional rifting (Noureldin et al., 2023). These faults define horst and graben geometries that segment

* Corresponding author: Muhammad Junaid
e-mail address: muhammadjunaidk22@gmail.com

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the basin and function variably as either hydrocarbon conduits or sealing barriers depending on lithological context (de Jager, 2020). Previous geophysical studies in comparable rifted basins have demonstrated that integrated interpretation of gravity-derived structural models can significantly improve the delineation of subsurface fault geometries and basin architecture (Setiahadi-wibowo et al., 2025).

The Lower Goru Formation has emerged as the principal reservoir unit, and its internal continuity is often inferred through amplitude anomalies such as bright spots and flat spots, indirect indicators of gas saturation (Singh, 2014). Nevertheless, seismic imaging alone suffers from attenuation, velocity ambiguity, and limited vertical resolution, especially across lithologically heterogeneous zones (Khaskheli et al., 2021). The basin's stratigraphy spans from the Precambrian to the Quaternary, reflecting a long history of marine transgressions, regressions, and sediment accumulation (Lučić & Bosworth, 2018). This complex depositional record has yielded multiple reservoir and seal pairs, notably within the Lower and Upper Goru, Sui Main Limestone, and Ranikot Formation. The Lower Goru Formation typically occurs at depths averaging ~2233 meters, while seismic profiles capture subsurface horizons between 1970 and 3220 milliseconds in two-way travel time (Mahmoud, 2015). These depth intervals suggest significant stratigraphic thickness and structural deformation, but detailed fault and formation correlations across the Khewari Block remain sparse in the literature (Zhou et al., 2025).

Regionally, the Lower Indus Basin has a tectono-sedimentary history that was influenced by post-Mesozoic extension and Himalayan orogeny (Inam et al., 2022). This history has given rise to a subsurface architecture characterized by the existence of many structural traps and tilted fault blocks (Dolson et al., 2018). Previous exploratory wells and geophysical surveys have only partially assessed the block's hydrocarbon potential (Sarhan, 2021). Nevertheless, analogs from other parts of the basin and comparable rift basins worldwide support the likelihood of commercially viable hydrocarbon systems yet to be fully delineated (Khan et al., 2024; Iqbal et al., 2022). Despite the fact that seismic interpretation is still at the heart of subsurface mapping, more and more current hydrocarbon exploration requires the assimilation of geophysical and geospatial data. Integrated seismic and gravity data have been shown to significantly enhance subsurface structural imaging and improve geological interpretation in complex rifted basins (Safari et al., 2026). Traditional seismic data, including SEG-Y profiles, usually have issues with noise, resolution, and a lack of surface context (Buttinelli et al., 2022). This is especially the case in structurally complicated areas such as the Khewari Block, where fault interactions, lithological contrasts, and vertical heterogeneities make the detection of hydrocarbons chal-

lenging. Moreover, legacy workflows do not pay significant attention to surface logistics, which include slope stability, land-use restriction, and infrastructure accessibility, which are key to operational planning (van Buren et al., 2019).

Geographical Information Systems (GIS) and remote sensing technologies provide useful answers to the interpretational gap between the surface measurements and the underground structures (Tshanga et al., 2024). Digital Elevation Models (DEMs), slope inclinations, lithological variations, and drainage networks are examples of useful proxies used to identify fault-controlled geomorphological features (Toppo & Sinha, 2024). These surface datasets are combined with subsurface seismic and gravity data, which increase the support of structural traps by giving spatial associations with morphological manifestations of buried faults (Lin et al., 2024). Moreover, the application of spatial analysis to hydrocarbon exploration processes contributes to the logistical and environmental planning of the process, as it identifies potential locales of drills, which are geologically and operationally appropriate, a facet that has been underrated in the conventional seismic-based approaches (Ali et al., 2024; Hussain et al., 2022).

Furthermore, incorporating spatial analysis and GIS-based mapping into hydrocarbon exploration workflows provides critical insight for logistical and environmental planning by pinpointing drilling zones that are not only geologically favorable, but also operationally accessible on a dimension often underrepresented in purely seismic-based studies (Saravanavel et al., 2020). In order to resolve the geoscientific and operational uncertainties, the proposed research applies a multidisciplinary approach to include detailed seismic interpretation, gravity anomaly analysis, remote sensing, and terrain evaluation based on GIS (Cao et al., 2024). Time and depth maps are created using seismic data, which are processed in Petrel, and can be used to define faults and reservoir geometry (Fan & Kong, 2023). Meanwhile, topography, land cover, and environmental constraints are mapped and analyzed in ArcGIS to increase the surface-to-subsurface correlation (Aboelhassan et al., 2024). The overall workflow, a combination of workflows, leads to a strong 3D geological model that reflects the structural, stratigraphic, and spatial complexity of the Khewari Block. It is intended to enhance hydrocarbon prospect appraisal and minimize exploration risk, as well as offer a viable, transferable model to explore undeveloped frontier basins with comparable data, geological, and logistical issues (Shastri et al., 2019).

2. Methods

2.1. Data Collection

The geophysical and geospatial data used in this study, which were supplied by the Directorate General

of Petroleum Concessions (DGPC) and Landmark Resources (LMKR), and the fundamental data consisted of high-resolution 2D seismic reflection profiles in SEG-Y format gained in 2023 in the Khewari Block. Major seismic lines such as 021-KWI-40, 021-KWI-39, and 011-KWI-16 formed vital depth and strike information that facilitated mapping faults, anticlines, and stratigraphic horizons, which were important in the entrapment of hydrocarbons and characterization of reservoirs. A mix of geophones, dynamite charges, and vibrosis sources was used to record data to obtain high-intensity reflection signals that can penetrate complex layers in the subsurface to enhance imaging of regions contaminated by unconsolidated sediments and enhance reflector clarity in structurally rich areas. To complement the seismic dataset, gravity survey results were integrated to detect density variations in subsurface formations, assisting in the identification of horsts, grabens, and major fault systems often unresolved in seismic profiles alone. In addition, topographical constraints, accessibility, and geomorphic features within deeper structure patterns were assessed by the production of slope, elevation, and drainage maps using Geographic Information System (GIS), which were used to assess the topographical constraints. Bringing together the seismic reflection data, data on the gravity anomalies, and GIS-based terrain modelling generated a multi-layered dataset that reduced the amount of uncertainty in delineating the traps and improved the overall structure of the exploration of the hydrocarbons in Khewari Block.

2.2. Data Processing

The seismic data were processed using a structured and project-specific workflow to enhance data quality and improve subsurface imaging. As summarized in the seismic processing flowchart (see **Figure 1**), the workflow began with geometry assignment followed by static and dynamic corrections to compensate for elevation differences and near-surface velocity variations. Demultiplexing was applied to separate the recorded seismic traces into individual channels, enabling subsequent filtering and analysis. Band-pass filtering was then used to suppress unwanted noise and enhance the frequency bandwidth of interest, thereby improving the signal-to-noise ratio. Common midpoint (CMP) stacking was performed to increase reflection continuity and reduce random noise, and finally, migration was applied to correctly position dipping reflectors and fault geometries, resulting in a more accurate spatial representation of subsurface geological structures.

Gravity, satellite, GIS, and well log datasets were processed using dataset-specific procedures to ensure consistency with seismic interpretations. Gravity data were corrected for drift, latitude, free-air, Bouguer, and terrain effects to generate Bouguer and residual anomaly maps suitable for structural analysis. Satellite imagery underwent radiometric and geometric corrections prior to line-

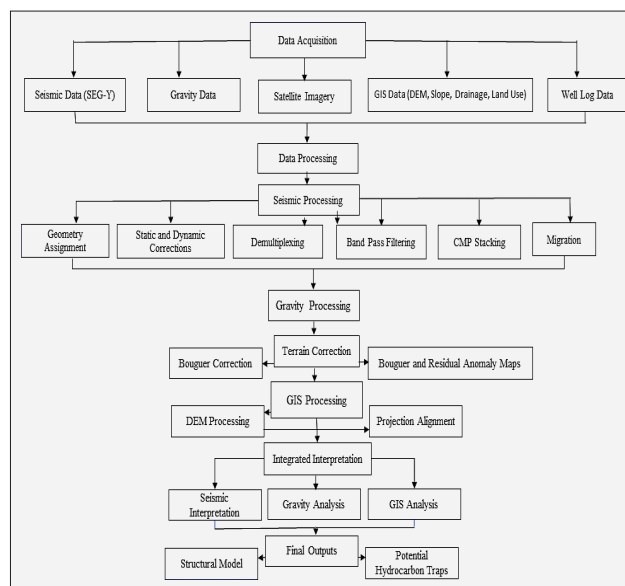


Figure 1: Integrated geophysical and geospatial workflow highlighting seismic, gravity, and GIS-based data processing and interpretation for the Khewari Block, Sindh, Pakistan.

ament extraction and surface structural interpretation. GIS-based datasets, including digital elevation models (DEMs), slope, drainage, and land-use layers, were standardized, reprojected into a common coordinate system, and prepared for spatial overlay analysis. Well log data were quality-checked and used to support lithological correlation and depth calibration where available. The integrated processing of all datasets ensured internal consistency and supported reliable multi-scale interpretation of subsurface structures and surface constrain.

2.3. Data Analysis

To evaluate the hydrocarbon potential of the Khewari Block, an integrated workflow combining seismic, gravity, and geospatial datasets was applied using Petrel 2010 and ArcGIS. These tools enabled consistent data processing, visualization, and interpretation across subsurface and surface domains.

1. Seismic Interpretation

In the analysis of 2D SEG-Y, seismic data was processed to identify the primary structural framework of the Khewari Block. The analysis focused on mapping key reflectors, faults, and stratigraphic horizons, with particular emphasis on the Lower Goru Formation, the main potential reservoir unit. Major extensional structures detected during the analysis are the horsts, grabens, fault-bounded closures, and rollover anticlines, which serve as hydrocarbon traps. Time contour maps represented the structural topography of subsurface zones with special emphasis on the Lower Goru Formation as the main potential reservoir (**Abdul-Majeed et al., 2020**). A depth conversion method was performed, based on average interval velocities derived from regional datasets and calibrated against the Khario-01

well. To provide structural consistency, several seismic lines were cross-correlated, which minimized the uncertainty in the interpretation and enhanced depth accuracy.

2. Gravity Analysis

The gravity interpretation method gave valuable information about lateral density variations and regional basin architecture. Bouguer and residual anomaly maps were generated to differentiate high gravity, which is usually defined as uplifted basement blocks or carbonate platforms, and from gravity lows that indicate sediments filled troughs or fault depressions. These anomalies validated and improved the seismic interpretation by highlighting deep structural trends and confirming the geometry of major fault systems.

3. GIS-Based Terrain and Suitability Analysis

The geospatial analysis was performed using ArcGIS to integrate and evaluate surface datasets derived from digital elevation models (DEMs), slope gradient, drainage systems, and land-use to determine the accessibility of the terrain accessibility and environmental suitability. Terrain parameters were systematically extracted to characterize changes in slope, elevation, and the morphology of the surface. The resultant thematic layers were spatially correlated with subsurface structural interpretations, to determine the relationships between geomorphological patterns and the underlying tectonic structures. This integrative evaluation helped to identify the areas with favorable topographic and logistical conditions for potential drilling operations, while also providing insight into the geomorphic factors that may have contributed to structural development within the Khewari Block.

4. Integrated Interpretation

An integrated geospatial system was developed to combine the results of seismic, gravity, and GIS-based analyses into a unified interpretational framework for the Khewari Block. The interpretation of seismic-derived subsurface structural features was spatially correlated with gravity anomaly patterns to confirm continuity and geometry of major fault systems, horst-graben structures, and uplifted basement blocks. The joint assessment indicates a high degree of correspondence between gravity highs and seismically mapped structural highs, while gravity lows are aligned with graben-like depressions identified on seismic time-structure maps. This cross-validation enhanced the confidence in the mapping of the possible traps of hydrocarbons and minimized structural uncertainty within the study area.

The integration of terrain suitability and geomorphological data based on GIS analysis further enhanced the interpretational context by linking surface morphology with subsurface deformation. The terrain layers were employed to evaluate logistical accessibility (slope, elevation, and drainage system) and to identify surface indicators potentially related to underlying tectonic activity. By merging these multi-source datasets within a

common geospatial environment, the study obtained a coherent structural and geomorphic understanding of the Khewari Block. This integrative interpretation refined the tectono-stratigraphic model, strengthened exploration reliability, and demonstrated how geophysical and geospatial data can be effectively harmonized without methodological repetition.

2.4. Data Acquisition

The geophysical and spatial datasets used in this study originated from Landmark Resources (LMKR) and the Directorate General of Petroleum Concessions (DGPC) of Pakistan. The Khewari Block has three key types of data: (1) two-dimensional (2D) seismic reflection profiles in SEG-Y format, (2) regional gravity survey observations, and (3) digital elevation models (DEMs) of surface morphology. Collectively, these datasets give complementary data on subsurface structure and surface topography, forming the foundation for the integrated geoscientific interpretation conducted in this research.

1. Seismic Interpretation Using Petrel Software

The seismic analysis was performed using Petrel to interpret subsurface structure within the Khewari Block. The 2D seismic profiles were traced using reflective horizons to locate major faults, folds, and stratigraphic boundaries. These interpretations provided a precise representation of the subsurface geometry and served as a foundation for depth conversion and subsequent integration with gravity and geospatial analyses.

2. Generation of Contour Maps and 3D Visualization

The interpretation of the seismic horizons was used to generate structural contour maps and three-dimensional (3D) visualizations to show the underlying structure of the Khewari Block. The time and depth map highlights major structural features, such as fault-bounded anticlines and horst-grabens, which are possible traps of hydrocarbons. Three-dimensional models of chosen seismic sections enhanced the spatial understanding of structural geometry and facilitated correlation between subsurface features and gravity anomalies.

3. Gravity Survey Integration

The gravity data were used to optimize the basin geometry and to define density changes in the subsurface throughout the Khewari Block. The interpretation of Bouguer anomaly maps indicated that there were such important structural trends as uplifted basement blocks and graben-like depressions, which correspond to regional tectonic lineaments. These gravity anomalies offered key limitations to confirming the seismic interpretation and outlining deep structural features, which were not completely clarified in the seismic profiles.

4. GIS-Based Terrain and Spatial Mapping

The integration of surface and subsurface data in a common spatiotemporal framework was conducted in ArcGIS to carry out geospatial analysis. Digital Eleva-

Table 1: Key research phases and tasks for data acquisition, processing, interpretation

Stage	Objective	Key Steps
Data Collection	Acquire all necessary geophysical and spatial datasets.	Collect 2D seismic (SEG-Y) from LMKR/DGPC- Obtain Bouguer and residual gravity data. Download DEMs and LULC layers
Data Processing	Prepare data for analysis by applying cleaning and georeferencing steps.	Apply filtering, stacking, migration in seismic software- Process gravity maps- Prepare GIS layers (slope, elevation)
Seismic Interpretation	Extract geological structures and horizon data from seismic profiles.	Interpret faults and horizons using Petrel- Generate time and depth maps for key formations
GIS-Based Mapping	Evaluate terrain conditions and integrate with subsurface models.	Use ArcGIS for slope/elevation/drainage modelling- Overlay seismic and gravity datasets spatially

tion Models (DEMs), slope gradients, drainage networks, and land-use layers were analyzed to generate thematic maps that characterize terrain morphology and surface constraints. These geospatial layers were later compared with seismic- and gravity-based structures to assess the spatial relationship between surface and subsurface deformation. This integration provided a basis for assessing terrain suitability for drilling operations and for linking geomorphological patterns with underlying tectonic structures in the Khewari Block.

5. Structural Analysis

Structural analysis was conducted by integrating seismic interpretations, gravity anomaly patterns, and geospatial datasets within a unified spatial reference system. The combined analysis enabled the identification and correlation of major tectonic features, such as fault zones, fold belts, and stratigraphic boundaries that determine the accumulation of hydrocarbons in the Khewari Block. This multidisciplinary methodology provided a refined understanding of the structural architecture and reservoir structure, forming a basis for interpreting the possible traps of hydrocarbons and evaluating the overall tectono-stratigraphic evolution of the study area.

2.5. Depth Conversion and Velocity Model Assumptions

In the absence of detailed velocity logs from multiple wells, depth conversion was carried out using average interval velocities derived from regional datasets and calibrated to the Khario-01 Well, where reliable velocity control was available. The conversion process was performed in Petrel 2023 with the assumption of laterally continuous velocity layers across the interpreted seismic horizons. This assumption creates possible uncertainty in regions with steep structural relief or lithological heterogeneity. To reduce the number of uncertainties, a variety of seismic lines were cross-referenced to ensure structural consistency, and the measured depths of key reflectors, especially the top of the Lower Goru Formation and Sui Main Limestone, were marked against well-log depth markers and stratigraphic expectations. In addition, gravity anomaly trends were employed as secondary validation tools to ensure depth consistency, especially within structurally complex zones.

The overall workflow of the data collection, data processing, seismic interpretation, and GIS-based integration that supported this phase are outlined in **Table 1** which summarises the key research phases, research objectives, and major tasks undertaken. This workflow provided a structured and integrated approach that strengthened interpretational reliability and ensured that each dataset contributed meaningfully to the tectono-stratigraphic understanding of the Khewari Block. Although a detailed uncertainty analysis of the velocity model was beyond the scope of this study, further research incorporating vertical seismic profiles (VSP) or sonic log data is recommended to refine interval velocities and enhance the accuracy of depth prediction in future studies.

3. Results

Systematic analysis of seismic, structural analysis, reservoir characterization, and entrapping hydrocarbons in the Khewari block of the Lower Indus Basin, Sindh, Pakistan, was evaluated. The study relied on the integration of seismic reflection profiles, well log analysis, GIS-based reservoir modelling, and supplementary geophysical surveys to delineate potential hydrocarbon-bearing formations and define exploration viability. The distribution of seismic attributes, depth structure maps, and subsurface geometries was interpreted in more detail to identify structural traps, stratigraphic discontinuities, and fault-controlled accumulation zones. The resulting seismic horizon maps, structural cross-sections, and prospectivity models will give vital information about the underground framework of the basin, which will help to refine the study of the petroleum system architecture.

3.1. Seismic Horizon Identification and Interpretation

Seismic interpretation was conducted to define the structural properties of the Khewari Block and to determine the existence of traps with hydrocarbons. Six seismic lines: O-011-KWI-15, O-011-KWI-16, O-011-KWI-25, O-021-KWI-26, O-021-KWI-39, and O-021-KWI-40 were studied with the help of Petrel. These lines

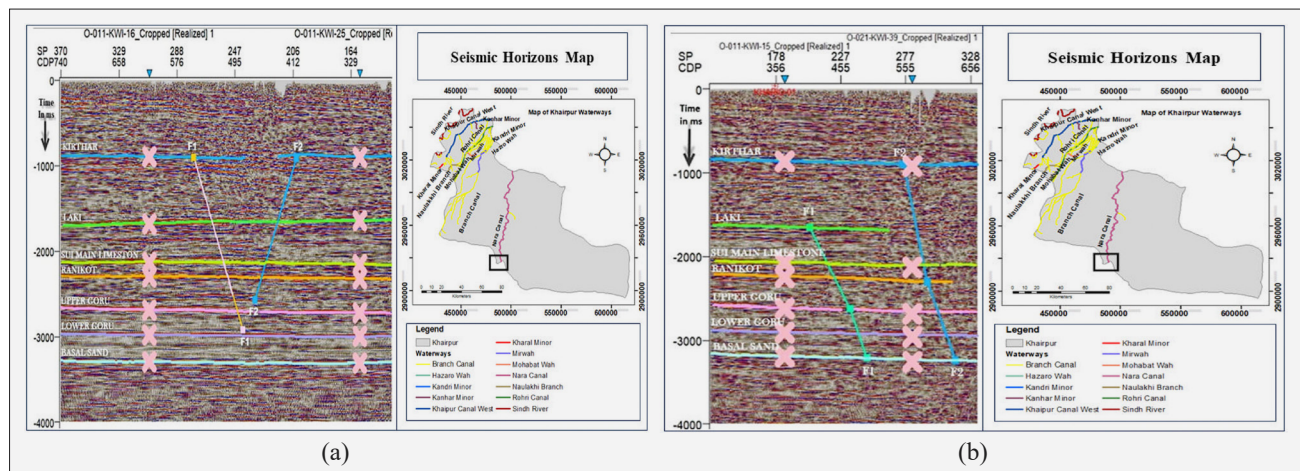


Figure 2: (a) Interpreted seismic line O-021-KWI-40, showing key reflectors, major faults (F1-F2), and a well log correlation from Khario-01. (b) Seismic line O-011-KWI-15 illustrates reflector's continuity and structural variations across faults. The Khario-01 well is represented by the pink X, and the inset maps denote the location of the lines within the Khewari Block.

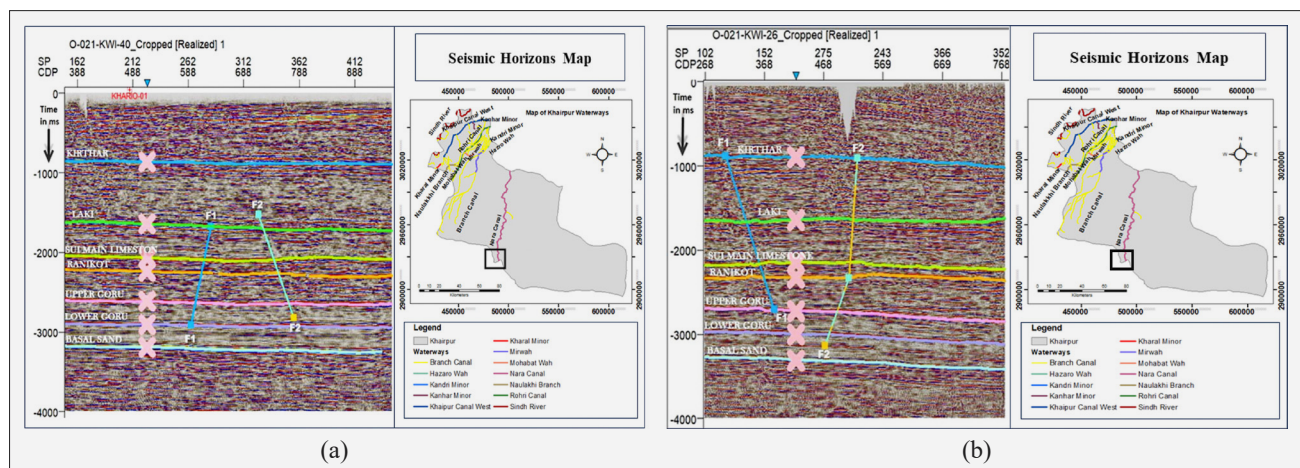


Figure 3: (a) Interpreted seismic line O-011-KWI-16 illustrating fault-controlled structural compartmentalization and the development of fault-bounded closures resulting from compressional overprinting of earlier extensional structures. (b) Interpreted seismic line O-021-KWI-26 reveals a fault-bounded structural high developed between faults F1 and F2, with adjacent down-dropped blocks consistent with graben development. The bounding faults demonstrate normal-fault geometry, as indicated by downward displacement of hanging-wall reflectors, reflector terminations, and vertical offset patterns. Insets show the spatial positions of the seismic profiles within the study area.

were chosen to ensure full coverage of the area and also to ensure regional structural variations. The seismic profiles identified a tectonically fragmented subsurface with horsts, grabens, fault blocks, and related folding designs as the primary landscape features. Key features that may control hydrocarbon entrapment were identified as reflector continuity, amplitude changes, and fault geometries.

Extensional tectonics are the dominant structural regime in the study area, as evidenced by the prevalence of NE–SW-trending normal faults that segment the subsurface into alternating horst and graben blocks. These features are particularly well developed on seismic lines O-011-KWI-15 and O-011-KWI-16, where high-angle fault planes define deep, structurally bounded grabens. The Lower Goru Formation and Sui Main Limestone, recognized as the region's primary reservoir units, are

clearly imaged within these grabens, highlighting their structural control and potential as hydrocarbon traps. The reflector terminations and variable fault throws within these horizons suggest vertical displacement and fault-assisted migration pathways.

Notably, compressional features were also identified in several sections, indicating that the area has undergone multiple tectonic phases. Seismic line O-021-KWI-39 clearly shows fault-propagation folds and reverse faults, which suggest a later phase of compressional deformation following the initial extension. These structures modify and uplift previously horizontal layers, leading to the formation of closed structures that can effectively trap hydrocarbons. In several places, reservoir formations are pushed against impermeable layers due to this folding and faulting, creating favorable conditions for hydrocarbon sealing. This overprinting of ex-

tensional features by compressional forces has significantly enhanced the structural complexity and trap integrity in parts of the study area.

The seismic features of reflector continuity, dip variation, amplitude dimming, and fault shadow zones offered further interpretative support. The properties assisted in confirming the geometry of large fault systems and detecting small-scale closures and secondary faults that might represent obstacles or pathways to hydrocarbon flow. In particular, dimming and reflector terminations near fault planes suggested possible lithological changes or fluid contacts. The interpreted data confirm the presence of multiple trapping mechanisms, including fault-assisted closures, roll-over anticlines, and tilted fault blocks. These findings form the basis for constructing time and depth structure maps and serve as essential inputs for drilling risk assessment and volumetric analysis in the Khewari Block.

The interpreted seismic sections in (see **Figure 2**) show the structural heterogeneity of the Khewari Block under an extensional tectonic regime. Seismic lines O-021-KWI-40 and O-011-KWI-15 (see **Figure 2a-2b**) depict NE-SW-oriented normal faults that divide the subsurface into horst and graben structures. These profiles also delineate the Lower Goru Formation and Sui Main Limestone, which are imaged as principal reservoir units within grabens. These seismic lines display reflector terminations, amplitude anomalies, and variable fault displacements, which draw attention to the role of fault geometries in trapping hydrocarbons and suggest the existence of fault-facilitated migration pathways. On the whole, the evidence that is provided in **Figure 2** highlights the pre-eminent role of the extensional tectonics in governing the possible trapping positions across the study region.

In addition, **Figure 3** shows the compressional overprinting that later reformed the extensional architecture of the Khewari Block. The fault-bounded closures and compartmentalized reservoirs can be identified with the help of seismic line O-011-KWI-16 (see **Figure 3a**), and the fault-propagation folds and reverse faults can be identified with the help of seismic line O-021-KWI-26 (see **Figure 3b**). These formations testify to the fact that the area experienced subsequent compressional activity, causing the upward movement of previously horizontal layers and creating closed structural traps that could favor the entrapment of hydrocarbons. Collectively, the interpreted passages of **Figure 3** validate the interaction of the extensional and compressional tectonics, resulting in a number of trap styles, such as rollover anticlines, tilted fault blocks, and fault-aided closures, that have a net effect of maximizing the prospectivity of the area in hydrocarbons.

Furthermore, the spatial relationship between seismic horizons and fault architecture suggests a strong structural control on reservoir compartmentalization within the Khewari Block. Variations in reflector continuity and local changes in dip along the Lower Goru Formation

and Sui Main Limestone indicate differential subsidence and uplift across fault blocks. In several seismic sections, the juxtaposition of reservoir units against sealing lithologies along fault planes implies the development of fault-bounded compartments that may enhance trap efficiency. These structural compartments are particularly significant in areas where extensional faults were later reactivated or modified during compressional phases, improving closure geometry and seal integrity. Such interactions between fault kinematics and stratigraphic horizons highlight the importance of integrated seismic interpretation for identifying viable hydrocarbon prospects and reducing subsurface uncertainty.

The interpreted seismic lines shown in **Figures 2** and **3** collectively illustrate the structural variability and stratigraphic complexity of the Khewari Block. **Figure 2a** and **Figure 2b** show seismic lines O-021-KWI-40 and O-011-KWI-15 have well-developed stratigraphic reflectors with the Sui Main Limestone, Lower Goru, and Basal Sand units being defined. Faults F1 and F2 show significant vertical displacement across these horizons, suggesting active structural control over reservoir positioning and potential trap formation. The fault-controlled compartmentalization, as seen in more detail in **Figure 3a**, which indicates line O-021-KWI-26, is further indicated by the visible offsetting of reflectors by a few faults crossing all of them. This reservoir zone classification is important in determining the distribution of hydrocarbons and possible obstacles to horizontal migration. Lastly, **Figure 3b** shows line O-021-KWI-16, whose line demonstrates a typical horst and graben system that has been formed by extensional tectonics and formed structural highs and lows conducive to the entrapment of hydrocarbons. The combination of these seismic sections demonstrates a structurally discontinuous basin structure, fault-assisted traps, stratigraphic endings, and geometries of folds interrelate and manage reservoir quality, continuity, and sealing.

3.2. Time and Depth Contour Maps

Time and depth structure maps were generated for four key formations: the Lower Goru, Upper Goru, Sui Main Limestone, and Ranikot. These maps were developed by converting interpreted seismic horizons from two-way travel time (TWT) to depth using velocity models. The time structure maps reveal major structural highs concentrated in the central and southwestern parts of the Khewari Block, particularly within the Lower Goru and Sui Main Limestone intervals. These structural highs are obvious in **Figure 4a**, Sui Main Limestone, and **Figure 4b**, Lower Goru, and are known as the most favorable areas of hydrocarbon entrapment because they are fault-bounded uplifted blocks observed in the seismic interpretation. On the other hand, fault-controlled lows and minor anticlines in the northeastern and central areas in time maps of the Ranikot and Upper Goru formations (see **Figures 5a** and **5b**) are indicative of secondary structural compartments that, as well, can be traps.

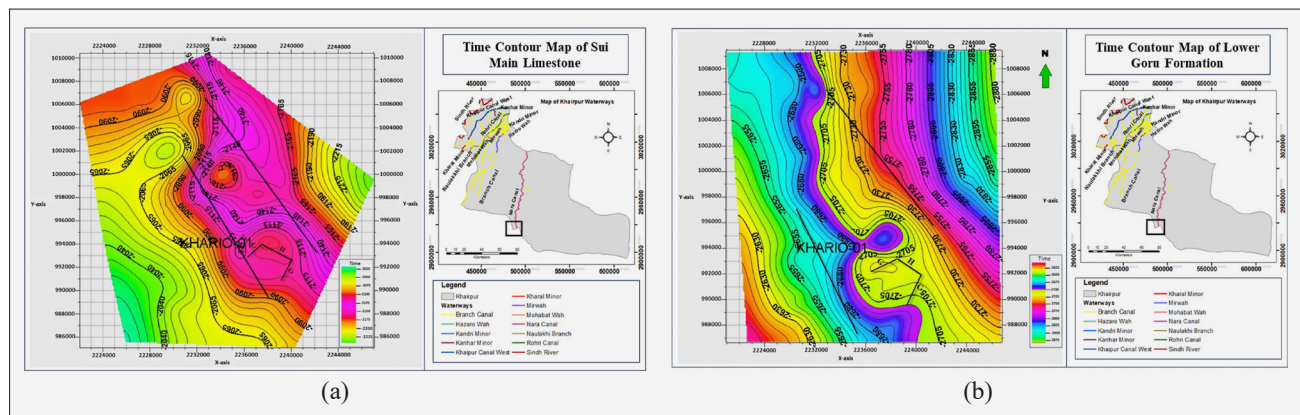


Figure 4: (a) Time contour map of the Sui Main Limestone showing NE-SW-trending fold structures and fault-bounded closures that influence reservoir development and hydrocarbon migration. The straight black lines represent interpreted fault traces identified from seismic data. (b) Time contour map of the Lower Goru Formation illustrating fault-controlled structural highs and lows that impact hydrocarbon migration pathways and reservoir sealing efficiency. All contour intervals are in milliseconds (ms), with coordinates referenced to the UTM projection used for the seismic.

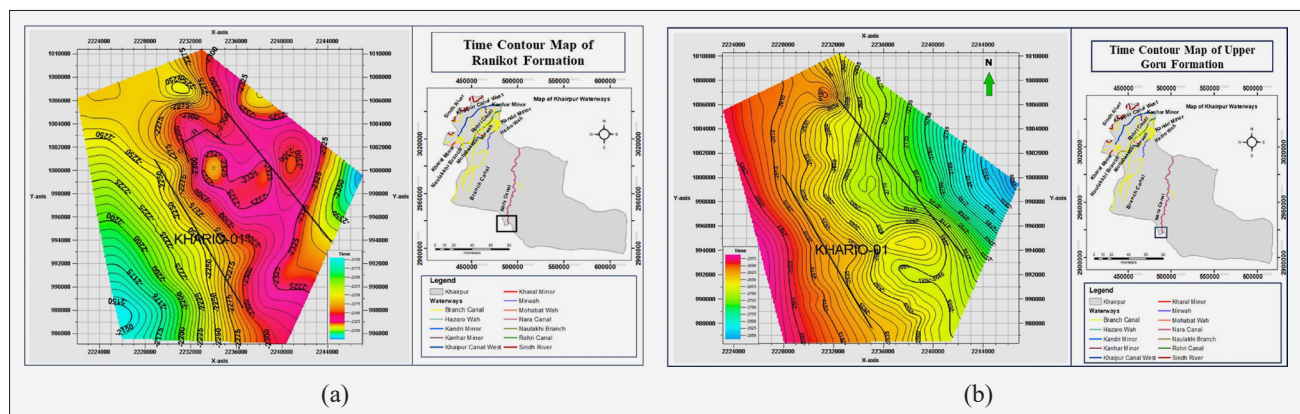


Figure 5: (a) Time structure map of the Ranikot Formation displaying fault-controlled reservoir segmentation and potential migration pathways. (b) Time contour map of the Upper Goru Formation depicting structural variations and mapped faults that affect reservoir connectivity and trap configuration. Straight lines represent interpreted faults, and contour values are in milliseconds (ms), referenced to the same coordinate system as the seismic and gravity datasets.

The depth structure maps further refine these observations by providing a more realistic representation of subsurface geometry and trap configuration. Depth conversion highlights the vertical separation between structural highs and lows and emphasizes the role of fault displacement in controlling reservoir thickness and closure extent. In particular, depth maps of the Lower Goru and Sui Main Limestone formations show well-defined fault-bounded closures with sufficient relief to act as effective structural traps. These closures are laterally continuous and coincide with areas of enhanced seismic reflector continuity, suggesting improved reservoir development.

In contrast, the depth maps of the Upper Goru and Ranikot formations display gentler structural relief, reflecting a diminished influence of faulting at shallower levels. Collectively, the integration of time and depth contour maps provides a robust framework for identifying drillable prospects and reducing structural uncertainty across the Khewari Block.

The time contour maps of the Sui Main Limestone, Lower Goru, Ranikot, and Upper Goru formations help to illustrate the most significant structural aspects that affect the migration of hydrocarbons and the formation of the reservoirs. The time contour map of Sui Main Limestone (see **Figure 4a**) shows the effect of folding in developing reservoirs, where structural highs indicate places that are conducive to the accumulation and migration of hydrocarbons. Faulting coupled with these folds gives the best conditions to trap the hydrocarbons. The Lower Goru Formation (see **Figure 4b**), shows the effects of faults on movement routes and the sealing efficiency of the reservoir as fault-bound compartments delimit portions that could potentially contain hydrocarbons. Fault-controlled reservoirs are observed in the Ranikot Formation (see **Figure 5a**), where faulting forms discrete migration pathways and reservoir compartmentalization. Finally, structural changes following faulting are demonstrated by the time structure map of the Upper Goru Formation (see **Figure 5b**), which affected the res-

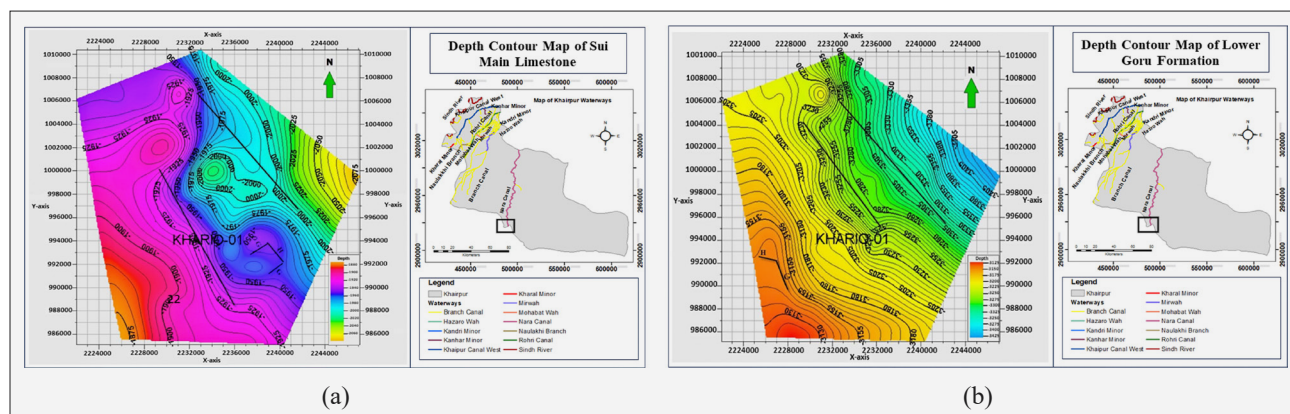


Figure 6: (a) Depth contour map of the Sui Main Limestone showing NE-SW trending structural elevations and fault-controlled closures interpreted as potential hydrocarbon traps. (b) Depth contour map of the Lower Goru Formation of depth variations and fault-controlled reservoir geometry. Straight black lines represents interpreted faults from seismic data, and contour values are in meters (m). Coordinates are referenced to the same UTM projection used for seismic and gravity datasets.

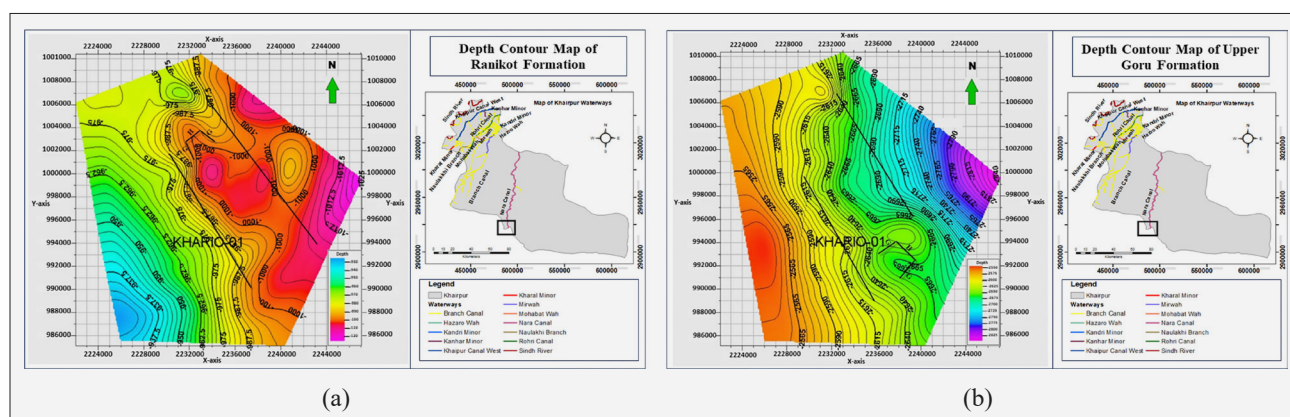


Figure 7: (a) Depth contour map of the Ranikot Formation showing complex fault-bounded depth structures and hydrocarbon-bearing zones. (b) Depth contour map of the Upper Goru Formation indicating the depth undulations and mapped faults that influence reservoir connectivity and potential trap formation. All contour are in meters (m), and coordinate references match the seismic and gravity interpretation framework.

ervoir connectivity and segmentation. Collectively, these maps offer important data on the structural dynamics of the Khewari Block and their contribution to the entrapment and migration of hydrocarbons.

3.2.1 Depth Contour Maps

The depth structure maps (see **Figures 6a** and **6b**) refine these interpretations by providing more accurate elevation data for the mapped closures. The depth map of the Lower Goru (see **Figure 6b**) confirms the presence of a well-defined closure at a drilling-accessible depth, supported by four-way dip and fault sealing conditions. Similarly, the Sui Main Limestone depth map (see **Figure 6a**) shows a NW–SE trending structural nose, flanked by bounding faults, confirming its structural isolation and reservoir potential. The Ranikot and Upper Goru (see **Figures 7a** and **7b**) show moderately inclined closures and inclined blocks of fault, which suggest smaller but potentially profitable traps. These maps, when combined with

the seismic interpretation, prove that the Khewari Block contains various types of traps, such as fault-assisted closures, rollover structures, and tilted blocks with diverse levels of potential exploration. The time and depth structure maps together give a vital system of well placement, risk analysis, and volumetric analysis.

Figures 6 and **7** depict Depth Contour Maps of the Sui Main Limestone, the Lower Goru, the Ranikot, and the Upper Goru formations, which are used to identify important structural features vital to the exploration of hydrocarbons. As seen in **Figure 6a**, the depth map of Sui Main Limestone shows that there is a structural high in the central area of the block, something viewed as a possible place of hydrocarbon traps. Fault systems enclose this high, and they may serve as sealing mechanisms by keeping the trapped hydrocarbons isolated. In **Figure 6b**, the Lower Goru Formation shows that depth variations are more significant, indicating a fault-controlled reservoir system. The faulting effects on the distribution of this formation have been noted by the map,

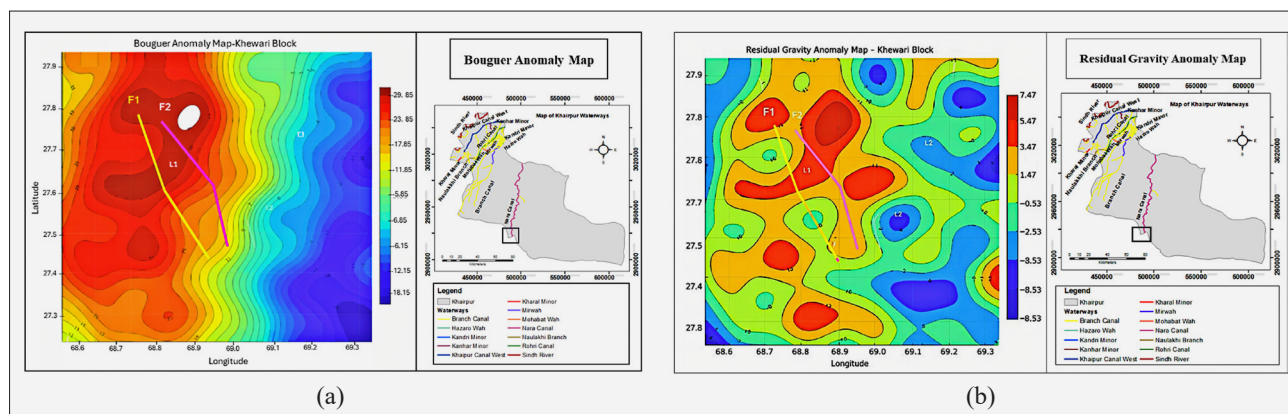


Figure 8: (a) Bouguer gravity anomaly map of the Khewari Block showing a prominent gravity high in the western sector (L1) and lower gravity values toward the eastern and southeastern areas (L2–L3), associated with structural variations and faults (F1–F2). (b) Residual gravity anomaly map highlighting localized density contrasts, including a central structural high (L1) and surrounding low-density zones (L2–L3) that reflect fault-controlled depressions and sediment-filled troughs.

with a several structural highs and lows indicating possible migration patterns and trapping areas. See **Figure 7a**, the Ranikot Formation of the faulted depth creating structural lows is depicted, which may be a sign of hydrocarbon accumulation or migration. Lastly, **Figure 7b** is the depth map of the Upper Goru Formation, which depicts a succession of tilted fault blocks having different depth contours that illustrate fault-controllable compartmentalization. All these depth maps contribute to the hypothesis of the presence of multiple structural traps throughout the Khewari Block, where faulting is very significant in the segmentation of the reservoir, migration of the hydrocarbons, and their entrapment.

3.3. Gravity Anomaly Analysis

Gravity anomaly analysis was conducted to complement seismic interpretation and give more restrictions on the density variations in the subsurface of the Khewari Block. Bouguer as well as residual gravity maps were used to outline regional as well as local structure maps, such as horsts, grabens, and buried uplift zones that are important in entrapment and migration of hydrocarbons. A general high appears in the central-western sector on the Bouguer gravity map (see **Figure 8a**), which is interpreted as hidden structural uplift that is probably related to carbonate platforms comprising the Sui Main Limestone. Conversely, the low gravity anomalies observed in the eastern region of the block are associated with fault-controlled grabens of the Goru Formation, which are troughs filled with sediments that could serve as the migration paths or potential traps. A localized minimum of gravity in the lowest eastward part of the area is associated with either shale or evaporite structures, possibly the Ranikot or Laki formations, which can serve as a stratigraphy seal in favorable structural situations.

Additional evidence of residual gravity anomaly mapping (see **Figure 8b**) is that of local, shallow density differences smoothed in the regional Bouguer field. The

high-density zones (L1) indicate the presence of uplifted carbonate or basement blocks, which are possible to support the existence of hydrocarbon migration and trapping, whereas the long and narrow low-density areas (L2 and L3) are correlated with fault-bounded grabens and structural sags on seismic and depth contour maps. The interpretation of faults (F1–F2) along with their steep residual gradients indicates that they play a key role in the segmentation of the reservoirs and their compartmentalization into structural blocks. The combination of the gravity data with seismic interpretation and the surface geomorphology enhances the confidence in outlining the hydrocarbon traps and confirming possible drilling regions in the structurally complicated regions of the Khewari Block. These analyses give strength to geophysical frameworks of defining potential reservoir areas and streamlining exploration plans.

The Bouguer anomaly map (see **Figure 8a**) reveals distinct gravity variations across the Khewari Block, with relatively higher gravity values in the west (L1) and lower values in the east (L2–L3). These contrasts denote uplifted carbonate or basement structures in the west and sediment-filled grabens or troughs in the east. Faults F1–F2 align closely with the gravity gradients, emphasizing the role of faulting in structural compartmentalization. The residual gravity anomaly map (see **Figure 8b**), which filters out regional trends, highlights localized density contrasts that refine this interpretation. The L1 zone represents high-density anomalies associated with uplifted carbonate or basement blocks, while L2 and L3 indicate low-density zones corresponding to deeper sedimentary basins or fault-bounded depressions. The spatial overlap between these anomalies and the mapped faults (F1–F2) underscores their control on reservoir segmentation, hydrocarbon migration pathways, and trap formation within the Khewari Block. These relationships are further summarized in **Table 2**, which correlates gravity anomalies (L1–L2) with their corresponding geological features.

Table 2: Gravity Anomalies and Corresponding Geological Features in the Study Area.

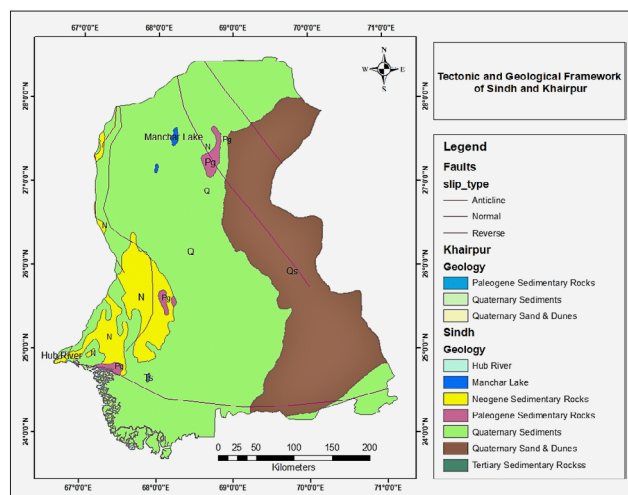
Gravity Anomaly	Gravity Type	Geological Feature
L1	High	Carbonate Dome / Structural High
L2	Low	Graben / Sediment-Filled Trough
L3	Local Low	Shale Sag / Salt Trap

The gravity anomaly domains L1–L3 were defined based on the magnitude, spatial continuity, and gradient characteristics of the Bouguer and residual gravity maps. High-gravity zones (L1) were identified where Bouguer anomalies exceeded the regional mean value and were associated with steep positive gradients and coherent high-density blocks, indicating uplifted basement or structurally elevated carbonate units. Conversely, low-gravity domains (L2–L3) correspond to areas with negative anomaly values and subdued gradients, reflecting thicker sedimentary sequences or fault-bounded depressions. The segmentation into L2 and L3 was further guided by anomaly wavelength and residual filtering, distinguishing localized low-density pockets (L3) from broader regional lows (L2). The spatial correlation of these gravity domains with mapped faults (F1–F2) and structural trends supports their interpretation as structural highs and sediment-filled troughs. This approach follows widely established relationships between gravity signatures and geological structures in sedimentary basins (Li et al., 2024; Safani et al., 2026).

3.4. Geological, Geomorphological, and Topographic Characteristics of the Khewari Block

3.4.1. Geological Characteristics

The Khewari Block has a complicated geologic structure that has a significant role in exploring hydrocarbons. The region is primarily covered by various sedimentary formations, including the Tertiary rocks, Sui Main Limestone, and Ranikot Formation, which can be easily identified as having the potential of containing hydrocarbons. Important reservoir terrains are the Lower Goru Formation and Basal Sands, with the Laki Formation being a regional seal, especially in regions of compressional tectonics. The geological map of the Khewari Block (see Figure 9) shows the dispersion of these formations, major fault systems, and the central point of Khario Well-1, which is strategically located to test the deposits bounded by faults, anticlinal trap, and deep-seated migration tracks. Normal and reverse faults and anticlinal folds are co-occurring features that form structural highs and closures and numerous routes of hydrocarbon migration, which increases the trap development and makes the intersection of faults and raised structures within the block attractive sites of hydrocarbon formation and thereby augments the prospective exploration of the area.

**Figure 9:** Tectonic map of Khairpur showing faults, stratigraphy, and Khario Well-01.

3.4.2. Gemorphological Characteristics

The Khewari Block is predominantly flat with smooth plains, smooth ridges, shallow depressions, and wind-shaped structures characteristic of arid regions. These geomorphological factors define the patterns of surface runoff and the local drainage. Slope models and Digital Elevation Models (DEM) focus on small alterations of elevation that are indicative of subsurface faults, horsts, and grabens that dictate the surface terrain and drainage distribution. The road and canal network, as depicted in the geomorphological map (see Figure 10a and 10b), indicates a high density of roads in the northern plains, which depicts stable ground, which can be used to settle people and develop infrastructure. The canal systems, including the Nara and Khairpur Canals, on the other hand, occur in low-lying regions and basins of depression which structurally are controlled by faults and are therefore considered important markers for mapping seismic surveys, locating appropriate drilling areas, and interpretation of structural traps of hydrocarbon traps.

The road and waterways maps presented in Figure 10a and 10b illustrate the geomorphological framework of the Khewari Block and its influence on surface accessibility and infrastructure distribution. The northern part of the block shows a dense concentration of local, secondary, and major road networks, indicating relatively stable, flat, and gently sloping plains. Such terrain conditions are favorable for transportation, settlement development, and hydrocarbon exploration logistics, as they allow easier movement of seismic equipment and drilling machinery. The well-developed road connectivity in this region suggests that the surface materials are comparatively compact and suitable for long-term infrastructure expansion, supporting field operations and resource management activities.

In contrast, the southern and eastern parts of the study area are dominated by canal systems and distributaries, including the Nara Canal and associated branch net-

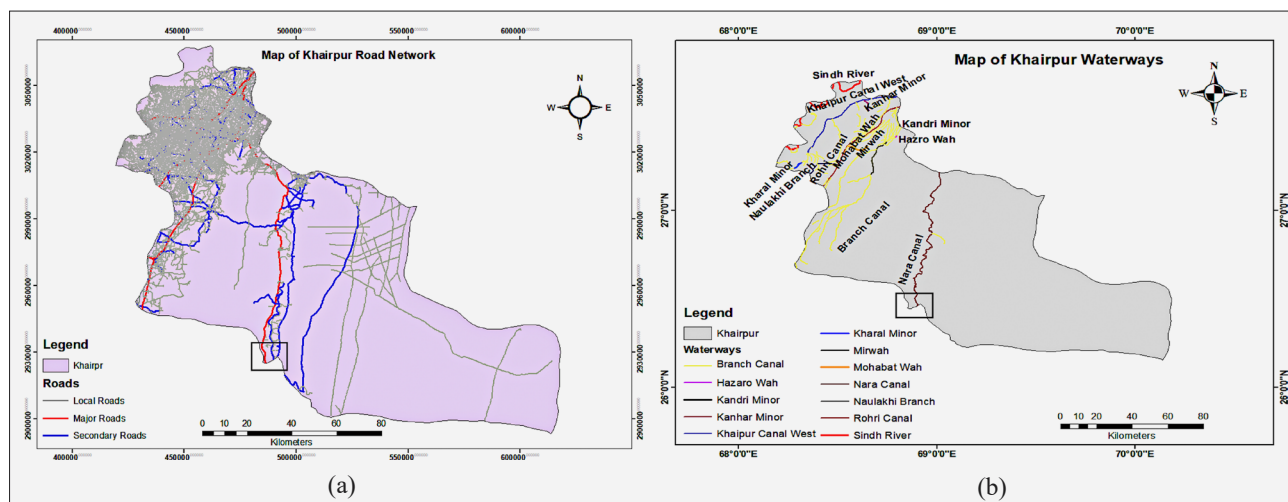


Figure 10: (a) Road map of Khairpur showing local roads, major roads, and secondary roads. (b) Waterways maps of Khairpur showing major canals and distributaries.

works, which follow natural topographic depressions and low-lying drainage pathways. The alignment of these waterways reflects the influence of subtle structural controls such as fault-related subsidence and sediment accumulation zones that guide surface water flow. These geomorphological patterns help in identifying structurally influenced landforms and provide essential information for planning water management and exploration access routes. The integration of road and canal network analysis therefore enhances the interpretation of terrain stability, subsurface structural trends, and the selection of operationally feasible locations for hydrocarbon exploration within the Khewari Block.

