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Meteorological data-driven approach for soil passability modeling in GIS using machine learning

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Vehicle mobility across different terrains depends on a multitude of geographical and meteorological variables. Traditional approaches rely on labor-intensive manual field measurements to assess soil conditions for military or humanitarian vehicle passage.

In this study, we aimed to explore novel methods for parameterizing the Cone Index, a fundamental metric for assessing passage feasibility, leveraging meteorological data from the global numerical model The Global Forecast System. Focusing specifically on chernosols, primarily agricultural soils found in flat, open regions conducive to military operations, we utilized machine learning methods to assess how soil conditions affect vehicle mobility.

Through rigorous exploratory analysis, we investigated correlations, model performance metrics, and the relative importance of predictors in Cone Index modeling. Our findings highlight the comparative efficacy of different modeling approaches, particularly emphasizing the utility of the Random Forest method. We identified key environmental conditions under which the model reliably predicts the Cone Index. This sets the baseline for spatial modelling in GIS.

Despite these insights, our study is constrained by data limitations and the inherent resolution constraints of The Global Forecast System model. The obtained solution lays the initial groundwork for implementing the model in a GIS environment to predict the trafficability of chernosols across the broader European region. Future research will aim to expand the dataset, spatial relationships, and employ models with higher resolution for more robust and accurate predictions.

Keywords: cone index, soil passability, machine learning, random forest, chernosols

1. Introduction

The soil as a top layer of terrain has a major impact on the mobility of vehicles off the roads. However, soil mobility properties are not constant over time and are mainly influenced by the physical properties and the amount of water contained in soils (Rybanský, 2009; US Army, 1993; Stevens et al., 2016; Raghavan et al., 1978; Mosaddeghi et al., 2000; Earl, 1997; Heštera and Pahernik, 2018; Shukla, 2014; Lapen et al., 2004). The soil properties mainly affect agricultural and forestry activities (Šušnjar et al., 2006; Sedara, 2019; Affleck et al., 2009; Uusitalo et al., 2019; Abbaspour-Gilandeh and Abbaspour-Gilandeh, 2019), and also has a significant impact on the movement of military equipment during combat operations. Unlike agricultural activities, which can usually be adapted to the current soil state, military units are forced to implement vehicle movement in any situation. For this reason, the issue of terrain clearance assessment has received much attention within all armies (Rybanský, 2009; Heštera and Pahernik, 2018; DoA USA, 1994; Hubaček et al., 2014; Cibulová and Sobotková, 2006; Jayakumar and Dash, 2016; Lessem et al., 1996; Heštera, 2020; Pimpa et al., 2014; Pokonieczny, 2017; Rosca and Ticusor, 2017; Suvinen et al., 2009). In particular, GIS tools have been used for many years to address this complex problem (Pimpa et al., 2014; Pokonieczny, 2017; Rosca and Ticusor, 2017; Hohmann et al., 2013; Hofmann et al., 2015; Dawid and Pokonieczny, 2021; Rybanský et al., 2015; Talhofer et al., 2015). Achieving the correct results in terrain passability modeling that commanders and staffs can use for their decision-making depends mainly on the quality of geographic data, the capabilities of the used GIS tools, and last but not least, appropriate procedures for modeling the influence of individual landscape components on mobility and linking the individual influences into a comprehensive result.

When assessing terrain passability, a number of authors have focused on evaluating the influence of single landscape components such as relief, roads, vegetation, water and built elements (Rybanský, 2009; Heštera and Pahernik, 2018; Pokonieczny, 2017; Suvinen et al., 2009; Rybanský et al., 2015). Parameterization of these phenomena for the implementation of GIS modeling is not easy but not impossible. In principle, two basic approaches are addressed.

The first principle is based on modelling the movement of the equipment on the surface in terms of the technical parameters of the vehicle and their relationship to the site and its characteristics (slope, obstacles, etc.). The chassis relationships are examined in detail, including the system of transmission of the drive force of the vehicle to the surface by wheels or tracks. These problems are mainly dealt with in terra-mechanics. An example of such a model is the NATO Reference Mobility Model (NRMM) (Heštera and Pahernik, 2018; Jayakumar and Dash, 2017; McCullough et al., 2017; Wong et al., 2020).

The second principle involves utilizing data from a multitude of vehicle movement measurements on the surface, which are then evaluated using geostatistical methods. This approach is adopted by the research team at the University of Defence, Brno (Rybanský, 2009; Hubáček et al., 2014; Hofmann et al., 2015; Rybanský et al., 2015; Talhofer et al., 2015; Rybanský, 2014; Rybanský et al., 2017; Hošková-Mayerová et al., 2020; Rada et al., 2021), and a similar methodology is proposed by authors from the Military University of Technology in Warsaw (Pokonieczny, 2017; Pokonieczny and Mościcka, 2018; Dawid and Pokonieczny, 2021; Pokonieczny and Dawid, 2023; Pokonieczny et al., 2023). However, it is essential to consider the content and quality of the underlying spatial data within GIS data models in both cases. The accuracy of model outcomes is significantly influenced by the quality of the underlying data, thereby affecting the consequent decision-making (Sanderson et al., 2007; Van Oort, 2006; Talhofer et al., 2012; Hošková-Mayerová et al., 2013).

Although the outputs described in the preceding paragraph can substantially aid the decision-making process, without considering the influence of soil, it remains a partial solution. Assessing and modeling the impact of soil on mobility pose the most complex challenges in the process, yet they are crucial for achieving accurate results. Typically, evaluating the influence of soil on military vehicle mobility involves assessing soil penetrometric resistance through on-site penetrometric measurements. These procedures are widely employed in military practice and form the basis for modeling soil passability in GIS. To assess intrinsic soil bearing capacity concerning specific vehicles, several authors (Rybanský, 2009; Heštera, 2020; Rosca and Ticusor, 2017; Mason et al., 2015; Li et al., 2007; Vennik et al., 2019; Vennik et al., 2017; Hubáček, 2018) have compared the Rating Cone Index (RCI) value with the Vehicle Cone Index (VCI) established by the US Army (US Army, 1993; DoA USA, 1994).