3.4.3. Topographical Characteristics

Khewari Block has a topography of mainly flat and slightly undulating land, having elevations between 24 and 144 meters above sea level. The regions at the center and south are made of low plain lands, and there is a gradual increase in elevation as one approaches the east and the north. Topographical differences are subtle features that indicate the geological formations, like faults, folds, and horst-graben systems. Such variations affect the surface drainage and the deposition of sediments and landform development, which must be a main consideration to determine the likely locations to explore and to plan the hydrocarbon operations.

3.4.3.1. Elevation

The topography of the Khewari Block ranges from approximately -7 m to 165 m above sea level. The terrain of the southern and western parts is dominated by flat, alluvial plains that are usually characterized by floods, whereas the central, eastern, and northeast parts have highlands, which are interpreted as structurally uplifted blocks. These high areas correspond to anticlinal and horst-type features identified in the seismic data,

suggesting that surface topography is influenced by underlying tectonic deformation. Such elevated regions are considered favorable sites for hydrocarbon accumulation but may pose logistical challenges for drilling due to steep slopes and limited accessibility. The distribution of the elevation is spatially consistent with the boundary of the Khewari used in the seismic and gravity interpretations, ensuring direct comparability between surface and subsurface datasets. The categorized floodplain elevations are highlighted in **Table 1**, and their distributions are represented in **Figure 11**, where low floodplains appear in brown/orange and structurally uplifted zones are depicted in green/yellow/blue.

The elevation pattern across the Khewari Block provides important insight into the surface expression of subsurface structural architecture. The contrast between low-lying floodplains and relatively elevated structural highs indicates spatially variable uplift and subsidence that are interpreted to be controlled by deep-seated faulting and folding. Structurally elevated zones coincide with areas interpreted as anticlines and horst blocks in the seismic profiles, suggesting a genetic link between surface relief and subsurface deformation. In contrast, lower elevations correspond to structurally depressed zones, which may represent synclinal features or down-thrown fault blocks. Although geomorphic processes such as erosion, sediment deposition, and seasonal flooding locally modify the topography, these processes do not obscure the regional pattern of elevation controlled by tectonic structures. Therefore, the elevation distribution serves as an independent qualitative indicator of structural segmentation within the Khewari Block and supports the integrated interpretation of seismic and gravity data in delineating potential hydrocarbon-prone structural highs.

The elevation map shows how the topography is changing in the Khewari Block, with the flood plains being low to the southwest in the west (brown/orange) and

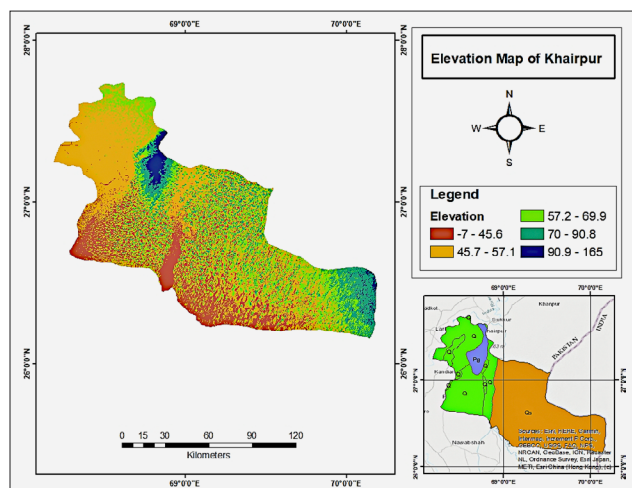


Figure 11: Elevation map (–7 m to 165 m) showing low floodplains (brown/orange) and higher uplands (green/yellow/blue)

Table 3: Elevation Classification of the Khairpur region

Class	Elevation Range (m)	Color on Map	Topographic Character
1	–7 – 45.61	Brown	Depressed plains, flood zones
2	45.62 – 57.08	Orange	Flat plains and low-gradient slopes
3	57.09 – 69.89	Green	Transitional uplands
4	69.9 – 90.8	Yellow	Gently elevated surfaces, structural warps
5	90.81 – 165	Blue	High terrain, potential horst/fault structures

the uplands slowly rising in the middle and northeast (green/yellow/blue). These differences represent fine geomorphological and structural controls, such as fault-related uplifts, horsts, and paleo-uplifted blocks. The plains are low and there is easy and stable land that can be used to build infrastructures, in seismic studies and drilling, but the plateaus are the highlands and are the possible structural traps of the hydrocarbons. The classifications of these elevation ranges and their associated topographic characters are compressed in **Table 3**, which provides a clear basis for planning field work with regard to surface elevation and accessibility.

3.4.3.2. Slope

The slope analysis indicates that the Khewari Block is made up of gentle slopes (less than 15 degree gradients). Such low gradients are favourable to seismic surveys, drilling, and infrastructural developments. The slope is between 15 to 30 degrees, which depicts mildly inclined slopes that are usually brought about by inclined tilting of the tectonic or the ground structure. The most frequently occurring moderately steep slopes (30–45°) are usually associated with erosional landforms, incised valleys, or fault-aligned escarpments. The steeper slides

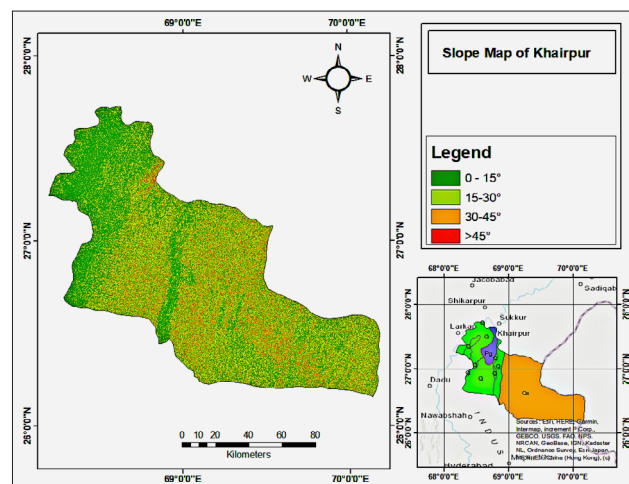


Figure 12: Slope distribution map of the Khairpur region, divided into four classes

(>45 degrees) are limited in area, but usually represent fault scarps, ridges, or blocks raised by the paleo-tectonic plate, and are indicative of some recent or past tectonic action. These gradients are represented in the slope distribution map (see **Figure 12**), which identifies plain, slightly inclined, moderately steep, and steep regions in the region. Slope changes are indicated by understanding of slope variations, which is significant in planning seismic surveys, determining structural complexity, and identifying potential hydrocarbon traps.

Spatial variations in slope across the Khewari Block reflect the interaction between tectonic structuring and surface geomorphic processes. Zones of relatively higher slope gradients commonly occur along lineaments that coincide with interpreted faults and fold hinges observed in seismic sections, indicating that slope breaks may mark the surface expression of subsurface structural discontinuities. In contrast, extensive low-slope areas represent relatively stable depositional surfaces where sediment accumulation has smoothed earlier relief. Although erosional processes locally modify slope angles, the regional pattern of slope distribution remains consistent with the underlying structural framework. Therefore, slope characteristics provide an additional qualitative constraint for delineating structurally controlled geomorphic features and for identifying zones of increased structural complexity that may influence hydrocarbon trap development and drilling feasibility.

The slope distribution map indicates the change in the terrain of the Khewari Block under four categories: flat to gently sloping (0 to 15°), mild slopes (15 to 30°), moderately steep slopes (30 to 45°), and steep areas (more than 45°). The topography (green) is flat and slightly sloping, and thus the majority of the area is favorable to seismic surveys, drilling, and infrastructural construction. Gently to moderate (yellow to orange) slopes are patchy and are often correlated to regions of fault alignment, block uplift or paleo-channel. The

Table 4: Slope Classification of Khairpur Region

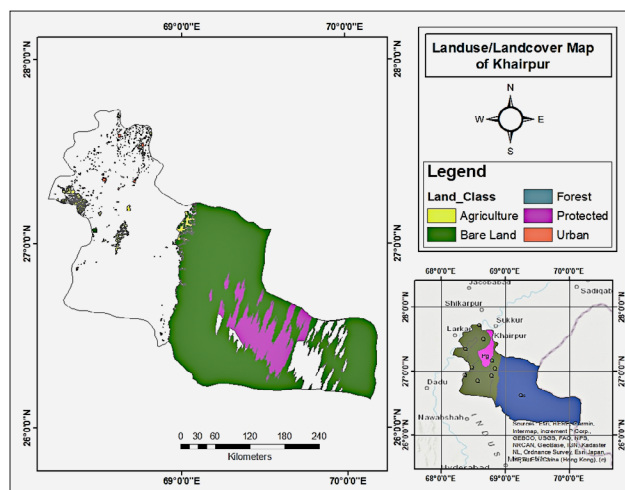
Class	Slope Range (°)	Colors on Map	Topographic Implication
1	0-15	Green	Flat to gently sloping terrain
2	15-30	Yellow	Mild Slopes; potential structural influence
3	30-45	Orange	Moderately steep; erosion-prone and structurally complex
4	>45	Red	Steep zones; rare, possibly fault-zones

steeper (steeper than 45°, red) areas are very small in scale and generally depict fault scarps, ridgelines, or structurally raised features, which can be potential hydrocarbon traps but pose logistical challenges. The classification of these slope ranges and their structural implications is highlighted in **Table 4**, which provides a clearer understanding of surface morphology and supports the identification of structurally significant zones for exploration planning.

3.4.3.3. Land Use

Khewari Block has low land use, which is attributed to the arid weather, low rainfall, and low groundwater. The western and southern regions have small plots that are concentrated around irrigation along canal systems, and are generally seasonal in nature. Most of the land features are barren alluvial plains, dry riverbeds, and natural scrublands having sparse, drought-resistant vegetation. Cities are small, and the infrastructure is inadequate, hence the area is not highly developed. According to the land use/land cover (LULC) map (see **Figure 13**), the area is characterized by five classes, namely agriculture, bare land, forest, protected areas, and urban spaces. The summarized LULC data (see **Table 5**) can be used to plan the surface access, reduce the conflict with human activity, and sustain the hydrocarbon exploration logistics.

The spatial distribution of these LULC classes provides important insight into operational feasibility and environmental planning within the Khewari Block. The predominance of bare land and scrub vegetation indicates relatively low anthropogenic disturbance, which favors seismic data acquisition and drilling activities due to reduced land clearance requirements. However, the scattered agricultural zones located along canal irrigation systems may impose seasonal accessibility constraints and require careful route planning to minimize impacts on cultivated land. Forested and protected areas, although limited in spatial extent, represent environmentally sensitive zones where exploration activities must comply with regulatory and conservation guidelines. Urban and settlement areas, though sparsely distributed, highlight localized infrastructure availability that may

**Figure 13:** Land Use/Land Cover map of the study area for impact assessment and surface planning.**Table 5:** Land Use Distribution and Boundary Extent in the Khairpur Region.

Land Class	Shape Length (km)	ShapeArea (sq.km)
Agriculture	10.036952	0.018225
Bare Land	19.286915	0.611315
Forest	0.08398	8.10E-05
Protected	2.984227	0.363805
Urban	7.041516	0.00491

support logistical operations such as workforce accommodation, transportation networks, and supply chain management. Therefore, integrating LULC analysis with terrain, slope, and drainage assessments enhances the identification of operationally suitable drilling locations while ensuring minimal environmental and socioeconomic disruption across the study area.

The Land Use/Land Cover (LULC) map shows the spatial distribution of various land types in the Khewari Block, such as agriculture, bare land, forested areas, protected areas, and urban settlements. The agricultural land is clustered on small pieces of land, mostly in the western and southern regions, which represent the areas with access to canal irrigation. Bare lands take over a large part of the area, which is an arid alluvial plain and poorly vegetated, sparsely populated land. Protected and forested areas are few, whereas urbanized areas are minimal, and this shows low anthropogenic impact. The numerical allocations of these land classes, including shape length and area coverage, is outlined in **Table 5**, which indicates that bare lands constitute the maximum portion of the region. This categorization is especially useful for planning exploration logistics, geophysical survey, and drilling operations as well as assessing ecological considerations for hydrocarbon explorations.

The geospatial analysis extended beyond base mapping to provide spatial validation for the geophysical interpretations. Compared quantitatively to the terrain mod-

els obtained by the DEM and slope methods and the structural uplifts observed in seismic and gravity datasets, a uniform correspondence of the surface uplifts with the subsurface horsts and anticlines is observed. Similarly, drainage orientations coincide with mapped fault traces, indicating tectonic influence on both geomorphic and subsurface frameworks. This spatial correspondence supports the interpretation that neotectonic activity has controlled both the present-day topography and subsurface structure of the Khewari Block, thereby confirming the effectiveness of integrating geospatial and geophysical data for hydrocarbon prospect evaluation.

4. Discussion

The combined study of seismic, gravity, and geospatial data provides a coherent understanding of the structural and petroleum potential of the Khewari Block. Seismic interpretation reveals a structurally heterogeneous subsurface dominated by NE–SW-trending normal faults, horsts, grabens, and later compressional overprinting, consistent with regional extensional tectonics reported for the Lower Indus Basin (Noureldin et al., 2023; de Jager, 2020). Time and depth structure maps highlight structurally elevated blocks of the Sui Main Limestone and Lower Goru formation, confirming the presence of fault-bounded closures, rollover geometries, and tilted fault block trap styles previously recognized in other segments of the basin (Sajid et al., 2021; Aftab et al., 2022). These structurally isolated highs represent the most prospective zones for hydrocarbon entrapment in the study area.

Gravity anomaly interpretation provides an independent line of evidence that supports these seismic results. Bouguer gravity highs (L1) are associated with seismically mapped uplifted basement or carbonate platforms, and gravity lows (L2–L3) align with fault-controlled grabens containing thick sedimentary fill, patterns consistent with regional gravity–structure relationships documented within the Indus Basin by Noureldin et al. (2023). Residual gravity anomalies sharpen these density contrasts and closely match the orientations of major faults (F1–F3), reinforcing the interpretation of structural compartmentalization and fault-mediated trap development. The correlation of gravity gradients and seismic relief affirms the reliability of determining reservoir level closures and migration routes.

Geospatial data contributes additional insight by illustrating the surface expression of subsurface structures. The elevation model (DEM) shows upland regions in the central and northeastern parts of the block that correspond spatially with seismic and gravity-defined structural highs, while low-lying floodplains match graben-bounded depressions, indicating a subtle geomorphic imprint of deep-seated tectonics (Khayitov et al., 2021). Slope analysis highlights gently sloping terrains over major grabens favorable for survey acquisition,

whereas moderate to steep slopes reflect fault scarps and paleo-uplifted blocks, consistent with the basin's known neotectonic deformation (Ehsan et al., 2021). Land-use and land-cover patterns further show that much of the Khewari Block consists of undeveloped barren land, minimizing anthropogenic interference and supporting logistical feasibility for exploration operations.

Collectively, these datasets converge to indicate a structurally complex but highly prospective petroleum system. Fault-assisted seals, rollover anticlines, and tilted fault blocks identified on seismic sections correspond with gravity-defined density contrasts and surface geomorphic patterns, reducing exploration uncertainty and strengthening the structural interpretation. Although variations in spatial resolution and acquisition scale limit perfect co-registration between all datasets, the combined results still establish a robust tectono-stratigraphic framework that improves understanding of reservoir geometry, seal integrity, and hydrocarbon migration pathways. This multidisciplinary strategy aligns with the suggestions of combined subsurface assessment of frontier basins (Oppert et al., 2022), demonstrating its applicability for structurally complex and underexplored regions such as the Khewari Block.

5. Conclusions

The integration of seismic, gravity, and geospatial data sets provides an integrated structural framework of the Khewari Block, demonstrating that the major tectonic elements identified on seismic profiles correspond directly with density variations observed in the Bouguer and residual gravity fields. Seismic sections delineate a system of NE–SW-oriented normal faults (F1–F3) that partition the subsurface into horsts, grabens, and tilted fault blocks. These same structures appear as gravity gradients in the Bouguer anomaly map (see **Figure 8a**), where the western high-amplitude anomaly (L1) coincides spatially with the uplifted structural highs mapped on the Sui Main Limestone and Lower Goru depth surfaces (see **Figures 6a–6b**). On the other hand, the low-amplitude anomalies (L2 and L3) directly overlap with the down-faulted graben complexes imaged along seismic lines O-011-KWI-15 and O-011-KWI-16. This geometrical correspondence between fault-bounded relief in seismic data and corresponding density contrasts in the gravity field substantiates the interpretation of structural closures and rollover geometries as viable hydrocarbon traps.

Geospatial datasets further reinforce this subsurface model, as they show that surface morphology is a reflection of the underlying tectonic arrangement. The digital elevation model (see **Figure 11**) has high topography in the central-northeastern parts of the block, which coincides with the structural culminations of the depth maps of the Lower Goru and Sui Main Limestone. In contrast, the southwestern depressed plains coincide with the

gravity low zones (L2–L3) and the seismic grabens that accommodate greater sediment thickness. The slope distribution (see **Figure 12**) also shows the orientation of the principal fault systems; linear slope breaks and gradient anomalies are spatially consistent with faults F1–F3, which means that basin-scale tectonics still have topographic control. These correlations are an independent confirmation that these geophysical interpretation signatures have been maintained in modern surface geomorphology and are a measure of structural segmentation that existed in the past.

The synthesis of seismic, gravity, and GIS analyses yields a robust multi-layered structural model in which the potential hydrocarbon traps are continuously found across all the datasets. Structural culminations mapped as closures on depth surfaces correspond to Bouguer gravity highs (L1) and to uplifted geomorphic highs in the DEM, reinforcing their status as high-certainty exploration targets. Conversely, gravity lows (L2–L3), seismic grabens, and low-lying plains delineate secondary compartments characterized by increased sediment fill and potential migration pathways but reduced structural integrity. This convergence of independent datasets significantly enhances confidence in the mapped trap geometries, improves prediction of reservoir continuity, and provides a more defensible basis for well-location selection, volumetric assessment, and overall exploration risk reduction within the Khewari Block.

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SAŽETAK

Integrirana geoznanstvena i geoprostorna analiza za istraživanje ugljikovodika u bloku Khewari, Sindh, Pakistan

Blok Khewari, smješten u strukturno složeno donjojndskom bazenu Sindha u Pakistanu, zauzima tektonski povoljan, ali nedovoljno istražen sektor mezozojsko-kenozojskoga riftnog bazena poznatoga po svojim potencijalima za ugljikovodike. Ova studija primjenjuje integrirani geofizički geoprostorni postupak za ograničavanje podzemne arhitekture i procjenu potencijala ležišta. Opsežna interpretacija 2D seizmičkih profila identificira sustav sjeveroistočno-jugozapadno orijentiranih normalnih rasjeda, horstova, grabena i lokalnih kompresijskih struktura, stvarajući širok raspon geometrija zamki, uključujući rasjedne zatvore, antiklinale prevrtanja i nagnute blokove rasjeda. Mapiranje vremenske i dubinske strukture poboljšava geometrije horizonta i identificira strukturno izolirane blokove s poboljšanim potencijalom zarobljavanja. Bouguerove i rezidualne karte gravitacijskih anomalija dodatno razjašnjavaju razlike u gustoći povezane s uzdignutim karbonatnim platformama i sedimentnim dolinama potvrđujući segmentaciju strukture na temelju seizmičkih podataka. Dopune površinskih skupova podataka, kao što su elevacija temeljena na DEM-u, modeli nagiba i klasifikacija korištenja zemljišta, nude daljnja ograničenja u pogledu pristupačnosti terena, sustava odvodnje i operativnih mogućnosti. Integracija površinskih i podzemnih skupova podataka smanjuje nesigurnost u procesu interpretacije, poboljšava razgraničenje zamki i doprinosi najučinkovitijem planiranju postavljanja bušotina. Multidisciplinarni pristup ilustrira učinkovitost integriranja seizmičke refleksije, gravitacijskoga modeliranja i površinske GIS analize kako bi se stvorio koherentan strukturni okvir graničnih bazena. Radni postupak prenosiv je na druge regije s ograničenim podacima i pruža čvrstu osnovu za istraživanje ugljikovodika i donošenje odluka temeljeno na dokazima.

Ključne riječi:

istraživanje ugljikovodika, seizmička interpretacija, gravitacijske anomalije, geoprostorna integracija, blok Khewari

Author's contribution

Muhammad Junaid (MSc): Conceptualization, investigation, software, data curation, formal analysis, methodology, visualization, writing – original draft. **Muhammad Sajid** (PhD): Supervision, project administration, writing – review & editing. **Taimoor Ahmad** (MSc): Investigation, validation, writing – review & editing. **Eko Kusratmoko** (PhD): Methodology, resources, supervision, writing – review & editing. **Reza Syahputra** (PhD): Validation, software, visualization, writing – review & editing. **Shaukat Khan** (PhD): Validation, writing – review & editing. **Adi Wibowo** (PhD): Validation, writing – review & editing. **Muhammad Kashif** (Ph.D.): Validation, writing – review & editing. All authors have read and agreed to the published version of the manuscript.

Statistical, Geostatistical and Spatial Analysis of Technology-Critical Elements in the Trepça Mine

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Original scientific paper



Berat Sinani¹ , Blazo Boev¹ , Arianit Reka^{2,3} , Bahri Sinani⁴ , Ivan Boev^{1*}

¹ Department of Petrology, Mineralogy and Geochemistry, Faculty of Natural and Technical Science, University "Goce Delchev", 2000 Stip, North Macedonia.

² Department of Chemistry, Faculty of Natural Sciences and Mathematics, University of Tetova, 1200 Tetovo, North Macedonia.

³ Albanian Unit of Nanoscience and Nanotechnology, NanoAlb, Academy of Sciences of Albania, Fan Noli Square, 1000 Tirana, Albania.

⁴ Department of Environmental Engineering, Faculty of Natural and Technical Science, University "Goce Delchev", 2000 Shtip, North Macedonia.

Abstract

This study investigates the presence, concentration, and spatial distribution of Technology-Critical Elements (TCEs) in the Trepça Mine, focusing on ore body horizons VIII-XI. During research in the relevant archives (Trepça, ICM, GSK), it was noted that no statistical, geostatistical or spatial studies have been conducted in the Trepça Mine for Technology-Critical Elements. Mineralizations in Trepça mainly occur as vein structures known as ore bodies. In this study, all existing ore bodies from horizons VIII-XI, were sampled. Representative samples were collected from each active ore body and analysed using Inductively Coupled Plasma Mass Spectrometry (ICP-MS) to quantify elements including Bi, Co, Ge, V, W, Li, Ga, In, Te, and Nb. Statistical and geostatistical analyses were performed using Microsoft Excel, R Studio, and Golden Software Surfer to assess variability, correlations, and spatial trends. The highest concentrations were observed for Bi (avg. 98.81 ppm; max. 610.4 ppm), W (avg. 28.68 ppm), and Co (avg. 28.47 ppm), with significant variability across horizons. Correlation analyses revealed strong positive relationships between several elements, such as W-V ($r = 0.70$), W-Ge ($r = 0.65$), and Bi-W ($r = 0.60$), suggesting possible common geological origins. These findings highlight the potential for the sustainable recovery of strategic elements from Trepça's polymetallic ore zones and underscore the mine's relevance, not only for traditional metals, but also for critical raw materials essential to low-carbon and high-tech industries.

Keywords:

Geostatistics; Spatial; Distribution; TCE; Trepça

1. Introduction

The evolution and rapid increase in modern technologies has led us to greater focus on another group of elements called Technology-Critical Elements (TCEs) (Zendehbad et al., 2021). These elements are the backbone for the development and advancement of technology, such as in electronics, renewable energy, transportation, agriculture, health, military, etc. These elements are called critical because of the risk of their supply. According to the latest report, about thirty elements and minerals are critical as defined by the European Commission (Dang et al., 2021). In addition to rare earth elements, Technology-Critical Elements also include the platinum group elements, as well as Te, Ge, Ga, In, Nb and Ta (Ebeling et al., 2022).

Although many researchers from all over the world have conducted numerous studies on the Trepça polymetallic deposit, the research of Technology-Critical Elements within the Trepça ore bodies remains unexamined. Elements such as Bi, Co, Ge, V, W, Li, Ga, In, Te and Nb have gained great importance due to their role in modern technologies. However, their presence and distribution in one of the most important polymetallic deposits in Southeast Europe have not been systematically documented. Existing research and studies mainly focus on Pb, Zn, and Ag, but not to the appropriate extent on the presence, distribution, and interrelation of these elements in the ore bodies of the Trepça Mine, then the areas with the potential for their highest concentration, creating a spatial analysis of their distribution. A review of the available literature and studies revealed no studies linking the distribution of these elements with statistical, geostatistical and spatial analyses. The lack of such studies limits the identification of the presence of Technology-Critical Elements, their concentration and the geochemical relationship between them. With the increasing

* Corresponding author: Ivan Boev

e-mail address: ivan.boev@ugd.edu.mk

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Table 1: Application of Technology-Critical Elements in modern technology

Elements	Application in
Li	Batteries for modern devices and EVs; military and nuclear industries; light alloy; thermonuclear (Neves et al., 2024).
Bi	Refinery, Medicine, Cosmetics, Paint industry, Metal industry (Liu & Handschuh-Wang, 2025).
Co	Batteries, Superalloys, Chemical and Ceramics, Cemented Carbides, Steels, Magnets (Graedel & Miatto, 2022).
Ge	Semiconductors; IR lenses/optics; fiber optics; PET catalyst; thermal detection (Abdou et al., 2023).
V	Steel, Aviation, Catalysts, Pigments and photosensitive materials (Storm, 1994).
W	Steel alloys, Lamp filaments, Electronics, Pigments, Lubricants, Catalysts, Radiation protection, Medical, Dental films (Christian et al., 2011).
Li	Batteries for modern devices and EVs; military/nuclear industry; light alloy; thermonuclear power (Neves et al., 2024).
Ga	MRI contrast agent; uses in glass, ceramics, glazes; nuclear applications (Abdou et al., 2023).
In	Electronics and displays; base metal sulphide deposits; solar cells (Abdou et al., 2023).
Te	Semiconductors; CdTe for solar panels; thermoelectric (Abdou et al., 2023).
Nb	Technology, Mobile Phones, MRI (Abdou et al., 2023).

global demand for critical minerals, studying their occurrence in the Trepça deposit has become essential, the reason for such a study is related to the study of Technology-Critical Elements in Pb-Zn polymetallic deposits around the world and comparison with them. Polymetallic hydrothermal deposits are a significant source of TCEs elements, such as Nanmushu Pb-Zn polymetallic deposit, China (Wu et al., 2023), Hehuashan Pb-Zn polymetallic deposit (Liu et al., 2024), Chipu Pb-Zn deposit, China (Tan et al., 2025), Badovc Pb-Zn deposit, Kosovo (Mederski et al., 2024), Zhugongtang Pb-Zn deposit, China (Song et al., 2023), Yangtze Pb-Zn polymetallic deposit, China, Pb-Zn deposit, Guangxi, (Yu et al., 2023), Pb-Zn hydrothermal deposit, Aershada, China (Li et al., 2023), Pb-Zn hydrothermal deposit, Zhenzigou, Diannan, Xiquegou and Erdao in Qingchengzi (Duan et al., 2024).

Considering that Trepça currently has all active exploration and exploitation in horizons VIII to XI, our study is also focused on these horizons. This study aims to provide a general assessment of the Technology-Critical Elements in the Trepça Mine by presenting these through statistical, geostatistical and spatial methods. This study aims to:

1. Identify the presence,
2. Assess the concentration and variability
3. Examine correlation and PCA
4. Model spatial distribution.

After this, a clear study will be presented regarding the presence and distribution of Technology-Critical Elements in these horizons that are currently active. This study, based on the first literature related to statistical, geostatistical and spatial methods, is a systematic assessment of these Technology-Critical Elements in the polymetallic deposit in Trepça. Also, through the aforementioned analyses, we see the interconnection and distribution of these elements, the areas with higher and lower concentrations, the direction and orientation of the

distribution of these elements, which will then pave the way for the Trepça Geological Service and the Mines for concrete actions in their utilization and the transition from the use of traditional metals to Technology-Critical Elements.

Table 1 presents some of the Technology-Critical Elements identified in this study and their use in modern technologies.

This study represents a shift in research perspective toward the investigation of critical elements and their spatial distribution. It expands the mining focus of the Trepça Mine-traditionally centered on Pb-Zn, Au, and Ag - into a new and promising field: the study of critical elements, their identification, analysis, and spatial distribution.

2. Methods

The Trepça Mine is an underground mine operation developed across horizons, each separated by approximately 60 m vertically. At present, mining activities occur only within horizons VIII–XI. Some ore bodies have been fully exploited, others remain active, while several have not started yet. Sampling has been conducted in all ore bodies that are active.

The main objective of this study is to determine the spatial distribution patterns of these elements within horizons VIII–XI, which contain the largest geological reserves. Golden Software Surfer was used to visualize spatial variations and identify zones with elevated concentration of technology-critical elements (Bi, Co, Ge, V, W, Li, Ga, In, Te and Nb).

Furthermore, the analysis of these chemical elements was performed using contemporary methods such as ICP-MS, supported by data processing and visualization tools including Microsoft Excel, R Studio, and Golden Software Surfer. These methods ensure a detailed and accurate representation of the distribution of Technology-Critical Elements.

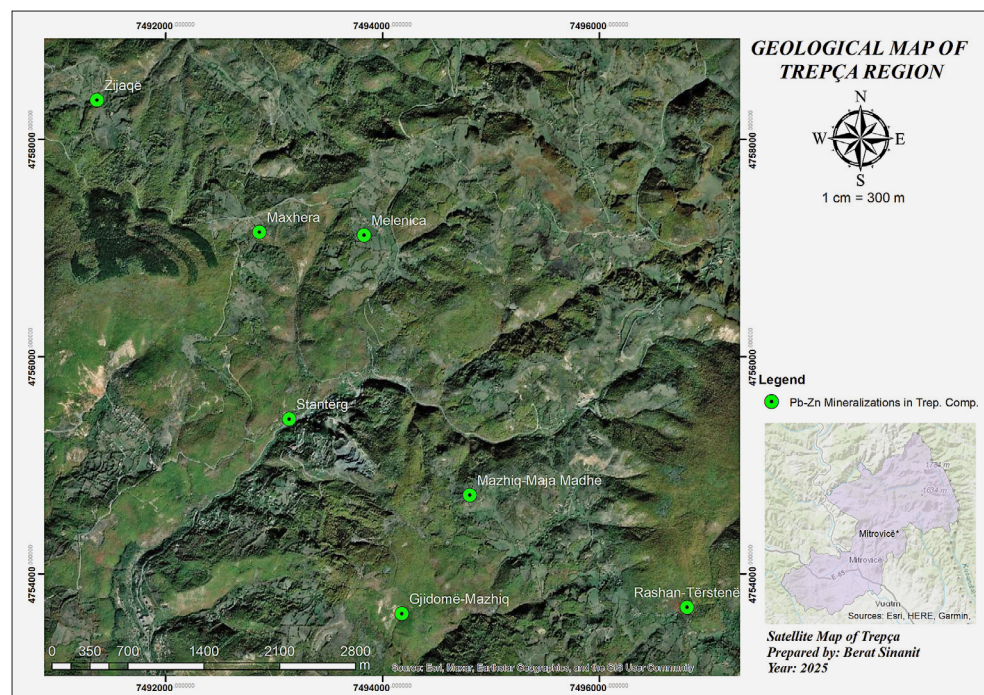


Figure 1: Satellite map of the study area

Efficient extraction of metals and metalloids requires understanding their geochemical behaviour, mineralogy, and precipitation (Wanhainen et al., 2017). The process of their precipitation is with particular emphasis on sulfur oxides where there may be concentrations of trace elements (Webster et al., 1998). Pb-Zn sulfide minerals are very particularly sensitive to oxidation, which may result in the enrichment Technology-Critical Elements.

Since antiquity times, minerals have been used for various purposes (Paçarizi et al., 2024). These minerals are extracted in millions of tons of ore every year, and this arises as a need for technological uses (Falagán et al., 2017). If the concentration of rare minerals is high, they can be reprocessed and extracted (Antonijević et al., 2008; Cook et al., 2009; Yin et al., 2018). The most important Pb-Zn-Ag deposits are in the Stan Terg, Artana, Hajvalia, Kizhnica, Belo Brdo, Crnac, and Drazhnje (Mederski et al., 2021). Pb-Zn mineral deposits especially sphalerite can accumulate or contain various critical metals (Mederski et al., 2024). For a long time, various studies have been on the distribution of Au, Ag, Pb and Zn in the Trepça Mine, but very few studies have focused on the spatial analysis of Technology-Critical Elements (Sinani et al., 2023). Figure 1 presents the Satellite map of the Trepça Mine complex.

The Shala e Bajgorës region lies in northern and northeastern part of Kosovo, covering over 400km² (Kelmendi et al., 2024). The Trepça Mine is situated approximately 10 km northeast of Mitrovica and one of the largest Pb-Zn mineral deposits in the south-eastern Balkans, where exploitation began in medieval times (Kolodziejczyk et al., 2016). In this area, at a distance of over 10km from the city of Mitrovica in the direction of Shala e Bajgorës, the Trepça Mine is located (Zeqiri

et al., 2022). The Trepça Mine is characterized by large reserves and a known source of Pb-Zn and Ag, but based on the knowledge of geology of Trepça Mine, the presence of Technology-Critical Elements should also be investigated. Therefore, this study was conducted on the distribution of Bi, Co, Ge, V, W, Li, Ga, In, Te and Nb in the Trepça Mine. This region is part of the Serbian-Kosovo-Macedonian metallogenic province. This area is located in the Vardar zone (Elezaj & Kodra, 2007).

These deposits, like Trepça, offer opportunities to revisit previously exploited ores using modern analytical tools and sustainable extraction frameworks. Such an approach aligns with global trends toward low-impact mining and circular material flows.

Mitrovica, located in the northern part of Kosovo, has a long history of lead and zinc mining. The history of lead and zinc mining is directly linked to the history of the entire country of Kosovo. Until recent decades, Trepça was known for its high exploitation of lead and zinc, for which it is still known today (Hyseni et al., 2010). The name “Trepça” was first mentioned in 1303 in some documents in the Archives of Dubrovnik in Croatia. The development of mining in this area dates back to Illyrian and Roman times, while the greatest development is known in the 13th century (Shala, 2014). Kosovo is known for its variety of complex geological formations (Peci et al., 2014). In recent decades, Trepça was known as one of the most successful companies in the former Yugoslavia (Hetemi & Kastrati, 2008). In 1926, the British bought the concessions and on September 9, 1927 they formed the company under the name “Trepça Mines Limited”, which functioned until the end of World War II (Nikolić et al., 2017).

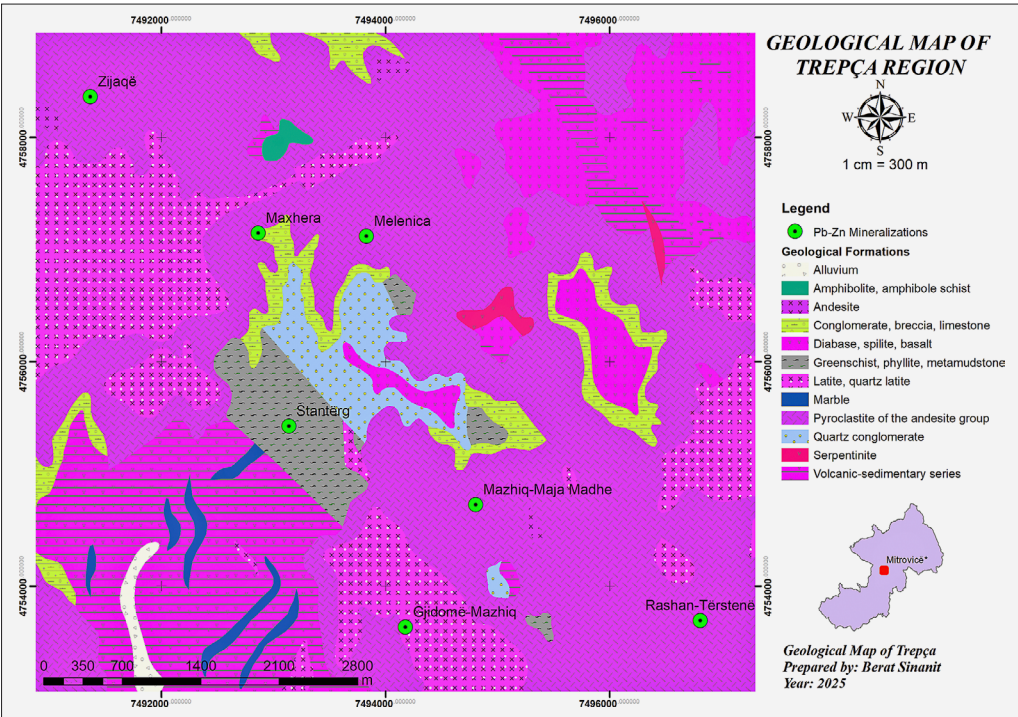


Figure 2: Geological map of the study area

Table 2: Mineral Reserves of Trepça Mine and concentration of Pb, Zn, and Ag (Hetemi & Kastrati, 2008)

Nr	Mines	Tones of Reserves	Concentration (%)			Reserves (t)		
			Pb	Zn	Ag (g/t)	Pb	Zn	Ag(kg)
1.	Stantërg	20,754,000	4.02	4.02	76.0	834,311	674,505	1,577,304
2.	Melenica	2,552,000	5.80	5.80	85.0	148,016	107,184	216,920
3.	Maxhera	600,000	3.80	3.80	72.0	22,800	18,000	43,200
4.	Mazhiq-Maja Madhe	1,500,000	3.30	3.30	60.0	49,500	42,000	90,000
5.	Gjdomë-Mazhiq	2,000,000	3.30	3.30	60.0	66,000	56,000	120,000
6.	Rashan-Tërstenë	2,500,000	3.30	3.30	60.0	82,500	70,000	150,000
7.	Zijaqë	5,175,000	2.83	2.83	16.0	146,453	112,815	82,800
8.	Total	35,081,000	3.85	3.85	65.0	1,349,579	1,080,504	2,280,224

2.1. Geological characteristics of study area

The geological structure of ‘Trepça’ consists of volcanic rocks and sedimentary formations that control mineralization. The ore bodies of the Trepça Mine mainly consist of:

- A) in contact with limestone and breccia’s and
- B) in contact with limestone and shales as shown in geological map of the study area in **Figure 2**.

Most of the ore bodies are created between green shales and limestones in the Trepça Mine (**Hetemi & Kastrati, 2008**). Two main mineral groups are present:

- [1]. Skarn group - Epidote, Garnet, Actinolite, Hedenbergite and Ilvaite
- [2]. Hydrothermal group - Pyrrhotite, Pyrite, Galena, Sphalerite, Arsenopyrite, Rhodochrosite, Aragonite, Calcite, Gypsum, Quartz and others (**Hetemi & Kastrati, 2008**).

Table 2 presents mineral reserves of Trepça Mine and concentration of Pb, Zn and Ag.

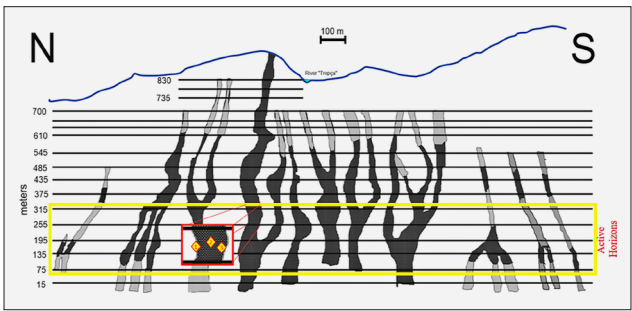


Figure 3: Spatial distribution of ore bodies within the Trepça Mine and the sampling location

The Trepça Mine mineral deposit has a hydrothermal origin; the mineralization is developed mainly in contact between schists and limestone within mineralization veins. Sampling was carried out for all bodies (three samples for each ore body) to analyze Technology-Critical Elements in the Trepça Mine. **Figure 3** presents Trepça ore mine bodies and sampling for each ore body.

Table 3: Analytical parameters for selected elements analyzing in NexION 300D

Element	LOD_ppt	LOQ_ppt	Standards	Calibration	Recovery	Analytical Error
Bi	5-10	15-30	Multi-element; CRM	4-6 points; IS: In/Bi	90-105	RSD 1-3%; $\pm 5-10\%$
Co	2-5	6-15	Multi-element; CRM	4-6 points; IS: Sc/Rh	95-105	RSD 1-2%; $\pm 5\%$
Ge	10-20	30-60	Multi-element + individual	4-6 points; IS: Rh/In	85-110	RSD 2-4%; $\pm 10\%$
V	20-40	60-120	Multi-element	4-6 points; IS: Sc	90-105	RSD 3-5%; $\pm 10\%$
W	5-10	15-30	Multi-element	4-6 points; IS: Re/Bi	90-110	RSD 2-4%; $\pm 10\%$
Li	<1	2-3	Multi-element	4-6 points; IS: Sc	95-105	RSD 1-2%; $\pm 5\%$
Ga	5-10	15-30	Multi-element	4-6 points; IS: Ge/In	90-105	RSD 1-3%; $\pm 5-10\%$
In	1-3	3-9	Multi-element	4-6 points; IS: Rh	95-105	RSD 1-2%; $\pm 5\%$
Te	20-40	60-120	Individual standard	4-6 points; IS: Bi/Rh	80-110	RSD 3-5%; $\pm 10\%$
Nb	10-20	30-60	Multi-element	4-6 points; IS: Rh/In	85-105	RSD 2-4%; $\pm 10\%$

2.2. Sampling and analysis methodology

To ensure the safety and reliability of the results obtained for the Technology-Critical Elements, a rigorous QA/QC protocol was applied, including sample blanks, duplicates, calibration verification and instrument performance monitoring. Duplicate analyses improve data reliability, especially for Bi, W and Co.

2.2.1. Analytical Quality Control

Quality control has also been increased by analyzing duplicate samples, and their comparison, using statistical methods and analyzing the standard deviation, making us have the most reliable results, with special emphasis on Bi, W and Co that indicate geological anomalies of some ore bodies. Thus, they have contributed to the maximum increase in data quality.

Table 3 presents the operating and performance conditions of the ICP-MS device in analyzing technology-critical elements.

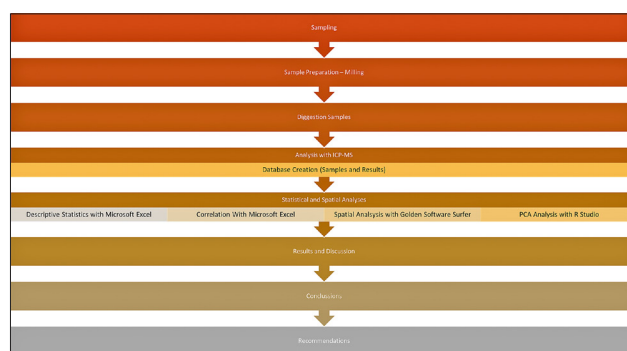
2.2.2. Sampling in the Trepça Mine

Sampling at the Trepça Mine was carried out in a structured and representative manner, covering all active ore bodies in horizons VIII-XI. For each ore body, 3 samples were taken (in the left, central and right parts of the ore body), to ensure sample homogeneity and local variations. Samples were collected with accurate data for each ore body, to enable the use of geostatistical and spatial analyses.

To carry out this study, the procedure as shown in **Figure 4** was followed as below:

Sampling was done in each ore body, the samples were described and placed in bags for processing in the laboratory, where the following steps were carried out in the laboratory:

- Drying the samples for 24 hours at 105°C, the samples were ground and dried for 24 hours at a temperature of 105°C (Sinani et al., 2023), after which

**Figure 4:** Flowchart of realization of this study

the samples were ground in the primary and secondary mills.

- Grinding in the Primary Mill
- Grinding in the Secondary Mill
- Digestion of samples and
- Analysis with ICP-MS (PerkinElmer NexION 300D), one of the most advanced techniques in the identification of technology-critical elements at very low levels. Analyses were conducted using a Perkin Elmer NexION 300D ICP-MS instrument. Inductively Coupled Plasma Mass Spectrometry (ICP-MS) is a powerful analytical method that allows for the fast, accurate, and highly sensitive determination of a broad spectrum of elements in both solid and liquid matrices. Utilizing ICP-MS technology, up to 76 elements can be measured simultaneously at extremely low concentrations, ranging from nanograms to picograms per liter. The system enables the detection of approximately 35 elements within a single sample in as little as three minutes.

The instrument operates by generating a high-energy plasma using argon gas, into which the prepared liquid sample is introduced. This process atomizes and ionizes the elements present in the sample. The resulting positively charged ions are then accurately detected by a mass spectrometer, enabling precise elemental analysis of the solution. The focus of this study is:

v The elements taken in the study are Bi, Co, Ge, V, W, Li, Ga, In, Te and Nb. In many studies and research works in Pb-Zn deposits, the concentration of these elements have been studied, therefore these elements have been selected.

- Processing and creation of the database obtained from laboratory analyses.
- Initially, descriptive statistics such as Minimum, Median, Maximum, Mean and Standard Deviation are presented, were used to assess variability.
- Correlation – were used to identify geochemical relationships between these elements.
- PCA analysis were used to identify grouping of elements and
- Spatial Analysis was performed using Golden Software Surfer which is used to present the distribution of each Technology-Critical Element, Interpolation was carried out using the Kriging method. Where, the value of X represents the concentration of the element), the areas with the highest concentration of certain elements and the direction of distribution by presenting it for each horizon.

The limitations of this work are mainly as a factor of the exploitation of the uppermost horizons, as well as the access to the 12th horizon, which is not yet open or active.

Samples were taken only in ore bodies that are active or that have not started to be exploited and the studies are oriented only in the ore bodies and not in the surrounding rocks.

After performing the laboratory analyses and obtaining the chemical results, we used software for specific purposes:

- Microsoft Excel for Descriptive Statistics which were used from Data Analysis ToolPak and Correlations also to present distribution correlation between Technology-Critical Elements.
- Golden Software Surfer is used for spatial distribution of Technology-Critical Elements. In Surfer, the 3-dimensional representation method is used where the Z value represents the concentration of specific chemical element, this indicates that at points where we have a higher concentration the colors will be more pronounced.
- R Studio for PCA analysis for PCA analysis. We used the software packages ("FactoMineR") and ("factoextra") of the R Studio language to calculate and present the PCA analysis.

Geostatistics introduces geological modelling by providing advanced tools for representing the variability of both geological formations and their spatial distribution (Hosseini et al., 2019). Also, geostatistical analysis shows spatial variability and clear spatial correlation between studied variables (Shao, 2024). Digital transformation" describes the transformation process of any mine industry or business model to the implementation of digital technologies (Barnewold & Lottermoser,

2020). Golden Software Surfer has a powerful tools and function for interpreting geochemical data (Valls, 2019). The first two columns in both cases are the X and Y coordinates, and the next columns are the corresponding parameter Z (Ali, 2024). The following section presents a breakdown of Technology-Critical Elements using Microsoft Excel and Golden Software Surfer was used to present the spatial distribution of each Technology-Critical Element for each horizon in the Trepça Mine. By applying statistical and geostatistical methods, we can delineate the spatial distribution and potential origins of the chemical elements (Schiavo et al., 2024). To reduce the amount of data with minimum loss of important information (Taşan et al., 2022) we have used Principal Component Analysis (PCA). Classical PCA was used to identify covarying elements associated with different compositions and generations of minerals.

Thus, a combination of statistical, geostatistical and spatial analysis of the Technology-Critical Elements distributions, provides a clear understanding of distribution patterns of Technology-Critical Elements. Upon completing the statistical, geostatistical, and spatial analyses, we obtained a clear picture of the distribution of some Technology-Critical Elements in the Trepça Mine.

3. Results

3.1. Statistical and geostatistical analysis of Technology-Critical Elements in Trepça Mine

Descriptive statistics are tools that summarize the structure and variability of the obtained results (Dong, 2023). The parameters presented in this study are the minimum, median, maximum, mean, and standard deviation for the selected elements, as shown in Table 4.

Table 4 illustrates the statistical analysis of the concentrations of the selected elements in the analyzed samples, including minimum, median, maximum, means and standard deviations for the selected elements.

The values of Bi show high variability, with a mean concentration of 98.81 ppm (SD = 181.74) and a maximum value of 610.4 ppm, indicating an uneven distribution of this element.

Co has a smaller spread of values, with a mean of 28.47 ppm (SD = 21.12) and a maximum value of concentration of 81.64 ppm. The median value (22.02 ppm) indicates a relatively symmetrical distribution of Co.

The Ge concentrations show low variability, with a mean of 0.32 ppm (SD = 0.25) and a maximum value of 0.96 ppm, suggesting that this element is found in low and stable concentrations in the samples. A similar situation is observed for Nb (Niobium), with a mean of 0.41 ppm (SD = 0.25). W exhibits considerable variability, with a maximum value of 308.82 ppm and a high standard deviation (SD = 66.56) which may be related to specific mineralogical phases and will be examined through

Table 4: Descriptive statistics of the selected elements (ppm)

	Minimum	Median	Maximum	Average	Standard Deviation
Bi(ppm)	3.15	18.58	610.4	98.81	181.74
Co(ppm)	8.5	22.02	81.64	28.47	21.12
Ge(ppm)	0.01	0.22	0.96	0.32	0.25
V(ppm)	5.59	13.29	39.2	14.74	8.82
W(ppm)	2.08	14.8	308.82	28.68	66.56
Li(ppm)	0.27	0.65	21.12	2.67	5.38
Ga(ppm)	0.17	1.47	6.94	2.18	2.06
In(ppm)	0.1	1.16	12.08	2.38	3.46
Te(ppm)	0.02	0.25	41.8	2.68	9.28
Nb(ppm)	0.07	0.41	0.93	0.41	0.25

correlation analysis. For other elements, such as V, Ga and In, the means and standard deviations suggest a different distribution of these elements with low concentration within these horizons. Graphical representations allow researchers to show correlations and the distribution of data (Alabi & Bukola, 2023), where through visual representation, the distribution and direction of the spread of these data can be presented. The distribution and concentration of Technology-Critical Elements are shown by histograms in Figure 5.

Figure 5 illustrates the histograms for the distribution of the investigated Technology-Critical Elements. Trepça is a highly heterogeneous mineral complex, and this heterogeneity is reflected in the distribution of these elements. The elements Bi, W and Co present the greatest variability, which is reflected in the histograms presented above which present geochemical anomalies. Bi shows right-skewed distribution, which confirms the high mean and the very large variation. W presents two different groups suggesting two mineralogical phases in different geochemical environments.

While other elements such as Ge, Ga, Nb and Li, although in low concentration, have given more balanced histograms with a uniform presence and absence of different geochemical anomalies. Ge and Nb show similar intervals suggesting a homogeneous distribution. While Te and In have given some high results showing geochemical anomalies in some samples which indicate the localization of mineralization in certain areas. In general, just as the Trepça Mine is characterized by a fairly large geological complex, the distribution of these is also quite complex and characterized by large anomalies.

The relationships between the variables are illustrated by the scatter plot shown in Figure 6.

The distribution of Technology-Critical Elements in this diagram shows a considerable variability in both concentration and spatial pattern, suggesting formation under distinct geochemical and mineralogical conditions. To examine the relationships between these elements in more detail, a correlation analysis was performed.