RCI, derived from terrain surveys, integrates two crucial parameters: the Cone Index (CI) for soil compaction and the Remolding Index (RI) for soil deformation after repeated passages (DoA USA, 1994). Multiple studies emphasize soil moisture's importance, particularly its impact on fine-grained soil compaction and vehicle load-bearing capacity (Hubáček, 2018; Priddy and Willoughby, 2006; Sirén et al., 2019; Uusitalo et al., 2016; Ayers and Perumpral, 1982). However, there is a lack of methods to quantify soil moisture's influence on vehicle load-bearing capacity in existing literature. Instead, more measurable meteorological factors, such as precipitation, are commonly used to assess soil passability and its impact on vehicle mobility (Heštera and Pahernik, 2018; Heštera, 2020; Bosbach, 2024; Frankenstein and Koenig, 2004; Frankenstein, 2008; Reintam et al., 2016; Vennik, 2023). Numerous researchers have investigated the relationship between soil properties and military vehicle performance, examining various aspects of this issue (Rybanský, 2009; Hubáček et al., 2014; Cibulová and Sobotková, 2006; Hofmann et al., 2015; Rybanský et al., 2015; Talhofer et al., 2015; Rybanský, 2014; Rybanský et al., 2017; Hošková-Mayerová et al., 2020; Rada et al., 2021; Hubáček, 2018; Hubáček et al., 2017; Hubáček et al., 2016).

Hubáček's research (Hubáček, 2018; Hubáček et al., 2017; Hubáček et al., 2016) advances understanding of meteorological factors' influence on passability limits. He notes the absence of suitable soil moisture data for modeling soil load-bearing capacity in the Czechia. Consequently, his models rely on parameters like precipitation, air temperature, soil moisture and snow cover. Additionally, model (Hubáček, 2018) categorizes soils into several types based on soil type and texture, applying different meteorological parameters to these categories, which enables more accurate modeling of passability. For example, chernosols are divided into fine-grained and coarse-grained categories, with different meteorological parameters applied to each of them. This approach enhances the accuracy of passability predictions based on the specific soil conditions. However, these models are limited to using national meteorological and soil data, restricting their application to Czechia. Therefore, our research explores the potential of using selected meteorological events from The Global Forecast System (GFS) (National Centers for Environmental Prediction et al., 2015) and European Centre for Medium-Range Weather Forecasts (ECMWF) (National Centers for Environmental Prediction et al., 2015) models for parameterization. If correlations between weather parameters and CI index values, which exhibit more variability than RI index values, are identified, existing national solutions could be applied to model soil passability at least in the neighboring countries. Identifying relationships between CI values and weather parameters in global models presents a promising avenue for developing a new soil passability assessment method within GIS tools.

For addressing this pilot verification of the feasibility of utilizing a global meteorological model, only one soil group was selected. This group comprises chernosols, which are agriculturally cultivated and typically found at lower elevations (Shukla, 2014). Their distribution corresponds to areas where intensive military activities usually occur during armed conflicts (Caldwell et al., 2004). Notably, such regions include areas of chernozem soils found, among other locations, in Ukraine, where military conflict is currently ongoing (Lebed, 2024).

The key insights from the study dealing with the modelling soil compaction in agricultural applications (Abbaspour-Gilandeh and Abbaspour-Gilandeh, 2019) show that reliable predictions of the relationship of CI to soil moisture and other soil parameters can be obtained by appropriately chosen machine-learning techniques based on field-measured data. This assumption was also used in the case of this work, based on the assumptions obtained during field measurements. During these measurements, the relative soil moisture was measured, which shows relatively strong correlations with the passability indices. This encourages the use of statistical and machine learning methods that are able to interpret and quantify complex relationships between predictors and predicted values. The integration with meteorological models represents a promising initial step towards future advancements in predicting soil passability based on numerical weather forecasts. The authors acknowledge the inherent limitations associated with the utilization of global models, and thus, the paper does not seek to perfectly predict CI values from such models with absolute accuracy. Instead, its objective is to lay the groundwork for procedures and methods that could be later implemented when utilizing local models within the GIS. This includes several components, such as comparing machine learning models, selecting predictors, interpreting results, and evaluating the potential for locations classification based on the predictability of individual models.

The aim of the present study is to investigate the possibilities of parameterization of the Cone Index based on measured soil bearing capacity and meteorological data from global meteorological models. This is done on the basis of selected meteorological variables through machine learning methods. The study aims to develop procedures for parameterizing the bearing capacity of chernosols concerning military vehicle passability. Finally, the research endeavours to set the benchmark for spatial modelling of the soil passability using GIS tools.

2. Materials and methods

To address identified challenge, obtaining necessary data and selecting suitable data collection sites was crucial. As previously outlined, the focus of this study narrowed down to modeling soil passability within the chernosols group. Of the soil types that are significantly influenced by weather, chernosols are the most prevalent in area of Czech Republic, found mainly in extensive lowland regions. Selection of sites for periodic field measurements of CI values involved several considerations. These were the prevalence of chernosols soil type, site accessibility, and terrain diversity, which influences rainwater runoff from the measurement sites.

Meteorological data were sourced mainly from the GFS (grid resolution 0.25 degrees) model. Due to its global availability and open continuous archive containing runs from 0 up to more than 380 hours, it provided potential for further improvement in predictions.

The European ECMWF model has also been considered and tested, but it did not provide a sufficient time archive within the available database. It has a higher resolution and is overall a suitable tool to be included in further research.

2.1. Penetrometry and the soil data

To obtain the CI parameter, the E-960 Soil Trafficability Kit, designed and manufactured by Geotest Instrument Corporation for the U.S. Army Corps of Engineers, was used. The kit consists of a cone penetrometer, soil sampler, remolding equipment and hand tools (Fig. 1). The measurement procedure corresponds to the field manual (DoA USA, 1994). Simultaneously, during the penetrometric measurements, the volumetric soil moisture content at the surface was measured using a ThetaProbe ML3 soil moisture sensor.

Figure 1. The original E-960 Soil Trafficability Kit, including attachments designed by the research team for easier handling and the ThetaProbe ML3 portable soil moisture sensor.