Correlation analysis is a statistical method used to evaluate relationships between two or more variables

(Liu et al., 2025). The correlation coefficient is one of the most important statistical parameters that represents the similarity and relation between two given variables (Balabanova et al., 2010), thus the correlation matrix will present the relation of each element with each other element. While now the correlation of the selected elements are presented, the correlation matrix presents the relationship between selected elements and their distribution within horizons 8, 9, 10 and 11. Table 5 shows the correlation matrix which presents the interrelationship of each analyzed chemical element.

The correlation matrix shows the following relationships between selected elements:

Vanadium (V) and Tungsten (W) show a strong positive correlation ($r = 0.70$) suggesting a common geological source or similar formation processes.

Germanium (Ge) and Tungsten (W) with a correlation coefficient ($r = 0.65$) indicates a possible relationship between the mineralization of these elements.

Tungsten (W) and Bismuth (Bi) with a correlation coefficient ($r = 0.60$), this shows a strong positive correlation between these two elements. Same also for Vanadium (V) and Germanium (Ge) with a correlation coefficient ($r = 0.58$). Niobium (Nb) with Tungsten (W) and Vanadium (V) with a correlation coefficient ($r = 0.54$) between Nb and W, and ($r = 0.56$) for Nb and V presents a strong correlation between them.

Tellurium (Te) and Cobalt (Co) show a weak negative correlation ($r = -0.10$), while Indium (In) and Cobalt (Co) exhibit a stronger negative correlation ($r = -0.38$), suggesting different geological formation processes.

3.2. Spatial Distribution of the selected elements in four horizons

Before presenting the distribution of technology-critical elements, it is important to note that the ore bodies are mainly hydrothermal deposits, formed in contacts mainly between limestones and schists. Also, some northern ore bodies are built in cracks in limestones. Figure 7 illustrates the location of ore bodies in horizons VIII-XI and geological formation contact with them.

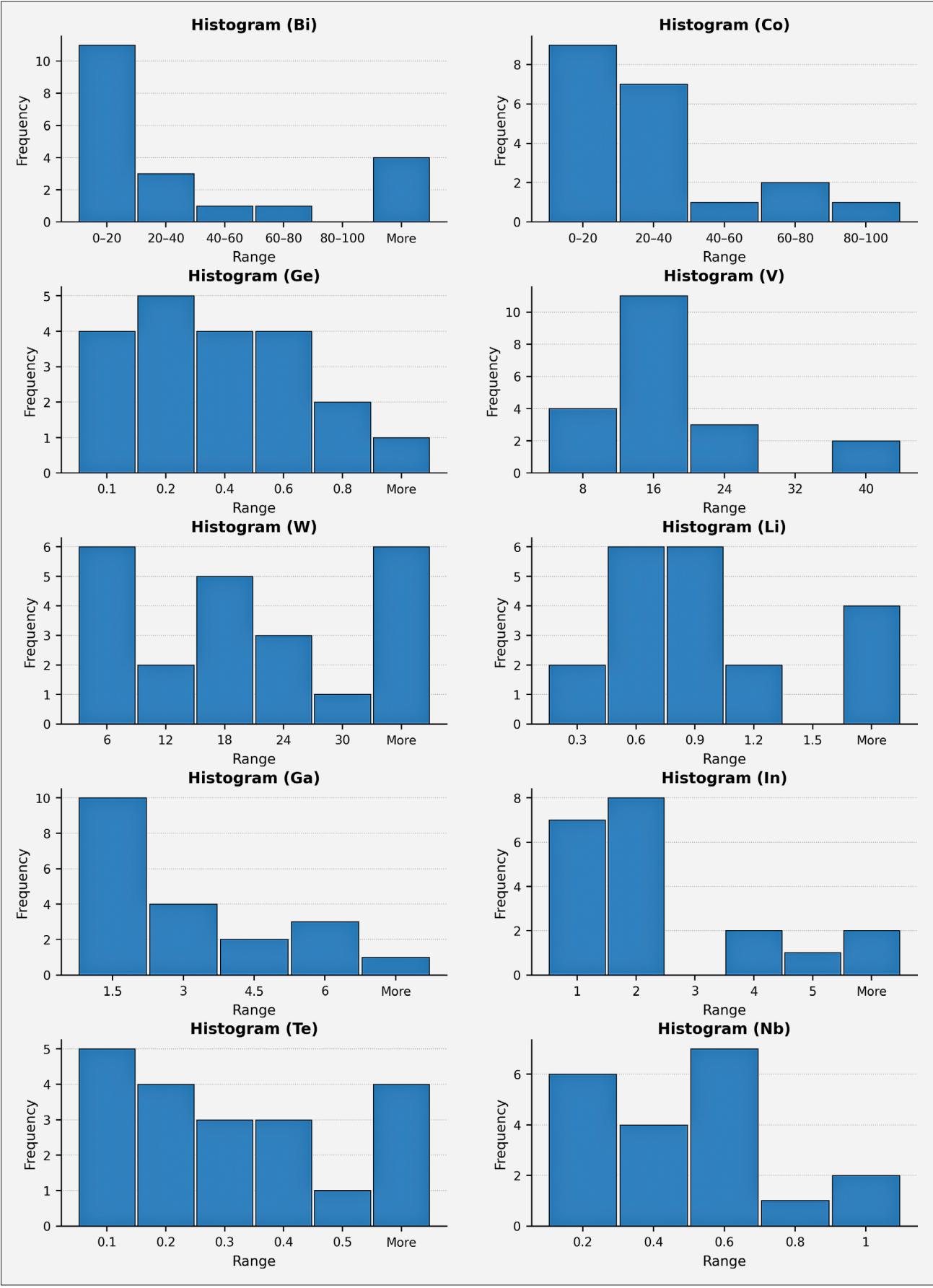


Figure 5: Distribution histograms of selected Technology-Critical Elements concentrations

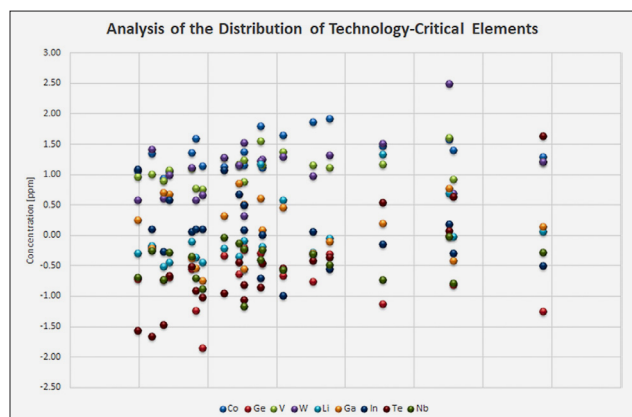


Figure 6: Scatter Plot diagram and relation of Technology-Critical Elements

Figures 8 – 13 illustrate the spatial distribution of Technology-Critical Elements and their horizontal concentration in ore bodies and horizons VIII - XI is presented.

Distribution of Bi in horizons VIII – XI

Figure 8 illustrates the distribution of Bi in four horizons studied in the Trepça Mine, where, for each horizon in which directions this element is most concentrated, as well as the degree of its concentration in the direction of depth.

Figure 8 shows the distribution of Bi in four horizons in active ore bodies. Bi is mainly concentrated in the southern ore bodies, although its distribution expands toward northern bodies with increasing depth. The figure shows that the highest concentrations are in ore bodies 127, 136, 146, and 156.

Distribution of W in horizons VIII – XI

In **Figure 9** we will see spatial distribution of W in horizons 8, 9, 10 and 11 in the Trepça Mine, where we will see for each horizon in which directions this element is most concentrated, as well as the degree of its concentration in the direction of depth.

Figure 9 shows the distribution of W in active ore bodies in horizons 8, 9, 10 and 11. W is more widely distributed than Bi, although its highest concentration remains localized in the southern ore bodies, but even this is distributed only in the southern ore bodies, while in horizon 9 it has given a distribution also in the southern bodies up to horizon 11. But with increasing depth, W begins to decrease in concentration values.

Distribution of Co in horizons VIII – XI

In **Figure 10** we will present the distribution of Co, in horizons 8, 9, 10 and 11, where we will see for each horizon in which directions this element is most concentrated, as well as the degree of its concentration in the direction of depth.

Figure 10 shows the distribution of Co, in active ore bodies in horizons 8, 9, 10 and 11. Laboratory analyses show that Co, occurs in both southern and northern ore bodies. The highest concentration was observed in Horizon IX within the northern bodies, whereas in Horizon XI a higher concentration was detected in the southern bodies, with significantly lower levels in the northern ones.

Distribution of Li in horizons VIII – XI

In **Figure 11**, we will present the distribution of Li in four horizons studied in the Trepça Mine, where we will see for each horizon in which directions this element is most concentrated, as well as the degree of its concentration in the direction of depth.

Figure 11 shows the distribution of lithium (Li) in active ore bodies from horizons VIII to XI. Li exhibits pronounced anomalies, particularly in Horizon IX, where a strong concentration peak is observed in ore body 136.

Distribution of Te in horizons VIII – XI

In **Figure 12**, we will see spatial distribution of Te in horizons 8, 9, 10 and 11 in the Trepça Mine, where we will see for each horizon in which directions this ele-

Table 5: Correlation Matrix of selected elements

	Bi (ppm)	Co (ppm)	Ge (ppm)	V (ppm)	W (ppm)	Li (ppm)	Ga (ppm)	In (ppm)	Te (ppm)	Nb (ppm)
Bi (ppm)	1									
Co (ppm)	0.08	1								
Ge (ppm)	0.19	0.16	1							
V (ppm)	0.34	0.35	0.58	1						
W (ppm)	0.60	0.10	0.65	0.70	1					
Li (ppm)	0.16	0.26	-0.01	0.45	0.16	1				
Ga (ppm)	0.06	-0.18	0.25	0.52	0.41	0.12	1			
In (ppm)	-0.23	-0.38	0.03	-0.10	-0.08	-0.22	0.10	1		
Te (ppm)	0.32	-0.10	-0.27	0.02	-0.03	-0.01	-0.11	-0.17	1	
Nb (ppm)	0.14	-0.08	0.51	0.56	0.54	-0.13	0.49	0.26	0.07	1

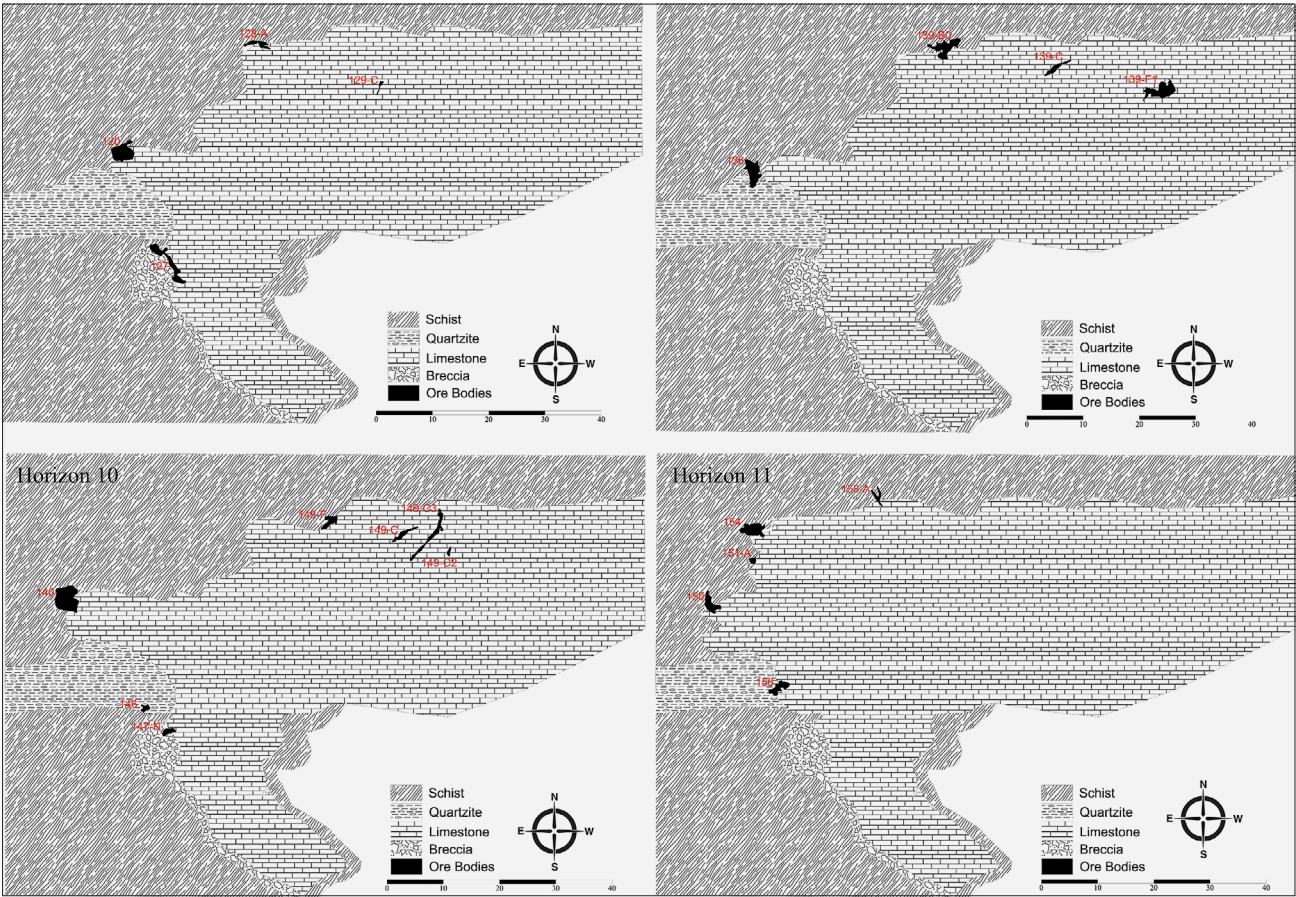


Figure 7: Ore bodies, geological formations and their location

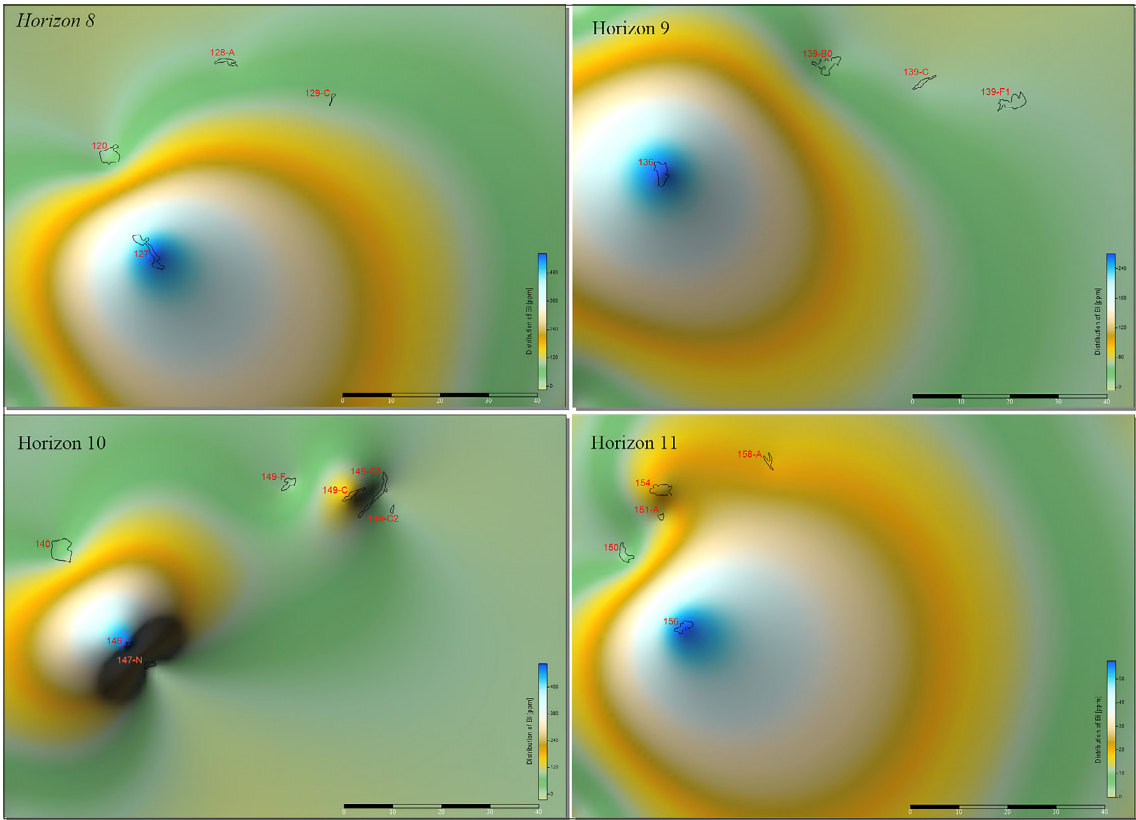


Figure 8: Distribution of Bi in horizons 8 – 11

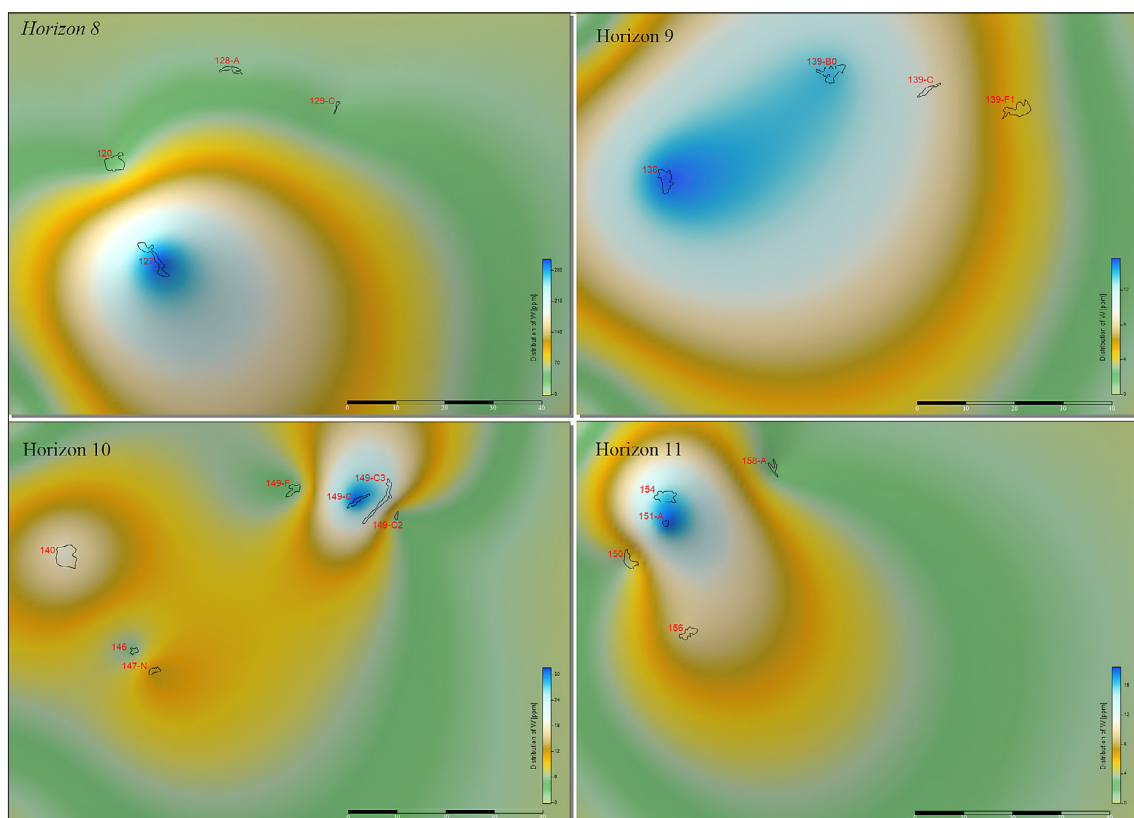


Figure 9: The vertical distribution of W, as a function of depth

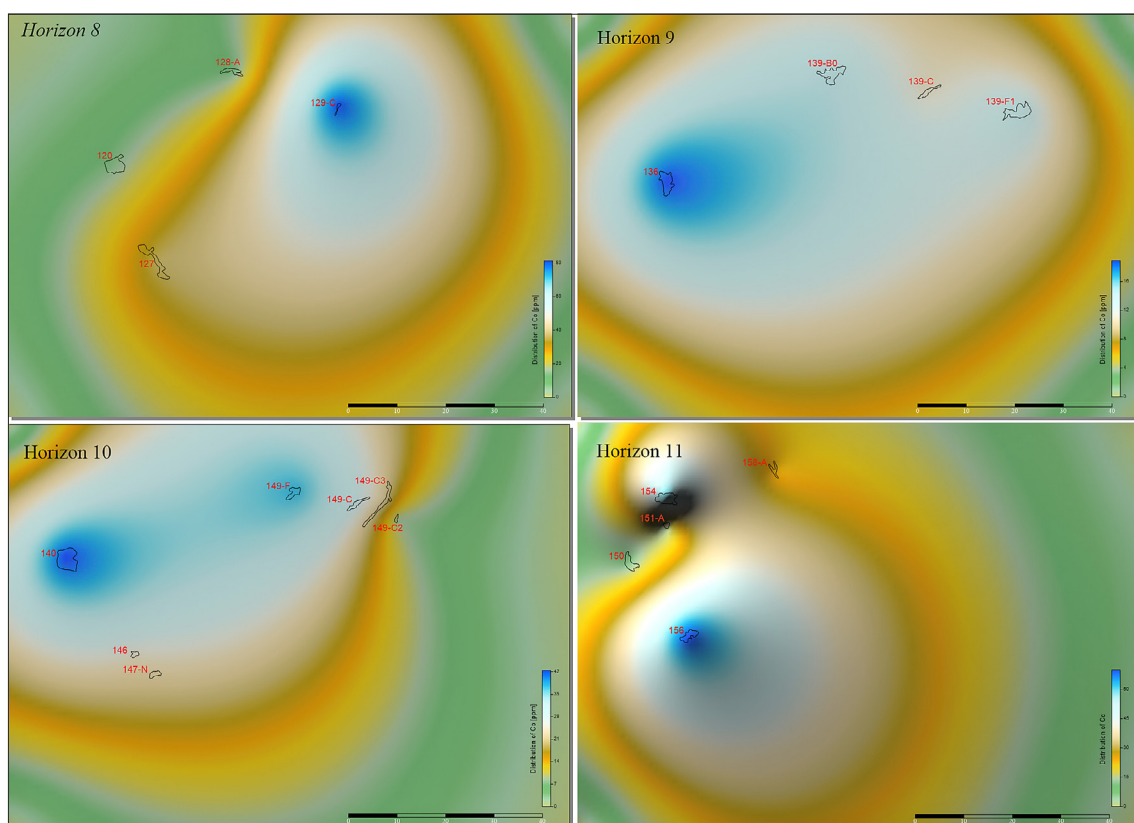


Figure 10: The vertical distribution of Co as a function of depth

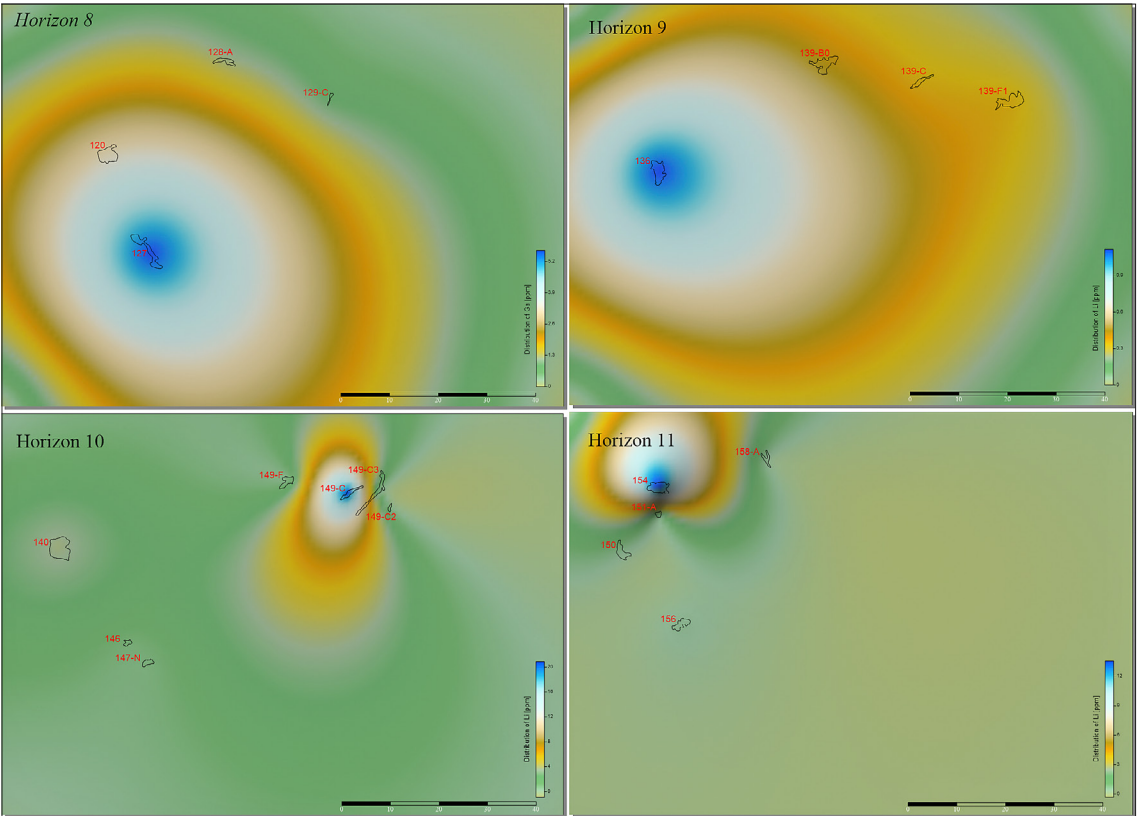


Figure 11: Distribution of Li in horizons 8 - 11

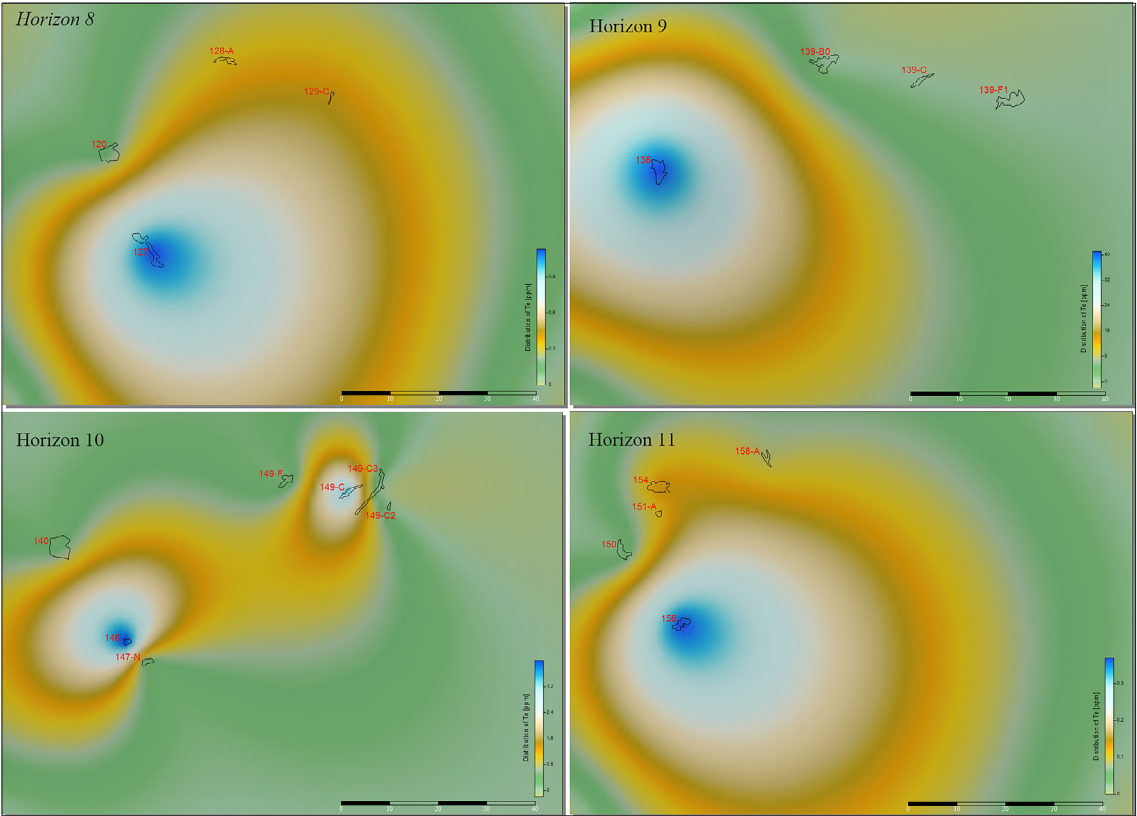


Figure 12: Distribution of Te in horizons 8 - 11

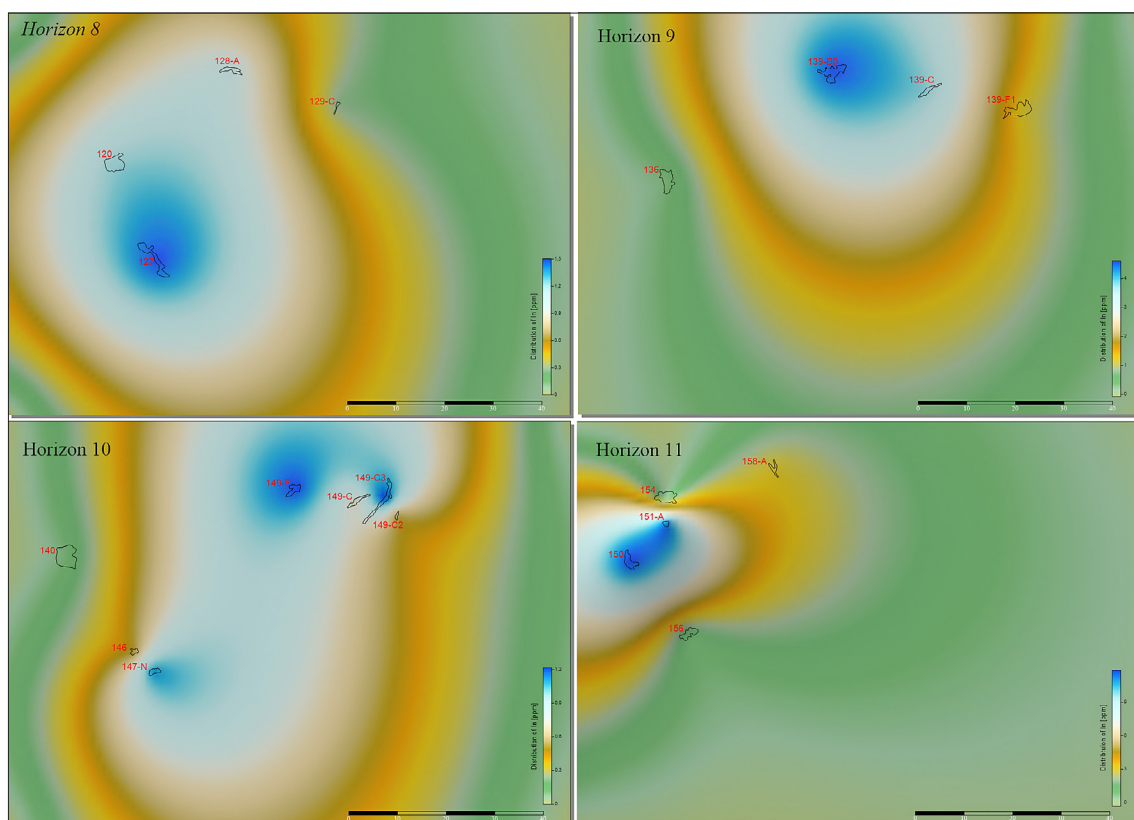


Figure 13: Distribution of In in horizons VIII - XI

ment is most concentrated, as well as the degree of its concentration in the direction of depth.

Figure 12 shows the heterogeneous distribution of Te across horizons VIII - XI, with higher concentrations consistently observed in the southern ore bodies 127, 136, 146 and 156 respectively. Te shows consistently higher concentration in the southern bodies, indicating a localized mineralization.

Distribution of In in horizons VIII – XI

In **Figure 13** we will present the distribution of In in four horizons studied in the Trepça Mine, where we will see for each horizon in which directions this element is most concentrated, as well as the degree of its concentration in the direction of depth.

Figure 13 illustrates the heterogeneous distribution of In across horizons VIII - XI. In, as in the correlation analysis that did not give a good correlation with any other element, In shows increasing concentration with depth, particularly within the central ore bodies, but decreases their concentration in southern and northern ore bodies.

3.3. PCA Analysis of Technology-Critical Elements

PCA was used to identify how Technology-Critical Elements group according to geological processes in the Trepça Mine. The groups of elements that appear in the PCA space represent potential mineralogical associations that can serve as indicators for prospecting and

Table 6: PCA Eigenvalues and Explained Variance Table for Technology-Critical Elements

PC	Eigenvalue	Percent variance	Cumulative percent
PC1	3.180	31.780	31.780
PC2	2.130	21.250	53.030
PC3	1.780	17.820	70.850
PC4	1.000	9.980	80.830
PC5	0.680	6.800	87.630
PC6	0.550	5.510	93.150
PC7	0.300	3.040	96.190
PC8	0.260	2.570	98.760
PC9	0.120	1.170	99.930
PC10	0.010	0.070	100.000

geochemical modelling. Variables in the PPCA analysis were standardized prior to PCA. The 2D graph presents the projection of variables (elements) into the first two principal components (Dim1 explains 31.8% of the variance and DIM2 explains 21.3% of the variance, DIM3 17.8% of the variance), which together account for 70.8% of the total variance of the data.

Te and Bi appear oriented mainly towards the positive axis of Dim2, with a high and close loading between them, suggesting a strong correlative relationship and perhaps a similar source or mineralization process especially

Table 7: Loading matrix for Technology-Critical Elements

Variable	Dim.1	Dim.2	Dim.3	Dim.4	Dim.5
Bi	0.010	0.971	0.194	-0.062	0.054
Co	0.195	0.046	-0.762	-0.333	0.268
Ge	0.765	-0.228	-0.001	-0.412	0.006
V	0.899	0.163	-0.214	0.125	0.138
W	0.848	0.108	0.004	-0.136	-0.117
Li	0.259	0.129	-0.596	0.636	0.254
Ga	0.635	-0.083	0.270	0.490	-0.347
In	0.002	-0.374	0.659	0.140	0.606
Te	-0.110	0.961	0.207	-0.007	0.088
Nb	0.738	0.060	0.462	-0.128	0.110

in hydrothermal mineralization or skarn deposits like the Trepça Mine. **Table 6** presents the eigenvalues and loading matrix data for the technology-critical elements.

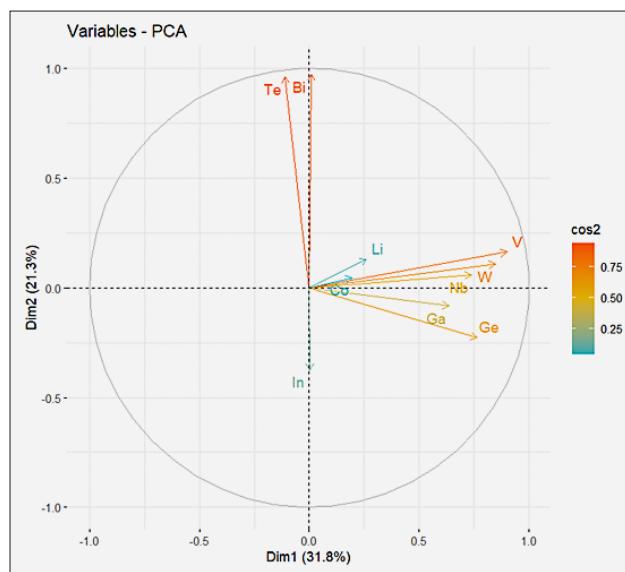
Table 6 presents the eigenvalues and the percentage of variance for each technology-critical element analysed through PCA in R Studio, this provides a clear overview of these elements by orientation and group. From the Eigenvalues table we see that the first component PC1 represents 31.78% of the variance and the component PC2 21.3%, showing that these two chemical processes dominate the variability of the samples. PC1 is dominated by V, W, Nb, Ge and Ga. While PC2 is dominated by Bi and Te, which are chemically related to hydrothermal mineralization, and PC3 is dominated by Li and Co. From this we see that we have three groups of Technology-Critical Elements. The loading matrix from the analysis is presented in **Table 7**.

Table 7 presents the variable loadings for the main components of the PCA analysis of technology-critical elements in the Trepça Mine, which indicate the contribution and direction of each chemical element in shaping the components. Positive or negative values reflect the strength and orientation that an element has an association with the component.

The loading matrix represents the chemical and geochemical direction of each component. Component PC1 shows a strong positive loading for V (0.899), W (0.848), Ge (0.765), Nb (0.738) and Ga (0.635), where these elements have strong positive loadings. In contrast, in PC2 we have very high loadings of Bi (0.971) and Te (0.961), where they are typical elements for hydrothermal phases. While the other elements present more complex but not dominant relationships in this group. Now, through the PCA plot, the grouping of Technology-Critical Elements will be graphically illustrated in **Figure 14**.

Figure 14 illustrates Principal Component Analysis plot for Technology-Critical Elements. The figure clearly separates the elements into three main groups:

- (1) V-W-Nb-Ge-Ge (PC1)
- (2) Bi-Te (PC2)
- (3) Co-Li (PC3)

**Figure 14:** Principal Component Analysis Graph of TCE elements

4. Discussion

The spatial distribution of Technology-Critical Elements in Trepça shows notable similarities with several deposits worldwide regarding the concentration of these elements in hydrothermal systems. The elevated concentrations of Bi, W, and Co identified in several ore bodies of the Trepça deposit exhibit a strong resemblance to those observed in the Pyrenean hydrothermal deposit (Cugerone et al., 2020), where these elements are concentrated within the framework of sphalerite mineralization.

In this study, high concentrations of W, V, and Bi were also encountered. According to Vikre et al. (2023) such elements are found in significant amounts within sulfide mineralizations in the western United States, where their mobility is closely associated with hydrothermal processes.

Similarly, in the polymetallic deposit of Chamuhan, northeastern China (Wu et al., 2025), sulphide mineralization and hydrothermal processes exhibit a high presence of tungsten, showing a comparable pattern to horizons 8 and 9 of the Trepça Mine.

Through correlation analysis we have presented the correlation of the distribution of these elements. The statistical results are consistent with correlation matrix analysis, which confirms strong positive relationships such as W-V ($r = 0.70$), W-Ge ($r = 0.65$) and W-Bi ($r = 0.60$).

Although Niobium (Nb) occurs at low concentrations, it shows significant correlations with several other elements as Niobium (Nb) with Germanium (Ge) has given a moderate positive correlation ($r = 0.51$), then Niobium (Nb) with Vanadium (V) has a moderate positive correlation ($r = 0.56$) and Niobium (Nb) with Tungsten (W) has a moderate positive correlation ($r = 0.54$).

While other elements present a weak positive correlation or we even have the case where we have a weak negative correlation, such as the case between Tellurium (Te) and Germanium (Ge), with a correlation ($r = -0.27$), we also have a weak negative correlation between Lithium (Li) and Indium (In) with a value of ($r = -0.22$). Other elements have not presented a significant correlation between them. So this presents that the highest concentration of Technology-Critical Elements is in horizons 8 and 9, but with increasing depth, the concentration of these elements decreases, as has been proven through spatial analysis with Golden Software Surfer.

The identification of high concentrations of Bi, W, and Co in specific ore bodies suggests the feasibility of selective recovery, which is a key principle of sustainable mining. Moreover, the association of TCEs with hydrothermal mineralization zones offers a path to refine exploration models for other regions, enhancing resource efficiency and reducing unnecessary environmental disturbance.

5. Conclusions

The findings indicate that Technology-Critical Elements in the Trepça Mine are heterogeneously distributed, particularly across horizons VIII-XI. Bi, W and Co show the highest concentration, with Bi averaging 98.81 ppm, W 28.68 ppm, and Co 28.47 ppm, all exhibiting high variability. Despite this Ge, Ga, Nb and Li present a very low concentration but also with limited variability, so generally the four above-mentioned horizons can be characterized by the presence of Bi, W and Co in larger quantities.

Chemical analyses performed using the ICP-MS and spatial analysis have shown that Bi, W and partly Co exhibit high concentrations in horizons VIII and IX of the analysed ore bodies. In horizon IX, the concentrations are similar, but some anomalies appear like the Bi concentration, while with increasing depth in the X and XI horizons, respectively, elements such as Bi, W, Ga, Te and In display significantly lower concentrations.

These results are supported by the correlation analysis, which shows correlation among W, V, Ge and Bi indicating that their concentrations decrease consistently with depth.

Overall, both the chemical and correlation analyses suggest that the studied elements can be grouped into three groups and this is confirmed also by PCA analysis:

- (1) Bi and Te,
- (2) W, V, Ge, Ga, Nb and

(2) Co and Li which tend to show slightly higher concentration at greater depths. This behaviour is also supported by correlations such as V-W ($r=0.70$), and W-Ge ($r=0.65$). Co, in other hand, shows negative correlation with most elements, suggesting a different origin and mineralogical phases.

So, from this we can conclude that the Trepça Mine is a mine as a strategic object not only for traditional metallurgy and the exploitation of Pb and Zn, but also for modern technologies with the presence of these Technology-Critical Elements and their importance.

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SAŽETAK

Statistička, geostatistička i prostorna analiza tehnološki kritičnih elemenata u rudniku Trepča

Ova studija istražuje prisutnost, koncentraciju i prostornu raspodjelu tehnološki kritičnih elemenata (TKE) u rudniku Trepča s fokusom na horizonte rudnih tijela VIII-XI. Tijekom istraživanja relevantnih arhiva (Trepča, ICMM, GSK), uočeno je da u rudniku Trepča nisu provedene statističke, geostatističke ili prostorne studije tehnološki kritičnih elemenata. Mineralizacije u Trepči uglavnom se javljaju kao žilne strukture poznate kao rudna tijela. U ovoj studiji uzorkovana su sva postojeća rudna tijela iz horizonata VIII-XI. Reprezentativni uzorci prikupljeni su iz svakog aktivnog rudnog tijela i analizirani pomoću spektrometrije masa uz induktivno spregnutu plazmu (ICP-MS) kako bi se kvantificirali elementi, uključujući Bi, Co, Ge, V, W, Li, Ga, In, Te i Nb. Statističke i geostatističke analize provedene su pomoću softvera Microsoft Excel, R Studio i Golden Software Surfera u svrhu procjene varijabilnosti, korelacija i prostornih trendova. Najviše koncentracije uočene su za Bi (prosječno 98,81 mg/l; maksimalno 610,4 mg/l), W (prosječno 28,68 mg/l) i Co (prosječno 28,47 mg/l), sa znatnom varijabilnosti kroz horizonte. Korelacijska analiza otkrila je snažne pozitivne odnose između nekoliko elemenata, kao što su W-V ($r = 0,70$), W-Ge ($r = 0,65$) i Bi-W ($r = 0,60$), što upućuje na moguće zajedničko geološko podrijetlo. Rezultati istraživanja ističu potencijal za održivi oporavak strateških elemenata iz Trepčinih polimetalnih rudnih zona i naglašavaju važnost rudnika ne samo za tradicionalne metale već i za kritične sirovine bitne za niskougljične i visokotehnološke industrije.

Ključne riječi:

statistika, geostatistika, prostorno, raspodjela, TKE, Trepča, rudnik

Author's contribution

Berat Sinani (PhD Cand.): conceptualization; software; investigation; methodology; writing – original draft. **Blazo Boev** (Prof. Dr.): investigation; methodology; review and editing the paper. **Arianit Reka** (Prof. Dr.): data curation; validation; writing - review & editing. **Bahri Sinani** (PhD Cand.): investigation, software, visualization; **Ivan Boev** (Prof. Dr.): conceptualization; supervision; validation; writing, reviewing and editing the paper.

Numerical Modelling of Slope Stability for a Placer Deposit: Case Study of the Motronivskyi Open-Pit Mine, Ukraine

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Oleksandr Kovrov^{1*} , Borys Sobko² 

¹ Department of Ecology and Technologies of Environmental Protection, Dnipro University of Technology, Dmytra Yavornytskoho av. 19, Dnipro, 49005, Ukraine.

² Department of Surface Mining, Dnipro University of Technology, Dmytra Yavornytskoho av. 19, Dnipro, 49005, Ukraine.

Abstract

Open-pit development of placer deposits in moisture-sensitive, layered sediments requires slope designs that explicitly account for transient hydrology. This study assesses the stability of the eastern non-working wall at the Motronivskyi open-pit mine at Malyshevske zircon-rutile-ilmenite placer deposit (Vilnohirsk, Ukraine) composed of loams, clays, and Sarmatian sands. The research integrated engineering-geological survey data with stratigraphy and laboratory-measured strength parameters for “Northern”, “Central”, and “Southern” pit-wall profiles considering their geometry and hydrogeologic conditions. Numerical analyses used the Phase2 (Rocscience Inc.) finite-element method with a Mohr-Coulomb model and shear-strength reduction to obtain safety factors supported by a classification of landslide hazard levels. Under natural moisture, the safety factor values indicate generally stable conditions: “Northern” – 1.65, “Central” – 1.52, and “Southern” – 1.62. When water-saturated rock massif due to rainfall impact or groundwater rise, the safety factors drop to 1.20, 1.05, and 1.18, respectively. The analysis of shear strains and total displacements in the rock mass represents how wetting sharply lowers effective strength and shifts failure modes from shallow sloughing to coherent bench-scale slides, which can guide operational slope design and water-management strategies in similar placer-deposit settings.

Keywords:

open-pit mine; placer deposit; slope stability; numerical analyses; safety factor

1. Introduction

Optimizing parameters of quarry slopes and sides is an important technological task in the surface mining of mineral deposits (Sobko et al., 2022; Anisimov, 2015). As the steepness of the slope increases, the tangential (shear) stresses increase as well, and when they reach values that exceed the limit of the rock shear resistance, slope failure occurs with a certain displacement of the rock mass along the failure surface (Cherep, 2024; Moldabayev et al., 2021; Rakishev et al., 2014;). In addition to geometric parameters, rock properties, groundwater flow, hydrogeological characteristics of the deposit, and technological factors significantly affect the slope stability (Kovrov et al., 2016; Sdvizhkova et al., 2014). The continuous geotechnical monitoring consists of a set of measures to maintain slopes, pit sides, and overburden dumps in a stable state by changing their geometry and considering structural features of the rock massif and its variable physical and mechanical proper-

ties, hydrogeological and technogenic factors, etc. (Adamchuk et al., 2023; Anisimova et al., 2022; Babii et al., 2019; Chetverik et al., 2013; Chetveryk et al., 2017; Shashenko et al., 2019).

Open-pit mining of placer deposits commonly involves excavation through weakly consolidated, often stratified sediments (sand, gravel, silt, loam, and clay lenses). These deposits are highly sensitive to changes in moisture: infiltration from precipitation and changes to local hydrology substantially affect matric suction and pore-water pressure, which in turn control effective stress and shear strength of slope materials (Li et al., 2024; Yang et al., 2023). Recent studies emphasize the dominant role of transient hydrology in triggering slope failures in soft sediments and in open-pit settings (Babets et al., 2023; Shapoval et al., 2020). Placer deposits typically present strong stratigraphic contrasts including permeable sands and overlying less permeable silts or clays that create water tables, lateral seepage, and concentrated pore-pressure zones that commonly act as slip surfaces or trigger zones for slopes failures (Belay et al., 2025; Fredlund & Rahardjo, 1993).

Excavation changes hydraulic boundaries and may create perched water or concentrate lateral seepage at low-permeability interfaces, promoting deep or planar

* Corresponding author: Oleksandr Kovrov

e-mail address: kovralex1@gmail.com

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sliding. Field and numerical case studies for open pits show that mining-rainfall coupling can nonlinearly amplify deformation and accelerate slope failure (Rezaei et al., 2024; Li et al., 2024). These case studies of placer and other soft-rock open pits underline the importance of layered geometry and transient pore-pressure accumulation in determining failure type and timing.

Slope stability issues gain more importance at quarries with worked-out soft overburdened rocks. Thus, the development of placer deposits of titanium-zirconium ores, which are a valuable strategic raw material in Ukraine, is complicated by a complex of geological, hydrogeological, and man-made factors that affect mining technology (Lozhnikov et al., 2024). The substantiation of reducing the safety factor of the open pit side by only 5% allows to reduce the volume of overburdened rocks and the area of the pit from 1.5 to 20%, depending on the mining and geological conditions of the mineral deposit. It is also known that in quarries with a depth of up to 300 m, an increase in the resulting angle of inclination of the side by 3–4° allows to reduce the volume of overburden to 10–11 million m³ per 1 km of the working front, which increases the overall efficiency of surface mining operations (Kovrov et al., 2020).

Therefore, ensuring the stability of slopes and sides of pits during the development of mineral deposits is an element of technological and environmental safety in the context of the national strategies for sustainable development (Pivnyak et al., 2013; Saik et al., 2023; Cherep, 2024; Prokopenko et al., 2021).

Malyshevske deposit of zircon-rutile-ilmenite placer ore is located northeast of the city of Vilnohirsk (Central Ukraine) and developed via surface mining. The technological feature of this deposit is characterized by complicated and variable mining and geological conditions of development. Considering the hydrogeological conditions and water-saturated rock massif, there is a danger of landslides on the pit slopes and in the vicinity of overburdened heaps. A comprehensive geomechanical assessment of the slope stability and prognosis of landslide potential risks serve as a basis for safe and effective open pit mining technology (Sobko, 2008).

Despite numerous publications devoted to open-pit mining at the Malyshevske placer deposit, the integrated consideration of hydrogeological conditions and transient changes in the moisture state of layered soft rocks (loams, clays, and sands) and their coupled influence on pit-slope stability remains insufficiently investigated. This study addresses this gap by combining site-specific stratigraphy and laboratory-derived “strength-deformation” parameters with FEM-based shear-strength reduction analyses for three representative profiles of the eastern non-working wall at the Motronivskyi open-pit mine under natural-moisture and water-saturated conditions.

The purpose of the study is to determine the stability parameters of the slopes of the eastern non-working wall of the Motronivskyi open-pit mine by analyzing its three representative slope profiles (“Northern”, “Central”, and “Southern”) considering the geometry of slopes, physi-

cal and mechanical properties of soft sedimentary rocks, hydrogeological characteristics under natural-moisture and water-saturated conditions.

2. Methods

To evaluate the geomechanical stability of slopes at the open pit while developing the ore deposit, the data of engineering and geological surveys, technological schemes of surface mining operations, and physical-mechanical properties of sedimentary rocks were used. The finite element analysis module of the Phase2 software by Rocscience Inc. was applied for numerical simulation of slope stability. The maximum shear strains in the slopes are calculated according to the following expression:

$$\varepsilon_{\max} = \frac{\varepsilon_1 - \varepsilon_3}{2}, \quad (1)$$

Where:

ε_1 – maximum and minimum main deformations (dimensionless),

ε_3 – maximum and minimum main deformations (dimensionless).

The ε_1 and ε_3 correspond to the values of the maximum and minimum stresses σ_1 and σ_3 (RS2 Tutorials, 2021).

The empirical classification of maximum shear strain values which occur in slopes, quarry sides, and overburdened dumps (see Table 1) gives a range of landslide hazard effects due to the influence of natural or man-made instability factors (Kovrov et al., 2020).

This research considers a scenario of water saturation of the rock massif due to rainfall infiltration or groundwater table rise. In particular, the increase of water saturation in the massif of soft sedimentary rocks can lead to a decrease in the physical and mechanical properties of loams and clays, and the creation of unfavourable conditions for development of slip surface and landslide processes. The Mohr-Coulomb failure criterion was selected for evaluation of plastic deformations and shear strains in the rock massif.

In analytical studies of the parameters of the elastic-plastic state, Mohr's strength criterion with a linear envelope of the principal stresses circles is most often used. The physical and mechanical characteristics included in the condition of strength are the angle of internal friction ρ and cohesion C , or uniaxial compressive strength R_c and uniaxial tensile strength R_p .

When estimating the limit state, the Mohr-Coulomb linear relation is expressed as:

$$\tau = C + \sigma_n \tan \varphi, \quad (2)$$

Where:

τ – shear stress (kPa),

σ_n – normal stress (kPa),

C – cohesion (kPa),

φ – angle of internal friction (degree).

Table 1: Classification of maximum shear strains in the slopes and sides of quarries

Maximum shear strains	Values, dimensionless	Landslide hazard effects
Low	$\varepsilon_{\max} \leq 0.05$	Slight shifts or subsidence in the massif, local surface sliding processes on slopes
Moderate	$0.05 < \varepsilon_{\max} \leq 0.1$	Horizontal displacements dominate over vertical ones, zonal sliding processes and visible cracks in slopes
Average	$0.1 < \varepsilon_{\max} \leq 0.5$	Formation of landslide areas with local sliding surfaces, slope failure, rockfalls (rockflows) and landslides on slip surface
Critical	$0.5 < \varepsilon_{\max} \leq 1.0$	The formation of areas with continuous sliding surfaces and rock failure phenomena with landslides
Catastrophic	$\varepsilon_{\max} \geq 1.0$	Large-scale landslides in one or more slopes (sides) of an open pit

Table 2: Classification of landslide hazard of slopes and sides of quarries by SRF value

Levels of landslide hazard in slopes	SRF range	Classification of landslide hazard
Low	$\text{SRF} \geq 1.5$	I
Moderate	$1.2 < \text{SRF} \leq 1.5$	II
Average	$1.1 < \text{SRF} \leq 1.2$	III
Increased	$1.0 < \text{SRF} \leq 1.1$	IV
Critical	$\text{SRF} = 1.0$	V

The Shear Strength Reduction (SSR) function in Phase2 allows for the automatic performance of a finite-element analysis and the calculation of the critical Strength Reduction Factor (SRF) for the selected model, which is equivalent to the slope safety factor (SF). The algorithm for calculating the SRF values includes an iterative calculation of the strength in all elements within the slope model with the help of stepwise loading. It involves iteratively reducing the shear strength parameters (C and φ) of all materials until numerical non-convergence occurs, indicating slope failure. The factor by which strength is reduced at failure is the SRF. As a result, the stresses on the slope reach the shear strength limit and the rock mass displacement occurs. The process of SRF calculations is repeated until the moment of loss of the stable state by the slope that is graphically expressed in the form of the sliding surface in the rock massif (RS2 Tutorials, 2021).

The geomechanical criterion for assessing the state of natural slopes and man-made slopes is the SF or its equivalent represented as Strength Reduction Factor (SRF), which represents the ratio of the retaining F_{ret} and shearing F_{shear} forces in the slope area along the potential sliding surface, i.e. $\text{SRF} = F_{\text{ret}} / F_{\text{shear}}$. There are three possible states of slope stability, namely: if $\text{SRF} > 1.0$, the slope is stable; $\text{SRF} = 1.0$ corresponds to the limit state and initiation of a slope deformation, and $\text{SRF} < 1.0$ indicates the full failure with a landslide phenomenon.

The level of landslide hazard on the selected profiles of the eastern non-working edge of the quarry is determined by the results of calculating the SRF and comparing it with the landslide hazard scale (see Table 2).

The proposed classification makes it possible to determine the level of landslide hazard for natural and technogenic slopes and predict possible shear strains and displacements in the rock massif for further development of effective anti-landslides engineering protective measures.

Laboratory testing was performed on representative samples of loams, clays, and sand collected from the stratigraphic layers of sedimentary rocks. Bulk density and natural moisture content were determined by gravimetric methods, while shear strength parameters (C and φ) were obtained from standard shear tests. Deformation modulus E and Poisson's ratio ν were derived from "stress-strain" curves during standard compression tests. The resulting parameters were used as Mohr-Coulomb inputs for the numerical models.

3. Results

3.1. General geological data and physical properties of sedimentary rocks

The Malyshevske deposit of zircon-rutile-ilmenite placer ore is located northeast of the city of Vilnohirsk (Verkhnyodniprovskiy District, Dnipropetrovsk oblast, Ukraine) and developed via surface mining (see Figure 1). The geographical coordinates of the investigated site are 48.5707° north latitude and 33.9864° east longitude. The technological feature of this deposit is characterized by variable mining and geological conditions. Quaternary and Neogene rocks are involved in the geological structure of this territory. Soils of eolian-deluvial origin are presented by tough-plastic and soft-plastic loams. Hard, macroporous, brownish-yellow, pale-yellow loams are widely distributed, and they lie under the soil-vegetation layer. The thickness of loams of a solid consistency varies from 8-9 m. Plastic brownish-yellow loams lie under hard loams at a depth of 9-10 m. Deluvial soils are represented by red-brown clays that lie below the layer of eolian-deluvial soils. The thickness of clay layers achieves at least 10 m (Sobko, 2008).

The physical and mechanical properties of soils and soft sedimentary rocks (see Table 3) presented in the geological structure of the placer ore deposit as separate



Figure 1: Site location: a. Map of Ukraine (Retrieved from: <https://www.mappr.co/location/ukraine/>).
 b. Vilnohirska City area (Retrieved from: <https://www.mapquest.com/ua/dnipropetrovska-oblast/vilnohirska-364473355>).
 c. Motronivskyi open-pit mine location, Ukraine (48.5707° N and 33.9864° E), retrieved from Google maps.

engineering and geological elements (EGE) are obtained by standard geomechanical test techniques.

The results of studies of the physical and mechanical properties of the sands of the Sarmatian layer lying at the elevation points +110.0 m, +105.0 m, and +100.0 m are presented in **Table 4**.

According to the results of engineering and geological measurements, it was determined that Sarmatian sands have variable values of the angle of internal friction and specific cohesion, which depends on the water saturation of geological layers due to the rise of groundwater level.

The slope stability calculations were carried out for 3 profiles of the eastern non-working side of the Motronivskyi open pit mine of the Malyshevske placer deposit, which are named as “Northern”, “Central” and “Southern” (see **Figure 2**).

Boundary conditions for the geometry of the selected profiles of the open pit are as follows:

“Northern” – 121 m from the upper crest of the first bench to the toe (elevation +105 m), and the distance of 133 m to the protective bench. The resulting angle is 16° (to the protective bench) and 18° (to the toe).

“Central” – 127 m from the upper crest of the first bench to the toe (elevation +105 m), and the distance of 138 m to the protective bench. The resulting angle is between 18° (to the protective bench) and 20° (to the toe).

“Southern” – 143 m from the upper crest of the first bench to the toe (elevation +105 m), and the distance of 167 m to the protective bench. The resulting angle is 16° (to the protective bench) and 19° (to the toe).

Slope stability assessment for the eastern non-working side of the Motronivskyi open pit is carried out with

Table 3: Physical and mechanical properties of soils and soft sedimentary rocks

Engineering and geological elements (EGE)	Soil specific gravity γ , kN/m ³ *	Specific cohesion C , kPa*	Angle of internal friction, ϕ , degree*	Deformation modulus E , kPa*	Poisson's ratio μ , dimensionless
EGE-1 – Soil-vegetation layer	15.5/14.0	-	-	$\frac{2800}{1200}$	0.35
EGE-2 – Hard, macroporous, brownish-yellow loams	16.0/15.8	16/7	16/14	$\frac{6800}{4200}$	0.35
EGE-3 – Rigid loams	19.7/19.5	27/14	22/18	$\frac{25000}{18000}$	0.35
EGE-4 – Soft plastic loams	19.6/19.5	22/16	18/15	$\frac{20000}{13000}$	0.35
EGE-5 – Red-brown clays	19.5/19.2	51/22	20/16	$\frac{35000}{20000}$	0.42
EGE-6 – Sands	19.8/19.0	2/0	31/12	$\frac{40000}{25000}$	0.30

* Indicators of sedimentary rock properties in natural (numerator) and water-saturated state (denominator)

Table 4: Physical and mechanical properties of Sarmatian sands

Engineering and geological elements (EGE)	Soil specific gravity γ , kN/m ³ *	Specific cohesion C , kPa*	Angle of internal friction, ϕ , degree*	Deformation modulus E , kPa*	Poisson's ratio μ , dimensionless
Fine sand	Elevation mark +110 m				
	16.7/16.7	39/18	30/25	$\frac{25000}{18000}$	0.3
	Elevation mark +105 m				
	17.1/17.1	35/17	31/28	$\frac{25000}{18000}$	0.3
	Elevation mark +100 m				
	19.7/19.7	39/32	25/23	$\frac{25000}{18000}$	0.3

* Indicators of sedimentary rock properties in natural (numerator) and water-saturated state (denominator)

consideration of geometric parameters, physical and mechanical properties of soft sedimentary rocks.

3.2. Slope stability assessment for selected quarry profiles

3.2.1. “Northern” profile

The “Northern” profile of the eastern non-working side of the pit side consists of 5 benches with Quaternary deposits like loams and clays, and Sarmatian sands (see **Figure 3**). The geological layers have a slight inclination in the direction of the quarry working area. The absolute elevation mark of the day surface is +146 m, the level of the lower bench toe is +105 m. The width of the benches varies in the range of 10-28 m. The angle of inclination of the bench slopes is up to 56°.

The “Northern” profile has SRF = 1.65 under natural moisture conditions. The level of landslide hazard is low. Shear strains in the slope rock massif are insignificant: $\varepsilon_{\max} = 0.05-0.07$ (see **Figure 4**). The layers of loam on the 2nd and 3rd benches are subjected to the greatest

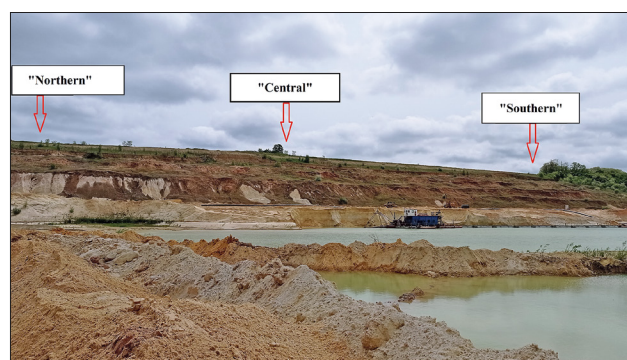


Figure 2: General view of the Eastern non-working side of the open pit with selected profiles: “Northern”, “Central”, “Southern”

deformations in the form of rockslide without the formation of a continuous sliding surface. Total displacements in the massif of rocks are also insignificant $U_{x-y} = 0.2-0.3$ m, which do not pose a threat of rock displacement.

Under conditions of the slope water saturation due to atmospheric precipitation or hydrogeological factors,

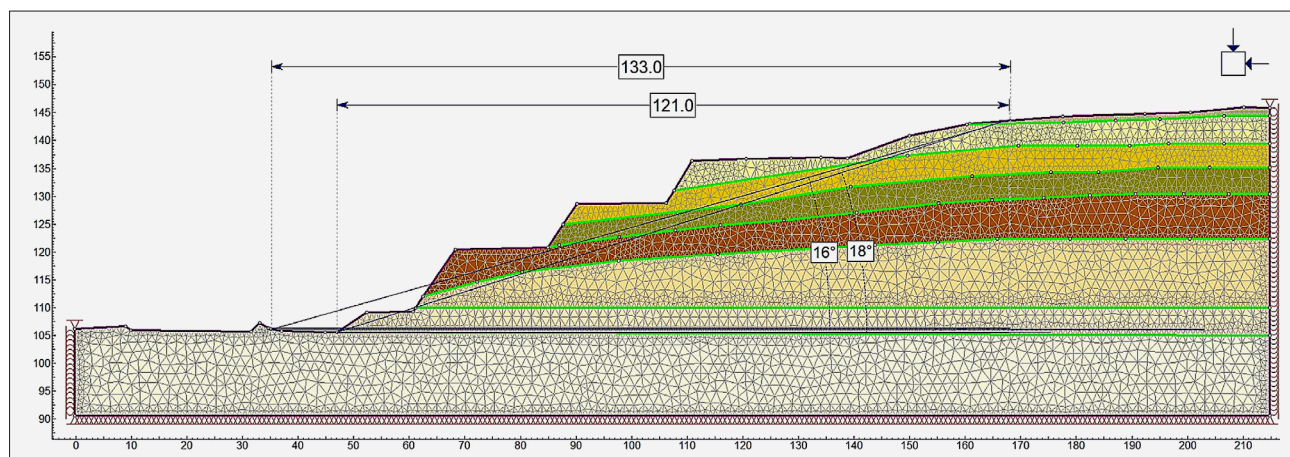


Figure 3: "Northern" profile of the eastern non-working side of the quarry

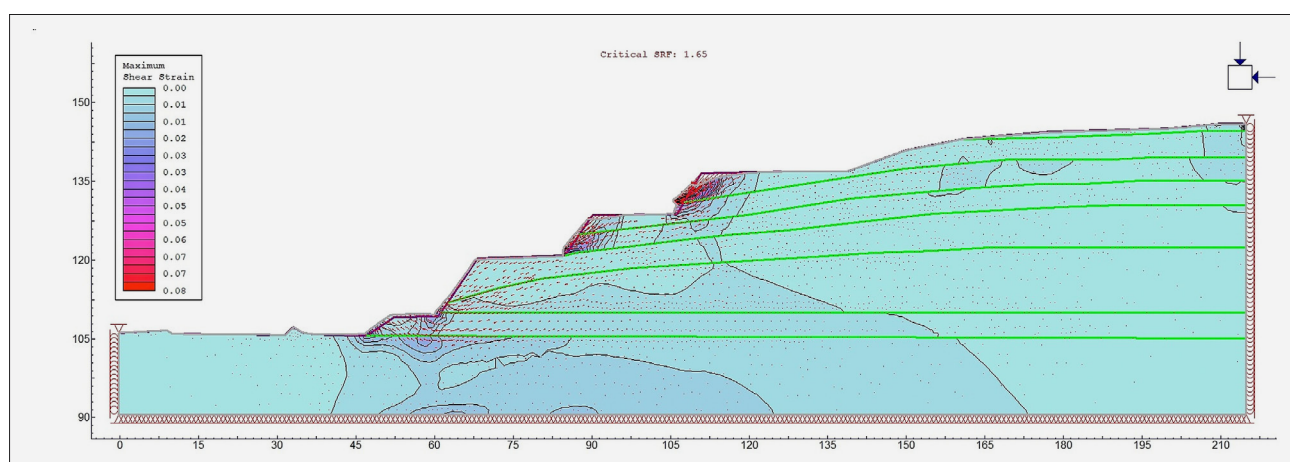


Figure 4: General shear deformations along the "Northern" profile

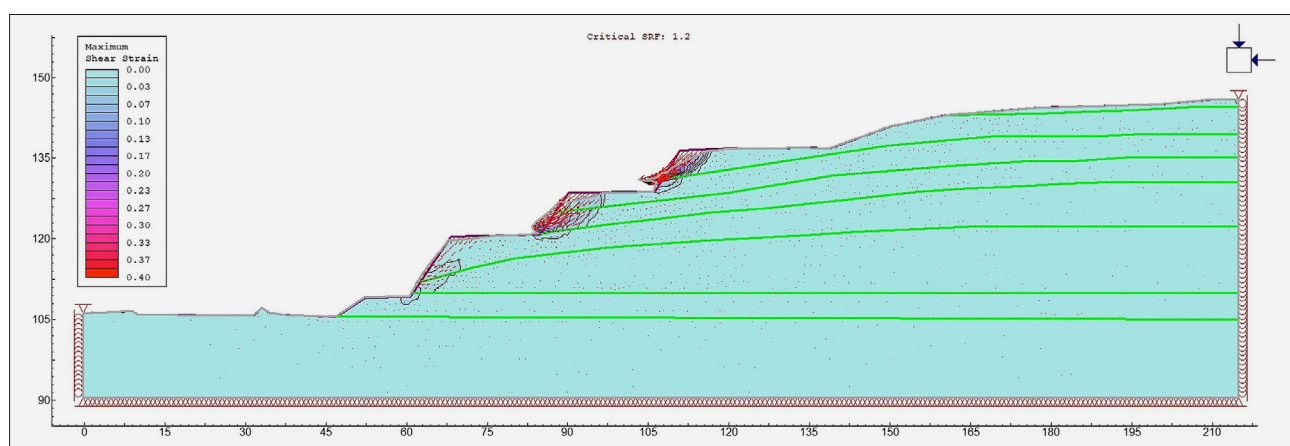


Figure 5: Shear strains in the water-saturated slope along the "Northern" profile

the strength properties of the rock massif and the stability of the pit side decrease. In the water-saturated massif $\text{SRF} = 1.20$. The level of landslide hazard is average.

Shear deformations in the slope massif of rocks increase and become moderate: $\varepsilon_{\max} = 0.23-0.37$ (see **Figure 5**). The loam layers on the 2nd and 3rd benches undergo the greatest deformations in the form of landslides with the formation of local sliding surfaces. However,

the landslide masses are maximally displaced by 3-6 m on the lower benches. A continuous sliding surface is not formed and the side of the quarry remains in a stable state.

Total displacements in the massif of rocks in the water-saturated massif increase to $U_{x-y} = 0.6-0.9$ m in the form of local rockslides in 2nd and 3rd slopes. On the 4th bench, at the contact of layers of red-brown clays and

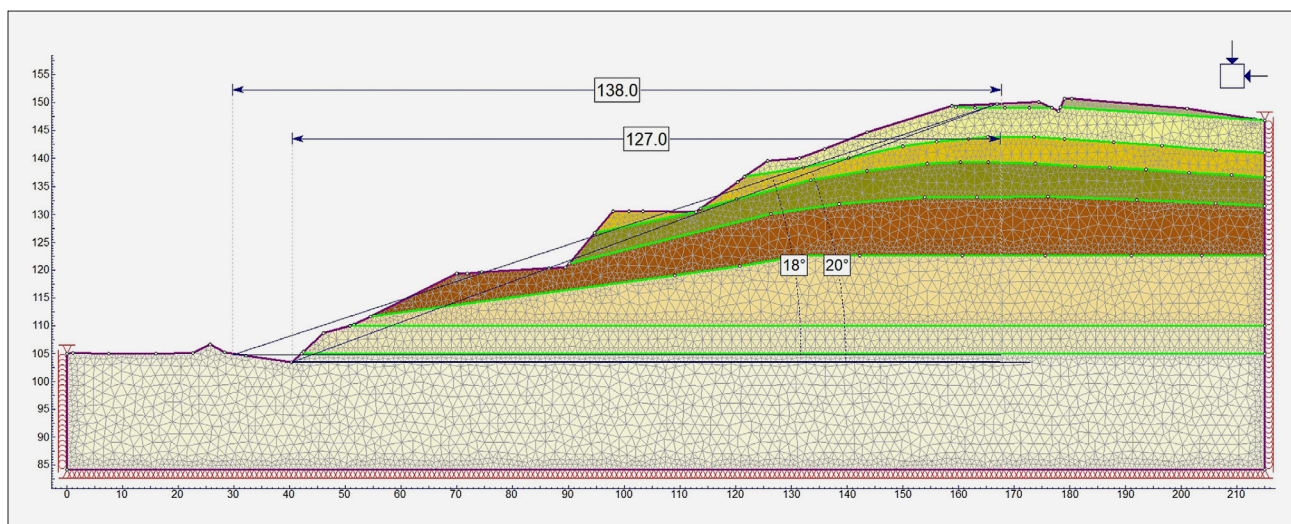


Figure 6: "Central" profile of the eastern non-working side of the quarry

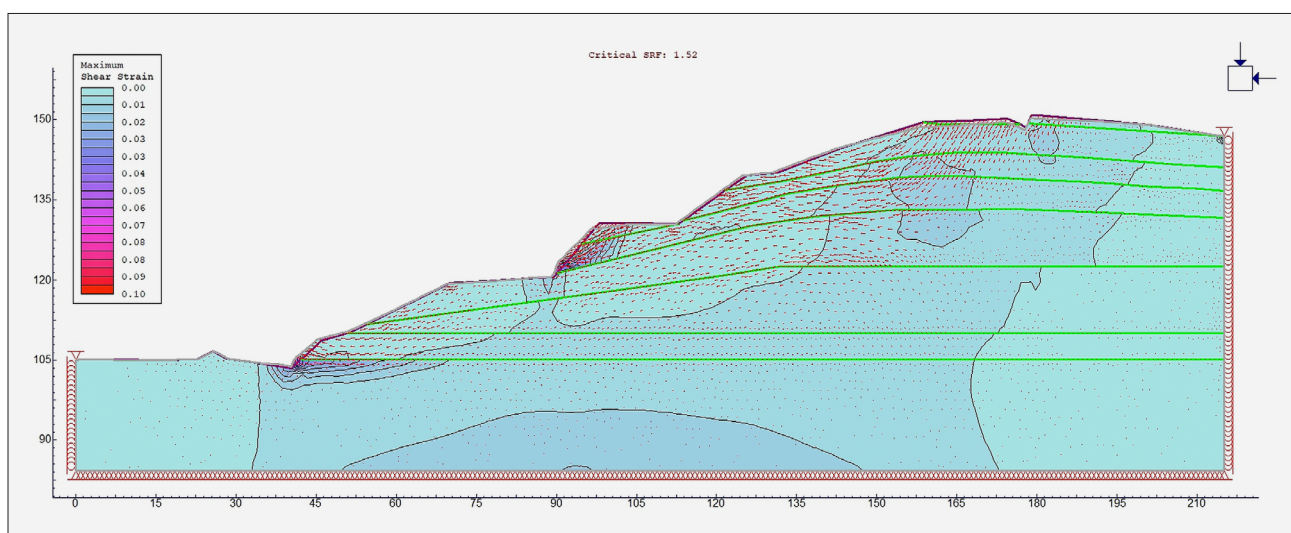


Figure 7: General shear deformations along the "Central" profile

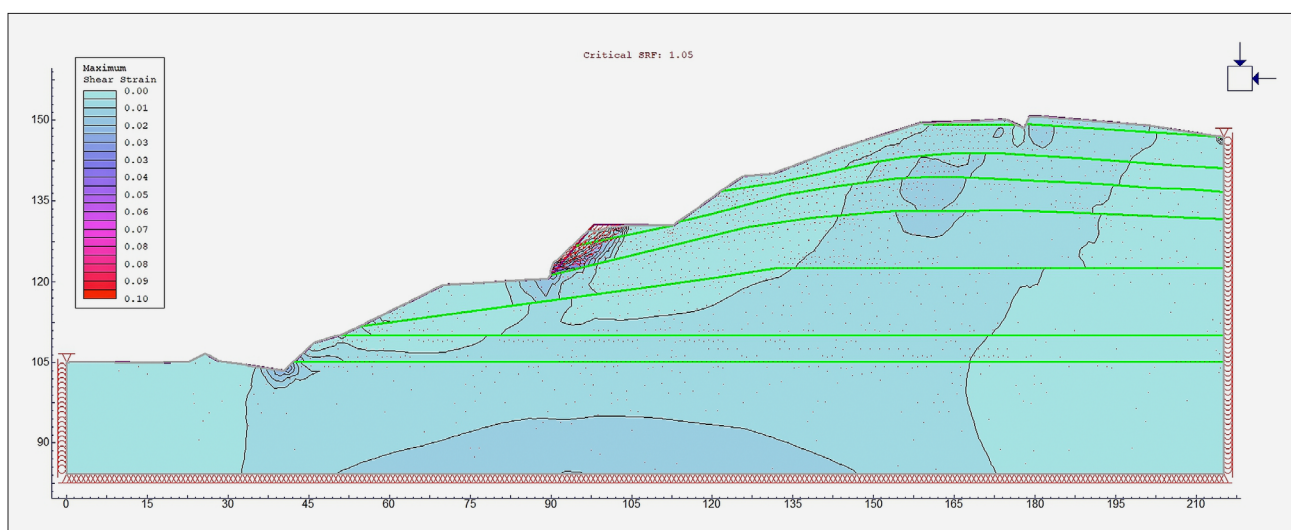


Figure 8: Shear deformations in the water-saturated massif along the "Central" profile

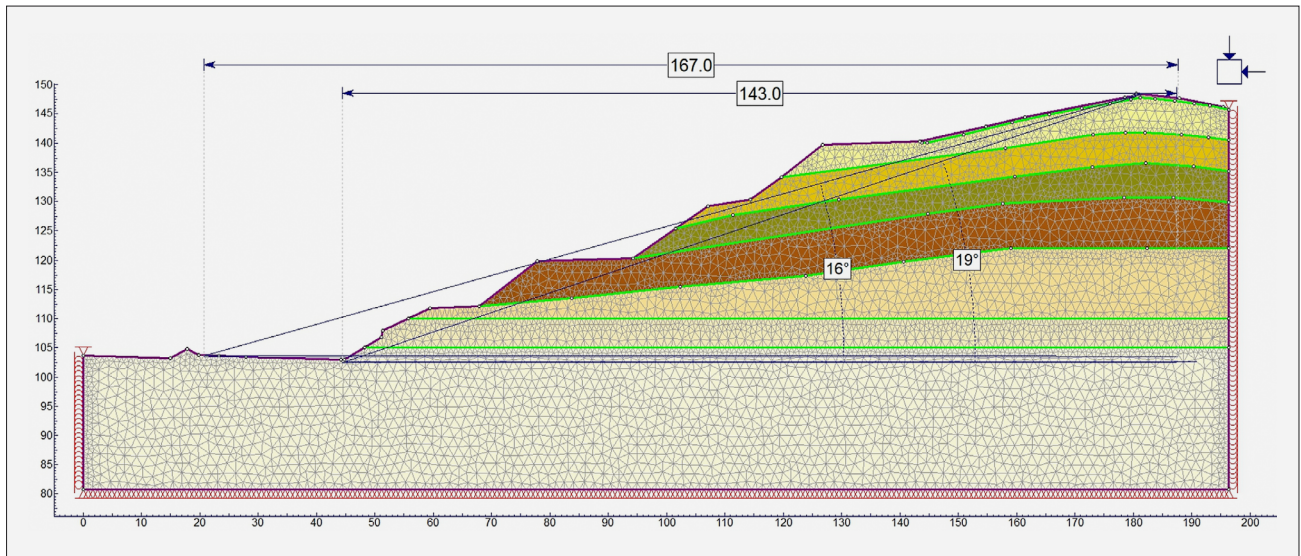


Figure 9: "Southern" profile of the eastern non-working side of the quarry

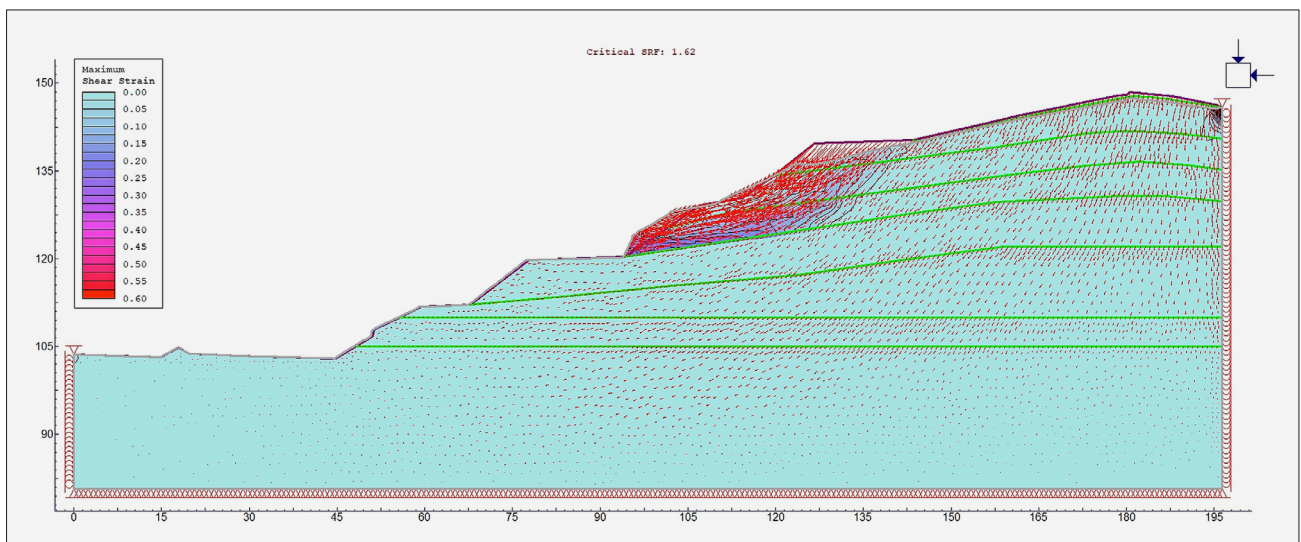


Figure 10: General shear deformations along the "Southern" profile

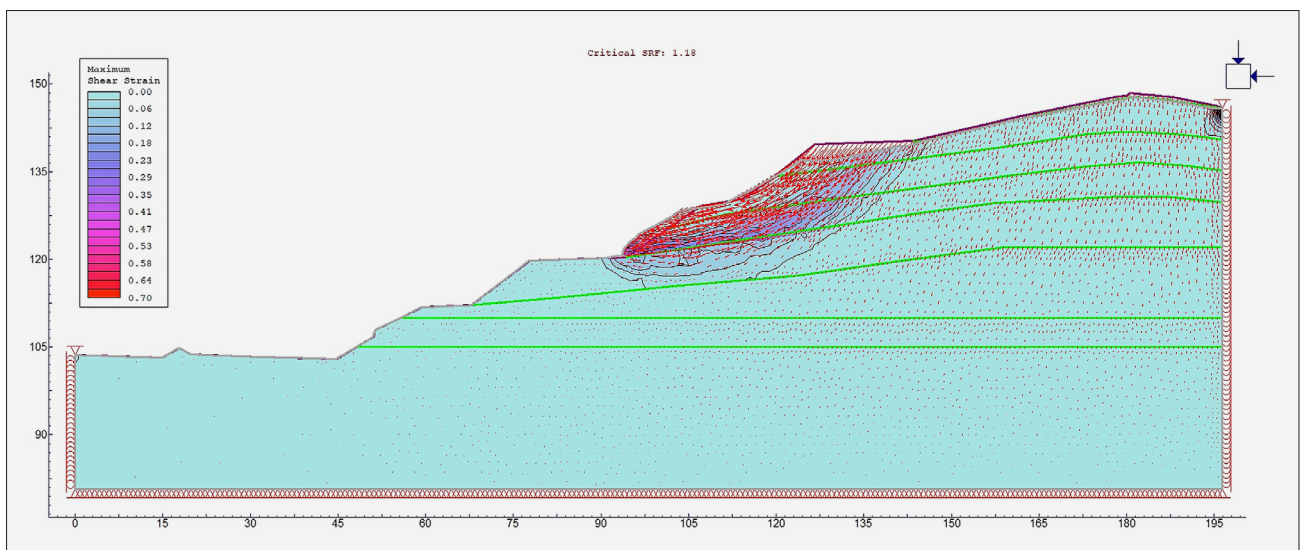


Figure 11: Shear deformations in the water-saturated slope massif along the "Southern" profile

Sarmatian sands, minor screes may occur, which do not pose a threat of landslide in the direction of the protective bench.

3.2.2. “Central” profile

The “Central” profile of the eastern non-working side of the quarry consists of 5 benches and includes Quaternary deposits of loams, clays and Sarmatian sands, the layers of which have an inclination in the direction of the mine working (see **Figure 6**).

The absolute elevation mark is +150 m, the level of the lower bench toe is +105 m. The width of the benches varies in the range of 10-28 m. The angle of inclination of the bench slopes is up to 56°.

The “Central” profile has $SRF = 1.52$ under conditions of natural rock mass moisture. The level of landslide hazard is low. Shear deformations in the adjacent massif of rocks are insignificant and $\varepsilon_{\max} = 0.07-0.10$ (see **Figure 7**). The third bench undergoes landslide deformations at the contact of loams and red-brown clays without the formation of a continuous sliding surface.

The general displacements in the massif of rocks extend for the entire open pit side, but their values are insignificant and $U_{x-y} = 0.10-0.16$ m, which does not pose a threat of a landslide.

Under conditions of water-saturated slope massif due to atmospheric precipitation or hydrogeological factors, the profile “Central” has $SRF = 1.05$. The level of landslide hazard is high. Shear deformations in the slope increase and become moderate: $\varepsilon_{\max} = 0.08-0.10$ (see **Figure 8**). The 3rd bench undergoes the largest deformations in the form of landslides with the formation of a local sliding surface. However, the sliding masses can move on the lower bench 3-4 m. A solid sliding surface is not formed, and the side of the quarry remains in a stable state.

The total displacements in the massif of rocks in the water-saturated massif increase to $U_{x-y} = 0.08...0.13$ m, however, a slight local shift in the form of a rockslide is possible only in the 3rd slope. The rest of the benches are in extremely stable condition, even under the conditions of an overmoistened massif.

3.2.3. “Southern” profile

The “Southern” profile of the eastern non-working side of the quarry side consists of 5 benches and includes layers of loams, clays and Sarmatian sands, the layers of which have a slight inclination in the direction of the mine working (see **Figure 9**). The absolute elevation mark of the day surface is +149 m, the point of the lower bench toe is +105 m. The width of benches varies in the range of 8-15 m. The angle of slopes inclination of benches is up to 45°.

The “Southern” profile has $SRF = 1.62$ under conditions of natural rock-mass moisture, corresponding to a low hazard level (see **Table 2**). Although localised maximum shear strains reach average-to-critical values ($\varepsilon_{\max}$

Table 5: Results of the slope stability simulation of the pit side according to selected profiles

Profiles of the quarry side	Shear reduction factor of the quarry side	
	with a natural moisture	in a water-saturated rock massif
“Northern”	1.65	1.20
“Central”	1.52	1.05
“Southern”	1.62	1.18

= 0.40–0.60; **Table 1**) and delineate a potential continuous sliding surface of total length 35–40 m within the loam layers, the global SRF indicates that the modelled slope remains in overall equilibrium under these boundary conditions. It means that high local strains can coexist with a globally stable SRF due to localized plasticity of soft sedimentary rocks.

The level of landslide hazard for the “Southern” profile is low. Shear deformations in the adjacent massif of rocks are average: $\varepsilon_{\max} = 0.40-0.60$ (see **Figure 10**). The 2nd and 3rd benches undergo deformations, in which a continuous sliding surface can be formed as a solid surface with a total length of 35-40 m in the loam layers.

Total displacements in the slope massif along the “Southern” profile propagate almost on the entire open pit side but 2nd and 3rd benches deserve special attention, in which there is a high probability of a solid landslide body formation with significant displacements $U_{x-y} = 1.28-1.70$ m. The lower benches remain in a relatively stable state.

Under conditions of the slope massif water saturation due to atmospheric precipitation or hydrogeological factors along the “Southern” profile, the $SRF = 1.18$. The level of landslide hazard is average. Shear deformations in the slope increase from medium to significant: $\varepsilon_{\max} = 0.47-0.70$ (see **Figure 11**). The largest deformations remain in the 2nd and 3rd benches in the loam layers in the form of landslides with the formation of a continuous sliding surface. The rest of the benches remain in a relatively stable state.

Total displacements in the water-saturated slope massif increase to the values of $U_{x-y} = 1.5-3.0$ m, which corresponds to the stage of a large-scale landslide up to 40 m along the quarry side. The rest of the benches are in boundary stable condition.

The results of numerical simulation of the open-pit stability are summarized in **Table 5**. Thus, the “Central” profile is the most prone to landslides, in which there is a threat of a large-scale landslide that can capture the 2nd and 3rd benches of the pit side. In general, the eastern non-working side of the Motronivskyi quarry is in a stable state, which depends mainly on the slope geometry and the rock water saturation effects.

A protective bench with a height of 2 m along the whole pit side was filled up as an anti-landslide measure, to prevent the mining area from sliding rock mass under

conditions of water saturation soft sedimentary rocks. The implementation of additional anti-landslide measures on the studied site of the eastern non-working side of the Motronivskyi quarry is not required, except for constant hydrogeological monitoring.

4. Discussion

The reduction in SRF after “water saturation” in all investigated slopes is consistent with classical laws of soil mechanics. Rainfall infiltration and groundwater rise reduce matric suction, increase pore-water pressure, and reduce apparent cohesion and frictional resistance of fine and mixed sediments. This behaviour is reported in many experimental and numerical studies and is frequently the dominant mechanism for rainfall-triggered instability in open-pit and natural slopes (Fredlund & Rahardjo, 1993; Li et al., 2024).

The drop from 1.65 to 1.20 in the slope of “Northern” profile is substantial: it represents the decrease from a low to average level of landslide hazard in the slope when additional destabilising effects of further water saturation could provoke larger failures. Strains $\varepsilon_{\max}$ rising from ~ 0.05 – 0.07 to ~ 0.23 – 0.37 (a ~ 4 – $6\times$ increase) indicates a transition from mostly elastic with small-strain response toward significant inelastic deformation and localized yielding in the loam and clay layers of benches 2–3. In many numerical and field studies, small strains (order 10^{-3} – 10^{-2}) correspond to elastic behaviour with negligible permanent displacement; larger shear strains (order 10^{-2} – 10^{-1} and above) mark plastic yielding, strain-softening or development of local failure zones (Coetsee et al. 2020).

Thus observed strain growth is a clear numerical signature of incipient local failure concentrated on weaker benches (2 and 3). Displacements U growing from 0.2–0.3 m to 0.6–0.9 m is consistent with field observations and numerical simulations of rainfall-induced shallow slides and bench-scale sloughing in open pits. Many case studies show that rainfall or pore-pressure increase leads to local displacements on the order of decimetres to metres depending on the geometry and material (Tang et al., 2024; Zhang et al., 2024). The magnitude fits the class of local bench failures rather than full-height slope collapses which are typically associated with through-going slip surfaces in much larger volumes.

The modelling shows the formation of local sliding surfaces in loam layers of 2nd and 3rd benches but not a continuous basal slip. The weaker loam layers are discontinuous or thin and occur at bench levels where localized saturation and loss of suction produce weak, shallow slip planes (typical in layered placer or colluvial deposits). The clay or low-permeability interbeds may impede full-depth saturation of the entire slope, producing perched zones that drive bench-scale failures rather than deep basal slides. Bench geometry (bench widths 10–28 m, steep bench face angles up to 56°) promotes

shallow sloughing at the face while the overall mass remains intact until a continuous slip plane forms. Similar patterns of shallow bench sloughing and local translational slides under wetting are well documented in open-pit and quarry case studies (Tang et al., 2024; Chen et al., 2023).

The “Central” profile with SRF = 1.52 under natural moisture indicates a low level of landslide hazard in the slope with small shear strains and deformations. Under the water-saturated condition SRF falls to 1.05, i.e. almost to the failure threshold (SRF ≈ 1.0). This large reduction with $\approx 30\%$ of relative drop is typical of variably saturated slopes where water saturation diminishes matric suction and raises pore pressures, thereby reducing apparent cohesion and effective stress (Fredlund & Rahardjo, 1993).

Shear strains values $\varepsilon_{\max}$ (0.07–0.10) localised at bench 3 imply small-to-moderate plastic strains concentrated at contacts between loams and clays on bench 3. Numerically, such strains indicate incipient to developing local yielding rather than wholesale deep-seated failure. This matches many open-pit case studies where weak interbeds or discontinuous loam layers produce local translational or bench-scale slides before the formation of a continuous basal slip surface (Moradi et al., 2024; Chen et al., 2023). Displacement magnitudes remain modest (0.08–0.16 m) that are consistent with local sloughing, bench-scale movement or limited rockslide blocks, not with full-height slope collapse. Such decimetre-scale movements under wetting are typical for layered, weakly consolidated quarry faces (Tang et al., 2024; Li et al., 2024).

The observed behaviour is due to the loss of matric suction with increasing pore pressure. Rainfall or hydraulic recharge reduces suction in the loam and sand units and raises pore pressures near the loam-clay contact; effective stress reduces and shear strength drops (Yeh et al., 2021). This single mechanism explains the SRF fall in the water-saturated scenario. The “Central” profile contains loams and red-brown clays, so perched water above clay lenses produces lateral seepage and concentration of pore pressure at the bench contacts (a common cause of localized planar slides in open pits). Bench 3 is the most affected because geometry and stratigraphy favour perched accumulation there. This mechanism is discussed in many slope case studies and numerical analyses. Since the result shows localised sliding rather than through-going basal failure, the clay layer(s) and stratigraphic arrangement likely prevented complete saturation of the deeper base of the slope, hence failure remains local. Similar behaviour is reported when permeability contrasts impede downward percolation and instead produce bench-scale instability (Yeh et al., 2021; Huang et al., 2025).

For the “Southern” profile the SRF = 1.62 indicates a low level of landslide hazard but vulnerable to changes because the slope already shows substantial shear defor-

mation indices ($\varepsilon_{\max}$ up to 0.60). The drop to $\text{SRF} = 1.18$ under increased saturation shows that the slope is hydrologically sensitive: moderate additional pore pressure increase or further weakening would approach failure ($\text{SRF} \approx 1$). This pattern presents a slope with a margin under dry conditions that is substantially reduced by wetting in variably saturated, layered sediments (Fredlund & Rahardjo, 1993; Li et al., 2024).

High shear deformation ($\varepsilon_{\max} \approx 0.40$ -0.70) magnitudes are substantial and indicate the development of broad plastic zones and strain localization. In practical terms, $\varepsilon_{\max} = 0.4$ -0.7 and correspond to major inelastic deformation and the formation of a coherent sliding mass in the loam layers of benches 2-3. Such behaviour predicts an already developing and potentially mobile slide mass. Similar strain indicators precede large bench slides in documented mine case histories (Tang et al., 2024; Chen et al., 2023). Displacements of $U_{x-y} \approx 1.28$ -3.0 m indicate large shallow and bench-scale landsliding. In an open-pit setting such movement typically results in bench collapse, loss of integrity, infrastructure damage at the toe, and serious safety risks. Many HM studies and field cases report similar metre-scale displacements where perched saturation and lateral seepage produce planar slides along weak interbeds (Li et al., 2024). The formation of a continuous sliding surface of 35-40 m length across benches 2-3 represents a coherent sliding body, not merely shallow sloughing. That the model predicts this under both natural and water-saturated states implies the geometry and stratigraphy are predisposed to translational sliding: thin, laterally continuous loam layers with low strength that dip unfavorably and receive concentrated infiltration or perched flow. Even though SRF under “natural” conditions exceeds 1.5, the combination of already large shear strains and the existence of a continuous weak layer make the “Southern” profile intrinsically vulnerable; additional wetting pushes it toward a large-scale bench slide.

Thus, the “Central” profile is most critical ($\text{SRF}=1.05$ when saturated), requiring the most vigilant water management and monitoring.

5. Conclusions

Slope stability in open-pit placer deposits composed of soft, moisture-sensitive sedimentary rocks is primarily a hydrology-controlled problem interconnected with rainfall infiltration, perched groundwater, and increases in pore-water pressure that causes instability phenomena. The results of slope stability assessment for the eastern non-working side of the Motronivskyi open pit of Malyshevske placer deposit allowed us to make the following suggestions.

1. The main factors of stability and sliding risk of benches and sides of the quarry are the geometry of slopes and benches, physical and mechanical properties of soft sedimentary rocks in natural conditions and the

water-saturated massif. The slope stability and landslide hazard assessment for the quarry sides was carried out based on the SRF calculated values and proposed landslide hazard scale.

2. For the “Northern” profile under the conditions of natural soil moisture $\text{SRF} = 1.65$. The level of landslide hazard is low. The total displacements in the massif of rocks are also insignificant $U_{x-y} = 0.2$ -0.3 m, which do not pose a rockslide threat. In the water-saturated massif the $\text{SRF} = 1.20$. The level of landslide hazard is average. General displacements in the rock massif in the water-saturated condition increase to the values of $U_{x-y} = 0.6$ -0.9 m in the form of overflows and landslides in slopes of 2nd and 3rd benches but do not pose a landslide threat in the direction of the protective bench.

3. For the “Central” profile under the conditions of natural soil moisture $\text{SRF} = 1.52$. The level of landslide hazard is low. The 3rd bench undergoes deformations in the form of overflows at the contact of loams and red-brown clays without the formation of a continuous sliding surface in the bench. The total displacements in the massif of rocks cover almost the entire massif, but their values are small $U_{x-y} = 0.10$ -0.16 m. Under water saturation conditions along the “Central” profile, the $\text{SRF} = 1.05$. The level of landslide hazard is high. Total displacements in the water-saturated massif are $U_{x-y} = 0.08$ -0.13 m, however, a continuous sliding surface is not formed, and the quarry side remains in a stable state.

4. For the “Southern” profile under the conditions of natural soil moisture $\text{SRF} = 1.62$. The level of landslide hazard is low. The 2nd and 3rd benches undergo deformations, in which a continuous sliding surface can be formed with a total length of the sliding body up to 35-40 m in the loam layers. Total displacements in the massif are $U_{x-y} = 1.28$ -1.70 m. In the water-saturated massif along the “Southern” profile the $\text{SRF} = 1.18$. The level of landslide hazard is average. The total displacements in the rock massif in the water-saturated massif increase to the values of $U_{x-y} = 1.5$ -3.0 m which corresponds to the stage of a large-scale displacement up to 40 m across the quarry side. The rest of the benches are in extremely stable condition.

5. Thus, the eastern non-working side of the Motronivskyi quarry is in a stable state, which depends mainly on the geometry parameters of the benches and the water saturation of the rock massif. The most landslide-prone is the “Central” profile which has a threat of a large-scale landslide on the 2nd and 3rd benches of the pit wall.

A protective bench with a height of 2 m along the whole pit side was filled up as an anti-landslide measure, to prevent the mining area from sliding rock mass under conditions of water saturation soft sedimentary rocks.

Therefore, the study demonstrates that transient saturation is the primary factor reducing the factor of safety from stable (1.52-1.65) to critical (1.05-1.20) levels in this placer deposit setting.

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SAŽETAK

Numeričko modeliranje stabilnosti kosina u nanosnome ležištu: studija slučaja površinskoga kopa Motronivsk, Ukrajina

Površinska eksploatacija nanosnih ležišta u slojevitim sedimentima osjetljivima na saturaciju vodom zahtijeva projektiranje kosina koje izričito uzima u obzir prolazne hidrološke uvjete. U radu se procjenjuje stabilnost neaktivnoga istočnog boka površinskoga kopa Motronivsk, koji se nalazi u ležištu cirkon-rutil-ilmenitnoga nanosnog tipa Mališevske (Vilnohirsk, Ukrajina), u kojemu prevladavaju ilovače, gline i sarmatski pijesci. Istraživanje objedinjuje podatke inženjersko-geoloških istraživanja sa stratigrafskim odnosima i laboratorijski određenim parametrima čvrstoće za profile „Sjeverni”, „Središnji” i „Južni” bok kopa, uzimajući u obzir njihovu geometriju i hidrogeološke uvjete. Numeričke analize provedene su metodom konačnih elemenata u programu Phase2 (Rocscience Inc.), primjenom Mohr-Coulombova modela te metode redukcije posmične čvrstoće za određivanje koeficijenta sigurnosti, uz pripadajuću klasifikaciju razina opasnosti od klizišta. U uvjetima prirodne vlažnosti dobivene vrijednosti koeficijenta sigurnosti upućuju na općenito stabilno stanje kosina: „Sjeverni” – 1,65, „Središnji” – 1,52 i „Južni” – 1,62. U slučaju zasićenja stijenske mase vodom uslijed oborina ili porasta razine podzemne vode koeficijenti sigurnosti smanjuju se na 1,20, 1,05 i 1,18. Analiza posmičnih deformacija i ukupnih pomaka u stijenskoj masi pokazuje da vlaženje naglo smanjuje efektivnu čvrstoću te uzrokuje prijelaz mehanizma nestabilnosti s plitkih površinskih odrona na klizišta cijele etaže kopa. Dobiveni rezultati mogu poslužiti kao podloga za projektiranje radnih kosina i planiranje odvodnjavanja u sličnim uvjetima eksploatacije ležišta nanosnoga tipa.

Ključne riječi:

površinski kop, nanosno ležište, stabilnost kosina, numerička analiza, koeficijent sigurnosti

Author's contribution

Oleksandr Kovrov (Professor): conceptualization, investigation and numerical simulation, writing – original draft.

Borys Sobko (Professor): data curation, formal analysis, resources, writing – review & editing

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Rahmi Mulyasari^{1*}, Muh Sarkowi², Angga Jati Widiatama³,
Hari Wiki Utama⁴, Andri Kurniawan², Rizky J Sianturi²

¹ Geological Engineering, Faculty of Engineering, Universitas Lampung, Lampung, Indonesia

² Geophysical Engineering, Faculty of Engineering, Universitas Lampung, Lampung, Indonesia

³ Geological Engineering, Faculty of Industrial Technology, Institut Teknologi Sumatera, Lampung, Indonesia

⁴ Geological Engineering, Faculty of Science and Technology, Universitas Jambi, Jambi, Indonesia

Abstract

The Suoh Depression (West Lampung, southern Sumatra) is an active volcanic basin along the Great Sumatran Fault (GSF), characterized by high seismicity and active geothermal manifestations. This study integrates satellite gravity data and regional seismicity to delineate the subsurface fault architecture that controls deformation in Suoh. We used 3,098 gravity points from the GGMPlus model and topographic information from the 30 m SRTM DEM. Earthquake data were compiled from the BMKG catalogue (1900–2024). Gravity processing included the calculation of the complete Bouguer anomaly (CBA), separation of regional and residual components, and the application of edge-enhancement filters such as horizontal gradients and second vertical derivatives. 2-D forward modelling and 3-D density inversion were subsequently conducted to resolve the geometry of the major fault strands. Seismicity was analyzed to validate gravity-derived structures and identify active segments. The CBA varies from ~35 to ~85 mGal, reflecting major density contrasts across the Suoh basin. The West and East Semangko Faults are the two main strands of the Semangko segment, as shown by derivative maps and inversion results. Additionally, there is a local Penetoh Fault that strikes northwest and extends to a depth of about 6 km. Earthquake clusters coincide with these structures, confirming their current activity. These findings demonstrate that Suoh is an actively deforming pull-apart depression governed by strike-slip kinematics. The updated fault configuration provides critical input for seismic-hazard mitigation, geothermal assessment, and land-use planning in West Lampung.

Keywords:

Gravity methods; Great Sumatran Fault; seismicity; Suoh pull-apart basin

1. Introduction

The Great Sumatran Fault (GSF) is a big tectonic structure that runs from Aceh to Lampung. It is where the Indo-Australian and Eurasian plates meet at an angle, which causes strike-slip deformation. The GSF is a very active right-lateral fault system that causes shallow earthquakes in Sumatra. It also changes the way the region deforms, its shape, and the seismic hazards along its trace (Irsyam et al., 2017; Hutchings & Mooney, 2021). The Semangko segment, which is in the southern part of the system, has complicated activity because it interacts with local structures and volcanic processes in the Bukit Barisan Range.

One of the most significant deformation zones along the southern GSF is Suoh in West Lampung. This area is a pull-apart tectonic depression that formed in a releasing

stepover between the Kumering and Semangko segments (Natawidjaja, 2007). This kind of shape causes high rates of deformation, a complicated network of fault strands, and strong geothermal activity like fumaroles, hot springs, and crater lakes (Iqbal et al., 2023; Marwan et al., 2021). Seismicity in this region is marked by shallow to intermediate-depth earthquakes linked to strike-slip activity and volcanic processes, establishing Suoh as a critical area for earthquake hazard evaluation.

Despite its importance, the subsurface structure of active faults in Suoh remains inconsistently mapped. This inconsistency stems from the limited visibility of outcrops and the inherent non-uniqueness of gravity data, where various geological configurations can produce analogous anomalies (Moges et al., 2024; Hofi et al., 2024). Thick vegetation and rough terrain make it even harder to see fault traces and rock offsets directly.