The sites were chosen based on soil classification from various soil databases, ensuring that the soil type at each measurement site corresponded to the black soils group according to the Czech taxonomic soil classification system (Němeček and Kozák, 2024). Based on the classification from the Special-Purpose Soil Database (SPSD) (MoD CZ, 2000), all measurement sites were fine-grained, which was subsequently confirmed by soil analyses indicating that all soils contained a higher clay content (Bajer, 2024). According to the soil analyses, the soils at the measurement sites exhibit comparable physical properties (Bajer, 2024).

Despite differences in the Czech classification scale, these soil areas align with international classifications such as the WRB (World Reference Base) (Němeček, 2002) and Soil Taxonomy (Němeček, 2002), encompassing soils classified as chernozems and phaeozems. Chernosols' properties are significantly influenced by soil moisture and associated precipitation, particularly during the cold season. Therefore, field measurements were conducted in two stages during the 2023–2024 period: the first stage from March to April 2023 and the second stage from October 2023 to January 2024. Measurements were repeated every 2–4 days during both stages, resulting in a comprehensive dataset of CI values at each site. A total of 21 measurements from Stage 1 and 18 measurements from Stage 2 were utilized for subsequent analysis. CI values were measured at four layers – 0, 6, 12, and 18 inches (0, 15, 30, 45 cm) - denoted as CI0, CI6, CI12, and CI18 respectively.

The CI values were measured at five sites in the South Moravian Region of Czechia, specifically within the Dyje-Svratka valley east of Brno (Figure 2). These sites are situated near the villages of Velešovice (sites 1 to 3), Zbýšov (site 4), and Těšany (site 5). Sites 2, 3, and 5 are characterized as wetter sites. They often experience rainwater accumulation and slow infiltration. Consequently, lower CI values were consistently observed at these sites, with prolonged rainfall resulting to waterlogging and the formation of shallow surface water pooling. In contrast, sites 1 and 4 can be categorized as drier sites, exhibiting efficient runoff of rainwater without surface retention. As a result, higher CI values were

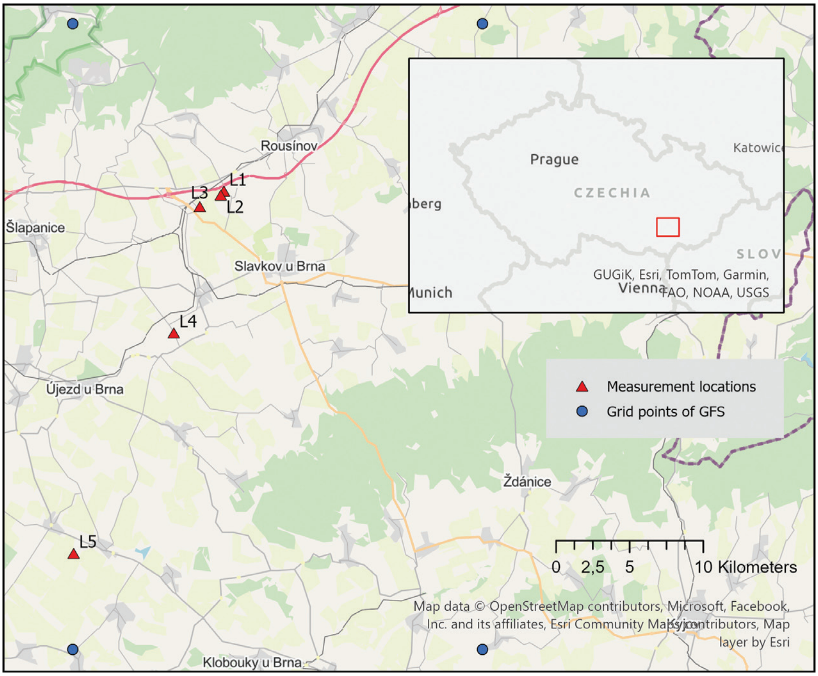

Figure 2. Measurements locations and GFS grid points.

generally recorded at these sites, and the disparity in CI rankings between wet and dry seasons was more pronounced.

Figure 2 shows that sites 1, 2, and 3 are relatively close, sites 4 and 5 are more remote. This may be particularly evident in the meteorological model data, which we have assigned from the closest point.

2.2. Meteorological model predictors

Accessing the National Center for Atmospheric Research's (NCAR's) GFS model archive (National Centers for Environmental Prediction et al., 2015) for training machine learning models was crucial for our study. We opted for a 24h forecast interval to meet operational and planning requirements, especially for larger vehicles. Based on the literature review and preliminary testing, the following predictors were extracted relative to the closest point from the measurement:

1. snow depth,
2. soil temperature (0–10 cm),
3. soil temperature (10–30 cm),
4. volumetric soil water (0–10 cm),

5. volumetric soil water (10–30 cm),
6. accumulated precipitation for 24 hours, and
7. accumulated precipitation for 48 hours.

We intentionally opted to utilize forecast values instead of analysis or reanalysis data, acknowledging the potential inaccuracies this decision may introduce into the model. However, these inaccuracies will also be present in subsequent experiments examining lead times and their impact on passability. Therefore, these predictions are primarily regarded as proxy values rather than direct determinants of passability.

2.3. Preprocessing

When testing a set of methods, a standard scaler expressed by the equation 1 was used for the linear regression and Bayes ridge regression models (Pedregosa et al., 2011):

$$z = \frac{x - u}{s}$$

where u is the mean of the training samples and s is the standard deviation of the training samples.

Presumably, linear models can benefit from feature scaling, as they assume a linear relationship between the features and the target. However, nonlinear models are less sensitive, and scaling might not have such, if any, influence.

Since all the features are ordinal, the use of encoding was not necessary.

2.4. Correlations

Because our data are a relatively small statistical set (about 60 measurements), do not have a normal distribution and are likely to contain outliers, it is appropriate to consider two types of non-parametric correlation (Croux and Dehon, 2010), whose essential properties for our research are:

1. Spearman Correlation:
    a. Suitable for monotonic relationships (not necessarily linear).
    b. Less sensitive to outliers than Pearson.
    c. Appropriate for ordinal or ranked data.
2. Kendall Correlation:
    a. Suitable for detecting any type of dependence between variables.
    b. Focuses on concordant and discordant pairs of data points.
    c. Robust against outliers.

These two correlation coefficients were computed for all considered predictors and based on them, assumptions for the success of machine learning models were formulated.

2.5. ML model training and validation

We used the Leave-One-Out Cross-Validation (LOOCV) (Sammut and Webb, 2011) method to split the training and test datasets, where every data point except one is used for prediction iteratively (Fig. 3).

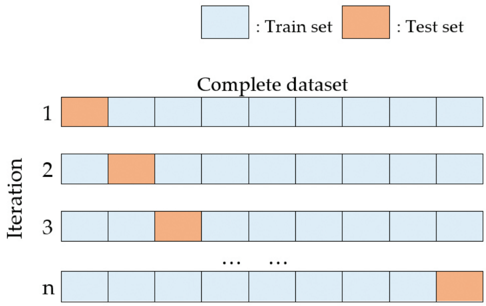

Figure 3. Schematic illustration of the training process employing the Leave-One-Out Cross-Validation (LOOCV) technique.

This method is ideal for smaller datasets as it utilizes all available data for training and testing. Additionally, it provides results for each measurement outcome separately, allowing us to identify any outlier points that may not be immediately apparent.

2.6. Tested ML methods

Following the exclusion of other algorithms due to inadequate accuracy with smaller datasets (e.g., Lasso, Polynomial, and Principal Component Regression – PCR), seven regression methods were chosen for further analysis. These methods provide diverse mechanisms or regularization approaches for predicting CI, ensuring the avoidance of outliers in the initial predictions as outlined in Tab. 1.

Table 1. Overview of tested ML regression methods (Pedregosa et al., 2011).

Method	Anticipated value
Linear regression	Simplicity and interpretability
Bayesian Ridge	Probabilistic, handles multicollinearity well and prevents overfitting
K-nearest neighbors	Can capture nonlinear relationships, understandable to human based decision-making
Elastic Net	Variable feature selection, shrinking low value predictors to 0 weight and variable regularization
Random Forest	Robustness to outliers and complex interactions among predictors
Gradient Boosting	Sequential, based on weak learners sets

Each method underwent rigorous testing and evaluation across all locations through cross-validation using a predefined grid of hyperparameters. While the authors acknowledge the limitations inherent to each method, it is assumed that any inaccuracies in the results are primarily attributed to the limited extent of the dataset, low resolution of the meteorological model, or insufficient geographic information. Consequently, among well-trained methods, the specific type of method may not always be the determining factor.

2.7. Cross-validation metrics

To maintain the interpretability of the results, two straightforward accuracy metrics were employed (Pedregosa et al., 2011). For a clear depiction of the ML prediction residual, the mean absolute error for n samples is defined as:

$$MAE(y, \hat{y}) = \frac{1}{n}\sum_{i=0}^{n-1}\left|y_i - \hat{y}_i\right|$$

where $\hat{y}$ is predicted value corresponding to the y measured value of *i-th* sample in the set of n measurements.

Additionally, for practical applications, it is important to understand the maximum error that may be encountered. This can be defined similarly as:

$$MaxE(y, \hat{y}) = \left(\left|y_i - \hat{y}_i\right|\right) .$$

These errors were the major accuracy metrics for the machine learning model accuracy estimations.

3. Exploratory findings

In this chapter, we present a summary of the exploratory analysis results, which either support or challenge our understanding and interpretation of the measured values and trends across various sites.

3.1. Soil water content and measured soil relative humidity

Since moisture conditions can be critical in terms of passability, the soil moisture values measured in the field and the predicted soil moisture were compared separately.

The aim was to estimate the relationship between these values at each site and based on this, to determine whether the moisture predictors are of sufficient quality, how they vary from site to site and how to treat each site. The following conclusions can be drawn from the results:

- The situation varies depending on the type of location. Except for partial extremes caused mainly by cases of soil freezing, a tendency towards a possible correlation between moisture contents can be observed in the standard sites (1 and 4).

- On the other hand, in waterlogged sites where rainfall accumulation occurs, it seems that no direct dependence can be observed and the search for dependencies is likely to be more complicated and influenced by longer-term phenomena.

Both assumptions confirming our perceptions obtained on site are shown in the graphs in Fig. 4, which shows the situation for Site 1 and Site 2. These sites are less than 500 m apart, both have the same soil properties and differ only in the long-term waterlogging at Site 2.