Satellite gravity models like GGMPlus work around these problems by giving you high-resolution, even coverage over difficult terrain (Hirt et al., 2013). To make sense of gravity data, though, you need to use strategies

* Corresponding author: Rahmi Mulyasari

e-mail address: rahmi.mulyasari@eng.unila.ac.id

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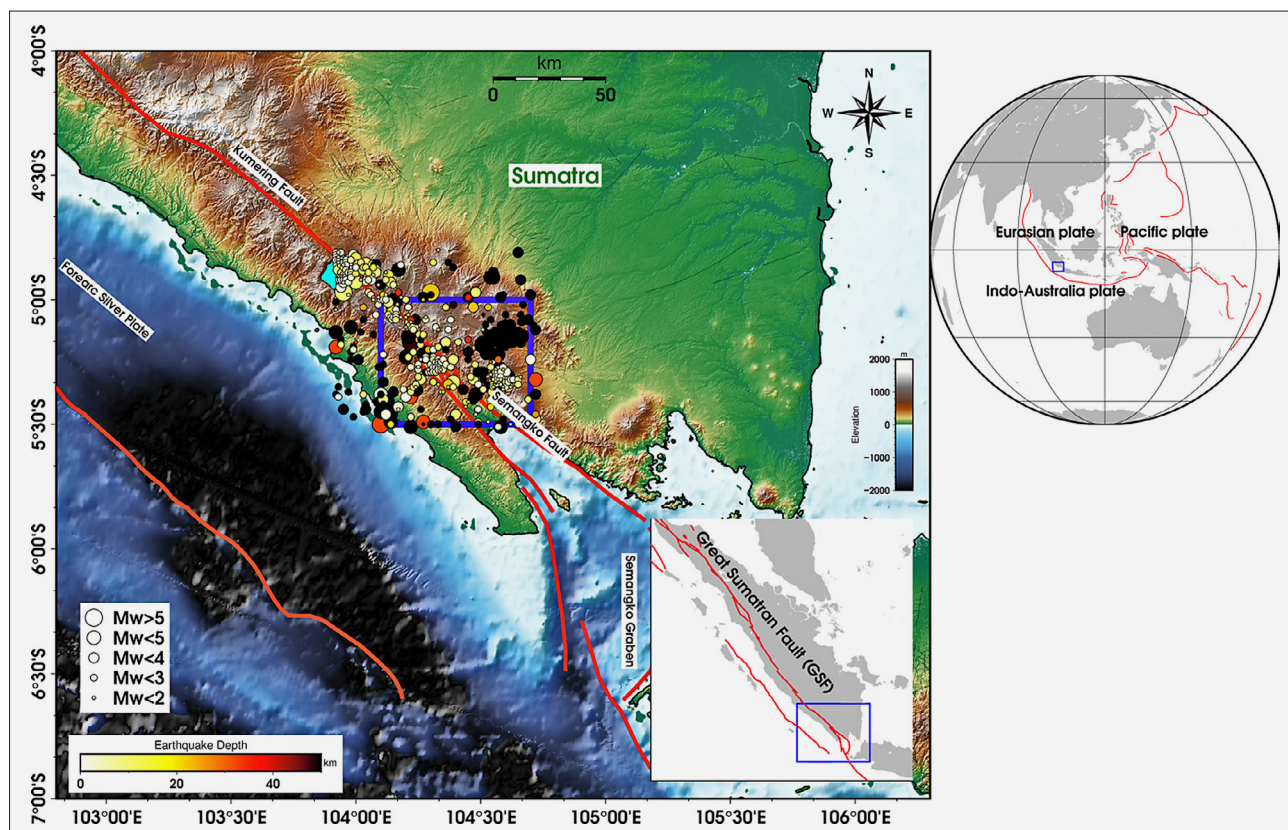


Figure 1: Seismicity and major faults in Lampung and surrounding Sumatra. The BMKG earthquake epicentres (time window given in Methods) are symbol-sized by magnitude (see legend) and colour-coded by hypocentral depth. Red lines denote the Great Sumatran Fault and the Sunda Trench; the blue dashed box outlines the Suoh study area. Basemap: SRTM15+ topography/bathymetry. The inset shows the regional plate-tectonic context. Fault traces simplified from [Sieh & Natawidjaja \(2000\)](#) and [Irsyam et al. \(2017\)](#).

that reduce ambiguity, like gradient-based operators such as the total horizontal gradient (THG), vertical derivatives, the tilt derivative, the balanced total horizontal derivative (BTHD), and Hilbert-transform-based vertical derivatives to improve structural boundaries and show density contrasts ([Pham et al., 2024](#); [Luo et al., 2025](#)). Research conducted in southern Sumatra has demonstrated that the integration of GGMPlus with contemporary edge-detection techniques, such as FSED, is effective for delineating geothermal and fault structures that are not readily discernible through surface observations ([Prasetyo et al., 2025](#)).

In addition to gravity, seismicity provides dynamic constraints that help identify active fault segments. By comparing gravity-derived edges with hypocenter distributions, it is possible to tell the difference between active faults and lithologic boundaries that are not active. Integrated gravity-seismic methods have been successful in Sumatra and Southeast Asia for locating blind faults, assessing segment continuity, and elucidating structural controls on geothermal manifestations ([Abdelrahman et al., 2024](#); [Dewanto et al., 2022](#); [Pranata et al., 2023](#); [Supendi et al., 2023](#); [Yanis et al., 2023](#)).

In light of this context, the current study concentrates on delineating active structures in Suoh by employing

high-resolution GGMPlus satellite gravity, gradient analysis, 2-D gravity forward modelling, 3-D density inversion, and regional seismicity analysis. The objectives of this study are to: (1) define the boundaries and segmentation of active faults in the Suoh Depression; (2) assess the efficacy of various gradient operators in identifying tectonically significant density boundaries; and (3) generate an updated active fault map that facilitates earthquake hazard assessment and geothermal system evaluation in West Lampung. The main contribution of this study is the development of an explicit and reproducible integrated workflow that reduces the non-uniqueness of gravity interpretation in a structurally and volcanically complex environment such as Suoh.

2. Regional Geology

Suoh is on the GSF, which is a dextral fault system that runs from NW to SE. A dextral fault is one where the block on the other side moves right from the observer's view. This type of movement is the most common in Sumatra's tectonic framework. The Kumering segment to the northeast and the Semangko segment to the west-south make a stepover in this area. This interaction creates a long tectonic depression with clear structural lineaments

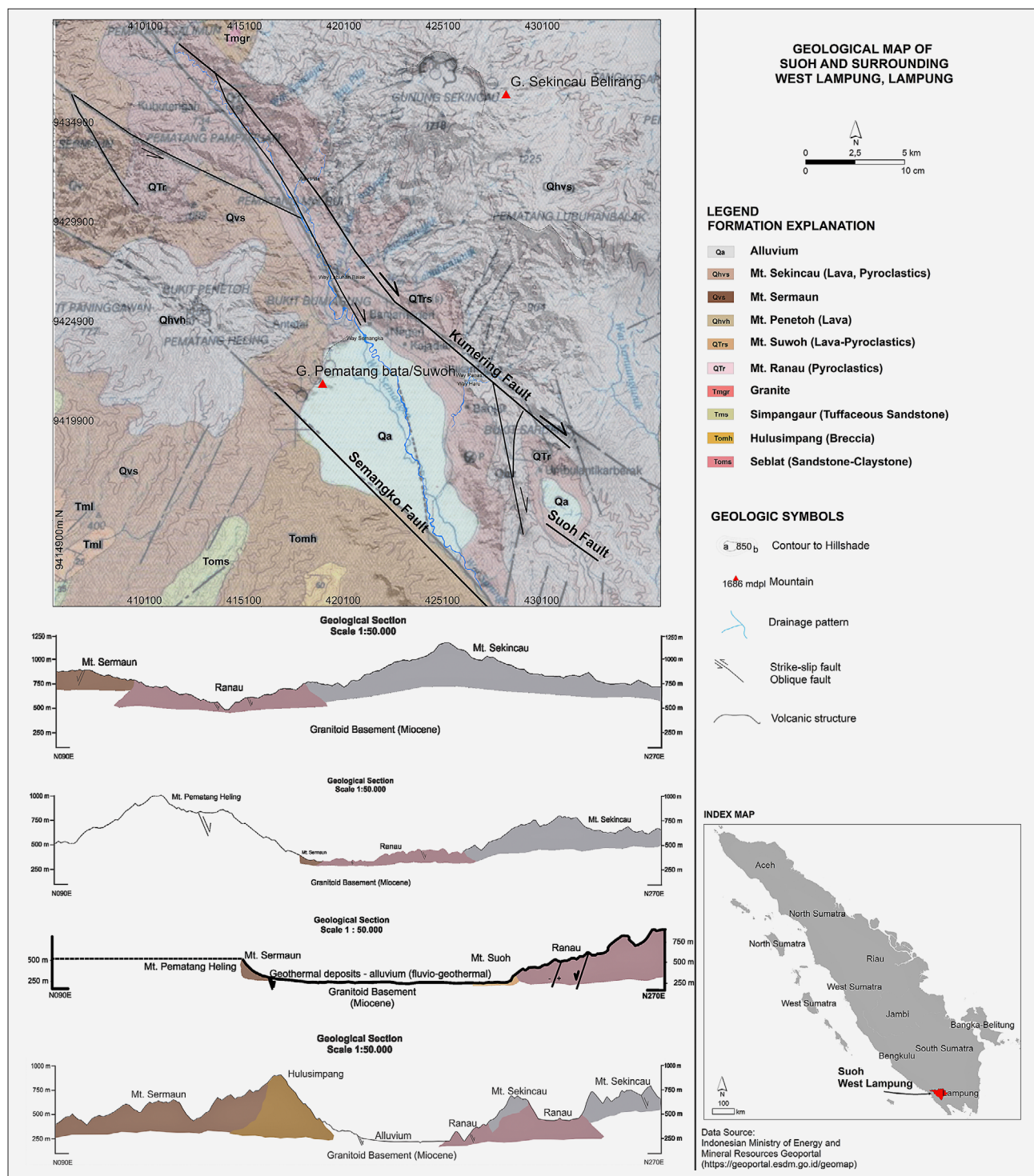


Figure 2: Geological map of the Suoh area, West Lampung (modified after **Amin et al., 1993**). Tertiary–Quaternary units include the Hulusimpang, Seblat, Simpangaur, and Ranau formations, overlain by Quaternary volcanic rocks and young alluvium. Thick lines trace the Semangko segment of the Great Sumatran Fault (West and East Semangko strands) and subsidiary faults; dashed outlines mark the Suoh grabens. The stratigraphic column and generalised section (right) summarise unit relationships and basin architectures. See the legend for symbols and scale.

(Natawidjaja, 2007; Sarkowi et al., 2022). The composite fault zone is linked to a lot of deformation and earthquakes, both in the past and now (see **Figure 1**).

Dextral overlap/overstep between the Kumering and Semangko segments facilitates the development of the

Ranau–Suoh pull-apart. Geometric discontinuities (restraining or releasing sections) and zones where the fault trace locally bends to create areas of compression (restraining) or extension (releasing) act as barriers and triggers for rupture propagation while also focusing hy-

drothermal fluid pathways along zones of elevated permeability (Bellier et al., 1997). Neotectonic and paleoseismic evidence for fine-scale segmentation explains why some sub-segments are seismically active while others appear comparatively quiescent on decadal time-scales (Sieh & Natawidjaja, 2000; Burton & Hall, 2014). Within this framework, Suoh evolved first as a subsiding basin formed by the overlap of the two GSF segments and deepened through time; a linking strand, the Suoh Fault, subsequently developed between the segments and, together with the Semangko segment, produced a younger and shallower pull-apart depression (Putra & Husein, 2016) (see Figure 2). This step-over architecture governs not only fault segmentation but also fluid migration in the Quaternary volcanic setting.

Historically, the February 15, 1994 Mw 6.8 Liwa earthquake is a key event on the Semangko segment within a complex, arc-related fault network (Widiwijayanti et al., 1996). Since 1994, small-to-moderate earthquakes have clustered along several Semangko sub-segments, aligned with positive structural zones (transfer zones), highlighting the role of segmentation in stress accumulation and release (Supendi et al., 2022). Regionally, the Ranau–Suoh corridor ranks among Indonesia's most active (Hutchings & Mooney, 2021) and is a focus area in the national seismic source and hazard map (Irsyam et al., 2017).

The West Lampung area, including Suoh, comprises Tertiary to Quaternary units: the Hulusimpang, Seblat, Simpangaur, and Ranau formations, overlain by Quaternary volcanic rocks and young alluvium (Amin et al., 1993). Key lithologies include andesitic lavas, volcanic and pumice breccias, tuffs, and local limestones, together with hydrothermal alteration products that commonly exhibit high permeability. This lithologic assemblage produces pronounced density contrasts and mechanical heterogeneity, which are advantageous for gravity-based mapping of structural boundaries (Wibowo et al., 2022).

The dominant NW–SE fault traces are intersected by near-orthogonal secondary structures, generating elongated surface fractures, steep basin margins, and clusters of geothermal manifestations (hot springs, fumaroles) along high-lineament corridors. Satellite imagery and lineament analysis indicate high fault density, particularly around Lake Suoh and Penetoh Hill, consistent with structure-controlled permeability in an active tectono-volcanic system (Iqbal & Juliarka, 2019; Zaenudin et al., 2021). Complete and residual Bouguer anomalies, which represent gravity values corrected for topography and separated into regional and local components, vary systematically along the NW–SE trend and match the GSF framework. Derivative-based edge indicators such as the First Horizontal Derivative (FHD), which enhances lateral density contrasts, and the Second Vertical Derivative (SVD), which sharpens shallow anomaly sources, highlight several candidate boundaries interpreted as active structures that govern the local geological architecture (Zaenudin et al., 2021; Wibowo et al., 2022).

3. Materials and Methods

This study aims to refine the delineation of active faults in Suoh, West Lampung, Sumatra, by integrating gravity, topographic, seismicity, and geological data. Four primary datasets were compiled for this purpose. First, satellite gravity data from the GGMPlus model (sourced from <https://murray-lab.caltech.edu/GGMplus/index.html>) sampled at 3,098 points with approximately 200 m spacing, were used to resolve lateral density variations associated with subsurface structures. Second, the 30 m SRTM Digital Elevation Model (DEM) provided terrain information required for Bouguer corrections and for assessing geomorphological lineaments. Third, earthquake records from the BMKG catalogue supplied regional seismicity patterns that help identify active deformation zones. Finally, lithological and structural context was obtained from the 1:250,000 Geological Map of the Kota Agung sheet (Amin et al., 1993). All datasets were projected to WGS84/UTM Zone 48S and resampled to a uniform 200 m grid to ensure consistency during subsequent gravity modelling and gradient-based structural analysis.

Gravity processing was conducted to produce the Complete Bouguer Anomaly (CBA), which represents gravity values corrected for elevation, topographic mass, and terrain effects. The CBA serves as the foundation for identifying density contrasts associated with faults and lithologic boundaries. Surface rock density was estimated by Parasnis regression (free-air anomaly vs. Bouguer correction) over lithologically homogeneous areas, yielding an effective Bouguer density of $\rho \approx 2.4 \text{ g cm}^{-3}$ (Parasnis, 1967; Telford et al., 1990). Normal gravity was computed using Moritz's formulation; free-air and Bouguer corrections were then applied, followed by curvature and terrain corrections (LaFehr, 1991; Nowell, 1999; Rollin, 1990; Sarkowi, 2014). For clarity, the key equations are summarised below.

Normal gravity (Moritz, 2000) (Equation 1):

$$g_{\varphi} = 978.032,7(1 + 5.3024 \cdot 10^{-3} \sin^2 \varphi - 5,8 \cdot 10^{-6} \sin^2 2\varphi) \quad (1)$$

Bouguer slab (Bullard A; LaFehr's constant) (Equation 2):

$$Bc = 2\pi G\rho h = 0.04193\rho h \quad (2)$$

where ρ is the average density (g cm^{-3}) and h is elevation (m).

CBA is defined as (Equation 3 and Equation 4):

$$\Delta g(x, y, z) = g_{obs} - (g_{(\varphi)} - FAC + BC - TC) \quad (3)$$

$$g(x, y, z) = g_{obs} - g_{(\varphi)} + 0,308765h - 0.04193\rho h + TC \quad (4)$$

with FA the free-air term ($0.308765 \text{ mGal m}^{-1}$), BC the Bouguer correction, and TC the terrain correction derived from SRTM.

To isolate near-surface anomalies, the CBA field was separated into regional and residual components using a moving-average filter with a cut-off radius chosen based on sensitivity testing (Izvoltova et al., 2022). Residual anomalies highlight shallow density variations associated with faulting, basin-fill distributions, or intrusive contacts.

To enhance density boundaries associated with faults and formation contacts, we computed derivative-based edge detection methods that were applied to the residual field to sharpen fault-related boundaries. These include First Horizontal Derivative (FHD): enhances lateral density changes, Second Horizontal Derivative (SHD): emphasises shallow, high-frequency sources, Second Vertical Derivative (SVD): highly sensitive to near-surface density contrasts on the residual field (Elkins, 1951; Al-Khafaji, 2017; Saibi et al., 2006; Sarkowi, 2010; Sumintadireja et al., 2018; Sarkowi & Wibowo, 2021). Discrete formulations are used in this study.

First horizontal derivative (component form) (Equation 5):

$$SFHD = FHDx + FHDy \quad (5)$$

SFHD : Sum of First Horizontal Derivatives

FHD : First Horizontal Derivative

$$\text{With: } FHDx = \frac{\Delta g}{\Delta x} = \frac{g_2 - g_1}{x_2 - x_1} \text{ and } FHDy = \frac{\Delta g}{\Delta y} = \frac{g_2 - g_1}{y_2 - y_1}$$

Second horizontal derivative (Equation 6):

$$SSHHD = SHDx + SHDy \quad (6)$$

SSHHD = Sum of Second Horizontal Derivatives

SHD = Second Horizontal Derivatives

$$\text{With: } SHDx = \frac{FHDx_2 - FHDx_1}{\Delta x} \text{ and } SHDy = \frac{FHDy_2 - FHDy_1}{\Delta y}$$

Second vertical derivative (from Laplace's equation) (Equation 7 and Equation 8):

$$\nabla^2 \Delta g = 0 \text{ or } \frac{\partial^2 \Delta g}{\partial x^2} + \frac{\partial^2 \Delta g}{\partial y^2} + \frac{\partial^2 \Delta g}{\partial z^2} = 0 \quad (7)$$

$$\frac{\partial^2 \Delta g}{\partial z^2} = - \frac{\partial^2 \Delta g}{\partial x^2} + \frac{\partial^2 \Delta g}{\partial y^2} \quad (8)$$

The maxima and minima in SFHD, zero crossings in SSHHD, and instances where SVD equals zero were collectively used to delineate lateral density contrasts that are interpreted as structural edges. BMKG earthquake data within the study area were extracted, quality-checked, and restricted to crustal depths (≤ 40 km). To minimise catalogue bias, only events above the magnitude completeness threshold (M_c), defined as the smallest magnitude reliably detected, were retained, and duplicate or poorly constrained events were removed. Although double-difference relocation can improve hypocentre precision, it was not applied due to limitations of the available dataset. Seismicity was integrated with gravity-derived edges using two complementary

approaches: (i) qualitative comparison of epicentre patterns with gravity edges; (ii) quantitative proximity analysis that computes the distance of each event to the nearest edge using fixed buffers (e.g. 1–2 km). Summary statistics (median and inter-percentile range) are reported to characterise clustering along structural boundaries.

Representative transects crossing major edges were modelled using two-dimensional forward gravity modelling (Salem et al., 2014). For volumetric imaging, three-dimensional density inversion of the residual gravity field was performed using the GRAV3D software package (UBC-GIF) to produce a subsurface density model (Witter et al., 2016; Nyalugwe et al., 2020). The inversion incorporated depth weighting, smoothness constraints, and density bounds consistent with the regional geology. Modelling parameters, including cell size, padding, misfit targets, error floor, and stopping criteria, are reported with the results. Depth slices and vertical sections from the inversion were compared with mapped edges and seismicity patterns to assess structural consistency.

Validation consisted of evaluating spatial agreement between gravity-derived edges and mapped geological boundaries, analysing the proximity of seismicity clusters to the identified edges, and testing the stability of edge positions under variations in filtering windows and gradient operator parameters. Uncertainty in edge location is represented by differences among gradient operators, while uncertainty in the density model is conveyed through inversion misfit statistics and consistency across structural profiles.

4. Results and Discussion

4.1. Complete Bouguer Anomaly (CBA)

The CBA map of Suoh exhibits pronounced gravity variations at a regional scale that correlate with mapped tectonic structures (see Figure 3). Values range from approximately 35 mGal (low; blue–violet on the colour scale) to about 85 mGal (high; red–orange), indicating strong lateral density contrasts at structural depths.

A prominent high-anomaly domain occupies the southwestern part of the area and coincides with topographic highs (Panninggawan and Penetoh hills). These highs are consistent with shallow, relatively dense bodies, such as uplifted basement, shallow intrusive rocks, or compacted volcanic units, approaching the observation level and producing local gravity increases. In contrast, a broad low-anomaly field in the northeast around Mount Sekincau suggests lower-density material or mechanically weakened/alterated zones, plausibly related to hydrothermal alteration, young volcanic deposits, or fluid-bearing reservoirs.

The principal lateral gradient separating the high and low domains aligns with the Great Sumatran Fault (Semangko segment), which therefore marks the main grav-

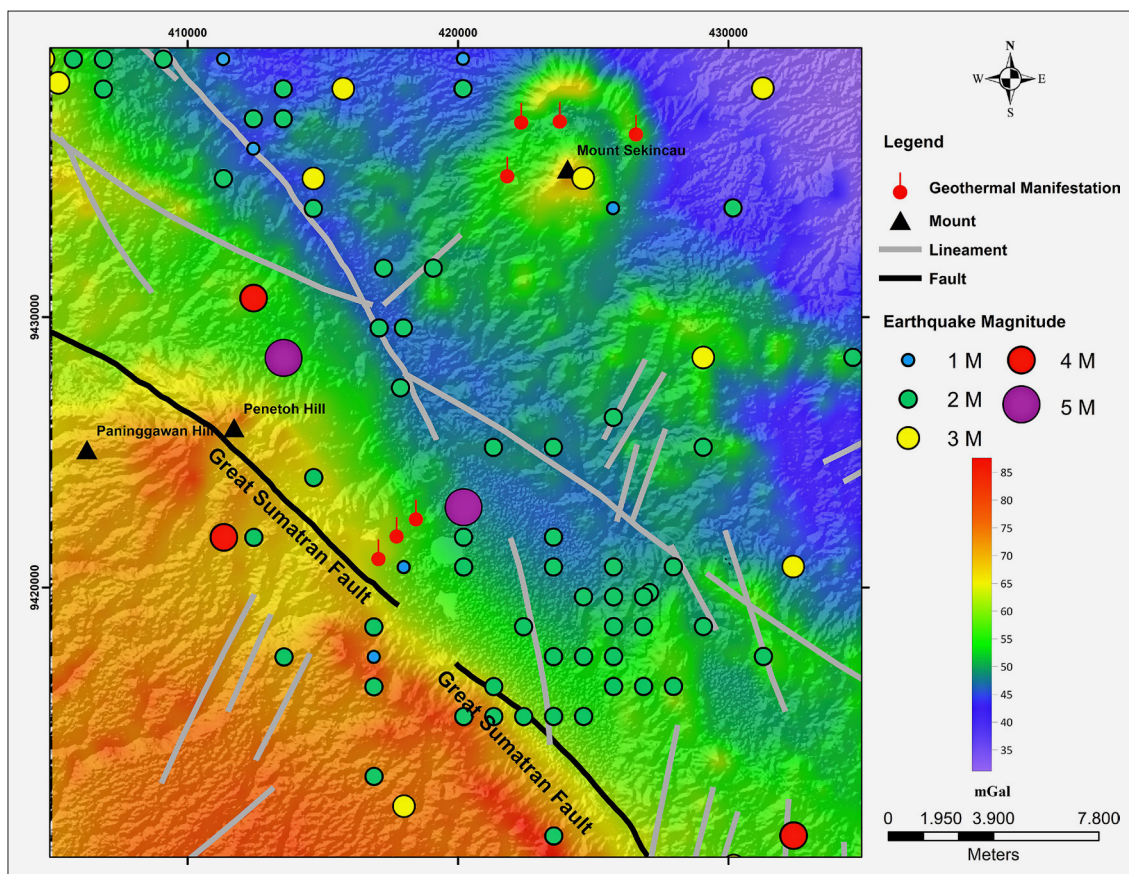


Figure 3: The Complete Bouguer Anomaly Map of the Study Area.

ity boundary: denser rocks to the west and less-dense rocks to the east. Oblique and subparallel secondary lineaments intersect this boundary, defining a complex structural fabric that likely localises strain and channels deformation and fluid flow.

Overall, the CBA pattern reinforces the view that fault architecture exerts first-order control on regional morphology and indicates an actively deforming zone. In concert with the historical seismic record for West Lampung, these contrasts highlight a significant earthquake hazard in the Suoh area.

4.2. Residual Bouguer anomalies

The residual Bouguer anomaly over Suoh ranges from roughly -4 to $+22$ mGal and emphasises shallow sources (see Figure 4). High residuals (yellow–red) cluster around Mount Sekincau, forming a rounded pattern indicative of a relatively shallow, dense body – consistent with an intrusion or compact volcanic unit.

In contrast, low residuals (blue–purple) dominate the central to southern sector, particularly along the trace of the Great Sumatran Fault (Semangko segment). These lows are interpreted as zones of reduced density produced by fracturing, tectonic weakening, and/or alteration, and they align with mapped faults and lineaments. The correspondence between low anomalies and fault

trends suggests structurally controlled weak zones that are prone to strain accumulation. Taken together, the residual field supports an actively deforming setting: low-density corridors coincide with active faulting and likely mark loci for future seismic energy release, underscoring elevated earthquake hazard across the Suoh corridor.

4.3. Second Vertical Derivative (SVD)

The SVD map over Suoh highlights second-order variations that sharpen lateral density boundaries (see Figure 5). The dashed contours mark $SVD = 0$, which by definition separates positive from negative curvature and commonly coincides with significant density contrasts; in gravity interpretation, these zero lines are diagnostic of major faults or lithologic contacts.

In map view, $SVD = 0$ aligns with the Great Sumatran Fault (Semangko segment) and with NW–SE and NE–SW lineaments, indicating that the master fault and its splays exert primary control on subsurface architecture. Intersections among these trends outline a complex deformation network that can localise strain and act as sources of seismic energy release.

Elevated SVD amplitudes (from green to red) cluster around volcanic centres such as Mount Sekincau, Paninggawan Hill, and Penetoh Hill, consistent with compact intrusive or volcanic bodies of relatively high den-

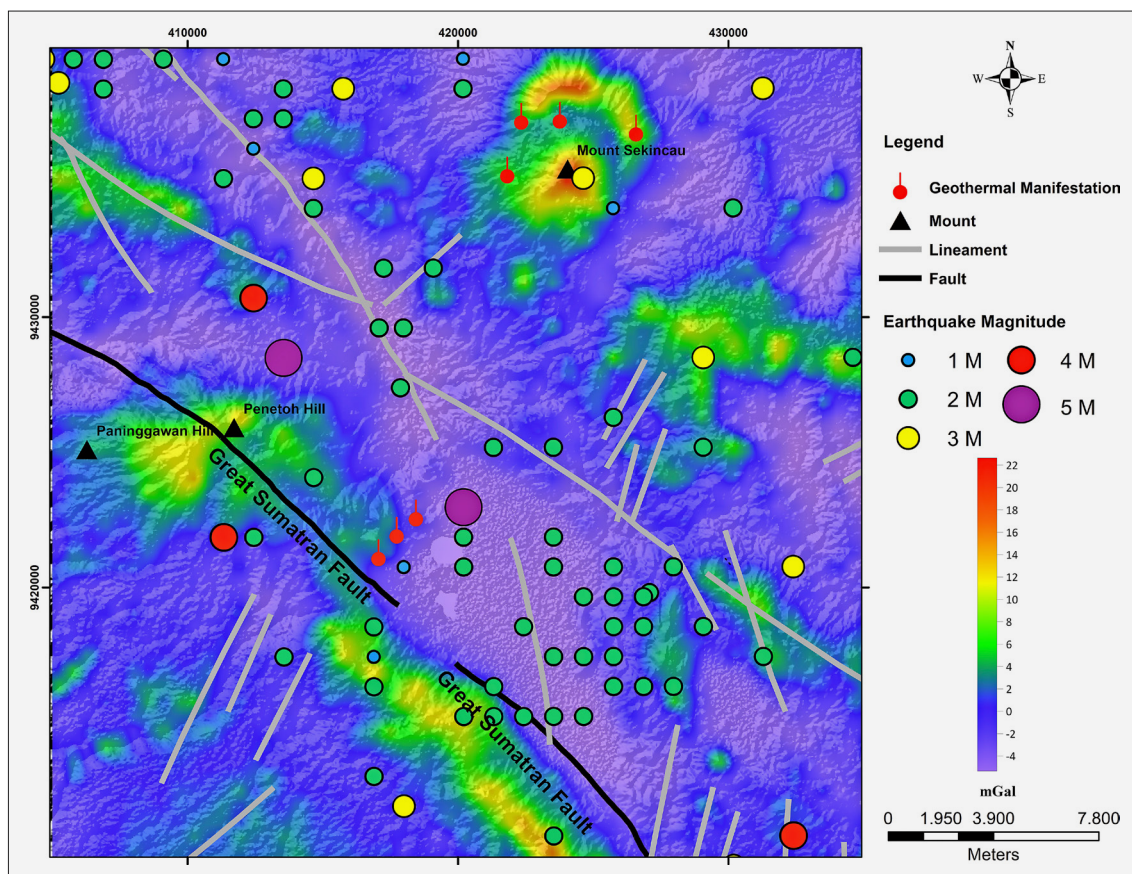


Figure 4: Residual Anomaly Map of the Study Area.

sity at shallow depths. Conversely, low SVD values (blue–purple) dominate depression zones adjacent to the fault strands and likely reflect unconsolidated sediments or mechanically weakened rocks. Together, the concentration of high SVD near volcanic edifices and the SVD = 0 traces along the main fault confirm intense tectonic activity and a strong structural control on the present-day deformation field in Suoh.

4.4. Suoh depression map

The depression map delineates a set of fault-bounded basins (see black dashed outlines in **Figure 6**). These elongate depressions parallel the Semangko segment of the GSF and its subsidiary lineaments, consistent with formation by extension and strike-slip step-over, ranging from small grabens to pull-apart basins. The Suoh basin was formed as a result of an overstep mechanism between two active fault segments, namely the Semangko segment and the Kumering segment. When these two segments moved dextrally but were not perfectly aligned, the space between them underwent transtension deformation, causing subsidence of the crust and the formation of the Suoh basin (**Putra & Husein, 2016; Ari-bowo, 2018**). Furthermore, recent studies indicate that volcanic and geothermal activities in Suoh are strongly influenced by this fault structure. The deep shear zones

along the fault facilitate the upward migration of thermal fluids from beneath the surface, making the Suoh area an active geothermal system (**Natawidjaja et al., 2017**). Overall, the GSF acts as the principal structural control governing the formation and evolution of the Suoh basin, influencing its geometric configuration and crustal deformation, as well as its volcanic and geothermal activity. This basin serves as a classic example of the relationship between strike-slip faulting and pull-apart basin formation in an active tectonic setting, analogous to the San Andreas Fault system in southern California (**Belli-er & Sébrier, 1994**).

Depression zones coincide with low Bouguer anomalies (blue–purple) that are compatible with porous, altered, or loosely consolidated materials. This association, together with the spatial clustering of geothermal manifestations (red dots) within or along basin margins, suggests that the depressions act as structural traps and preferred pathways for hydrothermal fluids. The proximity of several depressions to volcanic centres (e.g. Mount Sekincau) further indicates a combined volcanictectonic origin, where subsidence related to eruptive/explosive activity or shallow intrusion is later amplified by strike-slip deformation. Overall, the depression patterns record the interaction of regional fault kinematics with local volcanism and constitute key indicators of active deformation and potential seismic hazard in West Lampung.

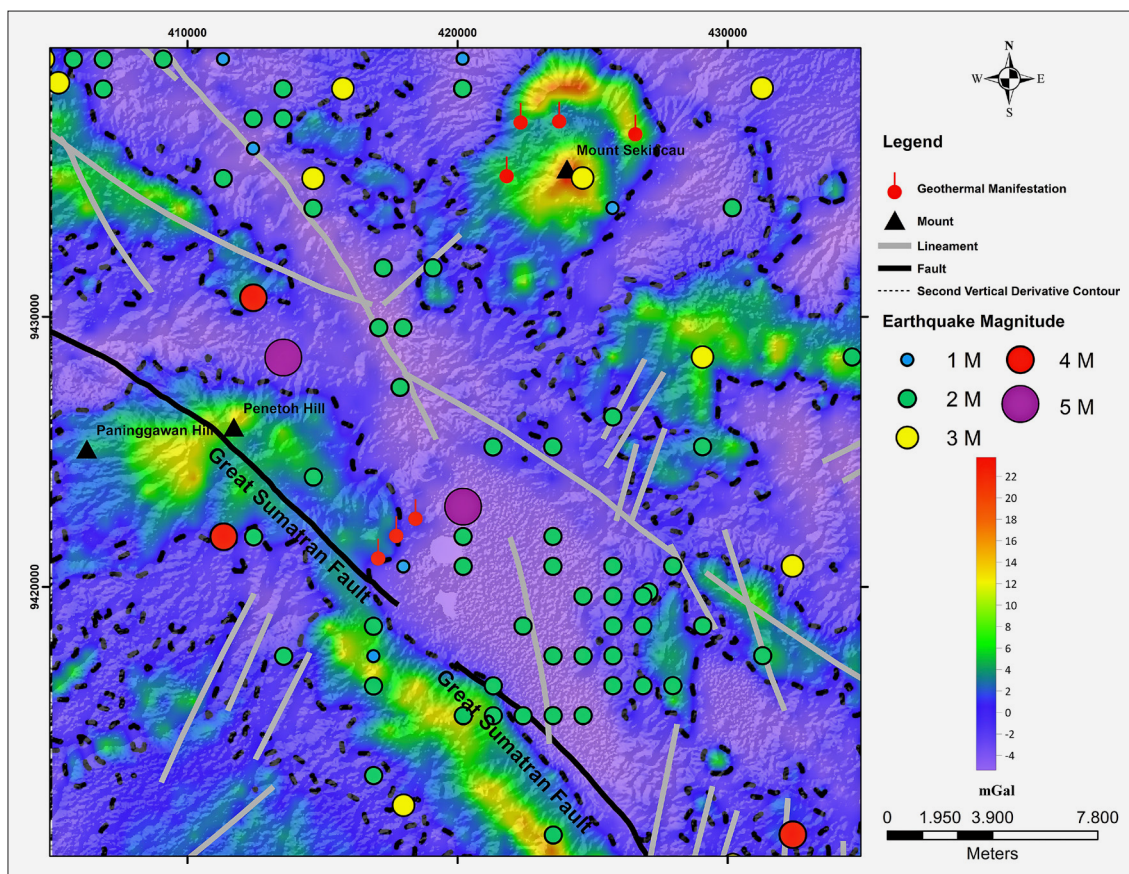


Figure 5: Second Vertical Derivative (SVD) Map of the Study Area

Gravity and seismic observations exhibit a strong correspondence. The CBA reveals a first-order density contrast across the Semangko segment: higher anomalies to the west (interpreted as dense basement or compact volcanic/intrusive rocks) and lower anomalies to the east (young volcanics and Quaternary sediments). Residual and derivative maps (FHD and SVD) delineate NW–SE and NE–SW lineaments consistent with the mapped fault fabric, defining a network of structural weaknesses that focus deformation and accommodate earthquake rupture. Earthquake hypocenters cluster along the Semangko strands and subsidiary faults, indicating that these structures are currently active and capable of generating future events. This interpretation accords with the historical record, including the damaging 1933 earthquake in West Lampung. Taken together, integrated gravity–seismic analysis provides an effective means of resolving subsurface fault architecture in this complex setting and has clear implications for hazard assessment.

4.5. Subsurface Model

The 3-D inversion of the residual field reveals a shallow, high-density anomaly (red–yellow) in the central sector, surrounded by lower-density volumes (blue–green) (see Figure 7). The high anomaly is interpreted as a compact intrusive/volcanic body, whereas the low-

density envelopes likely represent porous, altered, or mechanically weakened rocks. This juxtaposition produces strong contrasts that correlate with mapped faults and inferred zones of weakness, reinforcing the role of subsurface structure in focusing deformation and seismic hazard in Suoh.

Depth slices and four structural sections extracted from the model (see Figures 8–9) clarify these relations. Along line AA' (see Figure 9a), a medium-depth dense body beneath Mount Sekincau is flanked by lower-density domains; several fault planes cut the profile from surface to depth, linking the intrusive high to bounding weakness zones. Line BB' (see Figures 8, 9b) shows a similar pattern near Bukit Pongan, with a shallow, compact body set between lower-density materials and cross-cut by throughgoing faults. Along CC' (see Figure 9c), the Suoh Depression is expressed as a broad low-density package ($\approx 1.9\text{--}2.2\text{ g cm}^{-3}$) extending to $\sim 5\text{ km}$ depth and bounded laterally by the West and East Semangko faults. This low-density fill is consistent with Quaternary volcanoclastic deposits, deformed rocks, and basin sediments, implying a mechanically weak zone prone to strain accumulation. Line DD (see Figure 9d) shows the depression confined between the same major strands, with dominant low densities ($2.0\text{--}2.3\text{ g cm}^{-3}$) to $\sim 6\text{ km}$ depth and higher-density flanks ($2.45\text{--}2.8\text{ g cm}^{-3}$) that likely correspond to intrusive or basement rocks.

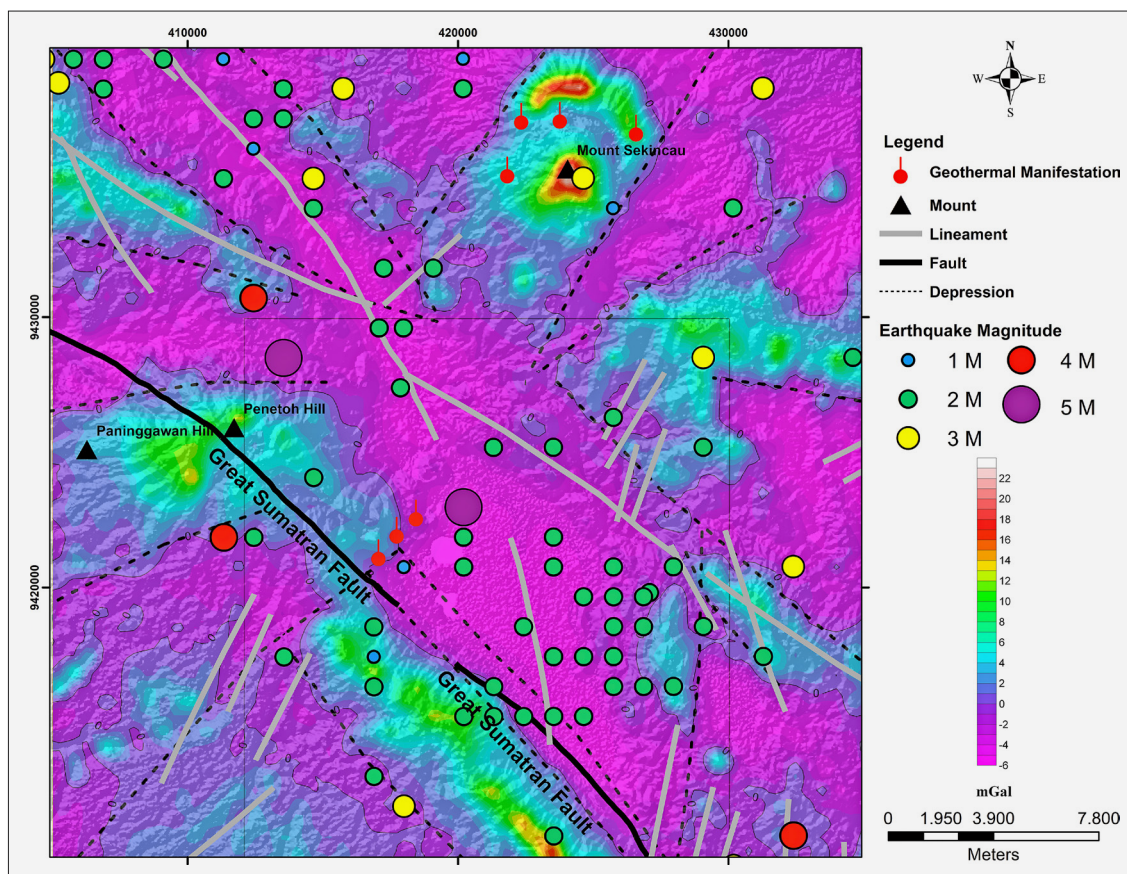


Figure 6: Depression Map of the Study Area

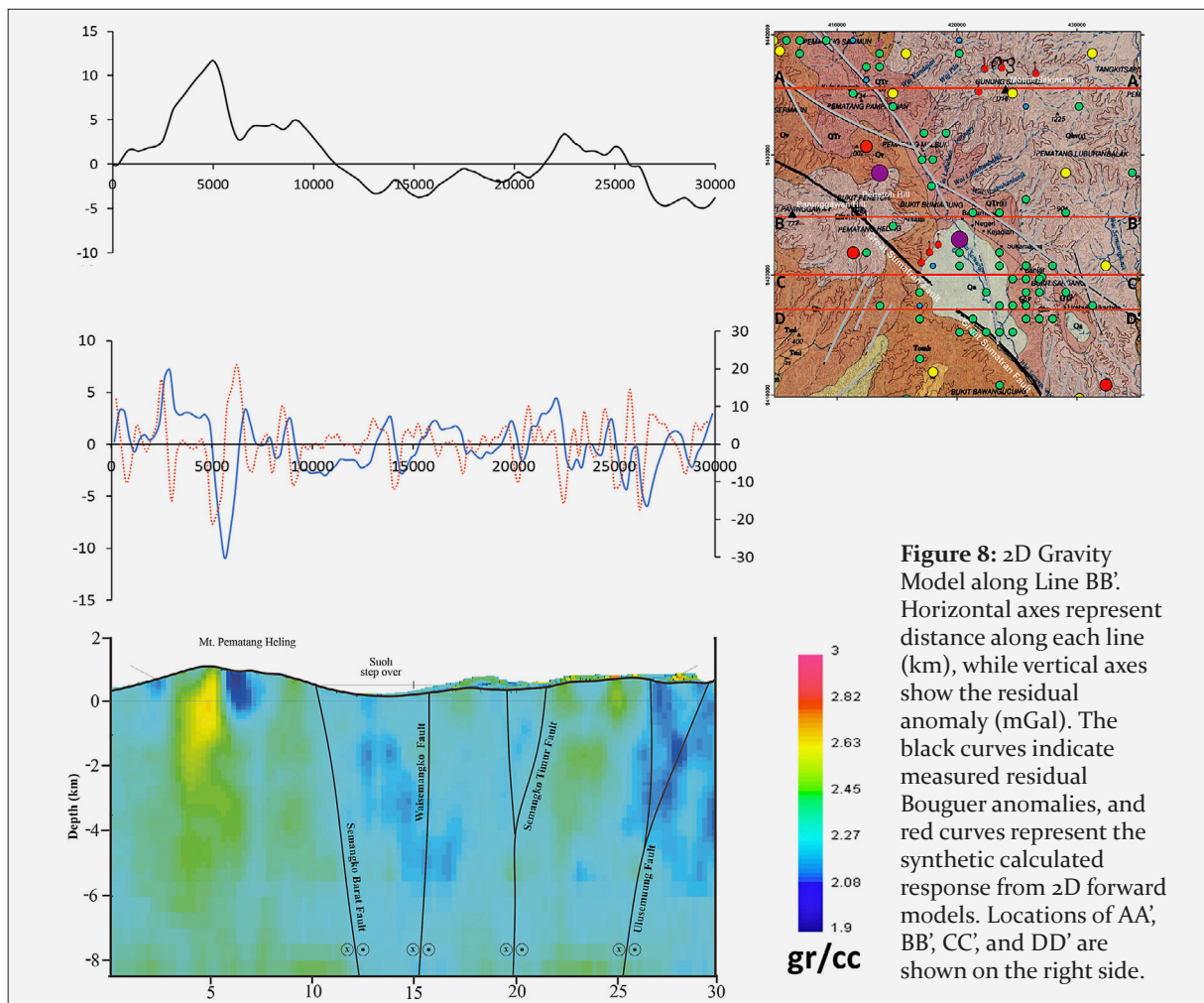
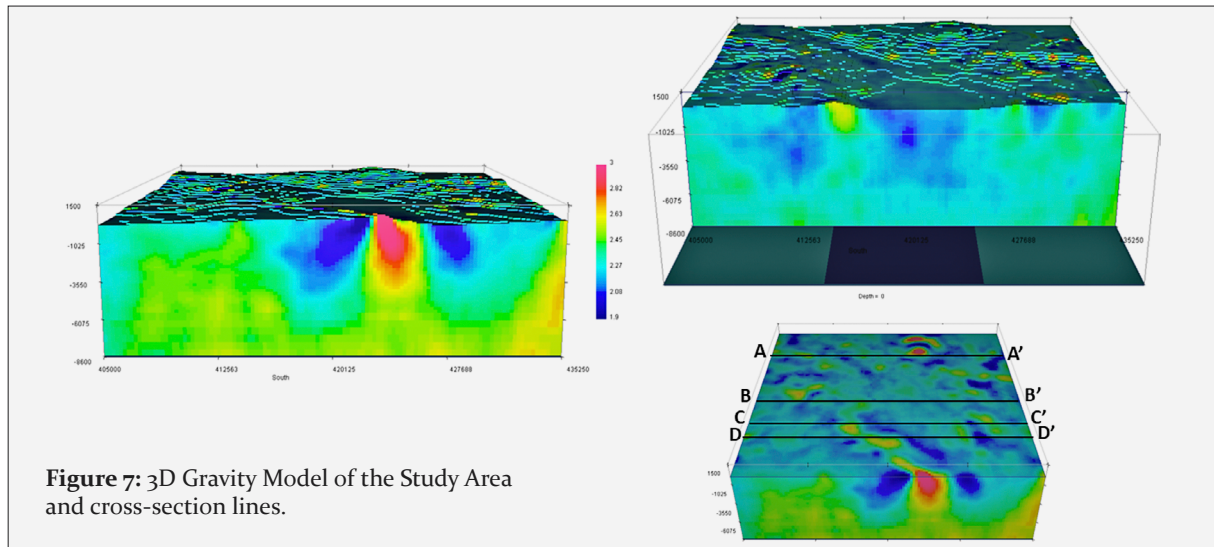
A localised shallow high-density body ($>2.6 \text{ g cm}^{-3}$) is identified on the eastern side (horizontal distance $\sim 24\text{--}26 \text{ km}$), whereas deeper levels ($>6 \text{ km}$) are comparatively homogeneous with moderate to high densities ($2.4\text{--}2.7 \text{ g cm}^{-3}$), consistent with basement or older compact volcanic rocks. Collectively, the 3-D model corroborates a tectonically controlled architecture: a weak, low-density Suoh Depression bounded by major Semangko strands and punctuated by shallow dense intrusions. This configuration is consistent with ongoing deformation and implies elevated earthquake hazard across the Suoh corridor.

The 3-D inversion highlights a shallow high-density volume (red yellow) in the central sector surrounded by lower-density domains (blue green) (see Figure 7). The high is interpreted as a compact intrusive/volcanic body, whereas the lows represent porous, altered or mechanically weakened rocks. This juxtaposition yields strong lateral contrasts that coincide with mapped faults and inferred weakness zones, underscoring the structural controls on deformation and seismic hazards in Suoh. Four orthogonal slices were extracted to interpret subsurface architecture (see Figures 8–9). Along line AA' (see Figure 9), a medium-depth dense body beneath Mount Sekincau is flanked by lower-density zones. Several fault planes cut the section from surface to depth, linking the intrusive high with bounding weakness cor-

ridors. The configuration shallow intrusion plus adjacent low densities – suggests an actively deforming domain prone to stress accumulation and seismic energy release.

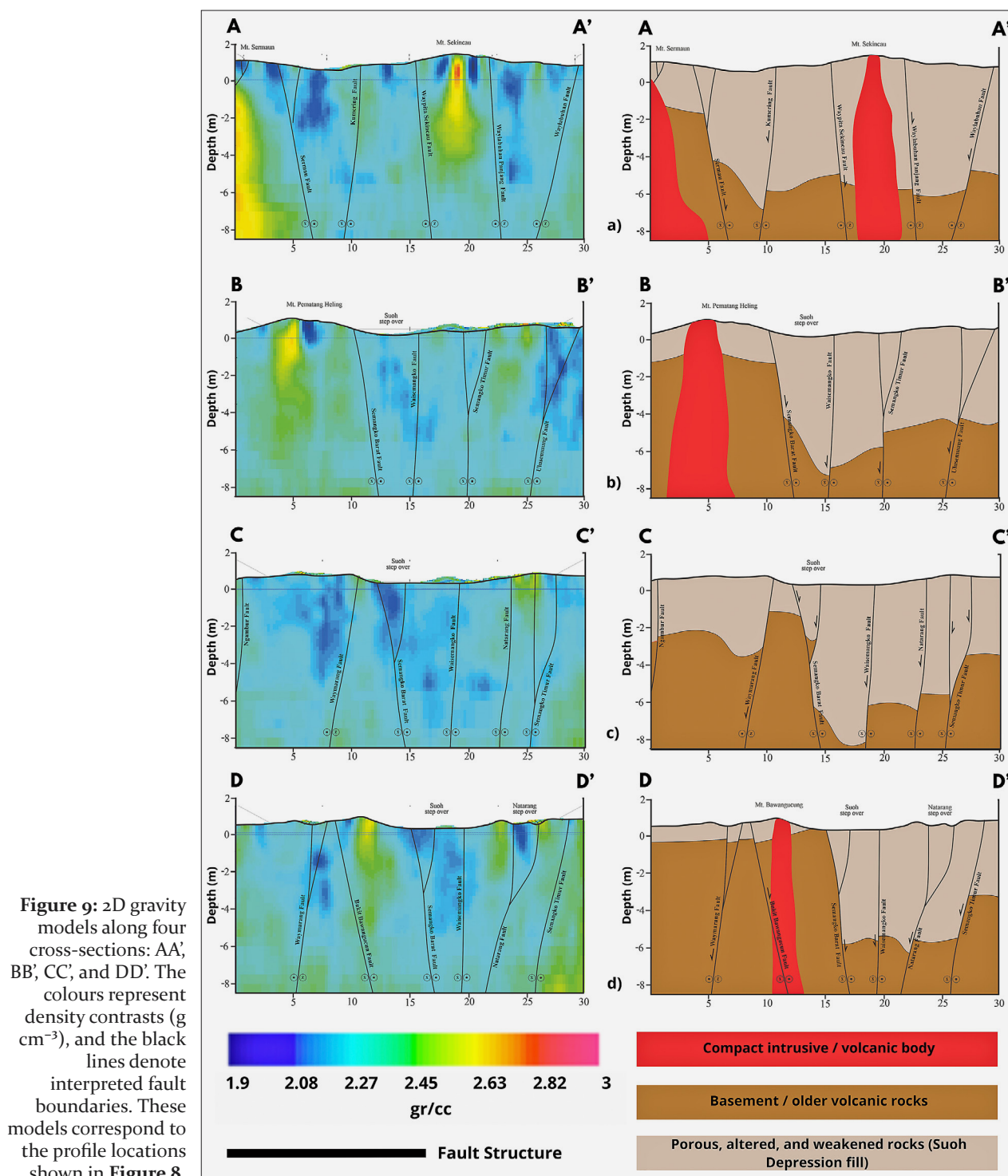
Along line BB' (see Figures 8, 9), a shallow high-density anomaly occurs beneath the western sector near Bukit Pangonan, bounded by lower-density volumes and dissected by throughgoing faults. These structures likely act as deformation pathways and zones of strain localisation, which is consistent with elevated seismic potential. Along line CC' (see Figure 9), the Suoh Depression emerges as a broad low-density package of approximately $1.9\text{--}2.2 \text{ g cm}^{-3}$ extending to $\sim 5 \text{ km}$ depth, bounded laterally by the West Semangko Fault (at $\sim 8\text{--}10 \text{ km}$ along profile) and the East Semangko Fault ($\sim 22\text{--}24 \text{ km}$). The low-density fill is compatible with Quaternary volcanoclastic deposits, deformed rocks and basin sediments – materials that are mechanically weak and susceptible to strain accumulation.

Line DD' (see Figure 9) similarly shows the depression confined between the West and East Semangko strands, with dominant low densities of $2.0\text{--}2.3 \text{ g cm}^{-3}$ to $\sim 6 \text{ km}$ depth, flanked by higher-density blocks ($2.45\text{--}2.8 \text{ g cm}^{-3}$) plausibly corresponding to intrusive or basement rocks. A localised shallow high-density body ($>2.6 \text{ g cm}^{-3}$) is resolved on the eastern side at $\sim 24\text{--}26 \text{ km}$ horizontal distance. At depths $>6 \text{ km}$, densities are comparatively homogeneous ($2.4\text{--}2.7 \text{ g cm}^{-3}$), consistent



with basement or older compact volcanic units. Overall, the 3-D model supports a tectonically controlled architecture: a weak, low-density Suoh Depression bounded by major Semangko strands and punctuated by shallow dense intrusions, consistent with ongoing deformation and elevated earthquake hazard.

The active faults in Sumatra are typically categorised into the northern, central, and southern sectors of the GSF (Sieh & Natawidjaja, 2000); the research area is in the southern sector. Suoh developed as a step-over depression between the Kumering and Semangko segments, a releasing geometry that produced a pull-apart basin (Sieh &



Natawidjaja, 2000; Natawidjaja et al., 2017). Strike-slip segmentation in southern Sumatra has been linked to focused volcanism (Sutrisno et al., 2019). In such releasing bends, increased permeability along fault zones, porous syn-tectonic infill and enhanced heat flow due to crustal thinning favour the development of high-temperature geothermal systems (Sutrisno et al., 2019). Within the Semangko segment, several pull-apart basins occur; the largest is the Suoh Depression (Sieh & Natawidjaja, 2000; Pramumijoyo, 2008).

Suoh is situated in the medial to distal volcanic facies, as the depression is filled by Quaternary volcanoclastic sediments that are sourced from nearby volcanic centres, including Mount Sekincau to the NE, Ranau and Semaun to the north, and Pematang Heling to the NW. Expected lithologies include ash and lapilli tuffs, volcanic breccias, and fluvio-lacustrine conglomerates, sands, and clays. Their low compaction and high porosity are consistent with low gravity values. Geothermal manifestations (hot springs and silica sinter) occur preferentially

along the step-over faults rather than in the central depo-centre, reflecting better porosity–permeability in alluvial-fan deposits along fault zones compared with finer-grained basin fills. The likely heat source for the Suoh hot springs is the Pematang Heling volcanic system, as suggested by a shallow magmatic conduit imaged on section B (see **Figure 9**).

5. Conclusions

This study delineates the active fault architecture of Suoh in West Lampung through an integrated analysis of satellite gravity data and regional seismicity. The Complete Bouguer Anomaly (CBA), which represents gravity values corrected for elevation, mass, and terrain effects, together with its residual component that isolates shallow geological sources, provides the primary basis for interpreting subsurface structures.

Derivative-based edge maps, including the First Horizontal Derivative (FHD) that enhances lateral density contrasts and the Second Vertical Derivative (SVD) that emphasises near-surface anomalies, help resolve the geometry of the Semangko segment of the Great Sumatran Fault and several subsidiary NW–SE and NE–SW structures that influence regional morphology and ongoing deformation. Two-dimensional and three-dimensional gravity modelling further reveal strong lateral density contrasts associated with major and secondary faults. Low-density zones correspond to mechanically weak corridors that act as preferred pathways for strain localisation, a process in which tectonic deformation becomes concentrated along specific zones. Consistent with these interpretations, shallow earthquakes cluster along the principal fault strands, demonstrating that tectonic activity in Suoh is ongoing.

Based on the combined lines of evidence, the Semangko segment and its subsidiary splays in the Suoh corridor are classified as active fault systems with clear implications for seismic hazard. These results refine the understanding of the geodynamics of southern Sumatra and provide essential input for earthquake risk reduction, geothermal assessment, and spatial planning in West Lampung.

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SAŽETAK

Integrirani gravimetrijsko-seizmički pristup kartiranju rasjeda u depresiji Suoh na Sumatri

Depresija Suoh (Zapadni Lampung, južna Sumatra) aktivni je vulkanski bazen duž Velikoga sumatranskog rasjeda (GSF), karakteriziran visokom seizmičnošću i aktivnim geotermalnim manifestacijama. U okviru ovoga istraživanja integrirani su podatci satelitske gravimetrije i regionalne seizmičnosti kako bi se ispod površine odredila struktura rasjeda koji kontrolira deformacije u Suohu. Korišteno je 3098 gravimetrijskih točaka iz GGMPlus modela te topografski podatci iz 30 m SRTM DEM-a. Podatci o potresima prikupljeni su iz BMKG kataloga (1900. – 2024.). Obrada gravimetrijskih podataka uključivala je izračun potpune Bouguerove anomalije (CBA), odvajanje regionalnih i rezidualnih komponenti i primjenu filtera za poboljšanje rubova kao što su horizontalni gradijenti i druge vertikalne derivacije. Provedeno je 2D izravno modeliranje i 3D inverzija gustoće kako bi se razriješila geometrija glavnih rasjednih osi. Seizmičnost je analizirana kako bi se potvrdile strukture interpretirane na temelju gravimetrijskih podataka i identificirali aktivni segmenti. CBA varira od ~35 do ~85 mGal, što odražava glavne kontraste gustoće u bazenu Suoh. Zapadni i istočni rasjedi Semangko dva su glavna dijela segmenta Semangko, što pokazuju karte derivacija i rezultati inverzije. Osim toga, postoji i lokalni rasjed Penetoh koji se proteže sjeverozapadno do dubine od oko 6 km. Klasteri potresa podudaraju se s definiranim strukturama, što potvrđuje njihovu trenutačnu aktivnost. Ova saznanja pokazuju da je područje Suoha aktivna ekstenzijska rasjedna depresija kojom upravlja kinematika horizontalnoga rasjedanja. Ažurirana konfiguracija rasjeda pruža ključne podatke za ublažavanje seizmičkoga hazarda, procjenu geotermalnoga potencijala i planiranje korištenja zemljišta u Zapadnome Lampungu.

Ključne riječi:

gravitacijske metode, veliki sumatranski rasjed, seizmičnost, ekstenzijski rasjedni bazen Suoh

Author's contribution

Rahmi Mulyasari (M.Eng., geological engineer with expertise in applied geology, particularly in tectonic geomorphology): performed data processing, interpreted data, and edited the draft. **Muh Sarkowi** (PhD, Professor of Gravity): performed data processing, interpreted gravity data, and edited the draft. **Angga Jati Widiatama** (M.Eng., geological engineer with expertise in applied geology): interpreted geological data and edited the draft. **Hari Wiki Utama** (M.Eng., geological engineer with expertise in applied geology): interpreted geological data and edited the draft. **Andri Kurniawan** (M.Eng., geophysical engineer with expertise in seismology): interpreted data and edited the draft. **Rizky J. Sianturi** (B.Eng., geophysical engineer): interpreted data and edited the draft. All authors have read and agreed to the published version of the manuscript.

Seismic Microzonation Based on Microtremor Data for Mapping the Damage Caused by an Earthquake on Bawean Island, Gresik, East Java, Indonesia

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Maulida Krisna Dewi¹ , Tasya Okta Irwanda¹ , Juan Pandu Gyah Nur Rochman^{1*} ,
Amien Widodo¹ , Firman Syaifuddin¹

¹ Department of Geophysical Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia.

Abstract

Bawean Island in Gresik is classified as an earthquake-prone area due to fault activity in the Java Sea. An example was the earthquake of March 22nd, 2024, which damaged thousands of houses and displaced tens of thousands of residents. The focus of this research is to carry out seismic microzonation utilizing the Horizontal to Vertical Spectral Ratio method with microtremor data to identify soil characteristics and vulnerability zones in the area. The microtremor data were processed through standard HVSR procedures, including signal windowing, frequency filtering, spectral analysis, and inversion, to obtain site specific seismic parameters. The results showed that the dominant frequency (f_o) ranged from 0.65 to 4.55 Hz and H/V amplitude (A_o) from 2.01 to 6.81 to reflect variations in impedance contrast. The seismic vulnerability index (K_g) was also from 1.04 to 29.54 s/cm², while the average shear-wave velocity up to a depth of 30 meters ($\bar{V}_{s30}$) was from 112.3 to 927.28 m/s. The correlation between damage data and K_g values showed that low damage corresponded to K_g values of 0-4.8, moderate to 4.8-15, and high to >15. The four parameters, including f_o , A_o , K_g , and $\bar{V}_{s30}$ were subsequently used in Fuzzy C-Means (FCM) clustering analysis to classify the area into three vulnerability zones. A microzonation map was also generated using 148 measurement points to show the strong correlation between K_g and the observed damage levels. The results are expected to support disaster mitigation efforts and resilient spatial planning.

Keywords:

Bawean Island; Fuzzy C-Means Clustering; HVSR; Microtremor; Microzonation

1. Introduction

A shallow crustal earthquake was experienced on March 22nd, 2024 at Bawean Island in Gresik Regency, East Java. The event was triggered by the activity of an active fault with a strike-slip mechanism in the Java Sea. The epicentre of the Bawean Earthquake was identified along the Muria Fault (offshore) classified as part of the old Meratus Pattern Fault Zone and suspected to have been reactivated (BMKG, 2024; Lunt, 2019). According to BMKG data, the epicentre was located approximately 126 km northeast of Tuban, at a depth of 11 km, and with a magnitude of M6. An aftershock with a magnitude of M6.5 was experienced offshore 4 hours following the earthquake at approximately 114 km northeast of Tuban and a depth of 12 km (BMKG, 2024).

The magnitude caused extensive damage on Bawean Island, Gresik, Tuban, Surabaya, Lamongan, and Madura. The data from East Java Regional Disaster Management Agency (BPBD) showed that a total of 4,679

houses were damaged, hundreds of public facilities were affected, and approximately 33,535 residents were displaced (CNN, 2024). Although the moderate magnitude of the earthquake, the extent of the damage caused is an indication of the influence of local site effects, which are associated with the subsurface soil conditions. This earthquake is an indication of the existence of active tectonic structures in the Java Sea region, which is normally regarded as a region with low to moderate seismicity conditions. These conditions are an indication of the need to undertake detailed seismic microzonation in the affected areas.

An earthquake is an unpredictable natural event, and this shows the importance of developing mitigation plans based on non-destructive methods, such as microtremors (Widodo et al., 2020). The method uses low-frequency vibrations of the Earth for its measurement. The sources of the vibrations vary and range from natural seismic phenomena to human-induced activities (Kanai, 1983). An example of the most common microtremor data analysis is Horizontal to Vertical Spectral Ratio (HVSR), which compares horizontal and vertical components of ground motion to identify soil characteristics (Nakamura, 1989; Hamimu et al., 2023).

* Corresponding author: Juan Pandu Gyah Nur Rochman
e-mail address: juanpandu@its.ac.id

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Microtremor measurements produce an HVSr curve, which can be used to estimate subsurface characteristics, including the average shear-wave velocity of the upper 30 meters ($\bar{V}_{s30}$), which represents soil conditions in the study area. This technique also enables one to invert field observation HVSr curves to estimate depth-dependent shear-wave velocity profiles. Field HVSr curves are constructed via Fast Fourier Transform (FFT) to discern the horizontal and vertical spectra. The dominant frequency (f_0), defined as the frequency at which the H/V spectral ratio reaches its maximum, reflects the resonance frequency of the subsurface. The H/V amplitude (A_0) represents the impedance contrast between sedimentary layers and the underlying bedrock. Subsequently, the $\bar{V}_{s30}$ value, the average shear-wave velocity in the top thirty meters of the subsurface, is calculated (Susilo et al., 2025). The values can be used to classify soil types based on SNI 1726:2019, which serves as part of the factors in determining earthquake hazard levels (Edison, 2022). However, the $\bar{V}_{s30}$ inversion process requires an initial velocity model as supporting data, which is determined based on the empirical model equation proposed by Parolai et al. (2002). The data used in this study were derived from both microtremor measurements and the building damage data from the Bawean Earthquake as a reference for classifying seismic vulnerability index (K_g) ranging from safe to hazardous. This correlation analysis between the actual damage conditions and microtremor parameters provides a more representative and realistic mapping of earthquake hazard potential.

BMKG data showed that aftershocks continued to occur on Bawean Island up to May 15th, 2024 with a total of 669 events recorded since the main earthquake on March 22nd, 2024. In South Egypt, while the regional seismicity is characterized as low to moderate, various studies have emphasized that local site effects play a critical role in controlling ground motion. In particular, studies that were conducted in New Luxor City revealed that areas affected by regional fault systems are likely to experience a considerable level of amplification in terms of ground motion as a result of a thick sedimentary cover, despite the absence of frequent large magnitude earthquake events (Abdelnasser et al., 2021). Therefore, this study used microtremor data for seismic microzonation to analyze soil characteristics in the earthquake-affected areas. This approach is consistent with previous studies that have demonstrated the widespread application of microzonation for mapping seismic conditions in various regions, including studies on liquefaction susceptibility in Mamuju and seismic vulnerability assessments in South Bengkulu (Hadi et al., 2024; Laode et al., 2025).

The analysis microzonation was conducted using parameters such as dominant frequency (f_0), H/V amplitude (A_0), seismic vulnerability index (K_g), and the average shear wave velocity up to a depth of 30 meters ($\bar{V}_{s30}$).

Furthermore, Fuzzy C-Means (FCM) Clustering method was applied to integrate the parameters into clusters, where each data point is assigned a membership degree for each cluster in order to produce an earthquake hazard zonation map that reflected the degree of building damage (Shihab, 2000). This integrated approach of using the HVSr and FCM methods has been gaining popularity in various international seismic microzonation studies to enhance the objectivity of hazard classification, particularly for regions with insufficient geotechnical data. The results of this study will help support the spatial planning and disaster mitigation activities for the island of Bawean.

2. Geological and Seismological Background

Bawean Island is located in Gresik Regency, East Java Province, covers an estimated area of 200 km², and is geographically situated between 5°43'–5°52' S and 112°34'–112°44' E (Hendratno & Khoir, 2019). It was formed by volcanic activity in Bawean Arc which separated East Java and Pati basins. Bawean Island lies in Muria-Bawean Back-Arc Volcanism zone characterized by a NE-SW structural orientation. This pattern is also in relation to Meratus lineament and Paleogene-Neogene tectonic pathway (Pulonggono & Martodjojo, 1994). Moreover, the subduction of the Bawean Arc is estimated to reach a depth of 600 km and is believed to have initiated during the Pleistocene period (Hafizh, 2022). This subduction process triggered volcanic intrusions and formed basement rock morphologies in line with the subduction pathway. The consistency of tectonic orientations from Paleogene to Holocene also shows that the area has remained tectonically and volcanically active in its geological history (Usman, 2012).

The Geological Map of Bawean and Masalembo Sheets (Aziz et al., 1993) in Figure 1 reflects that the stratigraphy of Bawean Island from the youngest to the oldest consists of Alluvium, Balibak Volcanic Rock Formation, Kepongan Sandstone Formation, and Gelam Limestone Formation. Alluvium (Qa) which is the youngest unit is distributed along coastal areas and is composed of cobbles, gravel, sand, and clay. The majority of the island is dominated by Balibak Volcanic Rock Formation (Qv) which is composed of lava, volcanic breccia, and tuff to form distinctive geomorphological features such as waterfalls, volcanic hills, and Lake Kastoba. Kepongan Sandstone Formation (Tmps) which consists of quartz sandstone intercalated with claystone and peat has a limited distribution. In several locations, Gelam Limestone Formation (Toml) of Tertiary age is also found to be composed of reefal, clastic, and crystalline limestones.

Bawean Island is located in the Meratus Pattern Old Fault Zone or near the Muria Fault system, considered the area suspected of experiencing fault reactivation that

Figure 1: Regional geological map of Bawean Island dominated by the Qv Formation (Balibak Volcanic Rock) and a geological cross-section along the red line (modified from Aziz et al., 1993).

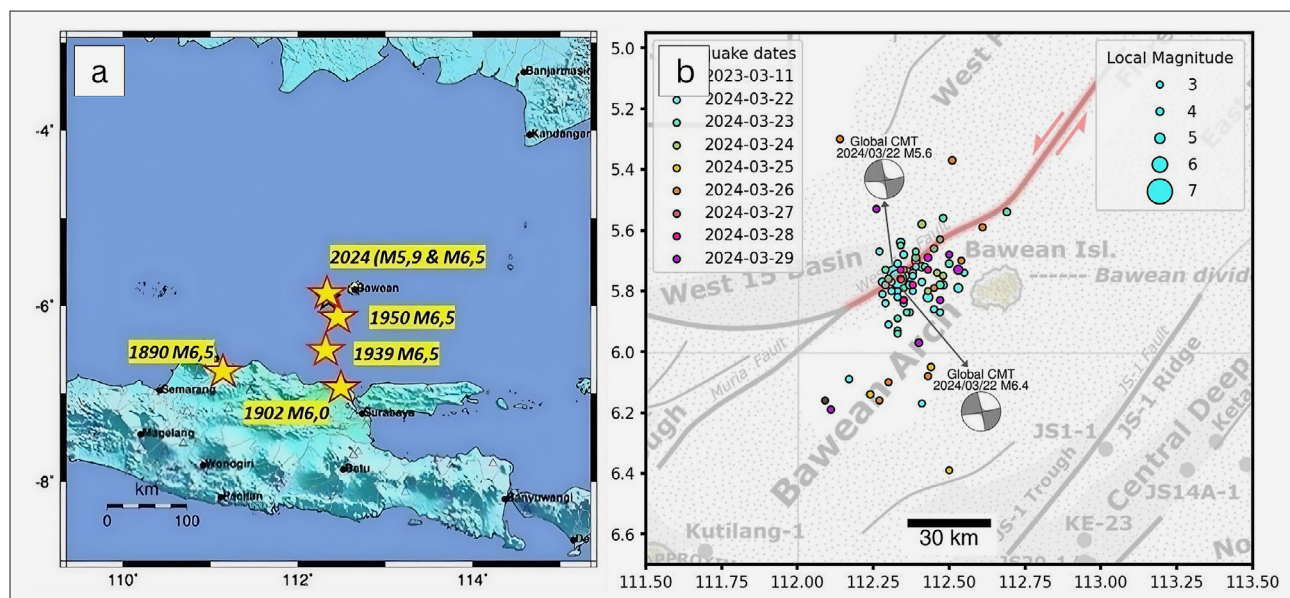
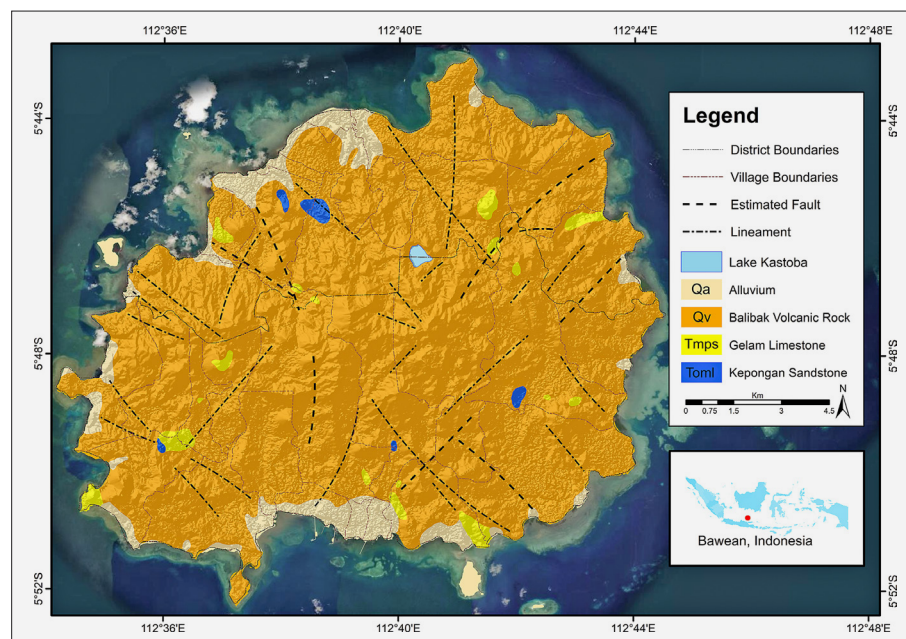


Figure 2: a) Historical earthquake data in the northern Java Sea with magnitudes $\geq M5.9$ from 1890 to the present (BMKG, 2024) and (b) earthquake data around Bawean Island in 2024 with magnitudes $\geq M3$, plot by Fian (2024) using BMKG data; basemap adapted from Lunt (2019).

triggered the earthquake (Lunt, 2019). The impact of this tectonic activity was the Bawean Earthquake experienced on March 22nd, 2024, at 11:22 local time (WIB). The epicentre was located offshore in 126 km northeast of Tuban, at a depth of 11 km, and with a magnitude of M6. The earthquake did not generate a tsunami, but a larger aftershock occurred at 15:53 WIB with a magnitude of M6.5, an offshore epicentre 114 km northeast of Tuban, and at a depth of 12 km.

The shaking intensity was relatively high and reached V–VI on MMI scale. This led to significant ground motion which caused the displacement of objects and low to high damage to several infrastructures. According to

BMKG, it was considered one of the strongest earthquakes in the Java Sea after the Semarang 1890 earthquake (M6.5), the Gresik 1939 earthquake (M6.5), and the Gresik 1950 earthquake (M6.5), as shown in Figure 2a. A minimum of 669 aftershocks with magnitudes ranging from M2.1 to M6.5 have been recorded after the main event, as presented in Figure 2b. This large number is attributed to the heterogeneous nature of the shallow crust beneath Bawean Island, which is brittle and easily fractured. The condition contrasts with oceanic crust earthquake, where the rocks are generally more homogeneous and elastic to produce fewer aftershocks even in large-magnitude events (Karyana, 2024).

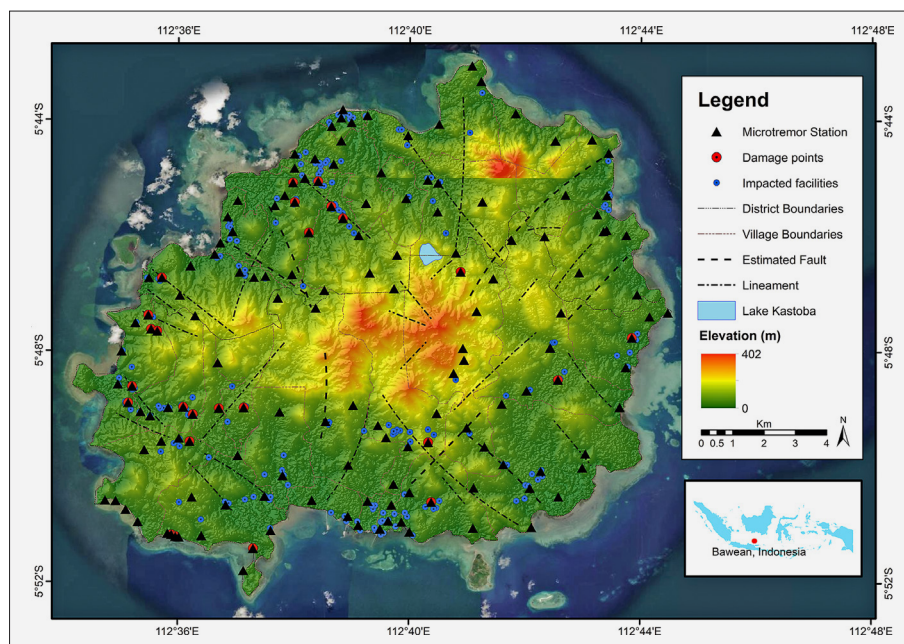


Figure 3: Microtremor stations are represented by black triangles with reference to impacted facilities in red with identified damage points caused by the 2024 Bawean Earthquake.

3. Methods

3.1. Study Area

This study used data from 148 measurement points distributed across Bawean Island in Gresik. Data acquisition was conducted from September 7th to 12th, 2024, using a Seismograf Rakyat Indonesia (SRI) system equipped with a three component sensor. During data processing, a minimum window length of 200 s was applied for spectral analysis to improve frequency resolution and spectral stability. Each measurement was recorded for approximately 20 minutes per site. The recording duration was selected to ensure sufficient data for stable H/V spectral estimation, following the recommendations of **SESAME (2004)**. The spacing along measurements varied between about 0.22 to 1.65 km adjusted according to geological conditions, building damage locations from the earthquake, site accessibility, and spatial data coverage of the entire island. The distribution of measurement points is presented in **Figure 3**. The dataset acquired consists of ambient noise recordings comprising three components including two horizontal components which are east-west and north, south as well as one vertical component in the form of up-down.

3.2. HVSR Method

The processing of the microtremor data was done by following several standard procedures of HVSR. The measurement of the microtremor was done using the Seismograf Rakyat Indonesia (SRI), which is a three-component seismograph with two horizontal components aligned in the north-south (NS) and east-west (EW) directions and the vertical component (Z). The measurement was recorded with a constant sampling

rate based on the instrument specifications and an effective recording time of approximately 20 minutes. The measurements were usually performed at points at least 10 m away from residential buildings in an effort to reduce anthropogenic noise. However, in areas where buildings were damaged by the earthquake, the measurements were performed within these buildings, thus reducing the amount of human activity around the measurement points. This was mitigated by the careful selection of the data.

First, the continuous ambient noise recordings were divided into several time windows, with the minimum window length being 200 s in order to guarantee the stability of the spectral content. Windows with transient signals or heavy disturbances were eliminated by an anti-triggering method. Second, filtering was conducted to select and separate signals in the desired frequency range (**Supriyanto et al., 2023**). This process used a low-pass filter with a maximum frequency of 5 Hz and applied an anti-trigger to eliminate transient signals during acquisition. The maximum frequency of 5 Hz was selected to ensure that the analyzed frequency range remains well below the Nyquist frequency of the recorded microtremor data, thereby preventing aliasing effects. In addition, this frequency range corresponds to the dominant site frequencies associated with shallow to intermediate sedimentary layers and helps suppress high-frequency noise that is not relevant for HVSR analysis.

Third, the discrete microtremor signals in the time domain were transformed into the frequency spectrum through FFT, followed by a smoothing procedure. The signal was tapered using a cosine taper before applying spectral analysis. The spectral smoothing technique used was the Konno-Ohmachi algorithm with a constant bandwidth parameter. The smoothed spectral data of the

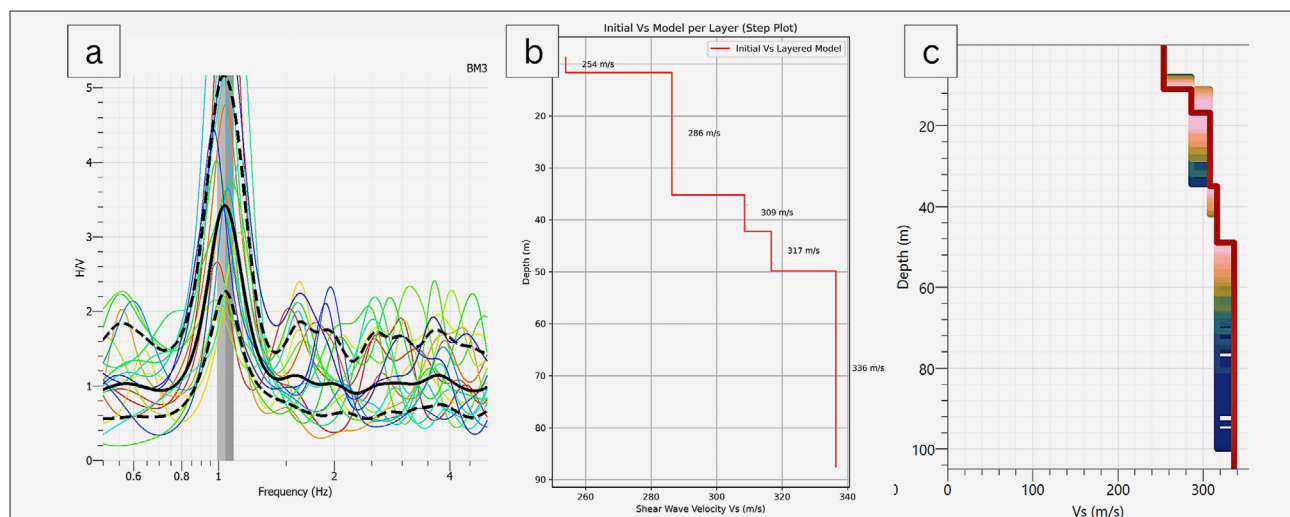


Figure 4: a) HVSR curve at BM3 obtained from Geopsy processing, (b) the initial model generated using Python, and (c) the inversion result of microtremor data showing the subsurface profile at BM3 using Dinver with the shear-wave velocity (V_s) distribution as a function of depth. The red line represents the best-fit inversion model while the shaded area is the model uncertainty and the boundaries of the identified subsurface layers.

horizontal and vertical components were used to obtain the HVSR curves. The average spectrum was computed for each measurement point. The dominant frequency (f_0) and H/V amplitude (A_0) were determined at the spectral peak using the average spectrum based after satisfying the reliability and clear peak criteria as shown in **Figure 4a** (SESAME, 2004). The reliability of the HVSR results was evaluated following the **SESAME (2004)** guidelines. The assessment included the presence of a clear and stable spectral peak, consistency of the dominant frequency across multiple time windows, and limited variability in H/V amplitude. Only curves that satisfied these reliability and clarity criteria were considered reliable and used for further analysis, while those that did not meet the criteria were excluded from subsequent interpretation.

f_0 is the most frequent value and is regarded as a characteristic of the rock layers below ground in individual sites. It allows the identification of the type and properties of the rocks. Meanwhile, A_0 is the physical contrast between the bedrock and overlying sediments due to density and seismic wave velocity contrasts, respectively (Molnar, 2018). f_0 and A_0 were subsequently used to calculate K_g to evaluate the degree of soil vulnerability to deformation caused by seismic shaking. The value was derived from the relationship between A_0 and f_0 , as formulated by Nakamura (2000) and further developed by Liu et al. (2023) in the following equation:

$$K_g = \frac{A_0^2}{f_0} \quad (1)$$

Where, K_g is seismic vulnerability index, A_0 represents H/V amplitude, and f_0 is the dominant frequency.

K_g values at the damage locations were correlated with the field-based damage assessment of the Bawean Earth-

quake. Moreover, the damage assessment was classified according to the building damage typology developed for the 2018 Palu Earthquake by BMKG and the reference from the Ministry of Public Works and Housing (PUPR, 2021). The three main categories are low, moderate, and high damage. Low damage is characterized by minor wall cracks, peeling plaster, minor discolouration of building components, and low damage to ceilings or eaves without any indication of structural damage. Moderate damage refers to more serious conditions such as larger cracks, low damage to main structural elements, and damage to structural walls that are still repairable. Meanwhile, high damage is characterized by significant structural failure, such as the collapse of main walls that compromise the general stability of the building, pose safety risks to occupants, and render the building uninhabitable. The determination of the damage levels was followed by the matching of each point with the corresponding K_g at the same location. This comparison was used to evaluate the extent to which K_g could represent seismic vulnerability of the buildings.

3.3. Inversion HVSR data

The absence of ground profile or direct geotechnical information from boreholes or in-situ tests showed the need for an initial model to serve as the basis for the inversion process. The initial model was constructed by inputting an HVSR curve, applying Konno-Ohmachi smoothing, and calculating the difference to evaluate amplitude variations with depth. This curve was subsequently converted into the depth domain to allow the identification of the impedance contrasts as subsurface layer boundaries. The shear-wave velocity (V_s) for each layer was determined through the empirical relationship proposed by Parolai et al. (2002) as follows:

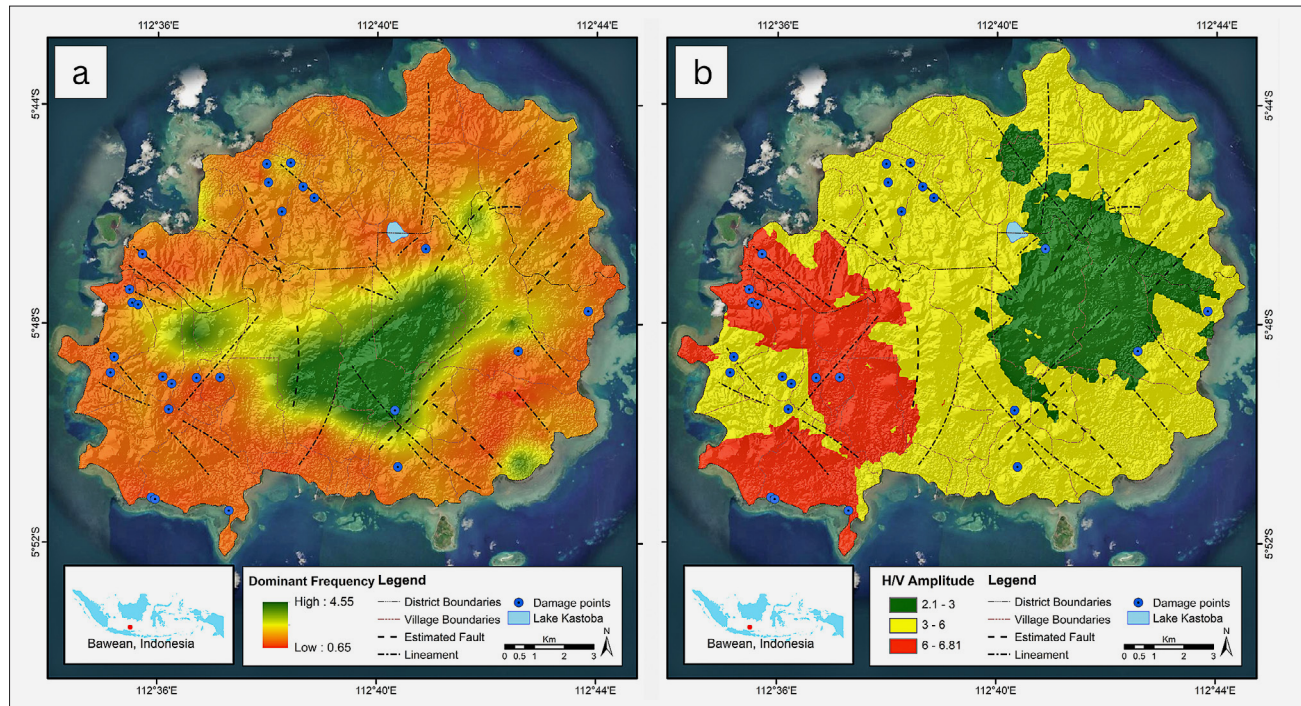


Figure 5: a) Distribution map of dominant frequency (f_0) values in Bawean Island ranging from 0.66 to 4.56 Hz, and b) distribution map of H/V amplitude (A_0) values in Bawean Island ranging from 2.1 to 6.81.

$$V_{s,z} = V_0 (1+Z)^x \quad (2)$$

Where, V_0 is the reference velocity (m/s), Z is the depth (m), and x is the empirical exponent (dimensionless) from the local USGS $\bar{V}_{s30}$ values. An example of the initial model produced is shown in **Figure 4b** which presents the identified layer boundaries and V_s profile derived from HVSR data processed.

The inversion procedure is performed by means of Dinver sub-software in the Geopsy package. The required input included HVSR curve obtained in .hv format from the previous processing stage. The others were V_s , compressional-wave velocity (V_p), Poisson's ratio (ν), and density (ρ) derived from the initial model. The inputs were used to iteratively conduct the inversion using an algorithm that adjusted the subsurface model up to the period a final V_s model was obtained in line with the characteristics of HVSR data measured. The inversion results were subsequently used to calculate the average shear-wave velocity in the upper 30 meters ($\bar{V}_{s30}$) at each measurement point.

$$\bar{V}_{s30} = \frac{30}{\sum_{i=1}^N \frac{h_i}{v_{si}}} \quad (3)$$

Where, h_i represents the thickness of the i^{th} sedimentary layer (m), V_{si} is the shear-wave velocity of the i^{th} layer (m/s), and N is the total number of layers (dimensionless). An example of the inversion result is shown in **Figure 4c** to show the subsurface profile at BM3 and depicts the distribution of V_s with depth. The estimation of V_s is important for effective earthquake disaster miti-

gation because the characteristics of the soil structure significantly influence risk evaluation (Susilo et al., 2025; Syaifuddin et al. 2016).

3.4 Fuzzy C-Means Clustering

The parameters obtained in the form of f_0 , A_0 , K_g , and $\bar{V}_{s30}$ were used to conduct a clustering analysis using the FCM method where each data point was assigned to clusters according to the degree of membership. The clustering process was conducted iteratively to improve classification accuracy by minimising the objective function that represented the distance between data points and the cluster centres determined based on membership values (Shihab, 2000). The measurements led to the identification of measurement points characterized by definite classes of seismic vulnerability, in relation to the parameter values under consideration. The information was used to delineate zones with different levels of potential earthquake-induced damage in the clustering map. The clustering was divided into three zones in this study according to the level of vulnerability to the Bawean Earthquake in line with the three categories of building damage analysis.

4. Results

4.1. Dominant Frequency (f_0)

f_0 was derived from the peak of HVSR curve on the x-axis to represent the soil response to seismic vibrations. Harder soils or bedrock generally produce a peak

response at higher frequencies while softer soils or rocks tend to respond at lower frequencies. Lower f_0 values are a greater indication that sedimentary layers are thicker and Vs decreases, particularly when propagating through soft rocks (Nakamura, 2008). In Bawean Island, f_0 ranged from 0.65 to 4.55 Hz with higher values concentrated in the central part dominated by hilly topography while lower values were predominantly found along the coastal areas as shown in Figure 5a. This distribution reflects variations in subsurface sediment thickness influenced by volcanic processes, weathering, and redeposition in the Balibak Volcanic Rock Formation (Qv). An important observation is that Qv is lithologically volcanic in nature but secondary weathering has produced several zones with soft sedimentary characteristics which play a significant role in amplifying local seismic response.

The variations in f_0 values in the same geological formation show the influence of geological structures such as faults and lineaments on sediment thickness and impedance contrasts. The areas located near faults generally exhibit lower and unstable f_0 values which lead to proneness to local resonance amplifying seismic waves. This was supported by the results that most building damage points were located in areas with low f_0 values of 0.74–1.57 Hz. The trend suggested a higher seismic hazard potential in areas characterized by thick sediments and soft soils.

4.2. H/V Amplitude (A_0)

A_0 was obtained from the peak of HVSR curve on the y-axis and was used to qualitatively identify subsurface structural conditions through impedance contrast between layers (Molnar, 2022). Figure 5b shows the spatial distribution of A_0 values in Bawean Island to range from 2.01 to 6.81. The classification by Ratdomopurbo & Suharna (2008) shows that low amplitudes (2.01–3) are distributed in the green-shaded areas, medium (3–6) in yellow, and high (6–6.81) in red. According to Gosar et al. (2010) and Molnar et al. (2022), A_0 reflects the impedance contrast with the bedrock but does not directly represent the actual soil amplification in a given area. The parameter is closely related to K_g because it is calculated through empirical equations with both A_0 and f_0 (Nakamura, 1996). Several studies also reported a correlation between H/V spectral peak and the distribution of earthquake-induced building damage (Drajat, 2013). Therefore, the interpretation of A_0 has certain limitations but remains relevant and practical for estimating seismic vulnerability in a particular area.

4.3. Seismic Vulnerability Index (K_g)

Microtremor data collected were supported by 25 visual documentations of building and infrastructure damage caused by the Bawean Earthquake. The documentations were used as supporting data to analyze the

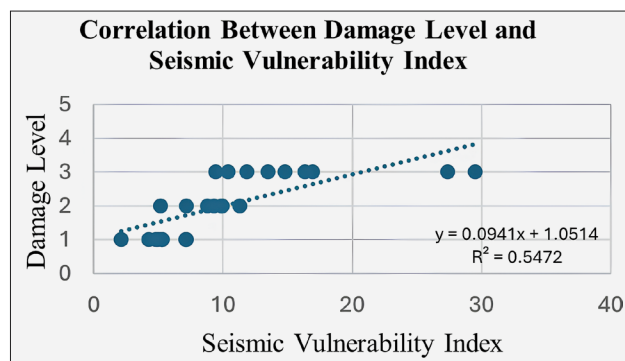


Figure 6: The relationship between seismic vulnerability index (K_g) and building damage levels based on linear regression analysis

relationship between K_g and the actual damage level observed in the field. This was achieved by classifying the damage qualitatively into three categories including low, moderate, and high. The criteria for each were based on the building damage typology from the 2018 Palu Earthquake. The damage analysis was subsequently correlated with the K_g values at the corresponding areas. The analysis was facilitated by symbolising the damage levels numerically using 1 for low, 2 for moderate, and 3 for high. A linear regression analysis was also conducted in Figure 6 to quantify the relationship between K_g and the damage levels.

The coefficient of determination R^2 was recorded to be 0.5472 and this showed 54.72% of the variation in building damage levels could be explained by the change

Table 1: Classification Results for Seismic Vulnerability Index

Seismic Vulnerability Index (K_g)	Damage Category	Damage Description
0 – 4.8	Low	No structural damage was observed. The damage was only minor, affecting non-structural elements such as paint and plaster. The building remains safe and habitable.
4.8 – 15	Moderate	Cracks appeared on the walls, and structural elements were slightly affected. Components such as doors and windows experienced functional disturbances. The building is still habitable with necessary repairs.
> 15	High	Significant damage occurred to the main structural components (beams, columns, foundations). Several parts of the building are at risk of collapse. The building is unsafe for occupancy and requires evacuation and reconstruction.

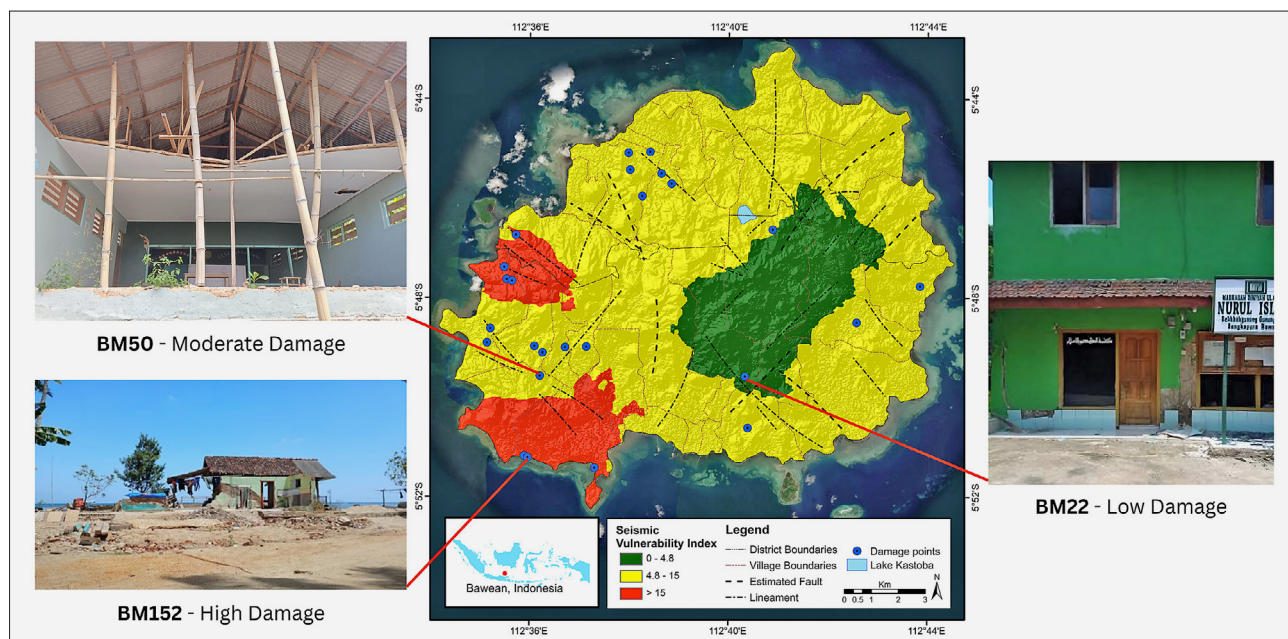


Figure 7: The distribution map of seismic vulnerability index (K_g) shows low damage at BM22 with a low-vulnerability zone (green), moderate damage at BM50 in the medium-vulnerability zone (yellow), as well as high damage and evidence of liquefaction at BM152 with the high-vulnerability zone (red).

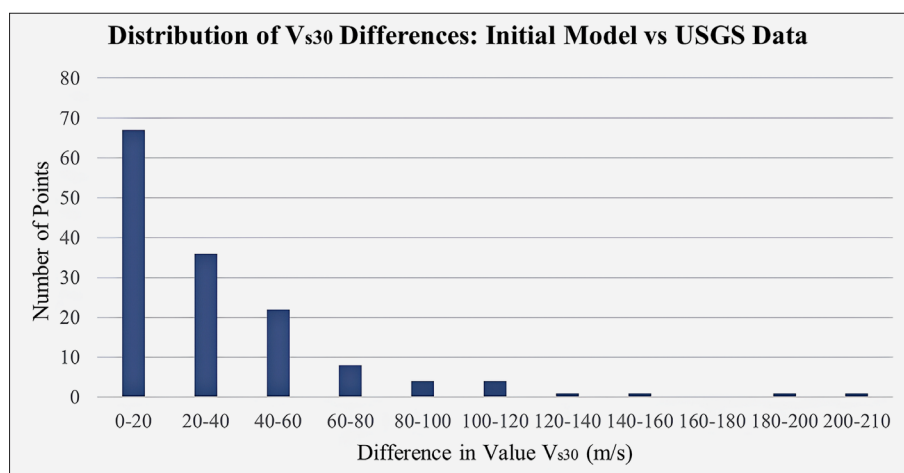


Figure 8: Histogram of the frequency distribution of the differences in $\bar{V}_{s30}$ values between the initial model and USGS data.

es in K_g . Cohen (1998) cited in Brydges (2019) categorized R^2 values ranging from 0.5 to 0.8 as a reflection of a reasonably good correlation. The trend showed that K_g significantly contributed to explaining the levels of building damage due to the earthquake impact in the study area. Moreover, linear regression equation $y = 0.0941x + 1.0514$ was used to calculate the damage classification, where x represents the K_g value for each data point. The equation determined the damage level values for each data point and the K_g threshold values corresponding to each category in **Table 1**.

The observation from the analysis is that Bawean Island has K_g values ranging from 1.04 to 29.54. **Figure 7** shows that areas with high K_g values tend to be associated with building damage caused by the Bawean Earthquake. For example, site BM152 experienced high damage that rendered the building uninhabitable and caused

ground subsidence with a K_g value of 27.37. A similar condition occurred at site BM151 which exhibited high structural damage with a K_g value of 16.32. Moderate damage was observed at site BM50 with 11.31 where part of the house structure collapsed but the building remained habitable. Meanwhile, low damage such as small cracks was found at site BM22 with 4.47. The results showed that higher K_g values reflected greater potential for building damage. This trend suggested that K_g classification closely corresponded to actual damage conditions observed after the earthquake. The spatial distribution of K_g values was further used to map seismic hazard zones, as shown in **Figure 7**. The green-shaded parts represent low vulnerability typically located in stable hilly areas with minimal active geological structures. Meanwhile, red-shaded parts show high K_g values in lowland areas near the Muria Fault and lineaments

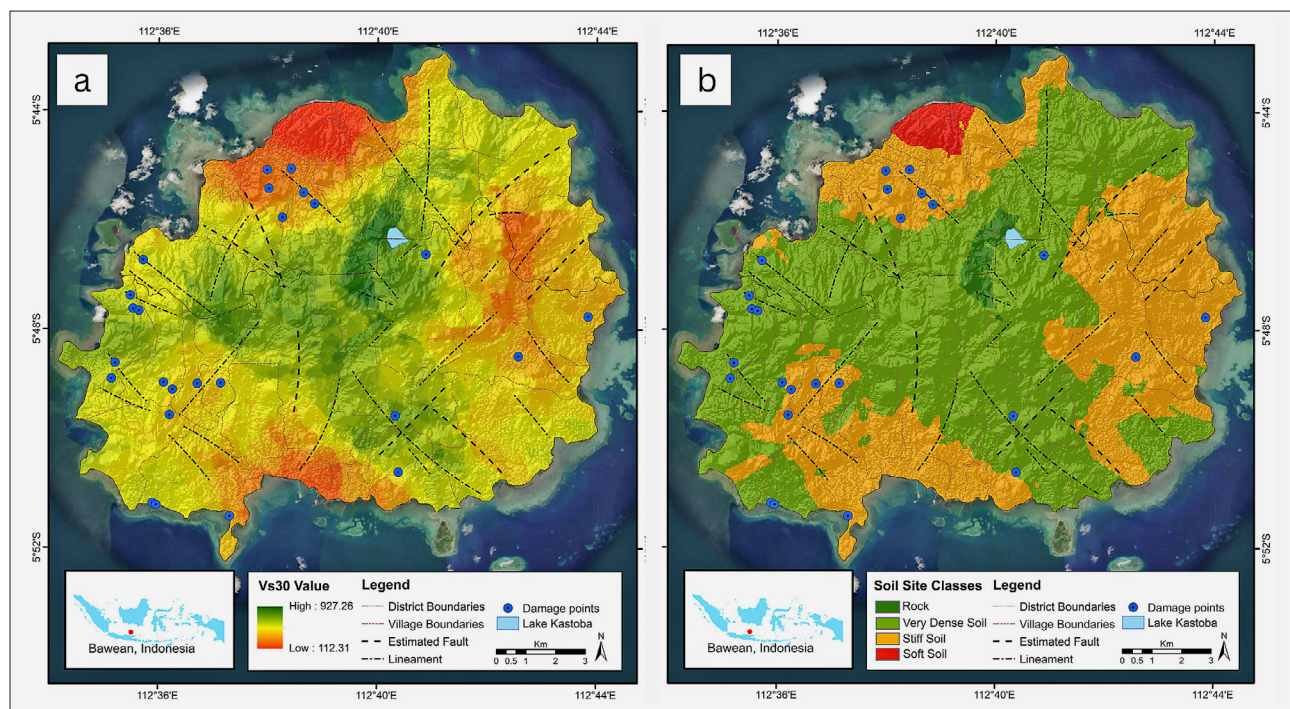


Figure 9: a) Distribution map of $\bar{V}_{s30}$ values in Bawean Island ranging from 112.31 to 927.26 m/s and b) soil site classification map based on $\bar{V}_{s30}$ values from soft soil to rock.

where heavy structural damage was recorded. The map is dominated by yellow-shaded parts representing moderately damaged areas that remain vulnerable. This was particularly focused on buildings that did not meet earthquake-resistant construction standards. The condition emphasizes that active geological structures and sediment thickness are significant in increasing K_g values and the potential for earthquake-induced damage.

4.4. Seismic Shear Velocity ($\bar{V}_{s30}$)

HVSR curves obtained in the previous step were used to construct an initial model to provide a preliminary approximation of subsurface conditions. The focus was on several soil or rock layers with each characterized by specific $\bar{V}_{s30}$ thickness, and density values.

The initial model was developed using Python software and considered valid because the differences in $\bar{V}_{s30}$ values compared to USGS data were relatively small. More than 65% were in the 0-20 m/s range and approximately 90% were below 60 m/s as shown in **Figure 8**. This reflects high consistency and accuracy which confirms the suitability of the model for further analysis and inversion.

Microtremor inversion process was used to determine the subsurface V_s profile using HVSR curves (*.hv) as the main input towards reflecting local resonance due to impedance contrasts. The ellipticity curve method in the Dinver module (Geopsy) was used for the inversion by matching the observed curves with theoretical models based on specific parameters. The iterations conducted up to 10,000 times produced a V_s profile with depth to

reflect the stratigraphic conditions and physical properties of the soil. The inverted V_s profiles showed the velocity variations across subsurface layers and served as the basis for calculating other parameters such as $\bar{V}_{s30}$ for each site using **Equation 3**.

The modelling results of $\bar{V}_{s30}$ in the study area are visualized in **Figure 9a** with values ranging from the lowest in red to the highest in dark green. $\bar{V}_{s30}$ values varied between 112.3 m/s and 927.28 m/s with the highest concentration in the central part of the island characterized by hilly to mountainous terrain and the area surrounding Lake Kastoba. The areas are represented in dark green to reflect stiffer and more consolidated soils. The correlation with the regional geology showed that high $\bar{V}_{s30}$ values were predominantly found in areas dominated by the Balibak Volcanic Rock Formation (Qv) considered geologically denser and more stable. Meanwhile, lower values were distributed widely in coastal areas, particularly along the northern margin of the island as reflected in orange to red. This condition shows the presence of softer surface materials which tend to amplify seismic wave amplitudes. The regional geology in the areas is dominated by Alluvium deposits (Qa) which are unconsolidated and mechanically weaker.