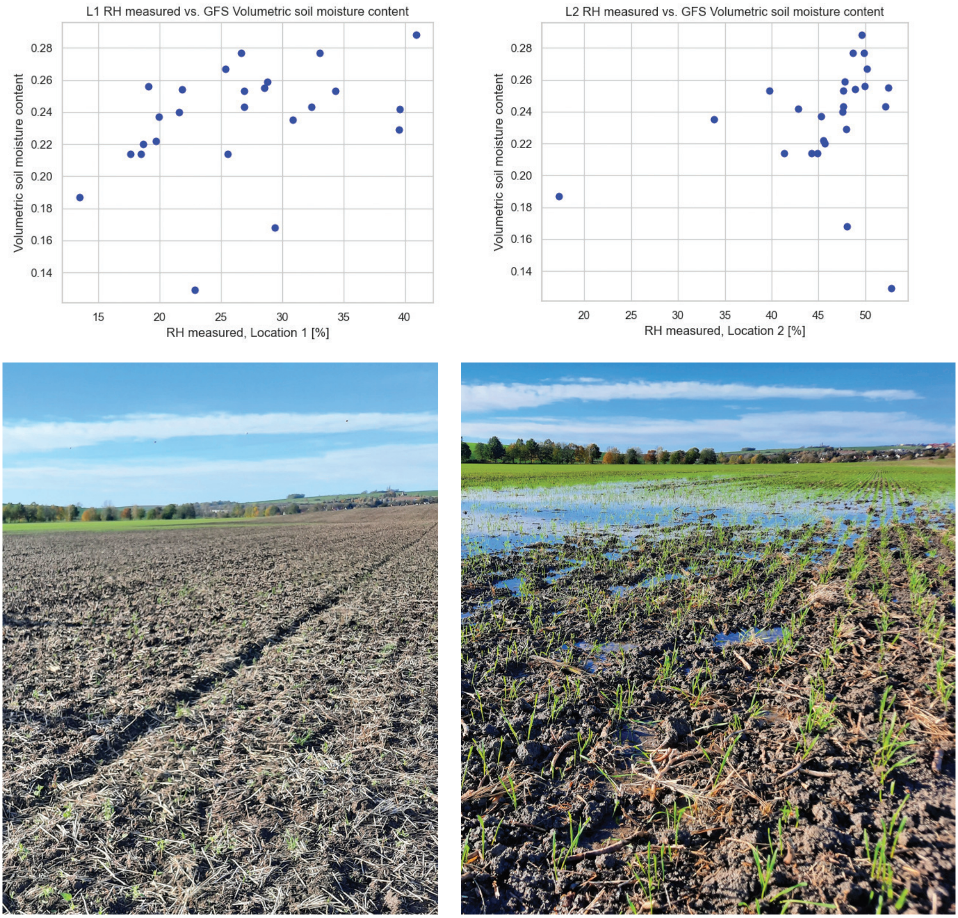

Figure 4. Comparison of measured soil humidity and GFS volumetric soil moisture content in the top layer (0–10 cm) at two nearby locations with similar soil characteristics. Location 2 experienced higher rainfall accumulation. (*a*) Location 1; (*b*) Location 2; (*c*) Location 1 photo; (*d*) Location 2 photo.

Figure 4 indicates higher soil moisture values and reduced variance at the wetter site. As expected, the global model fails to capture this variation. While this discrepancy may pose challenges for machine learning models, they can redirect their focus towards other predictors relevant to perpetually waterlogged areas. Consequently, we can infer the presence of two distinct types of areas within our sites - one consistent with the weather-related moisture patterns and another exhibiting limited response to short-term changes. Due to accumulated water, it reflects rather seasonal variations and long-term trends. This assumption is confirmed by further comparisons, where the shapes of the cluster of points at location 4 correspond to the drier location 1 and the wet location 3 exhibits the same shape as location 2. Site 5 presents a special case. While the situation remains consistent at high measured humidities, at lower humidities it shows characteristics reminiscent of a dry environment. This suggests an increased prone to sudden accumulation of water along with a pronounced response during drier periods. The thick layer of soil horizon accumulation may contribute to the observed water accumulation, resulting in the site's wet behavior during periods of rainfall and its standard behavior during drier periods, encompassing both defined types.

3.2. Predictors – CI correlations

Spearman and Kendall correlations were computed for all locations, layers, and predictors (Fig. 5). As there were no indications of significant differences

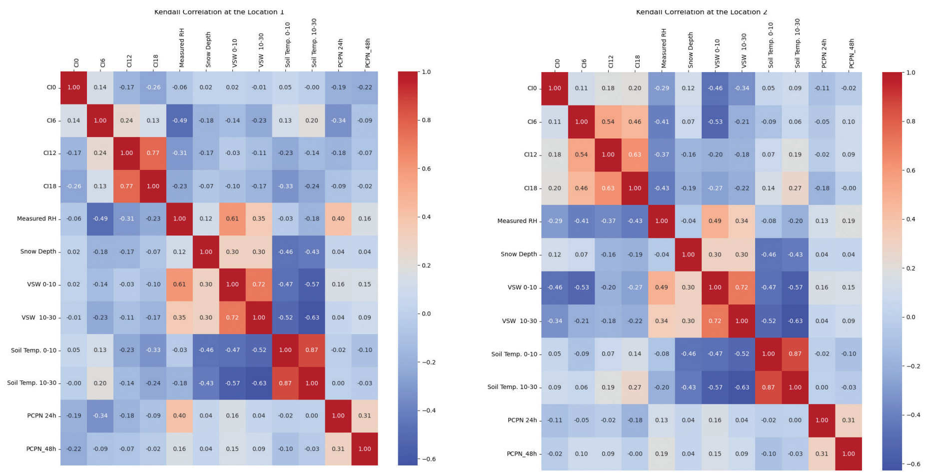

Figure 5. Comparison of Kendall correlation coefficients between predictors and measured Cone Indexes across different soil layers at two locations. (*a*) Location 1; (*b*) Location 2. Cone Index values (CI0-18) represent soil compaction measurements at various depths. Measured RH indicates relative humidity measured during penetrometry. VSW refers to Volumetric Soil Water content and Soil Temp. to temperature in layers of 0–10 cm and 10–30 cm, while PCPN represents precipitation sums for 24 and 48 hours.

between these two types of correlations, which might suggest, for instance, a stronger monotonic relationship in the data, we opted to present the Kendall correlations specifically for locations 1 and 2.

Focusing on the predictors of CI, there are relatively low correlations in the topmost layer in each layer in the first (dry) location. Here, accurate modelling of the loose layer cannot be expected. In the second layer of measurements, however, the situation is more stable and not so dependent on soil conditions and soil loosening. Thus, Site 1 shows a stronger correlation in the second measurement layer CI6 (about 15 cm), –0.14 and –0.23 for the second layer of the GFS model. The highest correlation for predictors in the driest layers is for 24-hour precipitation, –0.34, indicating that subsoil softening occurs at high rainfall. This is probably also related to the higher correlation with soil temperature in general, with both layers showing a positive correlation, i.e. that hardness increases with higher temperature. The effect of 48-hour precipitation is reduced and is only noticeable on the uppermost layer.

For location 2, quite significant values can be observed, such as –0.53 for Volumetric Soil Water and CI6 (15 cm). Partially higher (although only –0.11) correlation values can then also be observed on 24 h precipitation, whose significance decreases with depth. The opposite effect of modelled soil temperature is also evident for this site. That is, hardness increases at higher temperatures. This is mainly related to the drying of the wet area.

Although it has an unquestionable theoretical overlap, the influence of the snow cover must be tempered as it has not been detected many times and the inaccuracy in its modelling by the GFS model may be significant. Therefore, no broad conclusions can be drawn from the correlations on a limited dataset.

From the calculated correlations and by the comparison with other sites, we make the following assumptions:

- For drier sites, it will depend on more predictors whose importance may be more evenly distributed.
- For wetter sites, it will depend more on long-term drying trends, i.e. more on one or two predictors, and the influence of the others will be suppressed.

From these assumptions, we can draw two expectations for modelling with machine learning methods:

- At drier locations (with more predictors), models can provide more robust predictions due to the diversity of input variables. However, the ability of models to capture outliers or high variance may be limited.
- At wet locations (with one significant predictor), models may be simpler because they rely on a single variable. However, the effectiveness of these models depends largely on the quality and relevance of this single predictor. If the predictor accurately represents the target variable and is of high quality, the models may indeed be stable. However, they may have diffi-

culty capturing the complex relationships present in the data if the quality of the predictor is lower.

In summary, while the first dataset may offer greater diversity but potentially less ability to capture outliers, the second dataset may provide stability but may lack the complexity needed to accurately represent the variability in the data.

From a geographic modeling perspective, it becomes apparent that more precise delineation and downscaling of large land areas with the same soil type is necessary. While we primarily consider these areas homogeneous at our current resolution, our analysis reveals significant variations even between geographically proximate locations.

For further research, it is recommended to develop procedures for their accurate delineation. In this context, leveraging accurate digital elevation models obtained through techniques such as laser scanning, in combination with remote sensing data, will be crucial. These resources will help us to capture the nuances of long-term waterlogged sites throughout the year.

4. Results

We divide the results of the paper into several subsections according to our experiments.

- Analysis of the most successful ML models for each location and layer;
- Random Forest accuracy analysis;
- Analysis of the most important predictors for each domain and the Random Forest method;
- The ability of the RF model to predict CI at a location that was not included in the training set.

4.1. Models comparison

To select the most effective models, several regression techniques were evaluated. The outcomes may reveal insights into the critical factors influencing CI modeling. We hypothesized that model performance would vary depending on location complexity and type, as sites with higher predictor and measured value variances might yield superior results with certain methods.

For each target variable in the six regions, a model was trained and calibrated through searching best hyperparameters tuning using GridSearchCV (Pedregosa et al., 2011). Predicted values were compared to actual measurements, and the average MAE was recorded. The model with the lowest MAE was selected as the best performing (Fig. 6), although we acknowledge that employing different calibration or accuracy metrics could identify a different optimal method.

Figure 6 illustrates that as depth increases, the soil hardness also increases, resulting in higher MAE values for predictions. This trend is not necessarily indicative of poor performance but rather reflects the dependency of prediction errors on the measured values. We acknowledge that the differences between the best and second-best methods may not be substantial. Initial expectation was not necessarily for any one method to outperform the others. Additionally, inaccuracies observed are likely attributable to lower data quality or limited training samples for certain boundary conditions. Therefore, any method is expected to fail in the most extreme, unique or inaccurately predicted soil conditions.

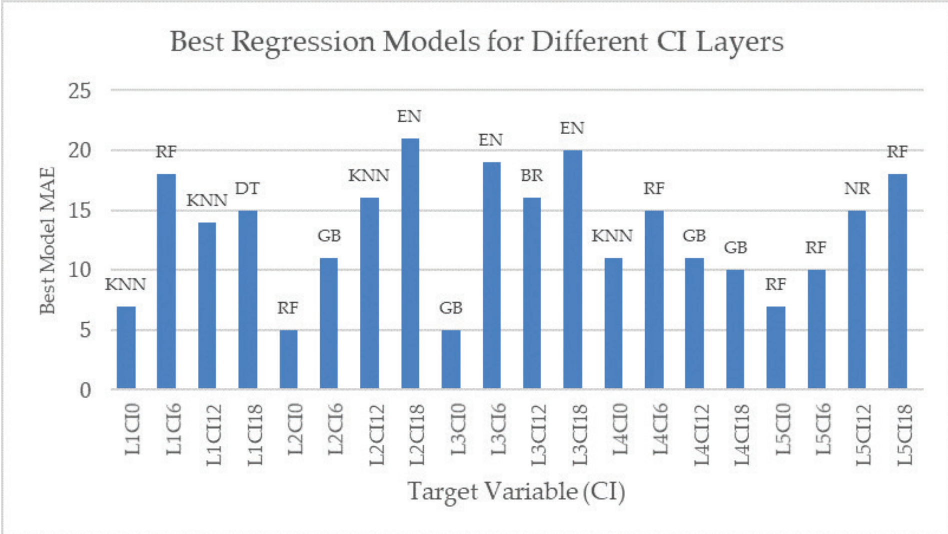

Figure 6. Comparison of MAE of different models for all the target locations and variables. Over each bar, the abbreviation of the most successful model is displayed (KNN: K-nearest Neighbors, RF: Random Forest, DT: Decision Tree, GB: Gradient Boosting, EN: Elastic Net, BR: Bayes Ridge).

Given the success of decision-tree-based methods, including Random Forest (RF), Gradient Boosting (GB), and Decision Trees (DT), along with their advantages such as interpretability, non-linearity handling, feature importance analysis, scalability, and robustness to outliers, we selected Random Forest for further analysis.

4.2. Comparison of measurements vs. model

After conducting predictions using the Random Forest method, the results were visualized (Fig. 7). From four measured depths at each of the five sites, resulting in a total of 20 predicted target values, we focused on specific sites for analysis. These selected sites are in close proximity (sites 1 and 2), facilitating a comparison between drier and wetter types of locations. Additionally, we specifically chose CI6 for examination due to its higher correlations with predictors. Since soil conditions exert a predominant influence at this depth and are more predictable than in the uppermost layer, CI6 was deemed particularly relevant for analysis.

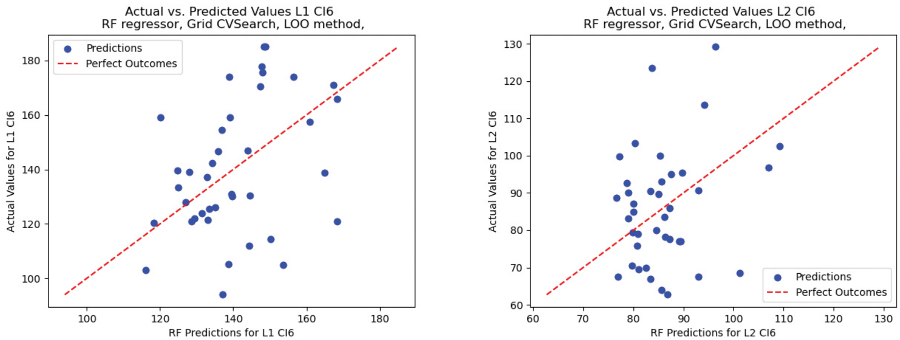

Figure 7. Predicted vs. actual values of Cone Index at the location 1 and 2, both in the second level of approximately 15 cm. (*a*) Location 1, Layer 15 cm; (*b*) Location 2, Layer 15 cm.