$\bar{V}_{s30}$ in Bawean Island was further classified according to Indonesian seismic code SNI 1726 to identify soil types and stiffness characteristics in **Figure 9b**. Higher values corresponded to stiffer and more stable soils. The classification led to four soil categories with the majority of the area represented by 103 points placed into the medium soil category (SD). The stiff soil and soft rock cat-

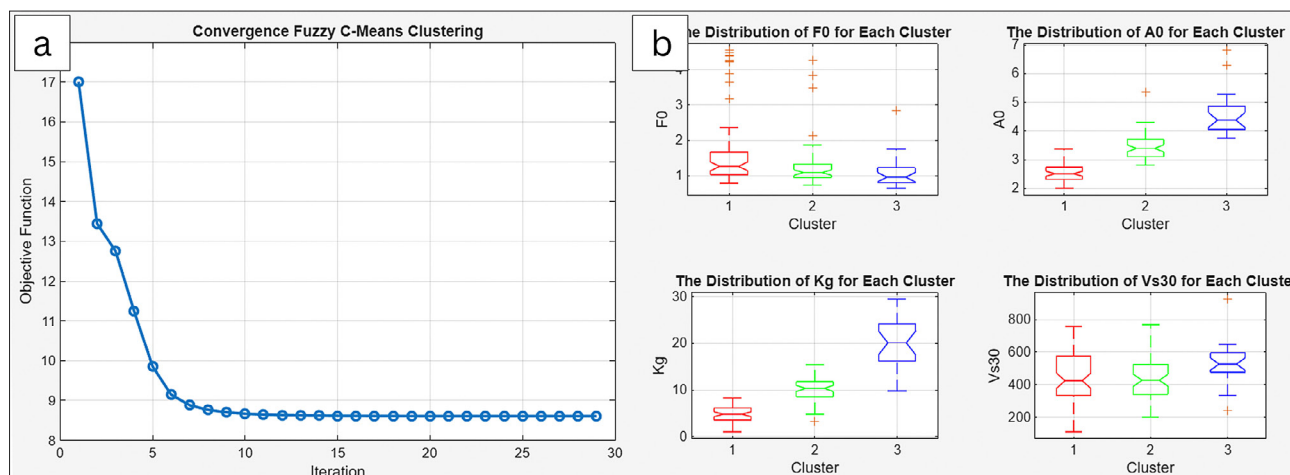


Figure 10: a) The variation of the objective function with respect to the number of iterations shows stability at the 8th iteration and b) the distribution of parameters (f_0 , A_0 , K_g , and $\bar{V}_{s30}$) in Cluster 1 (red), Cluster 2 (green), and Cluster 3 (blue).

egory (SC) had 40 points mostly located in areas underlain by the Balibak Volcanic Rock Formation. Meanwhile, the soft soil zone (SE) identified to have a higher potential to amplify ground shaking was mainly distributed in the northern part of the island and dominated by Alluvium deposits (Qa). The variation in $\bar{V}_{s30}$ values reflected the diverse geotechnical conditions and subsurface lithology where soft soils tended to amplify seismic shaking while stiff soils or rock layers provided better attenuation of ground motion.

5. Discussion

This study conducted clustering based on four key parameters, including f_0 , A_0 , K_g , and $\bar{V}_{s30}$ to map seismic hazard potential in Bawean Island. The FCM method was applied to divide the area into three hazard zones which were low, medium, and high. **Figure 10a** shows the convergence graph where the objective function reflects a significant decrease up to the 7th iteration and stabilizes after the 8th iteration. The trend is a sign that the clustering process has reached stability. Moreover, the four box plots on the right side in **Figure 10b** show the distribution of parameters in each cluster. Cluster 1 is generally characterized by relatively low f_0 and A_0 values, Cluster 2 by moderate values, and Cluster 3 by the highest values. K_g also increases progressively from Cluster 1 to 3 in line with the potential for ground amplification. However, $\bar{V}_{s30}$ exhibited a different pattern with Cluster 1 showing moderate values, Cluster 2 was lower, and Cluster 3 was higher. Although $\bar{V}_{s30}$ is used to describe the site's stiffness, the $\bar{V}_{s30}$ distribution obtained in this study may not show a monotonous relationship with the seismic hazard zones. This is an indication that the classification of the seismic hazards is influenced by the combined effect of various parameters such as the dominant frequency (f_0), H/V amplitude (A_0), and seismic vulnerability index (K_g).

Table 2: Results of FCM Clustering using f_0 , A_0 , K_g , and $\bar{V}_{s30}$ as input parameters.

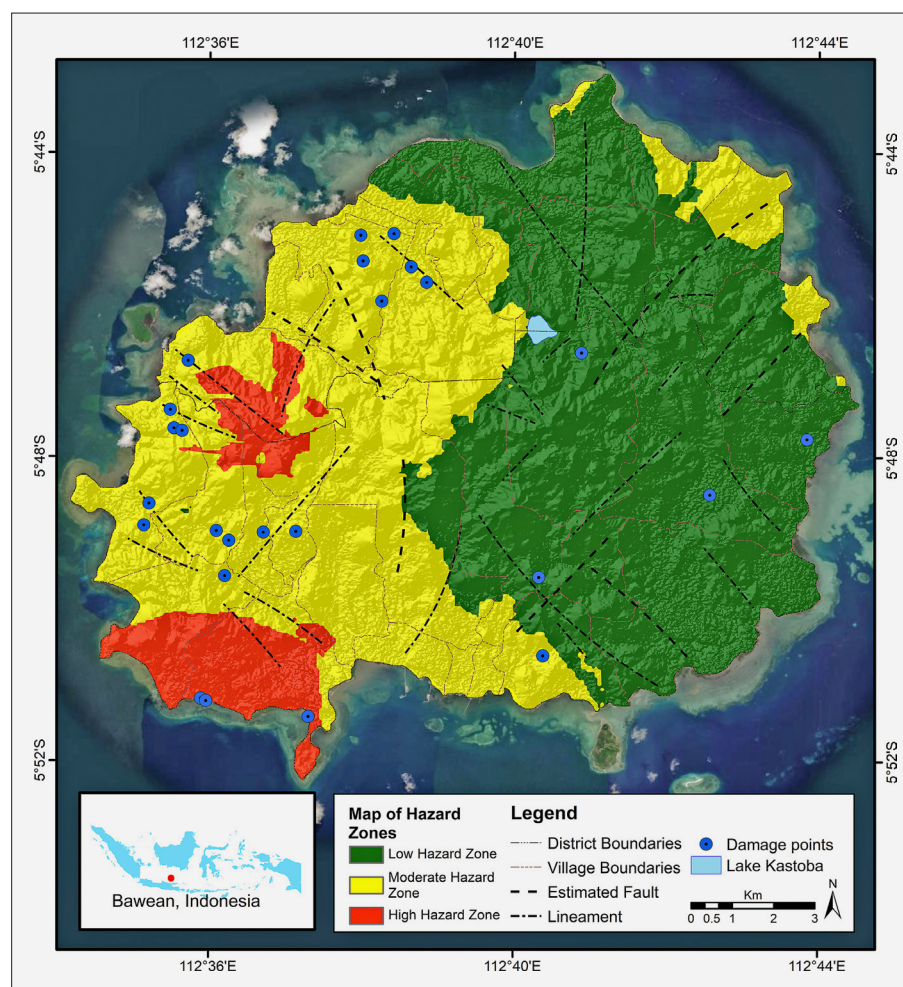
Parameter	Cluster 1	Cluster 2	Cluster 3
f_0	1.789	1.270	1.131
A_0	2.537	3.454	4.582
K_g	4.694	10.278	20.064
$\bar{V}_{s30}$	455.588	453.728	531.504

The irregularity was because the FCM method did not depend on a single parameter but rather optimized multidimensional membership weighting across all the parameters simultaneously. The trend showed the possibility of grouping a cluster with moderate $\bar{V}_{s30}$ (Cluster 1) with low f_0 and A_0 values while a cluster with low $\bar{V}_{s30}$ (Cluster 2) was associated with moderate A_0 and K_g . This reflected that FCM did not force $\bar{V}_{s30}$ to follow a single-value pattern but rather adjusted the clustering result based on the general combination of parameters.

The clustering results led to the zonation of seismic hazard levels in the study area into three clusters. This was based on a combination of seismic hazard potential and vulnerability levels associated with seismic activity in Bawean Island. The values listed represent the average of each parameter in the respective clusters.

Table 2 confirms that the clustering using FCM divides the study area into three seismic hazard zones, including Cluster 1 for low, Cluster 2 for moderate, and Cluster 3 for high. Cluster 1 is classified as a low-hazard zone characterized by the highest f_0 of 1.789 Hz, lowest K_g of 4.694, and a maximum A_0 of 2.537. The relatively high $\bar{V}_{s30}$ of 455.588 m/s also shows that the area is dominated by relatively hard rock layers with low potential for seismic wave amplification. Cluster 2 represents a moderate-hazard zone with a f_0 of 1.270 Hz, accompanied by a significant increase in K_g at 10.278 and A_0 with 3.454. This reflects the presence of softer soil layers with a greater potential for seismic amplification compared to

Figure 11: Seismic hazard zoning map of Bawean Island based on clustering of f_0 , A_0 , K_g , and $\bar{V}_{S30}$ using the FCM method



Cluster 1. The slightly lower $\bar{V}_{S30}$ value of 453.728 m/s is possibly due to thicker sediment layers which enhance the soil response to seismic waves.

Cluster 3 corresponds to the high hazard zone by showing the lowest f_0 of 1.131 Hz, the highest K_g of 20.064, and a very large A_0 of 4.582, all of which reflect very high seismic vulnerability. Interestingly, $\bar{V}_{S30}$ is 531.504 m/s which is higher than the values in Clusters 1 and 2. This elevated value is probably due to the presence of hard rock layers at greater depths in the cluster. However, the large values of A_0 and K_g categorize the area as highly vulnerable to seismic wave amplification. The non-monotonic pattern of $\bar{V}_{S30}$ between Clusters 1 and 2 is because the FCM method groups data based on the combined influence of all seismic parameters rather than a single variable. This shows that the large A_0 and K_g values justify the classification of Cluster 3 as a high hazard zone even though $\bar{V}_{S30}$ is higher.

The microzonation map in **Figure 11** shows the three seismic hazard zones which include low in green, moderate in yellow, and high in red. The low hazard zones are generally located in the eastern and central parts of the island dominated by hard rock layers, thin sediment thickness, high f_0 , low A_0 , low K_g , and relatively high $\bar{V}_{S30}$ values. The conditions are a reflection of a relatively low

soil response to seismic shaking. The moderate hazard zones are distributed across parts of the central and northern areas of the island characterized by thicker sediment layers and intermediate seismic parameter values. In this zone, the f_0 values are generally moderate, A_0 and K_g are at intermediate levels, and $\bar{V}_{S30}$ are relatively moderate. The trend shows that the potential for seismic wave amplification exists but not at a significant level as observed in the high hazard zones.

The high hazard zones are concentrated in several areas in the western and southwestern parts of Bawean Island and represented by high K_g , large A_0 , and low f_0 values. This shows the presence of thick sediment layers with a greater potential for seismic wave amplification. $\bar{V}_{S30}$ values are also generally low to reflect soft and less compact soil conditions considered more susceptible to strong ground shaking. The results were supported by field data which showed the building damage caused by the 2024 Bawean Earthquake included 60 in Lebak Village, 40 in Kumalasa Village, and 30 in Suwari Village. The spatial distribution of the hazard zones was influenced by local geological conditions including sediment thickness, rock properties, and the presence of active geological structures such as faults and lineaments. The high hazard zones are generally located near the geo-

logical structures which leads to more vulnerability to earthquake-induced ground shaking. The results of this microzonation study can serve as a scientific basis for spatial planning and disaster mitigation strategies particularly in identifying priority protection areas and planning earthquake-resilient infrastructure to minimize future seismic risks.

6. Conclusions

In conclusion, the results of analyses and mapping showed that the dominant frequency (f_0) values on Bawean Island ranged between 0.65–4.55 Hz. H/V amplitude (A_0) showed a high impedance contrast between layers at several points with values ranging from 2.01–6.81. The seismic vulnerability index (K_g) ranged from 1.04–29.54 s/cm² while the average shear-wave velocity up to a depth of 30 meters ($\bar{V}_{s30}$) was between 112.3–927.28 m/s. The correlation analysis data showed that areas with high K_g values generally experienced more high building damage. The trend reflected low damage category had K_g values ranging from 0 to 4.8, moderate from 4.8 to 15, and high was > 15. The clustering conducted using FCM produced three seismic hazard zones. These include the low zone category characterized by high f_0 , low A_0 , low K_g , and low $\bar{V}_{s30}$, moderate zone with intermediate parameter values, and high zone with low f_0 , high A_0 , high K_g , and high $\bar{V}_{s30}$. The results were supported by field data related to building damages in several villages including 60 in Lebak Village, 40 in Kumalasa Village, and 30 in Suwari Village due to the 2024 Bawean Earthquake. The produced zonation was considered accurate and could serve as an important basis for disaster mitigation, spatial planning, and infrastructure development prioritisation on Bawean Island. This study has several limitations, including the limited building damage data used for validation, the assumption of a one-dimensional subsurface structure in the HVSR method, and the estimation of $\bar{V}_{s30}$ values obtained indirectly through empirical relationships. In addition, the results of Fuzzy C-Means clustering depend on the parameters selected in the seismic hazard characterization. Therefore, further research is recommended to integrate additional geotechnical and geophysical data, such as drilled data, MASW, and combine them with maximum ground acceleration (PGA) data and earthquake scenario modelling to improve the accuracy of seismic microzonation.

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SAŽETAK

Seizmičko mikrozoniranje temeljeno na mikrotremorskim podacima za kartiranje oštećenja uzrokovanih potresom na otoku Bawean (Gresik, Istočna Java, Indonezija)

Otok Bawean u području Gresik svrstava se u područje s visokim seizmičkim rizikom zbog aktivnosti rasjeda u Javan-skome moru. Potres koji se dogodio 22. ožujka 2024. godine uzrokovao je oštećenje tisuća kuća i raseljavanje desetaka tisuća stanovnika. Cilj je ovoga istraživanja provedba seizmičkoga mikrozoniranja primjenom metode HVSR na temelju podataka mikrotremora kako bi se identificirala svojstva tla i zone ranjivosti. Podatci mikrotremora obrađeni su standardnim HVSR postupcima, uključujući segmentiranje signala, frekvencijsko filtriranje, spektralnu analizu i inverziju, kako bi se dobili lokacijski specifični seizmički parametri. Rezultati pokazuju da se dominantna frekvencija (f_0) kreće u rasponu od 0,65 do 4,55 Hz, dok se amplitudni omjer H/V (A_0) kreće između 2,01 i 6,81, što odražava varijacije u kontrastu impedancije. Indeks seizmičke ranjivosti (K_g) kreće se od 1,04 do 29,54 s/cm², dok je prosječna brzina posmičnih valova do dubine od 30 metara ($\bar{V}_{s30}$) u rasponu od 112,3 do 927,28 m/s. Korelacija između podataka o oštećenjima i vrijednosti K_g pokazuje da niska razina oštećenja odgovara rasponu 0 – 4,8, umjerena 4,8 – 15, a visoka vrijednostima većim od 15. Nadalje, uz primjenu metode grupiranja Fuzzy C-Means (FCM) i četiriju parametara (f_0 , A_0 , K_g i $\bar{V}_{s30}$) područje je klasificirano u tri zone seizmičke ranjivosti. Na temelju 148 mjernih točaka izrađena je karta mikrozoniranja koja pokazuje snažnu povezanost između indeksa seizmičke ranjivosti i opaženih razina oštećenja. Dobiveni rezultati mogu doprinijeti ublažavanju posljedica potresa i otpornijem prostornom planiranju.

Ključne riječi:

Fuzzy C-Means klasterizacija, HVSR, mikrotremor, mikrozoniranje, seizmička ranjivost

Author's contribution

Maulida Krisna Dewi contributed to field investigation, data processing, visualization, writing-original manuscript, writing-review, and editing. **Tasya Okta Irwanda** contributed to field investigation, data processing, and writing-original manuscript. **Juan Pandu Gyah Nur Rochman** contributed to review and editing, academic supervision, and overall guidance of the research. **Amien Widodo** and **Firman Syaifuddin** contributed to conceptual supervision and methodological guidance of the research.

All authors have read and agreed to the published version of the manuscript.

Comparative Analysis of the Performance of Palm Oil MES Surfactant and Pine Wood SLS Surfactant on Berea Sandstone in the Imbibition Process Using Neutron Computed Tomography Application

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Original scientific paper



Muhammad Furqon Haryono Bimantoro¹ , Rini Setiati^{1*} , Fahrurrozi Akbar² ,
Muhammad Taufiq Fathaddin¹ , Sulistioso Giat Sukaryo² , Bharoto Bharoto² ,
Iwan Sumirat² , Pauhesti¹ , Priagung Rakhmanto¹ , Refa Amelia Angelica¹ 

¹ Petroleum Engineering Department, Universitas Trisakti, Jalan Kiai Tapa, Jakarta, 11440.

² National Research and Innovation Agency (BRIN) of the Republic of Indonesia, KST B. J. Habibie, Jalan Raya Puspiptek, Muncul, Kec. Setu, Kota Tangerang Selatan, Banten, Indonesia, 15310.

Abstract

Surfactant flooding is one of the enhanced oil recovery (EOR) methods aimed at increasing crude oil production in Indonesia. This method is implemented after primary and secondary recovery phases, by reducing the interfacial tension (IFT) in reservoir system, when a significant amount of oil remains trapped and cannot be mobilized. This study employs two types of bio-based surfactants: palm oil-derived MES (Methyl Ester Sulfonate) and pinewood-derived SLS (Sodium Lauryl Sulphate). Both are considered promising alternatives to conventional synthetic surfactants. The methodology used involves experimental and analytical laboratory research. Compatibility tests were conducted on MES and SLS solutions with concentrations ranging from 0.5% to 2% at salinities between 5,000 and 10,000 ppm, using Berea sandstone cores and light crude oil samples. The surfactants were characterized at an EOR laboratory, focusing on compatibility testing, which included aqueous stability and phase behaviour evaluations. Further analyses comprised interfacial tension measurements, IFT stability tests, and both static and dynamic adsorption assessments. Core flooding experiments were then performed on Berea cores using injection and imbibition techniques. In addition, neutron tomography imaging was utilized during core flooding to visualize surfactant distribution within the core samples, allowing identification of surfactant flow zones. Analytical calculations were conducted to validate and enhance the interpretation of the recovery factors obtained through both imbibition and injection processes.

Keywords:

middle-phase emulsion; interfacial tension; light crude oil; neutron tomography

1. Introduction

Surfactant flooding is a chemical EOR (Enhanced Oil Recovery) method designed to improve oil recovery mechanisms by mobilizing capillary-trapped residual oil following waterflooding (Al-Jifri et al., 2021; Barati-Harooni et al., 2016). This method depends on the effective injection and distribution of surfactant in the reservoir (Zhao et al., 2015). During surfactant flooding, favourable phase behaviour is targeted to achieve ultralow interfacial tension (IFT) between oil and water, allowing the trapped oil to flow easily (Sandersen et al., 2012). Generally, crude oil contains various surface-active components such as organic acids, salts, and alcohols. When it comes into contact with brine, natural surfactant accumulates at crude oil–brine interface, forming an adsorbed film that reduces IFT at the crude oil–water

boundary (Olajire, 2014). The reduction in IFT minimizes the adhesive forces between oil droplets and the rock surface, thereby enabling easy mobilization toward production wells. The effectiveness of this method has been shown in previous laboratory studies (Setiati et al., 2019, 2020, Samsol et al., 2023), which support proper surfactant combinations injected at low salinity levels into core samples to reduce capillarity and prevent excessive oil entrapment (Johannessen & Spildo, 2013).

High pressures (10–20 MPa) and temperature variations are realistic and challenging reservoir conditions in Enhanced Oil Recovery (EOR) operations. At pressures of 10–20 MPa (approximately 1,450 to 2,900 psi), which are relatively high reservoir pressures, the primary impact on surfactant flooding is dominated by temperature changes and their interaction with formation water salinity. Pressures within this range tend to maintain the fluid phase, but temperature is a critical determinant that alters surfactant chemical behaviour.

The successful application of surfactant in EOR processes depends on the ability to form microemulsions

* Corresponding author: Rini Setiati
e-mail address: rinisetiati@trisakti.ac.id

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that significantly reduce oil–water IFT in the reservoir system. In EOR systems, microemulsions are thermodynamically stable, homogeneous mixtures of immiscible fluids, namely hydrocarbons and water, stabilized by surfactant acting at the interface (Sheng, 2011). The system can be designed to achieve ultralow IFT values (~ 0.001 mN/m) by formulating stable brine or hydrocarbon phases (Green & Willhite, 1998), which is beneficial for EOR applications (Alvarado & Manrique, 2010; Bealesio et al., 2021). Furthermore, in EOR processes, a ternary diagram is focused on the three-phase region. Ternary diagram types are commonly classified as Type II (lower-phase emulsions with excess oil), Type I (+) (upper-phase emulsions with excess water), and Type III (middle-phase microemulsions) (Du et al., 2016; Sugihardjo, 2022). In chemical EOR, specifically surfactant flooding, microemulsions are typically categorized as Winsor Type I (lower phase), Type II (upper phase), and Type III (middle phase). Type I microemulsions are oil-in-water (O/W) in equilibrium with excess oil, Type II represents water-in-oil (W/O) in equilibrium with excess water, and Type III is a middle-phase in equilibrium with both oil and water. At optimal salinity conditions, stable middle-phase microemulsions can be formed, which significantly reduces residual oil saturation (Sor). This middle-phase also shows ultralow IFT, large interfacial surface areas, thermal stability, and the ability to solubilize both oil and water (Sheng, 2015). The formation of W/O or O/W emulsions in porous media is primarily influenced by contact angle, with the non-wetting phase typically becoming discontinuous, causing droplet formation (Hu et al., 2020). Under ultralow IFT surfactant injection, residual oil becomes highly deformable and elongated, as shown in Figure 1.

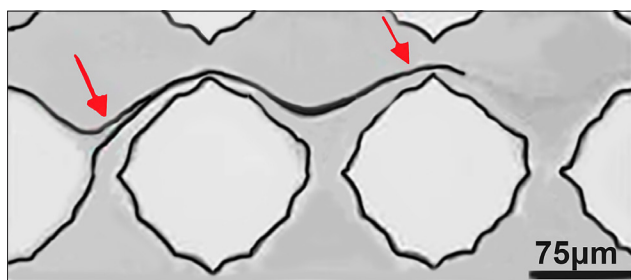


Figure 1: Residual oil condition during ultralow IFT surfactant injection (Tagavifar et al., 2017)

The apparent contact angle observed during immiscible displacement in porous media is governed by the balance between capillary and viscous forces, as it increases with the capillary number. In low IFT surfactant injection under water-wet reservoir conditions, the capillary number is insufficient to significantly increase the contact angle. This makes oil remain as the non-wetting phase, leading to the formation of O/W emulsions. Therefore, there is a need to understand the behaviour of contact angle by examining the underlying physics of interfacial interactions, specifically surface tension and

wettability. Surface tension originates from cohesive interactions among liquid molecules. When a liquid comes into contact with another phase, whether a solid surface or a gas, an interface is formed. This interface behaves analogously to an elastic film under tension, giving rise to surface tension, and is described by two parameters, namely the contact angle (θ) and the wetting surface tension (σ , N/m). Both properties are strongly influenced by the characteristics of liquid and the nature of the adjacent phase at the interface.

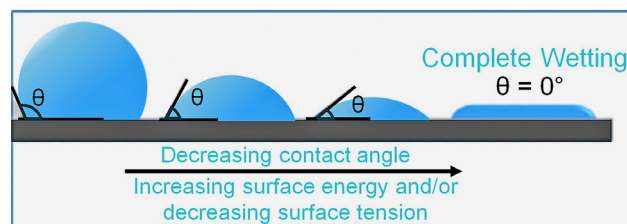
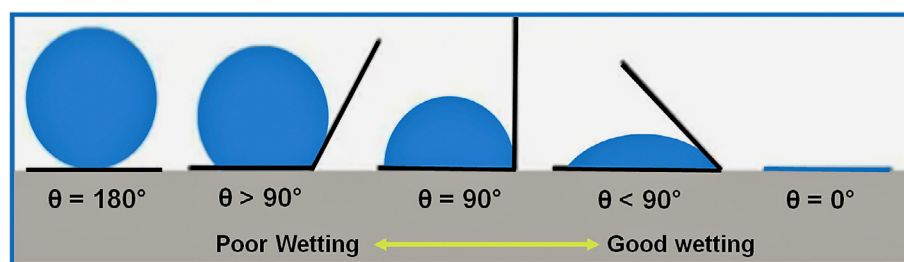


Figure 2: Variation of contact angle towards wettability (Bolke, 2023)

The wetting ability of surfactant is identified through the contact angle formed by liquid droplets on a solid surface. Generally, the reduction of surface or interfacial tension is also considered the most important property of surfactant in emulsion systems. In a liquid, surface molecules possess higher energy compared to those in the bulk phase. An effective surfactant, characterized by favourable contact angle and surface tension values, is expected to promote efficient wetting. A contact angle of 180° implies no interaction between the liquid and the solid substrate, indicating a non-wetting condition. When the contact angle falls between 180° and 90° ($180^\circ > \theta > 90^\circ$), surfactant shows hydrophobic behaviour, favouring the stabilization of W/O emulsions with poor wettability. However, contact angles between 0° and 90° ($0^\circ < \theta < 90^\circ$) signify favourable wetting, where surfactant demonstrates hydrophilic characteristics suitable for O/W emulsions, as presented in Figure 3.

In a water-wet reservoir with high capillary pressure, injecting low IFT surfactant can cause contact angles above 90° , promoting W/O emulsion formation rather than O/W during displacement (Dong, 2012; J.-C. Li et al., 2020; W. Yang et al., 2021). This is because surfactants reduce IFT between oil and water by adsorbing at their interface, displacing fluid molecules. After absorption, surfactant molecules are oriented with hydrophobic tails toward oil and hydrophilic heads toward brine. Moreover, one effective oil recovery method is spontaneous imbibition, which has been proven effective in water-wet to mixed-wet rock. This process is driven by capillary forces and gravity under low-IFT conditions. As IFT decreases, a significant transition occurs from capillary-driven spontaneous imbibition (counter-current flow) to gravity (co-current flow). Water imbibition is a physical process caused by the adsorption of water onto hydrophilic ionic groups, forming a

Figure 3: Wetting condition during surfactant contact angle formation (Akbari et al., 2018)



hydrophilic surface. In a reservoir with hydrophilic rock surfaces and lipophilic fluids such as oil, exposure to water causes spontaneous penetration to pore spaces and oil displacement. This physical phenomenon arises from forces acting within pore spaces, which are often conceptualized as capillary.

Capillary forces in porous media are influenced by mineral wettability, rock–fluid chemical interactions, and the saturation history of the reservoir. These forces play a critical role in spontaneous imbibition, a process that can be enhanced by the introduction of surfactant. The role of surfactant in imbibition is comparable to water in traditional water-driven recovery processes, reducing IFT and improving fluid displacement. The recovery factor achieved through surfactant application depends on both the rate and extent of spontaneous imbibition. In this process, displacement initially occurs through counter-current flow and gradually transitions to co-current flow. Furthermore, the capacity increases with greater contact area and higher porosity, but reduces due to higher initial water saturation (Liu et al., 2025).

Spontaneous imbibition is a displacement process in porous media that occurs due to differences in wettability between pore walls and fluids. This mechanism is strongly influenced by capillary pressure, which is related to wettability (Cai et al., 2022; Dou et al., 2021; Qin, 2007; R. Yang et al., 2019), interfacial tension (Wang et al., 2015), and pore radius (Karpyn et al., 2009). In water-wet formations, capillary forces can significantly enhance the imbibition of injected water, while in mixed-wet systems, the effect becomes negligible (Haqparast et al., 2024). Spontaneous imbibition experiments in porous media are among the most important methods for quantifying oil production and predicting recovery rates from reservoirs. In this procedure, oil-saturated core samples are placed into imbibition cell filled with either water or surfactant solution. The wettability of the core can be modified by pre-saturating it with crude oil. Subsequently, surfactant solution is absorbed into the core through spontaneous imbibition (Meng et al., 2017) and displaced oil accumulates above the water phase in Amott Cell. Numerous oil bubbles often adhere to the core surface, particularly when the crude oil has high viscosity, which can significantly reduce the accuracy of production measurements. Mason & Morrow (2013) reported that bubbles could be removed by gentle shaking or touching with a rod wetted

with oil. Besides Amott Cell, the weighing method is also commonly used to evaluate oil production during spontaneous imbibition (Y. Li et al., 2006). In this method, when the core is immersed in water, the weight is recorded, and oil production is estimated based on the density difference between oil and water. However, the accuracy of this method may be compromised when oil bubbles remain attached to the core surface.

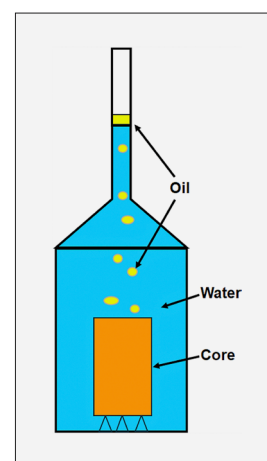


Figure 4: Amott Cell used in the spontaneous imbibition process (Meng et al., 2017)

Neutron tomography, is a method that generates cross-sectional images of internal structures (Putra et al., 2015). By rotating the sample 0°–360° under a neutron beam and capturing images at 1° intervals, detailed internal views were obtained. A CCD camera recorded each image as a 16-bit TIFF file through LabVIEW (Bharoto et al., 2020). These raw images were processed to analyze core samples before and after surfactant injection, showing surfactant distribution in pore spaces and enabling contact angle and volume estimation. Adsorption and wettability tests (Civan, 2023) complemented tomography for interpreting surfactant behaviour during fluid injection. The measurement method, which relies on neutrons generated from nuclear reactors or synchrotrons, offers distinct advantages for investigating low atomic number elements such as hydrogen and carbon (L'Annunziata, 2016; Penumadu et al., 2016; Schwarz et al., 2005).

Previous studies integrating porous rock samples and neutron imaging were conducted by Frikkie De Beer and F. Middleton (de Beer et al., 2004; de Beer & Middleton, 2006; Tengattini et al., 2021). Although the analysis did not specifically focus on reservoir rock samples,

there was a significant interest in applying Neutron Computed Tomography (NCT) in the oil and gas industry (Farrokhi et al., 2021; H. Lehmann, 2024; Hess et al., 2011; Pavan et al., 2022). In late 2019, a collaboration between a nuclear analyst and a university in Indonesia led to an in-depth investigation of Berea sandstone samples (Setiati et al., 2023). The university team developed a novel surfactant formula from sugarcane bagasse and explored both the quantitative and qualitative effects of surfactant in EOR processes (Akbar et al., 2021), including the visualization of Berea sandstone samples. The first phase of porosity measurement using NCT was also published (Setiati et al., 2021).

The assumptions and limitations of this study are partly related to the field scale. Implementing Enhanced Oil Recovery (EOR) technology from the laboratory scale to the field scale (up-scaling) is a complex process involving technical validation, mathematical modelling, and risk management. Not all successful laboratory results can be directly replicated in oil wells due to differences in volume, reservoir heterogeneity, and environmental conditions.

2. Materials and Methods

This study was conducted in a laboratory setting using core samples, which were synthetic Berea core, composed of homogeneous sandstone with specific physical properties, namely porosity and permeability, measured in the Reservoir Rock Characterization Laboratory. Each core was initially saturated using a desiccator under vacuum conditions for 24 hours, followed by brine through a core flooding apparatus to ensure that all pore spaces were filled (Okon & Edoho, 2016). The fluids used were synthetic formation water prepared based on a predetermined NaCl composition dissolved in D₂O, surfactant solutions at specific concentrations, made by mixing powdered surfactant (pinewood-derived SLS and palm oil-derived MES) with formation water at various salinity levels, and a light crude oil sample.

The experimental procedure consisted of several steps: preparation of synthetic formation water at salinities of 5,000 and 10,000 ppm, formulation of MES and SLS surfactant solutions at concentrations ranging from 0.5% to 1.5% and salinities between 5,000 and 10,000 ppm. The application of surfactants to injection water with salinities below 5,000 ppm (also known as Low Salinity Water-Surfactant Flooding or LSWF-S) often results in superior oil recovery efficiency compared to surfactant injection in high salinity environments (Bukhtikov, 2025). Optimal results are driven by two primary mechanisms working synergistically: More Efficient Interfacial Tension (IFT) and Wettability Alteration.

After preparation, several compatibility and performance tests were conducted with the crude oil samples. These included aqueous stability tests, phase behaviour analysis, IFT measurements, thermal stability, static and

dynamic adsorption, and wettability evaluations (Ansari, 2025, Massarweh & Abushaikh, 2020). Based on the results of these characterizations, surfactant concentration with the most favourable properties was selected for further neutron tomography testing (Scheffer et al., 2021). This included imaging of dry Berea cores, brine-saturated cores, and cores subjected to the imbibition process. Core Berea has characteristics such as porosity 20-22%, permeability 400-500mD N₂, length 2,4-2,6cm and diameter 2,59 cm.

After the imbibition process was completed, neutron tomography was performed on the imbibed cores (Lohvithee et al., 2022; Luo et al., 2022). The results were interpreted to analyze the distribution of surfactant in the core (Mathisen et al., 1995). Identifying the presence and distribution of surfactant enabled assessment of middle-phase emulsion formation between surfactant and oil in the system, which was associated with the reduction in IFT and improved mobilization of oil droplets from the core matrix (Samba, 2024).

Brine solutions were prepared to simulate reservoir conditions more accurately. The selection of brine salinity played a critical role in ensuring that the laboratory data were both accurate and representative of field conditions. Compatibility tests between surfactant and the crude oil sample were used to identify optimal performance at salinity levels of 5,000 ppm and 10,000 ppm. Brine was prepared using heavy water (D₂O) and sodium chloride (NaCl). To replicate formation water composition, 1 ppm salinity in 1000 mL of D₂O requires 1 mg of NaCl. Therefore, 5,000 ppm and 10,000 ppm brine solutions were made by dissolving 5,000 mg and 10,000 mg of NaCl, respectively, into 1 liter of D₂O. A magnetic stirrer was used to homogenize the solutions, serving as the base for preparing palm-based MES and pine-based SLS surfactant at concentrations of 0.5% and 2%. The compositions used to prepare surfactant solutions are shown in Table 1.

Table 1: Composition of Materials for the Preparation of Palm-Based MES Surfactant and Pine-Derived SLS Surfactant Solutions

Salinity (ppm)	Concentration (%)	Surfactant (g)	Brine (g)
5,000	0.5%	0.5	99.5
10,000	2.0%	2.0	98.0

3. Results

3.1. Spontaneous Imbibition

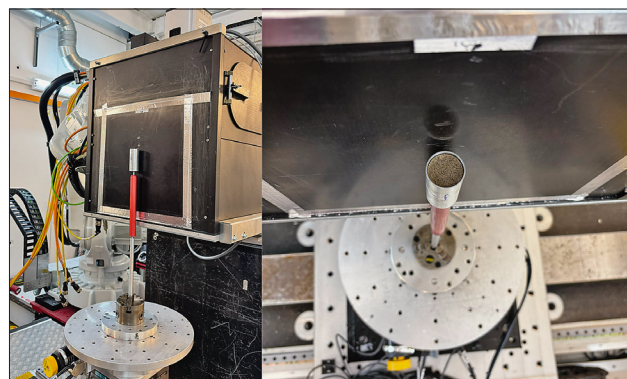
In the spontaneous imbibition test, Berea core samples (see Table 2) were saturated with light crude oil using a vacuum desiccator for 24 hours. The vacuum process ensured complete saturation by removing trapped air from the pore spaces, confirmed through the

Table 2: Core Data for Each Amott Cell

Core	Light Crude Oil (°API)	Surfactant	Salinity (ppm)
3A	39	Palm-based MES 2%	10,000
4B	39	Pine-based SLS 2%	10,000
5C	33	Palm-based MES 0.5%	5,000
6D	33	Pine-based SLS 0.5%	5,000

cessation of air bubbles. Once saturation was complete, core samples were placed into an Amott Cell filled with surfactant solution. The spontaneous imbibition process included the displacement of brine- and oil-saturated core samples by surfactant solution under static conditions at room temperature for 4 days. During this process, the wetting fluid was drawn into the pore spaces through capillary forces, displacing the resident oil. Subsequently, the expelled oil was collected and measured periodically to calculate the recovery factor, showing the effectiveness of each surfactant solution.

After 4 days of spontaneous imbibition (see **Figure 5**), the recovery factors were obtained, with Samples 3A, 4B, 5C, and 6D achieving 45.24%, 45.09%, 52.14%, and 38.68%. Among these, sample 5C, treated with 0.5% MES at a salinity of 5,000 ppm, showed the most effective oil recovery. This result showed the superior performance of MES in reducing IFT and facilitating the penetration of the wetting phase into the pore network, thereby enhancing overall recovery efficiency.

**Figure 5:** Spontaneous Imbibition Using Amott Cell**Figure 6:** Core Placement in Neutron Tomography Reactor

3.2. Neutron Tomography

Neutron tomography (see **Figure 6**) was used to visualize residual oil distribution after the imbibition process. The core samples were mounted vertically, two per scan session, in a neutron imaging chamber designed to minimize external disturbances. Each scan rotated the samples 360° over approximately 12 hours to acquire high-quality tomographic images.

The 3D tomography outputs enabled the analysis of oil distribution and the identification of trapped oil zones at the microscale. This visual data provides insight into flow patterns, sweep efficiency, and the effect of surfactant formulation on displacement behaviour (Scheffer et al., 2021).

The contact angles formed in each system in the core ranged from 7.43° to 45.17°, indicating that the surfactant system produced relatively small contact angle (< 90°). This value was observed when the liquid spread across the surface, with values below 90° signifying favourable surface wetting. Generally, the contact angle plays a role in emulsion formation and wettability (see **Figure 8**). The results only highlight the changes observed in the study only at salinities of 5,000 and 10,000 ppm, due to the characteristics of the palm oil MES surfactant which has good performance at low salinity, not at high salinity. The application of surfactants to injection water with salinities below 5,000 ppm (also known as Low Salinity Water-Surfactant Flooding or LSWF-S) often results in superior oil recovery efficiency compared to surfactant injection in high salinity environments. Optimal results are driven by two primary mechanisms working synergistically: More Efficient Interfacial Tension (IFT) and Wettability Alteration.

Table 3: Characteristics Test Surfactant – Crude oil

Core	Light Crude Oil (°API)	Surfactant	Salinity (ppm)	IFT (mN/m)	Contact angle
3A	39	Palm-based MES 2%	10,000	1.0489	14.17
4B	39	Pine-based SLS 2%	10,000	6.9544	45.17
5C	33	Palm-based MES 0.5%	5,000	0.5130	11.79
6D	33	Pine-based SLS 0.5%	5,000	6.3147	7.43

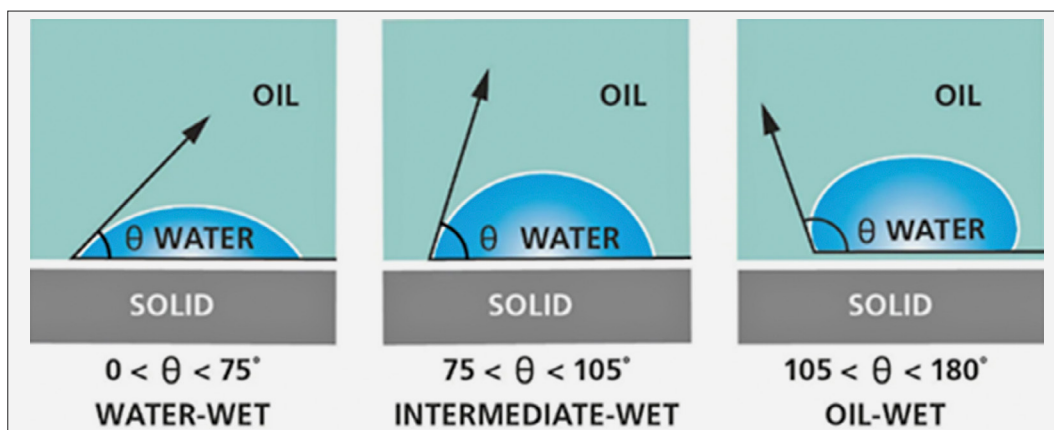


Figure 7: Contact Angle Vs Wettability (Marmur, 2017)

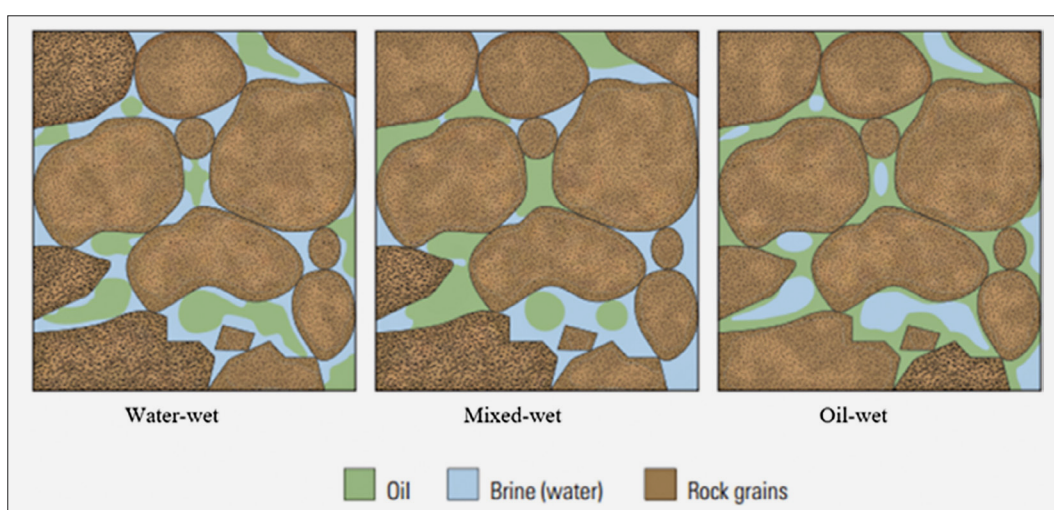


Figure 8: Type of Wettability (Richard, 2016)

In the context of surfactant imbibition, smaller values enhance the effectiveness of the imbibition mechanism. Based on the measured contact angle from the four core samples used in this study, all values were below 90° , confirming that the resulting wettability was water-wet. Wettability directly influences the volume of oil that can be recovered at the pore scale and is classified into water-wet and oil-wet in petroleum engineering.

In water-wet conditions, oil occupies the larger pores and becomes trapped during production due to disconnection from the main oil body. This phenomenon is observed in core samples. When a surfactant solution is introduced, there is a reduction in oil–water IFT, thereby increasing the capillary number (N_c). Furthermore, IFT serves as an indicator of solubility, with high and low values corresponding to immiscibility and miscibility in the system. At very low IFT, residual oil becomes more deformable and elongated, as shown in **Figure 7**. Evidence of miscibility can also be observed from phase changes, specifically the presence of a middle-phase emulsion. IFT formed in the surfactant–oil system influences capillary pressure, which governs fluid distribution and flow. This mechanism accounts for the measur-

able volume of oil obtained in an Amott Cell during spontaneous imbibition.

A total of four core samples were in this study, namely 3A, 4B, 5C, and 6D, each subjected to different treatment conditions, including variations in crude oil type, surfactant formulation, and brine salinity. Core samples 3A and 4B were saturated with crude oil of 39°API and exposed to two surfactant types prepared in brine with a salinity of 10,000 ppm. Meanwhile, 5C and 6D were saturated with crude oil of 33°API and treated with two surfactant types dissolved in brine with a salinity of 5,000 ppm. From **Table 3**, the lowest IFT value was obtained in core 5C, which was 0.5130 mN/m. With a surfactant concentration of only 0.5%, IFT could be effectively reduced.

The characteristics and concentration of surfactant influence performance in the reservoir system. Generally, the applied concentration must exceed Critical Micelle Concentration (CMC), as surfactant concentration directly impacts the reduction of IFT. Increasing concentration beyond CMC enhances the solubility of active substances due to interactions with micelle molecules, a process known as micellar solubilization. At concentra-

Table 4: Characteristics Core, Imbibition RF and Imaging NCT Test Results

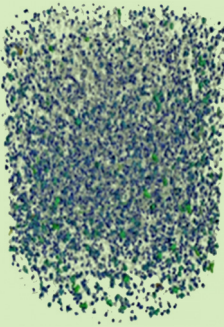
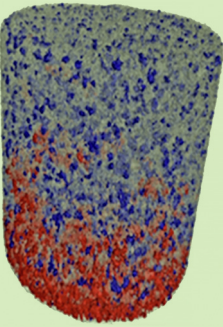
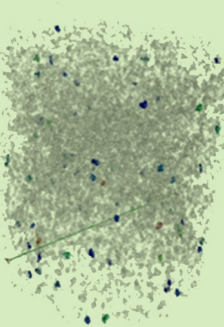
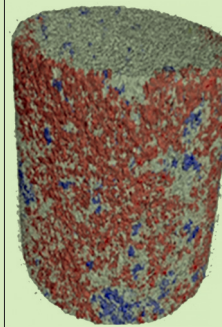
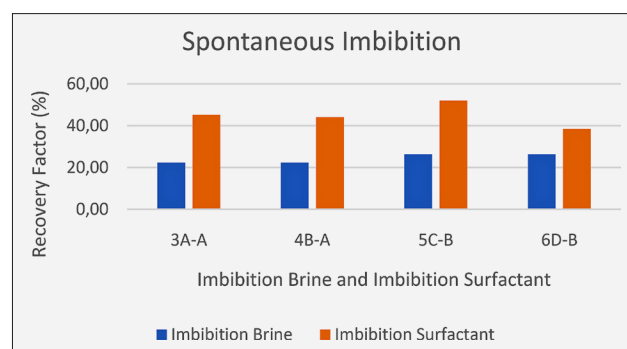
Parameter	Core 3A	Core 4B	Core 5C	Core 6D
Light Crude Oil (°API)	39	39	33	33
Salinity brine (ppm)	10,000	10,000	5,000	5,000
RF Brine imbibition (%)	22.35	22.35	26.38	26.38
Type Surfactant (concentration, %)	Palm-based MES 2	Pine-based SLS 2	Palm-based MES 0.5	Pine-based SLS 0.5
IFT (mN/m)	1.0489	6.9544	0.5130	6.3147
Contact angle	14.17	45.17	11.79	7.43
Imaging NCT at surfactant imbibition				
Imbibition results of oil expelled (%)	45.24	44.11	51.94	38.52

Table 5: Results of Oil Obtained Through the Imbibition Process

Core	Light Crude Oil (°API)	Surfactant	Recovery Factor (%)		Increased oil production (%)
			Water imbibition	Surfactant imbibition	
3A	39	Palm-based MES 2%	22.35	45.24	22.89
4B	39	Pine-based SLS 2%	22.35	44.11	21.76
5C	33	Palm-based MES 0.5%	26.38	51.94	25.56
6D	33	Pine-based SLS 0.5%	26.38	38.52	12.14

tions above CMC, surfactant adsorption decreases, allowing more molecules to function in lowering IFT.

In this study, neutron tomography visualization (see **Table 4**) of sample 5C showed a relatively small amount of residual oil, dispersed in isolated clusters, indicated by blue, green, and red spots unevenly distributed in the rock matrix. The application of palm-based MES surfactant at a concentration of only 0.5% with 5,000 ppm salinity successfully reduced IFT from 1.61 mN/m to 0.5130 mN/m for 33°API crude oil. Similarly, for 39°API crude oil, the same surfactant decreased IFT from 6.44 mN/m to 1.0489 mN/m. This efficiency was further shown in oil recovery factor, which reached 51.94%. When the same surfactant was applied at 2% concentration with 10,000 ppm salinity, the imbibition process achieved only 45.24% oil recovery. The higher intensity of blue spots observed in core 3A compared to core 5C showed that IFT reduction performance of palm-based MES surfactant was less effective in core 3A. These results suggested that for surfactant flooding systems, a relatively low concentration of palm-based MES surfactant (0.5%) was sufficient to achieve significant IFT reduction, without increasing the concentration

**Figure 9:** Result of Water Imbibition and Surfactant Imbibition

to 2%. In comparison, samples 4B and 6D showed a dense and nearly uniform distribution of residual oil in the core volume. The dominance of blue and red regions in the images indicated a high remaining oil saturation. This suggested that the imbibition process using pine-based SLS was less effective in displacing oil from the pore spaces. The limited performance was attributed to the lower efficiency of pine-based SLS with the crude oil samples tested.

Samples 4B and 6D showed significantly different residual oil distribution patterns. In sample 4B, zonation was observed, with red-dominated regions in the lower section and bluish-grey tones in the upper section. This indicated that a significant portion of oil was retained in the lower part of the rock due to gravitational effects or limited penetration of wetting fluid. The recovery factor confirmed this observation, with 44.11% of oil successfully produced. In comparison, sample 6D showed a more extensive and uniform distribution of residual oil, characterized by a strong dominance of red coloration across the entire rock volume. This pattern showed a low imbibition efficiency, consistent with the lowest recovery factor of 38.68% (see **Figure 9**). The results suggested that pine-based SLS surfactant, when applied to the 33°API crude oil system, was only marginally effective in reducing IFT, lowering it from 1.61 mN/m to 0.513 mN/m.

The performance of palm-based MES and pine-based SLS can be evaluated through imbibition tests combined with neutron computed tomography. As shown in **Table 5** and **Figure 7**, surfactant imbibition enhances oil recovery. The best performance was observed with 0.5% palm-based MES applied to 33°API crude oil. In contrast, 39°API crude oil required a higher concentration of 2%. This difference arises from the ability of surfactant to form micelles in crude oil. For the 33°API crude sample, micellar solubilization was already achieved at 0.5%, while the same concentration was insufficient for 39°API crude. Palm-based MES showed strong performance in both 33°API and 39°API crude oil, with recovery ranging from 21.76% to 22.86%. Meanwhile, pine-based SLS showed weaker performance compared to palm-based MES. Although a 0.5% concentration of palm-based MES was sufficient, pine-based SLS required higher dosages, up to 2%, to achieve significant oil recovery. These results show that palm-based MES and pine-based SLS perform differently depending on crude oil type, enhancing the rate of recovery, but their application must be tailored to the target, light crude oil.

5. Conclusions

In conclusion, this study shows that imbibition effectiveness is strongly influenced by the type of surfactant, solution concentration, and the rock properties tested. Sample 5C shows the best performance, with the highest recovery factor of 51.94%, achieved using a palm-based MES surfactant at a concentration of 0.5% and salinity of 5,000 ppm. This is supported by tomography results, which show active imbibition zones and minimal residual oil in the upper part of the core. In comparison, sample 6D shows the lowest performance, with a recovery factor of 38.52%, where tomography visualization displays widespread and uniform residual oil distribution in the rock volume, indicating low efficiency of the imbib-

ing fluid in mobilizing oil from the pore space. Samples 3A and 4B show approximately similar recovery factors (45.24% and 44.11%, respectively), but residual oil distribution in 3A is more localized. In 4B, residual oil distribution is denser and more dispersed, suggesting how tomography visualization can provide additional insight beyond numerical recovery values. The integration of quantitative data (recovery factor) and qualitative interpretation (tomographic images) offers a more comprehensive understanding of the imbibition behaviour in rock samples. These results show that spontaneous imbibition using palm-based MES surfactant at specific concentrations and salinities can enhance oil recovery more effectively than SLS derived from pine wood, particularly for light crude oil systems.

Surfactants are chemicals that are not cheap, but they can work effectively so they need to be assisted by reservoir simulations to bridge promising laboratory results to visible and profitable field implementation.

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SAŽETAK

Komparativna analiza učinkovitosti MES surfaktanta palmina ulja i SLS surfaktanta borovine na pješčenjaku Berea u procesu imbibicije korištenjem neutronske kompjuterizirane tomografije

Poplavljanje surfaktantom jedna je od metoda povećanja iscrpka nafte (engl. *Enhanced Oil Recovery*, EOR) usmjerenih na povećanje proizvodnje sirove nafte u Indoneziji. Ova metoda primjenjuje se nakon primarne i sekundarne faze proizvodnje smanjenjem međupovršinske napetosti (engl. *Interfacial tension*, IFT) u ležišnome sustavu, kada znatna količina nafte ostaje zarobljena i ne može se pokrenuti. U ovome su istraživanju korištene dvije vrste biosurfaktanata: MES (metil ester sulfonat) dobiven iz palmina ulja i SLS (natrijev lauril sulfat) dobiven iz borovine. Oba navedena surfaktanta smatraju se obećavajućim alternativama konvencionalnim sintetičkim surfaktantima. Korištena metodologija uključuje eksperimentalna i analitička laboratorijska istraživanja. Ispitivanja kompatibilnosti provedena su na MES i SLS otopinama u koncentracijama u rasponu od 0,5 % do 2 % pri salinitetu između 5 000 i 10 000 ppm uz primjenu jezgri pješčenjaka Berea i uzoraka lake sirove nafte. Ispitivanja surfaktanata provedena su u EOR laboratoriju, pri čemu je fokus stavljen na ispitivanje kompatibilnosti, što je uključivalo procjenu stabilnosti u vodi i procjenu faznoga ponašanja. Daljnje analize obuhvaćale su mjerenja međupovršinske napetosti, testove stabilnosti IFT te procjene adsorpcije u statičkim i dinamičkim uvjetima. Zatim su provedena ispitivanja poplavljanja jezgri na jezgrama pješčenjaka Berea korištenjem tehnika injektiranja i imbibicije. Kako bi se vizualizirala distribucija surfaktanata unutar uzoraka jezgre tijekom poplavljanja jezgre, korištena je neutronska tomografija, što je omogućilo identifikaciju zona protoka surfaktanata. Kako bi se potvrdila i unaprijedila interpretacija faktora iscrpka dobivenih procesima imbibicije i utiskivanja, provedeni su analitički izračuni.