At none of the locations did the results tightly cluster around the red curve representing perfect predictions (Fig. 7). However, certain situations indicated that the RF model captured the conditions reasonably well, although there were outliers for both. These outliers often occurred in situations with more extreme effects or highest values in the measurements. It is evident that the method tends to align more closely with the mean values rather than accurately predicting outliers, which is inherent to the nature of the method.

In terms of operational deployment, the results suggest that for a single pass, with lighter off-road vehicles, most of the predictions would be suitable, particularly at location 1. However, a drawback is that the method tends to avoid predicting the lowest values. This could lead to overestimation of the subgrade hardness in critical situations, potentially causing vehicle sinking. The trained and calibrated model tends to overestimate the low values for both dry and wet sites. Comparison of the individual measured and predicted values shows that this tendency is not absolute, although it is prevalent - the cause may be due to insufficient detail in the meteorological data or a small time series of measurements. For the prediction of the determination of the passage of vehicles through the area, the question arises how reliable the predicted values are.

To address this issue, one approach could involve using multiple methods with different calibrations and designing various scenarios. Alternatively, calibrating the RF method using special cross-validation could be considered, biasing it towards false alarms rather than overestimating the Cone Index. The second part of the approach will entail a rigorous analysis of the predictors and their values, estimation of factors that lead to bias, and mapping of factors contributing to lower confidence in modelling lower CI values.

4.3. Predictors importance

Permutation importance quantifies the reduction in model (here RF) performance when randomly shuffling the values of a specific feature (predictor). The actual importance of features for predicting the Cone Index across all five locations is illustrated in the Fig. 8. We used this metric to estimate what are the most important predictors for the Cone Index estimation and how they differ within the locations.

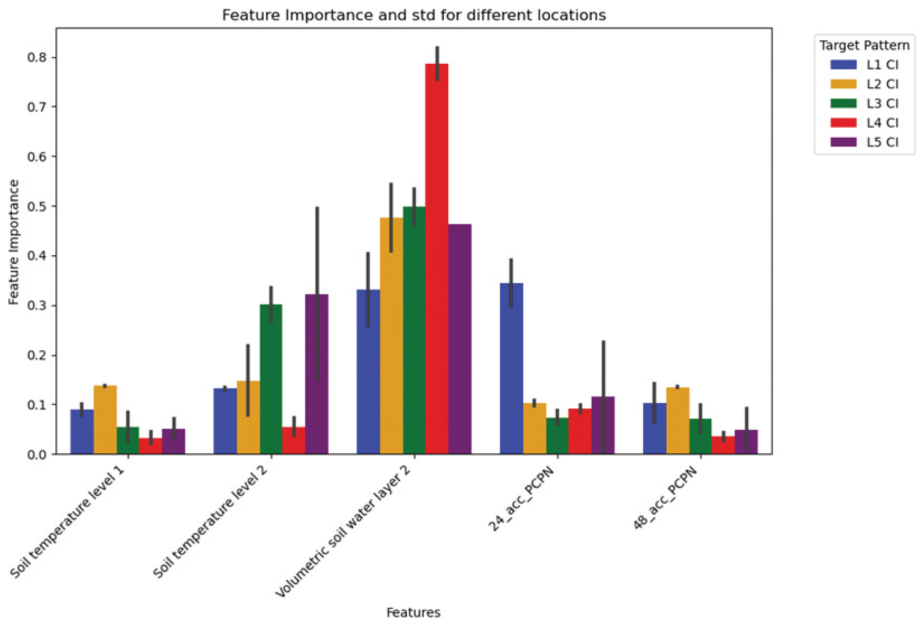

Figure 8. Feature importance and its standard deviation (std) for calibrated Random Forest model tested on locations of measurements.

The findings presented in Fig. 8 highlight several key observations. The model exhibits a strong importance of Volumetric Soil Water in layer 2 (10–30 cm), particularly evident at the drier location 4. This reliance suggests that this characteristic, influenced by longer-term soil water transport models, serves as a reliable indicator for determining Cone Index (CI). This corresponds to the

Kendall's correlation coefficients that suggested strong associations between VSW L1 and CI6 (–0.63) and CI12 (–0.58), further establishing the relationships between the waterlogged sites (location 2 and 3) and the dry sites (location 1 and 4). In addition, location 1 shows higher contributions of the precipitation predictor (PCPN 24) compared to location 4. This may be due to increased runoff and faster drying, thus suppressing the effect of long-term soil water accumulation.

Overall, the selection of predictors for Random Forest (RF) aligns well with the properties of the Kendall correlation coefficients. This scatter of correlations leads to a constant reliance on Volumetric soil water in the second layer, which is offset by the varying support of the other predictors. This means that the model uses a different set of predictors for each layer, which primarily indicates high inconsistency between layers.

However, it is important to note that this analysis may underestimate the importance of predictors if they are highly correlated.

4.4. Cross-location model testing

For final testing of the RF model capability, 18 measurements were predicted and evaluated at the Tovačov site (Fig. 9). This location 40 km northeast of the five sites where measurements were carried out, was selected for its similar soil classification. At the same time, independent penetrometric measurements were available from 2014 to 2018, especially in the winter period of the year (October to April). However, the 2014–2018 period was considered exceptionally dry in the spatial context of Central Europe, where the Tovačov site is located.