Ključne riječi:

srednjofazna emulzija, međupovršinska napetost, lagana sirova nafta, neutronska tomografija

Author's contribution

Muhammad Furqon Haryono Bimantoro (Student, Master of Petroleum Engineering) prepared cores for the imbibition process and analysis by neutron tomography, **Rini Setiati** (Dr, Petroleum Engineering, lecturer, expertise in Enhanced Oil Recovery) has proven the mechanism of action of surfactant flooding on EOR. **Fahrurrozi Akbar** (MSc, Researcher/ Instrument Scientist) performed neutron tomography data analysis, measurement and interpretation results. **Muhammad Taufiq Fathaddin** (PhD, Professor, Petroleum Engineering) analyzed the results of the neutron tomography interpretation of the performance of the oil mechanism. **Sulistioso Giat Sukaryo** (MSc, Researcher/ Material Scientist) contributed to the manuscript editing and interpretation of the results. **Bharoto Bharoto** (MSc, Researcher/ Computer Scientist) prepared the data acquisition of neutron tomography software. **Iwan Sumirat** (Dr. Eng., Researcher/ Instrument Scientist at Neutron Scattering Laboratory) set up the neutron tomography experiment method. **Pauhesti** (Petroleum Engineering, lecturer, expertise in Enhanced Oil Recovery) has proven the mechanism of action of surfactant flooding on EOR; **Priagung Rakhmanto** (PhD, Petroleum Engineering, lecturer) analysis; **Refa Amelia Angelica** (Student of Petroleum Engineering) prepared cores for the imbibition process.

Evaluation of a new composition for enhanced demulsification and deposit control in resinous heavy oil emulsions

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Aysel Gasimzade^{1*} , Vali Nurullayev² 

¹ Azerbaijan State Oil and Industry University, Department of Transportation and Storage Oil and Gas, Baku, Azadliq Avenue, 34, AZ1010.

² State Oil Company of the Azerbaijan Republic, Baku, Khojali, Baku, Khatai, AZ1025.

Abstract

This study investigates the demulsification performance, deposit formation tendencies, and rheological behaviour of highly resinous crude oils and their blended systems using both an individual demulsifier and a newly formulated laboratory composition. Crude oils X (27% water), Y (32% water), and Z (48% water), along with the mixed emulsions A (31% water) and B (41% water), were examined under various temperatures, reagent dosages, and a demulsification duration of 120 minutes. The individual demulsifier ND-12 and the newly developed W composition were evaluated by determining their optimal dosages and comparing the resulting amounts of residual and ballast water after treatment. Under conditions of 60°C and 120 minutes, the optimal ND-12 dosage was found to be 200 g/t for X, 800 g/t for Y, and 1000 g/t for the highly stable Z emulsion, reducing ballast water to 0.05%, 0.07%, and 0.8%, respectively. Owing to its strong aggregative and kinetic stability, the Z emulsion was also analyzed at 85°C, where the required ND-12 dosage decreased to 750 g/t, and ballast water was reduced fourfold to 0.2%. For the mixed A (X+Z) and B (Y+Z) systems, the optimal ND-12 dosages at 60°C were 1300 g/t and 1100 g/t, achieving ballast water levels of 0.3% and 0.2%, respectively. Compared with individual reagents, the laboratory-prepared W composition showed higher demulsification efficiency, reduced sediment formation related to asphaltenes, resins and paraffins, and a significant decrease in viscosity. The required reagent dosage for treating mixed oil emulsions A and B was reduced by about 2.5 times, while viscosity decreased by approximately six times. In addition, the application of the composition produced a multifunctional inhibiting effect on crude-oil complications by preventing the formation of a structural network of $C_{17}-C_{40}$ fractions, which are prone to rapid solidification.

Keywords:

water-oil emulsion; demulsification; paraffin hydrocarbons; resinous crude oil; deposit

1. Introduction

It is well known that the stability of water-oil emulsions is primarily governed by the presence of high-molecular-weight compounds, naphthenic acids, and various surfactants that are intentionally injected into wells to enhance oil recovery. These high-molecular-weight components, particularly resins and naphthenic acids, are predominantly present in resinous crude oils, especially those with high viscosity and density (Matiev et al., 2018a; Choi and Chan 2019).

Resinous crude oils contain large quantities of resins and asphaltenes, which play a crucial role in the formation and stabilization of water-oil emulsions. These compounds create strong interfacial films around water droplets, leading to the development of highly stable emulsions that are exceptionally difficult to separate.

The intense mixing of formation water with resinous crude oil under fluctuating production conditions (pressure and temperature variations) further increases emulsion stability, making phase separation even more challenging and resource-intensive (Oh et al., 2002; Jia et al., 2021).

Moreover, the abundant dispersed particles found in resinous crude oils, including resins, asphaltenes, and paraffin components, not only enhance emulsion stability, but also induce severe rheological complications. The interaction among these particles leads to the formation of complex three-dimensional network structures, which act as natural emulsifiers and significantly elevate the apparent viscosity of the emulsion systems. This rheological complexity results in higher flow resistance, reduced pumpability, and increased operational difficulties during processing and transportation (Ma et al., 2022; Yonguep et al., 2022; Al-Sabagh et al., 2006; Huang et al., 2024).

Traditional thermal approaches alone are often insufficient to destabilize emulsions formed from resinous

* Corresponding author: Aysel Gasimzade

e-mail address: qasimzade92@inbox.ru

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crude oil, as the permissible operational temperature of 60°C generally fails to achieve effective separation. Although higher temperatures, such as 85°C, can improve demulsification rates, they are not always favorable due to potential negative impacts on oil quality and increased costs. Consequently, chemical demulsifiers and, more recently, specially designed synergistic compositions have emerged as effective solutions for treating resinous crude oil emulsions (Lim et al., 2015; Thompson et al., 1985; Al-Sabagh et al., 2008; Mushtaq et al., 2023).

Additionally, emulsions originating from different resinous crude oils are often mixed in storage tanks, resulting in systems with highly variable compositions and water contents. This blending further complicates the rheological behaviour and overall stability of the emulsions, making their treatment a critical issue for the oil industry (Hu et al., 2018; Chen et al., 1994; Matiev et al., 2018b; Singh and Pulikkal, 2024).

Considering these challenges, selecting reagents with superior surface activity relative to the interfacial tension of resinous crude oil and evaluating their performance under controlled laboratory conditions is an essential and urgent focus in the field of demulsification research (Tan et al., 2007; Jinxin et al., 2006; A-Sabagh et al., 2003).

This study aimed to comprehensively evaluate how different reagents and synergistic compositions influence the demulsification performance, deposit reduction, viscosity behaviour, and paraffin hydrocarbon distribution in water-oil emulsions with different stability characteristics.

2. Materials and Methods

In this study, a comprehensive set of laboratory-based experimental methods was employed to investigate the demulsification behaviour, deposit formation, viscosity changes, and paraffin hydrocarbon distribution in water-oil emulsions derived from resinous crude oil samples. The overall methodology included the stages as follows.

2.1. Selection and preparation of oil samples

Crude oil samples were collected from three different fields: Surakhani (X), Pirallahi (Y), and Umbaki (Z). Each oil emulsion used as the object of study differs in composition, namely in the content of high molecular weight components, as well as in the aggregate and kinetic stability of the emulsion. Furthermore, since it is known that another factor complicating emulsion breaking at oil terminals is oil blending, mixed oil A was prepared by blending oils X and Z, while mixed oil B was prepared by blending oils Y and Z. The selection of these combinations is based on the fact that numerous studies have shown that the main reason for increased complexity of emulsified crude oils is the mixing of highly stable emulsions with easily separable emulsions. For this rea-

son, the combination of oils X and Y was not considered in this study. The initial water content of 27%, 32%, and 48% was not arbitrarily chosen; these values correspond to the natural water saturation levels observed during field sampling. To obtain reproducible laboratory emulsions, water-oil mixtures were homogenized using a high-shear mixer at 2000 rpm for 10 minutes, a widely used condition for preparing laboratory emulsions of viscous crude oils (Jennings and Weispenning, 2005; Ala and Daraboina, 2024; Sjöblom, 2006a).

2.2. Determination of emulsion stability (bottle test)

The stability of the prepared emulsions was evaluated using the conventional bottle test method. Emulsions were transferred into graduated glass cylinders and allowed to settle under static conditions at laboratory temperature (~20°C). The volume of the separated water phase was recorded over 24 hours. This test provided baseline information about the inherent stability of each emulsion before adding demulsifiers and follows established procedures commonly applied in crude-oil emulsion studies (Gasimzade, 2024).

2.3. Investigation of demulsifier effect

The effectiveness of the commercial demulsifier ND-12 and the newly synthesized W composition (ND-12 + chloroprene + isopropanol) was examined across concentrations of 200–1400 g/t. The main experiments were performed at 50°C and 60°C, reflecting typical field operating temperatures. For the most stable emulsions, particularly Z, an additional test was performed at 85°C to understand behaviour under accelerated separation conditions. During each experiment, the demulsification process was monitored for 2 hours. After settling, the residual water and ballast water contents were determined gravimetrically. This approach enables quantitative evaluation of demulsifier efficiency and is consistent with standard methodologies reported in literature (Jennings and Weispenning, 2005).

Depending on the demulsification ability of the tested demulsifier, the amount of separated water is recorded at various time intervals. The amount of separated water is calculated using the following mathematical relation (Gasimzade, 2024):

$$X\% = \frac{w}{w_0} 100\% \quad (1)$$

where, w_0 is the initial water content in the emulsion (mg), w is the separated water content during demulsification (mg).

Additionally, the amount of ballast water in the oil sample after demulsification is calculated using the following empirical formula, which incorporates the amount of water separated from the emulsion and the

Table 1: Physicochemical properties of oils

Parameters	X	Y	Z	Methods of conducting analyses
Water content, %	27	32	48	Dean–Stark method according to GOST 2477 using an AKOV-10 (T-AKOV-10) distillation unit with condenser and calibrated receiver, manufactured in the Russian Federation (LOIP)
Density, g/cm ³	862.9	916.8	947.5	Pycnometric density determination according to GOST 3900 using PZh-2 laboratory pycnometers and a temperature-controlled bath, manufactured in the Russian Federation (Khimlaborpribor)
Asphaltene, %	1	3	8	Asphaltene precipitation and gravimetric determination according to GOST 11858-66 using standard laboratory extraction, filtration, and drying equipment (e.g. ARN-2 extraction apparatus), commonly manufactured in the Russian Federation and other CIS countries
Resin, %	10	15	12	Adsorption liquid chromatography (SARA fractionation) using laboratory chromatographic columns, baths, and standard adsorbents, manufactured in the Russian Federation
Paraffin, %	2	4	7	Paraffin content determination according to GOST 11851 using a controlled cooling and filtration laboratory setup, manufactured in the Russian Federation

initial water content of a 100 gram oil sample at various temperatures over a two-hour period (**Gasimzade, 2024**):

$$S\% = \frac{m_1 - m_2}{m_3 - m_2} 100\% \quad (2)$$

where, S is the percentage of ballast water after demulsification, (%), m_1 is the amount of water in the oil before demulsification (mg), m_2 is the amount of water separated from the oil during demulsification, (mg), m_3 is the initial mass of the emulsion sample before demulsification, (mg), $m_3 - m_2$ is the mass of the remaining (treated) emulsion after water separation (mg).

All demulsification experiments were conducted at the SOCAR Oil Pipelines Department laboratory (Baku, Azerbaijan).

2.4. Viscosity analysis

Viscosity measurements were performed to analyze the flow behaviour of the oil phases before and after demulsification. A rotational rheometer (Anton Paar MCR series or equivalent) was used, equipped with a concentric cylinder geometry. Measurements were carried out at 20°C under varying shear rates (1–1000 s⁻¹) to simulate different flow conditions. The results provided insights into the impact of demulsifiers and compositions on the rheological properties of resinous crude oils (**Nurullayev et al., 2020a; Aveyard et al., 1990**). A rotational rheometer (Anton Paar MCR series) was used to analyze the flow behaviour of the oil phases. Measurements were carried out at the SOCAR Oil Pipelines Department laboratory (Baku, Azerbaijan).

2.5. Deposit analysis (cold finger test)

To evaluate deposit formation, a cold finger apparatus was used. Oil and emulsion samples were subjected to controlled cooling cycles to simulate pipeline and processing conditions. The amount of asphaltene-resin-par-

affin deposits (ARPD) was measured gravimetrically after exposure. Inhibition efficiency of ND-12 and W composition was calculated by comparing deposit mass in treated and untreated samples (**Padula et al., 2020; Yaghy et al., 2021; Peng et al., 2018; Ismayilov et al., 2022**). Deposit formation experiments were performed at the SOCAR Oil Pipelines Department laboratory (Baku, Azerbaijan).

2.6. Paraffin hydrocarbon distribution analysis

The detailed composition of paraffin hydrocarbons in the deposits was analyzed using gas chromatography-mass spectrometry (GC/MS). The deposits were extracted and dissolved in n-hexane, then filtered and injected into a GC/MS analysis was performed using a Shimadzu GCMS-QP2020 system equipped with a capillary column (TR-5MS, 30 m length, 0.25 mm ID). The operating temperature program included an initial hold at 80°C followed by a ramp to 300°C. This analysis allowed quantification of short-chain (C₁₂–C₁₆) and long-chain (C₁₇–C₄₀) paraffin fractions, providing insight into molecular transformations induced by different demulsification treatments (**Nurullayev et al., 2020b; Huang et al., 2003; Ganeeva et al., 2016; Ismayilov et al., 2025; Ismayilov et al., 2017**). GC/MS analysis of paraffin hydrocarbons was carried out at the Intertek International Laboratory (Baku, Azerbaijan).

2.7. Data analysis and evaluation

The collected data were statistically analyzed to determine the effects of temperature, reagent concentration, and composition type on demulsification efficiency, deposit reduction, viscosity stabilization, and paraffin hydrocarbon profile. Comparative evaluations were performed among individual oils and mixed systems to identify optimal treatment strategies for resinous crude oil emulsions (**Jennings and Weispenning, 2005; Wang et al., 2025; Zu et al., 2024**).

Table 2: Demulsification of oil samples at different temperatures

№	Oil samples	Amount of separated water, %				Residual water amount, %	Ballast water amount, %
Demulsification time, hour		0.5 h	1.0 h	1.5 h	2.0 h		
T=50°C							
1	X	9.7	13.8	17.9	24.3	2.7	3.6
2	Y	8.9	14.2	18.4	23.9	8.1	10.6
3	Z	3.8	6.2	8.6	10.0	38	42.2
T=60°C							
1	X	10.5	16.8	21.5	26.6	0.4	0.5
2	Y	9.6	15.7	20.5	25.1	6.9	9.2
3	Z	8.6	12.5	17.4	25.5	22.5	30.2

Table 3: Demulsification of oil samples with the participation of ND-12 demulsifier at a concentration of 50°C

№	Oil samples	Amount of separated water, %				Residual water amount, %	Ballast water amount, %
		0.5 h	1.0 h	1.5 h	2.0 h		
C=200 g/t							
1	X	16.4	22.6	25.8	26.9	0.1	0.14
C=800 g/t							
1	Y	19.6	24.8	28.7	31.5	0.5	0.7
C=1000 g/t							
1	Z	23.2	30.9	35.8	41.4	6.6	11.3

To achieve the research objective under laboratory conditions, oil samples X (27% water), Y (32% water), and Z (48% water) were selected. Notably, oils Y and Z form stable emulsions, whereas oil X produces an unstable emulsion. The physicochemical properties of these samples are summarized in **Table 1**.

All initial physicochemical parameters presented in **Tables 1–10** were not arbitrarily selected. The water content values (27%, 32%, 48%) correspond to the natural water-cut measured in the respective oil fields using the Dean–Stark method. Density, asphaltene, resin, and paraffin contents correspond to the real production characteristics of these oils, which were confirmed by laboratory analyses. The selection of these specific oils was intended to cover a wide stability range, from low-stability emulsions (X) to highly stable emulsions (Z), thereby enabling systematic comparison across all experimental stages.

The physicochemical characteristics of the studied oil samples are shown in **Table 1**. Sample X, with lower asphaltene and resin content, formed unstable emulsions, while Y and Z, with higher levels of heavy components, produced more stable systems.

3. Results and discussions

Following this characterization, the next stage of the study focused on evaluating the demulsification behaviour of the samples at different temperatures. The demulsification times (0.5–2 h) were selected according to standard bottle test procedures described in ASTM

D4007 and GOST 6370, allowing time-dependent observation of separation kinetics. The results of this investigation are summarized in **Table 2**.

Table 2 presents the demulsification results of these samples at 50°C and 60°C. At 50°C, sample X showed the highest separation efficiency and lowest residual water. Increasing the temperature to 60°C improved separation in all samples, though Y and Z retained higher residual water, confirming their stronger emulsion stability. In demulsification studies, a higher amount of residual water after chemical treatment is a widely accepted indicator of stronger emulsion stability. Stable water–oil emulsions typically exhibit small water droplet sizes, a dense interfacial film enriched with asphaltenes and resins, and slow coalescence kinetics. These structural features prevent efficient water release even when temperature and demulsifier concentration are increased (Schramm and Kutay, 2009; Sjöblom, 2006b; Schramm, 1992). In the present study, samples Y and Z contained a higher proportion of polar resins and asphaltenes (see **Table 1**), which is consistent with their higher residual water levels, confirming that they form more stable emulsions compared with sample X.

After assessing the general demulsification behaviour at different temperatures, further detailed experiments were conducted to evaluate the performance of the ND-12 demulsifier at optimal concentrations for each oil sample at 50°C and 60°C. The summarized results of these optimized demulsification tests are presented in **Tables 3** and **4**.

Table 4: Demulsification of oil samples with the participation of ND-12 demulsifier at a concentration of 60°C

№	Oil samples	Amount of separated water, %				Residual water amount, %	Ballast water amount, %
Demulsification time, hour		0.5 h	1.0 h	1.5 h	2.0 h		
C=200 g/t							
1	X	17.9	22.8	26.8	26.96	0.04	0.05
C=800 g/t							
1	Y	23.9	27.5	29.8	31.95	0.05	0.07
C=1000 g/t							
1	Z	30.8	39.1	44.2	47.6	0.4	0.8

Table 5: Demulsification of Umbaki oil sample at 85°C with the participation of ND-12 demulsifier

№	Oil samples	Amount of separated water, %				Residual water amount, %	Ballast water amount, %
Demulsification time, hour		0.5 h	1.0 h	1.5 h	2.0 h		
C _{reag} = 750 g/t							
1	Z	33.5	41.3	45.6	47.91	0.09	0.2

As shown in **Tables 3** and **4**, increasing ND-12 concentration and temperature notably improved water separation in all samples. At 50°C, higher dosages enhanced separation, though sample Z maintained higher residual water, indicating strong stability. At 60°C, demulsification further improved; sample X achieved near-complete separation with minimal residual water, while Y and Z also showed significant reductions. Sample Z reached its best efficiency at 1000 g/t but still had higher residual levels than X and Y. These results confirm that higher reagent dosage and temperature are essential for effective demulsification, especially for stable resinous crude oil emulsions.

To evaluate the influence of temperature on demulsification performance, the results obtained at 50°C (see **Table 3**) and 60°C (see **Table 4**) were compared. A direct deviation analysis between corresponding samples shows the improvement achieved at elevated temperature. For sample X (200 g/t), the amount of separated water after 2 h increased from 26.9% to 26.96%, corresponding to a deviation of +0.22%. For sample Y (800 g/t), the separation increased from 31.5% to 31.95%, giving a deviation of +1.42%. For the most stable emulsion (sample Z, 1000 g/t), separation increased from 41.4% at 50°C to 47.6% at 60°C, resulting in a deviation of +15.0%. This clearly demonstrates that temperature elevation has its strongest effect on highly stable systems rich in resins and asphaltenes, such as sample Z. The term “near-complete separation” is used for sample X because the residual water after 2 h decreased to 0.04–0.05% at 60°C, which falls within the range typically considered as almost fully dehydrated crude oil in standard demulsification practice. According to established literature on demulsifier performance (**Jennings and Weispenning, 2005; Schramm and Kutay, 2009**), residual water levels below 0.1% are widely accepted as indicative of near-complete water separation under labo-

ratory conditions. The values obtained for sample X therefore satisfy this definition, confirming that the emulsion formed by oil X is weak and readily destabilized at moderate temperature. At 60°C, the demulsification performance showed a clear improvement across all samples, which is quantitatively supported by comparing the values in **Tables 3** and **4**. For sample X, the amount of separated water increased from 26.9% (50°C) to 26.96% (60°C) at 200 g/t, while the residual water decreased from 0.10% to 0.04%, corresponding to a 60% reduction in residual water content. A similar trend was observed for sample Y: at 800 g/t, separation increased from 31.5% to 31.95%, and residual water decreased from 0.5% to 0.05%, demonstrating a tenfold improvement in water removal efficiency. The most pronounced enhancement occurred in sample Z. At 1000 g/t, the separated water increased from 41.4% to 47.6%, representing a 15% relative improvement, while residual water decreased from 6.6% to 0.4%, corresponding to a 93.9% reduction. These deviations clearly confirm that the higher temperature accelerates droplet coalescence and destabilizes the interfacial film, resulting in significantly greater demulsification efficiency.

To further evaluate demulsification under extreme conditions, additional tests were performed on the most stable Umbaki (Z) oil sample at 85°C using ND-12 at the optimal concentration, where C_{reag} denotes the reagent concentration and C_{comp} denotes the composition concentration. The results are presented in **Table 5**.

As shown in **Table 5**, at 85°C and an optimal demulsifier concentration of 750 g/t, sample Z demonstrated markedly improved separation performance. After 2 hours, the amount of separated water reached 47.91%, while the residual water content decreased to 0.09% and the ballast water content to 0.2%. These results confirm that elevated temperature substantially accelerates the breakdown of highly stable resinous emulsions and sig-

Table 6: Some physicochemical properties of oil mixtures

Parameters	A	B	Methods of conducting analyses
Water content, %	31	41	Dean–Stark method according to GOST 2477 using an AKOV-10 (T-AKOV-10) distillation unit with condenser and calibrated receiver, manufactured in the Russian Federation (LOIP)
Density, g/cm ³	968.1	894.7	Pycnometric density determination according to GOST 3900 using PZh-2 laboratory pycnometers and a temperature-controlled bath, manufactured in the Russian Federation (Khimlaborpribor)
Asphaltene, %	7	2	Asphaltene precipitation and gravimetric determination according to GOST 11858-66 using standard laboratory extraction, filtration, and drying equipment (e.g. ARN-2 extraction apparatus), commonly manufactured in the Russian Federation and other CIS countries
Resin, %	13	14	Adsorption liquid chromatography (SARA fractionation) using laboratory chromatographic columns, baths, and standard adsorbents, manufactured in the Russian Federation
Paraffin, %	6	5	Paraffin content determination according to GOST 11851 using a controlled cooling and filtration laboratory setup, manufactured in the Russian Federation

Table 7: Demulsification of oil mixtures at 50°C with the participation of ND-12 demulsifier

№	Oil samples	Amount of separated water, %				Residual water amount, %	Ballast water amount, %
Demulsification time, hour		0.5 h	1.0 h	1.5 h	2.0 h		
C _{reag} = 1200 g/t							
1	B	19.0	27.5	34.4	40.7	0.3	0.5
C _{reag} = 1400 g/t							
1	A	18.0	21.6	26.8	30.6	0.4	0.6

Table 8: Demulsification of oil mixtures at 60°C with the participation of ND-12 demulsifier

№	Oil samples	Amount of separated water, %				Residual water amount, %	Ballast water amount, %
Demulsification time, hour		0.5 h	1.0 h	1.5 h	2.0 h		
C _{reag} = 1100 g/t							
1	B	19.2	29.1	36.0	40.9	0.1	0.2
C _{reag} = 1300 g/t							
1	A	17.5	22.5	27.6	30.8	0.2	0.3

nificantly reduces the amount of water remaining dispersed within the oil phase.

Although the improvement is notable, such high temperatures are not typically feasible in field operations due to increased energy consumption and the risk of altering crude oil quality. Therefore, laboratory testing at 85°C was performed strictly to understand the limiting behaviour of the most stable emulsion (sample Z) under extreme conditions.

The conducted investigations demonstrate that the breakdown mechanism of crude oil emulsions rich in resins and asphaltenes is directly dependent on temperature and on the strength of the interfacial film formed around the water droplets. In such emulsions, the high concentrations of resins and asphaltenes increase the elasticity of the interfacial layer and hinder the collision and subsequent coalescence of droplets. Experiments performed in the range of 50–60°C confirm that although droplet mobility increases at these temperatures, the interfacial film remains highly resistant; therefore, demulsification becomes possible only at very high demulsifier dosages. This approach is not considered economically

practical, as it results in increased reagent consumption and prolonged processing time.

Raising the temperature to 85°C weakens the surface tension and structural strength of the interfacial film, which sharply enhances droplet coalescence and leads to significantly faster demulsification. The results obtained for highly stable emulsions, such as the Z crude oil sample, clearly indicate that temperature elevation is the primary factor ensuring the accelerated separation of the aqueous phase. However, the use of such high temperatures may negatively affect certain quality characteristics of the crude oil and require additional energy input under field conditions. Therefore, from an operational standpoint, the main objective is to identify a demulsifier capable of effectively weakening the interfacial film at lower temperatures (50–60°C). This makes the determination of an optimal demulsifier for use within this moderate temperature range a priority for practical application.

Table 9: The composition and mole ratio of the mixture

W	ND-12 + Chloroprene + Isopropanol	4:0.75:0.25
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Table 10: Demulsification of oil mixtures at 50°C with the participation of the composition.

№	Oil samples	Amount of separated water, %				Residual water amount, %	Ballast water amount, %
Demulsification time, hour		0.5 h	1.0 h	1.5 h	2.0 h		
$C_{\text{comp}} = 700 \text{ g/t}$							
1	B	20.4	26.8	35.3	40.9	0.1	0.2
$C_{\text{comp}} = 800 \text{ g/t}$							
1	A	18.7	24.4	28.6	30.8	0.2	0.3

Table 11: Demulsification of oil mixtures at 60°C with the participation of the composition.

№	Oil samples	Amount of separated water, %				Residual water amount, %	Ballast water amount, %
Demulsification time, hour		0.5 h	1.0 h	1.5 h	2.0 h		
$C_{\text{comp}} = 450 \text{ g/t}$							
2	B	20.5	30.4	37.3	40.92	0.08	0.1
$C_{\text{comp}} = 650 \text{ g/t}$							
1	A	18.9	25.2	29.3	30.9	0.1	0.1

To further investigate how blending affects demulsification performance, two mixed oil systems were prepared by combining individual crude samples: mixture A (X + Z) and mixture B (Y + Z). Their key physicochemical properties are summarized in **Table 6**, enabling a comparison between individual oils and mixed systems under identical experimental conditions.

As shown in **Table 6**, mixture A (X + Z) contains less water but exhibits higher density and a greater proportion of asphaltenes, indicating a composition with stronger intermolecular interactions and higher structural complexity. In contrast, mixture B (Y + Z) has a higher water content together with lower density and asphaltene levels, which reflects a comparatively less compact and more flowable system.

To evaluate how these compositional differences influence separation behaviour, demulsification tests for both mixtures were performed using ND-12 at elevated concentrations at 50°C and 60°C. The corresponding results are summarized in **Tables 7** and **8**.

As shown in **Tables 7** and **8**, increasing both the ND-12 dosage and the temperature resulted in higher separation efficiency for the mixed oil systems. At 50°C, mixture B (Y + Z) responded more readily to the demulsifier, reaching residual and ballast water levels of 0.3% and 0.5% at 1200 g/t. The reagent concentration required to achieve significant demulsification of oil A, a blend of oils X and Y, was relatively high (1400 g/t). This is attributed to the higher asphaltene content of oil A, which maintains the emulsion in a more stable state compared with oil B. An increase in temperature to 60°C led to an enhanced demulsification rate. Mixture B achieved optimal results at a lower concentration (1100 g/t), with residual and ballast water contents reduced to 0.1% and 0.2%, respectively. Mixture A also showed enhanced performance at 1300 g/t but still retained marginally more residual water than mixture B, which reflects the higher resistance of this mixture arising from its greater

proportion of heavy polar components. These findings confirm that both temperature elevation and increased demulsifier dosage are crucial for effective treatment of mixed resinous crude oil emulsions, with mixture composition playing a significant role in determining optimal conditions.

Following the tests with ND-12, a new synergistic composition labeled W was prepared to enhance demulsification efficiency. The composition and its mole ratio are presented in **Table 9**.

To evaluate the performance of the newly prepared W composition, demulsification tests were further conducted on the oil mixtures at 50°C and 60°C. The summarized results are presented in **Tables 10** and **11**.

As shown in **Tables 10** and **11**, the W composition demonstrated superior demulsification performance at both temperatures and lower concentrations compared to ND-12 alone. At 50°C, mixture B achieved the lowest residual and ballast water contents (0.1% and 0.2%) at 700 g/t, while mixture A showed good performance at 800 g/t. At 60°C, even better results were obtained: mixture B reached minimal residual water (0.08%) and ballast water (0.1%) at only 450 g/t, whereas mixture A achieved similarly low values at 650 g/t. These findings highlight the strong synergistic effect of the W composition, enabling effective emulsion breaking with reduced reagent dosage and confirming its potential as a promising alternative to conventional demulsifiers for resinous crude oil emulsions.

The comparison of the demulsification of oil mixtures at 60°C using the composition versus the individual demulsifier is shown in **Figures 1** and **2**.

To assess the rheological behaviour of the treated oil samples, viscosity measurements were carried out at 20°C under varying shear rates. Viscosity values shown in all rheological curves represent the dynamic viscosity of the crude oil samples, measured using a rotational viscometer at 20°C. The curves correspond to the optimal reagent

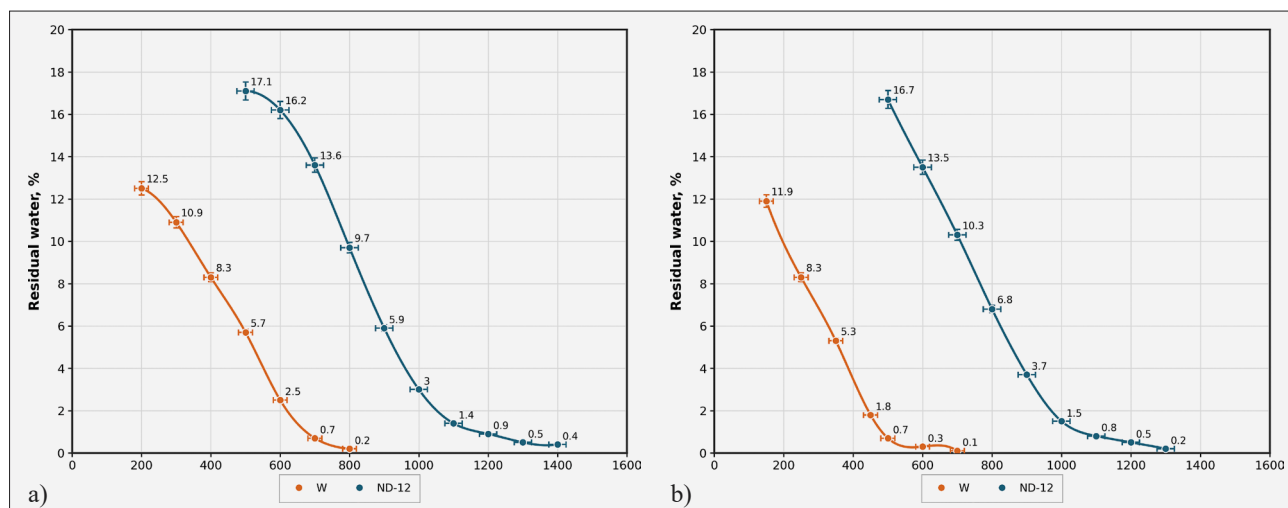


Figure 1: Dependence of ballast water amount on the concentration of ND-12 reagent and composition during the demulsification of oil A a) $t=50^{\circ}\text{C}$, b) $t=60^{\circ}\text{C}$.

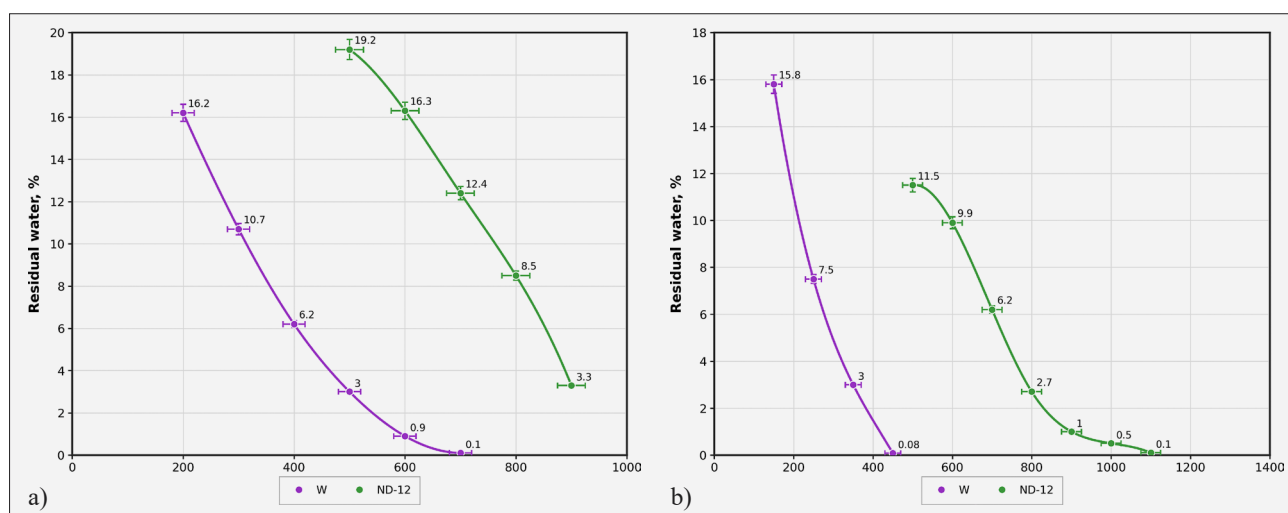


Figure 2: Dependence of ballast water amount on the concentration of ND-12 reagent and composition during the demulsification of oil B a) $t=50^{\circ}\text{C}$, b) $t=60^{\circ}\text{C}$.

concentrations, selected after preliminary efficiency screening. The results are illustrated in **Figures 3–6**.

The viscosity versus shear rate curves in **Figures 3–6** show that both oils experience their strongest viscosity drop in the low-shear region (approximately $5\text{--}40\text{ s}^{-1}$). This behaviour is characteristic of resinous and asphaltenic systems, where even mild deformation begins to break the weak associative networks. The wider spacing observed between the concentration curves in this zone indicates that the additives exert their greatest influence when the structural framework of the oil is still largely preserved. As shear rate increases, the curves gradually move closer together, which suggests that mechanical disruption becomes the dominant factor in the breakdown of the internal structure.

For oil A, increasing the ND-12 dosage from 500 to 1400 g/t leads to a steady reduction in viscosity, with the largest deviation appearing at 5.4 s^{-1} . At higher deforma-

tion rates, the curves converge, confirming that chemical dosage becomes less critical once the internal network is already weakened by shear. The W composition behaves somewhat differently- its concentration curves remain closer throughout the mid-shear region (around $27\text{--}80\text{ s}^{-1}$), yet it still produces the lowest viscosity values at all deformation rates. Oil B shows a similar general pattern, but its absolute viscosities are lower, most likely because of differences in the stability of resin and asphaltene aggregates. Here again, the W composition results in a narrower spacing between concentration curves, while ND-12 shows a more pronounced dependence on dosage.

The dual mechanism underlying the two systems, namely enhanced demulsification and viscosity reduction, can be attributed to their interactions with both the interfacial film and the bulk structural components of the crude oil. The additives contain amphiphilic molecules that are capable of penetrating the asphaltene-resin layer

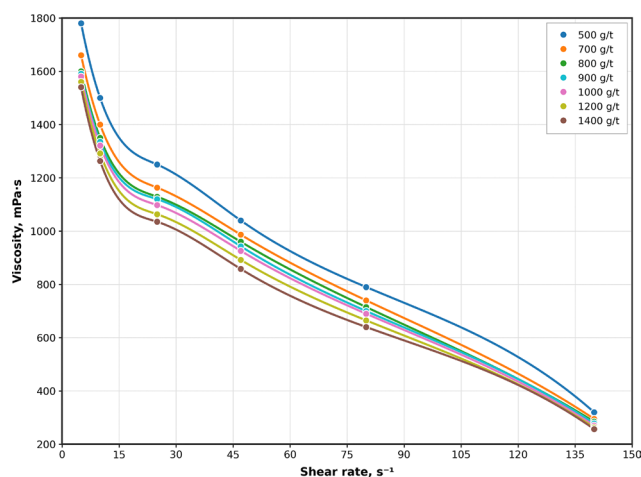


Figure 3: Viscosity changes of oil A under the influence of ND-12 demulsifier at different concentrations and shear rates at 20°C.

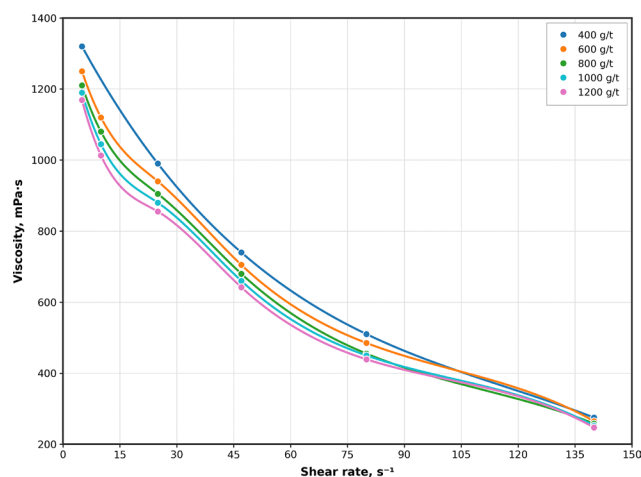


Figure 5: Viscosity changes of oil B under the influence of ND-12 demulsifier at different concentrations and shear rates at 20°C.

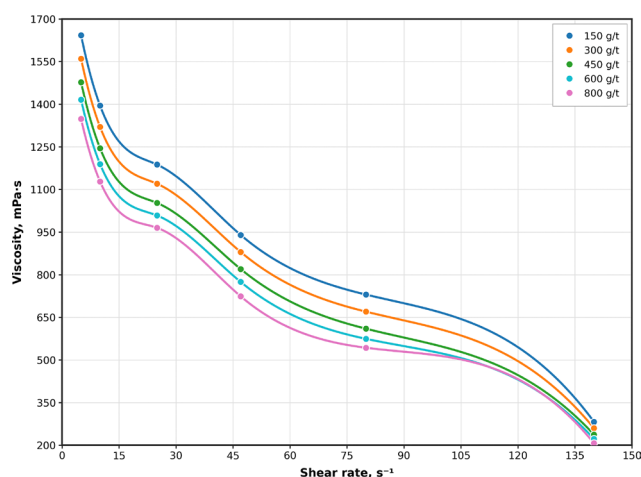


Figure 4: Viscosity changes of oil A under the influence of the W composition at different concentrations and shear rates at 20°C.

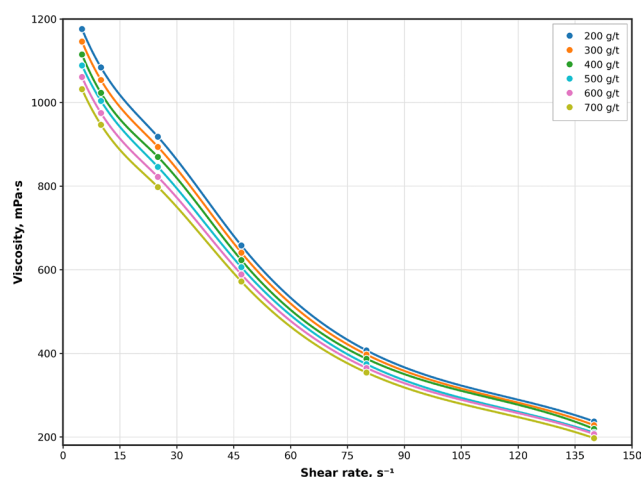


Figure 6: Viscosity changes of oil B under the influence of the W composition at different concentrations and shear rates at 20°C.

surrounding dispersed water droplets. By weakening the π - π stacking and hydrogen bonding that stabilise this film, they facilitate droplet coalescence and promote water separation. At the same time, their adsorption onto polar sites of asphaltenes and resins partially detaches these components from paraffin crystals, decreasing the connectivity of the aggregate network that contributes to high viscosity. The W composition exhibits a stronger effect because it contains more polar functional groups with higher affinity for both interfacial and bulk structural elements, making it more effective in disrupting stabilising interactions within the system.

Altogether, the rheological trends and the underlying molecular interactions show that the W composition produces a more uniform and efficient modification of the structural networks in both oils. This explains why it achieves stronger viscosity reduction while simultaneously enhancing demulsification performance.

To evaluate the impact of reagents on deposit formation, both dry crude oil and water-oil emulsion samples

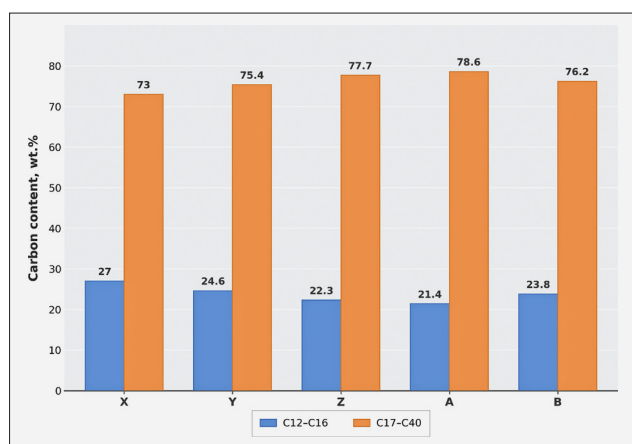
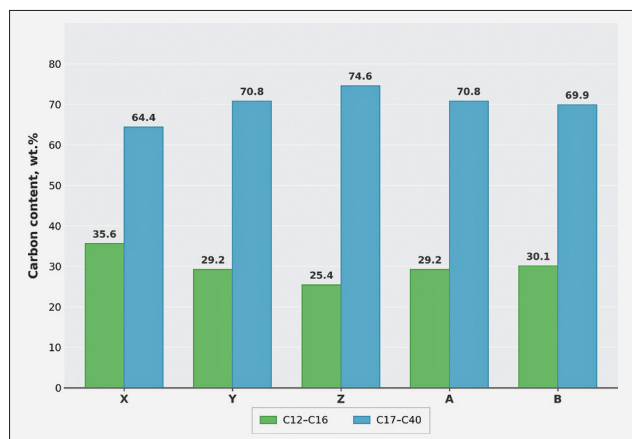
were analyzed. The summarized results are presented in **Table 12**.

As shown in **Table 12**, the application of ND-12 and the W composition significantly reduced deposit (ARPD) amounts in both dry crude oil and water-oil emulsions. In all cases, the W composition achieved higher inhibition efficiency, leading to lower deposit masses compared to ND-12. This effect was more pronounced in emulsion systems, where the W composition reached up to 85% inhibition. These results confirm the superior performance of the W composition in minimizing deposit formation, which is critical for reducing operational challenges such as pipeline blockages and flow assurance problems in resinous crude oil systems. This enhanced performance can be attributed to the amphiphilic nature of the W composition, which improves its interaction at the oil-water interface and promotes more effective disruption of stabilizing structures.

To further analyze the structural characteristics of the deposits, the distribution of paraffin hydrocarbons (C_{12} –

Table 12: Deposit formation in dry crude oil and water-oil emulsions

Sample	Amount of ARPD, g/100 g	ND-12		W	
		amount of ARPD, g/100 g	degree of inhibition, %	amount of ARPD, /100 g	degree of inhibition, %
X (dry crude oil)	20.8	6.86	67	5.62	73%
X (27% emulsion)	18.4	4.23	77	2.76	85%
Y (dry crude oil)	27.4	10.41	62	8.22	70%
Y (32% emulsion)	26.2	7.34	72	5.76	78%
Z (dry crude oil)	35.8	14.32	60	11.46	68%
Z (48% emulsion)	32.1	10.27	68	8.03	75%
A mixed oil (dry crude oil)	40.3	19.34	52	15.31	62
A mixed oil (31% emulsion)	39.8	15.92	60	6.37	84
B mixed oil (dry crude oil)	37.6	16.54	56	13.16	65
B mixed oil (41% emulsion)	37.2	13.02	65	6.7	82

**Figure 7.** Paraffin hydrocarbon composition in deposits derived from water-oil emulsion samples (ND-12)**Figure 8.** Paraffin hydrocarbon composition in deposits derived from water-oil emulsion samples (W composition)

C_{16} and C_{17} – C_{40}) in the emulsion samples was determined. Importantly, the analysis was conducted on the separated crude oil phase obtained following demulsification of the emulsions. The results are illustrated in **Figures 7 and 8**.

As shown in **Figures 7 and 8**, treatment with the W composition consistently increased the proportion of lower-molecular-weight paraffin hydrocarbons (C_{12} – C_{16})

in all emulsion samples, whereas the corresponding share of heavier paraffins (C_{17} – C_{40}) decreased when compared with ND-12. This shift in the paraffin profile is important from an oil-quality perspective, because a higher content of C_{12} – C_{16} hydrocarbons is typically associated with lower crystallization temperatures, reduced structural stiffness, and improved flowability.

At the molecular level, the observed increase in lighter paraffins suggests that the W composition more effectively interferes with interactions between long-chain paraffins, resins, and asphaltenes. These interactions usually promote the formation of dense, high-viscosity deposits. By weakening these associations, W facilitates the breakdown of larger paraffin clusters and prevents the formation of rigid, tightly packed structures.

As a result, the deposits formed in the presence of W are less ordered and less prone to agglomeration, which reduces their ability to accumulate on equipment surfaces. This behaviour is consistent with a lower pour point and a reduced tendency toward wax-related flow complications, both of which are critical for maintaining stable operation in resin-rich crude oil systems.

The findings show that the W composition not only improves demulsification and decreases the total amount of deposited material but also modifies the molecular characteristics of the deposits in a way that enhances the operational quality of the crude oil.

The visual effect of the composition and the ND-12 reagent on crude oil A, based on the conducted experiments, is shown in **Figure 9**.

4. Conclusions

1. The results show that the efficiency of demulsification using the individual demulsifier ND-12 strongly depends on emulsion stability and temperature. For single crude oils, the required ND-12 dosage increased from 200 g/t for the least stable emulsion (oil X) to more than 1000 g/t for the most stable system (oil Z). Increasing the temperature to 85°C for oil Z significantly reduced the required dosage and lowered the ballast water content, con-

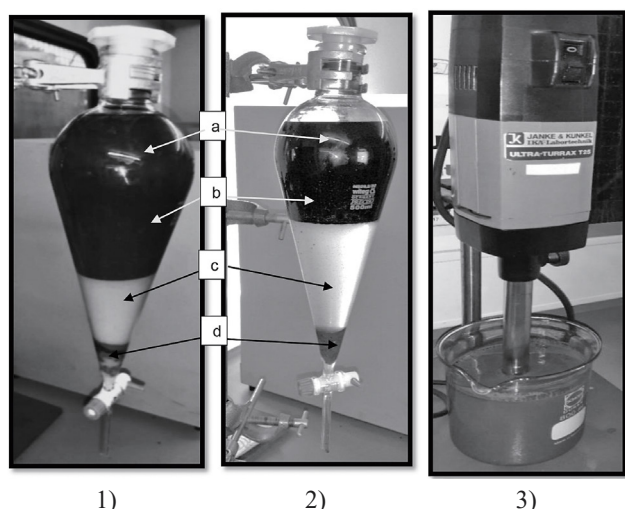


Figure 9: Crude oil A: 1) effect of ND-12 reagent at 1300 g/t; 2) effect of composition W at 650 g/t; 3) initial crude oil–water emulsion prepared using a high-speed homogenizer; (a) crude oil layer at the top, (b) emulsion zone in the middle, (c) separated water phase below, and (d) sediment layer at the bottom.

firming the dominant role of temperature in destabilizing highly stable emulsions.

- For mixed crude oil emulsions A and B, substantially higher ND-12 dosages were required to achieve effective separation at 60°C. In contrast, the laboratory-developed W composition demonstrated markedly superior performance, providing effective demulsification at significantly lower dosages. Application of the W composition reduced reagent consumption by approximately 2.5 times and decreased the residual ballast water content to 0.1% in both mixed systems.
- Rheological and structural analyses further confirmed that the W composition effectively disrupted the associative network formed by resins, asphaltenes, and paraffins. The most pronounced effects were observed at low-shear rates, accompanied by modifications in the distribution of heavy paraffin fractions, reduced sediment formation, and improved flow stability. These findings indicate that synergistic demulsifier compositions represent a promising approach for improving demulsification efficiency and flow assurance in resin-rich crude oil systems.

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SAŽETAK

Procjena nove mješavine za poboljšano deemulgiranje i kontrolu naslaga u emulzijama teške nafte s visokim udjelom smola

Ovo istraživanje ispituje učinkovitost deemulgiranja, sklonost stvaranju naslaga i reološko ponašanje sirovih nafte s visokim udjelom smola i mješovitih sustava koji ih sadržavaju, korištenjem pojedinačnoga deemulgatora i novorazvijene laboratorijske mješavine. Sirove nafte X (27 % vode), Y (32 % vode) i Z (48 % vode), zajedno s miješanim emulzijama A (31 % vode) i B (41 % vode), ispitane su pri različitim temperaturama, količinama reagensa i trajanju deemulgiranja od 120 minuta. Pojedinačni deemulgator ND-12 i novorazvijena mješavina vode W procijenjeni su određivanjem njihovih optimalnih količina i usporedbom dobivenih količina zaostale i balastne vode nakon obrade.

U uvjetima od 60 °C i 120 minuta, optimalna količina ND-12 iznosila je 200 g/t za X, 800 g/t za Y i 1000 g/t za visoko stabilnu emulziju Z, pri čemu je količina balastne vode smanjena na 0,05 %, 0,07 % i 0,8 %. Zbog svoje snažne agregacijske i kinetičke stabilnosti emulzija Z dodatno je analizirana pri 85 °C, gdje je potrebna količina ND-12 smanjena na 750 g/t, a udio balastne vode smanjen je četiri puta, na 0,2 %. Za mješovite sustave A (X + Z) i B (Y + Z) optimalne količine ND-12 na 60 °C iznosile su 1300 g/t i 1100 g/t, pri čemu je udio balastne vode bio 0,3 % odnosno 0,2 %.

U usporedbi s pojedinačnim reagensima laboratorijski pripremljena mješavina vodene pjene W pokazala je veću učinkovitost deemulgiranja, smanjeno stvaranje naslaga povezanih s asfaltenima, smolama i parafinima te znatno smanjenje viskoznosti. Potrebna količina reagensa za obradu mješovitih emulzija nafte A i B smanjena je za oko 2,5 puta, dok je viskoznost smanjena za otprilike šest puta. Osim toga, primjena novorazvijene mješavine proizvela je višenamjenski inhibicijski učinak na probleme povezane sa sirovom naftom sprječavajući stvaranje strukturne mreže frakcija C17-C40, koje su sklone brzom skrućivanju.

Ključne riječi:

emulzija vode u nafti, deemulgiranje, parafinski ugljikovodici, sirova nafta s visokim udjelom smola, naslaga

Author's contribution

Aysel Gasimzade (Associate Professor): conceptualization, investigation and software. **Vali Nurullayev** (Associate Professor): investigation, acquisition of crude oil samples, and definition of the scientific direction.

All authors have read and agreed to the published version of the manuscript.

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