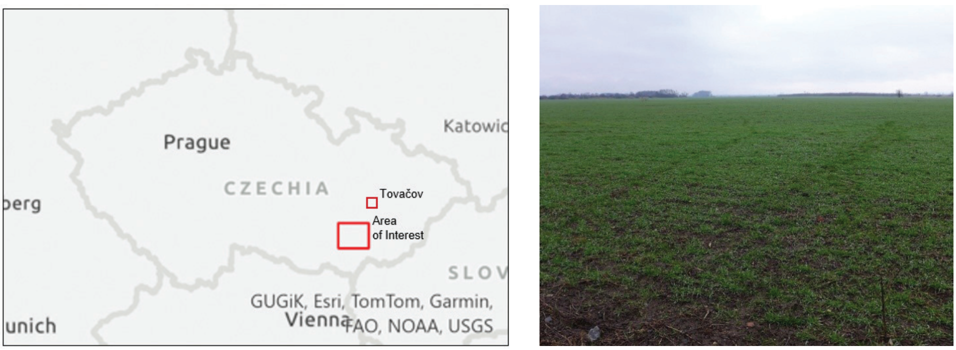

Figure 9. Tovačov site: (*a*) Spatial relationship with area of interest; (*b*) Location photo.

Related soil moisture drought had been evaluated as exceptional in the context of past 253 years (Moravec et al., 2021). Conversely, 2023–2024 measurements correspond to normal long-term soil moisture conditions. Thus, both datasets represent different background environments. CI was modelled based on

Figure 10. Absolute errors for each prediction, with each color representing the site used as the training dataset.

a training set of our five sites, each separately. Each model was then separately evaluated for absolute error (Fig. 10) and compared graphically using a scatter plot (Fig. 11).

The highest absolute error among the 18 measurements (indexed from 0) was observed for measurements 6 and 15. These instances occurred when the soil was frozen, resulting in maximum measured hardness. Consequently, the high error can be categorized as a false alarm. In these cases, the model predicted a lower value, while the actual hardness was higher, leading to the high error magnitude. It is evident that the model did not account for such scenarios, indicating potential inadequacies in expressing the meteorological conditions predicted by the model.

The increased error can also be attributed to measurements 2, 12, and 13, which were conducted during the dry summer period (June to September), when the soil was exceptionally dry (Moravec et al., 2021), and the model was not trained for such conditions. This discrepancy is particularly noticeable in relation to site 4, where the soil's behavior was most in line with expectations for chernosols. In comparison to site 1, which experienced similar dryness, the dry period did not lead to significantly greater differences.

The Tovačov site demonstrated the best prediction accuracy when trained on data from sites 1 and 4, which share similar moisture characteristics. However, site 4 exhibited a higher variance in predictions, suggesting its potential

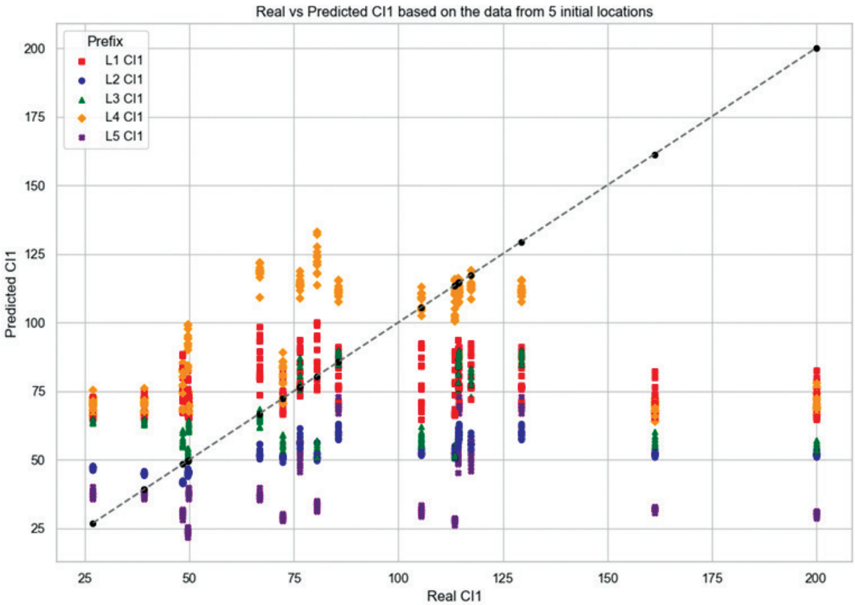

Figure 11. Comparison of the real and predicted Cone Index based on data from the five sites, predicting the Cone Index at the Tovačov site.

to respond to changing conditions. Conversely, site 1 consistently produced results within the range of approximately 70–100, indicating a more stable predictive outcome.

5. Discussion

Our study contextualizes the modeling of the Cone Index against the background of cited sources, which have delved into various aspects of modeling (Heštera and Pahernik, 2018), (DoA USA, 1994), (Cibulová and Sobotková, 2006), (Jayakumar and Dash, 2016). We introduce newly considered variables discovered during our analysis as predictors for machine learning-based terrain passability prediction.

Our results revealed some favorable properties of machine learning methods, although they must be well-supported by a comprehensive and extensive dataset of reliable measurements and accurate geographical and meteorological models (Van Oort, 2006), (Talhofer et al., 2012). We selected soil moisture and temperatures in the first two layers of the GFS model, along with precipitation over 24 and 48 hours, as the main predictors.

The study successfully achieved its objective of mapping the capabilities of machine learning methods for modeling passability based on meteorological variables (Hubáček et al., 2016). As anticipated, the model demonstrated strong performance in typical scenarios, but in extreme conditions like frozen ground or severe droughts, profound human interpretation of the results was necessary. These challenges were primarily attributed to factors such as the lower resolution of the meteorological data, the limited extent of manual measurements, or the absence of spatial relations or advanced geographical and soil attributes at the measurement sites.

The correlations of predictors suggest that soil characteristics and a model with very low resolution can be suitable features for machine learning models. This offers hope for research using higher-resolution models and more sophisticated soil behavior schemes (Rybanský et al., 2017).

The comparison of models across all sites did not demonstrate one model significantly outperforming all others. While Random Forest was selected as the most successful, performance may vary for different locations and under different conditions (e.g., summer-only or winter-only measurements, different regions of the world, etc.).

Generally, machine learning methods provide a solid foundation for modeling static site properties and their passability. They effectively capture long-term characteristics and aid in site and condition comparisons. Unlike previous studies, we explore the possibilities of utilizing numerical weather prediction models, which could form the basis for passability prediction with accurate geographical models in the future.

However, it is evident from the results and exploratory analysis that significant portions of predictors and target values are missing in the models - either measurements on-site or a method to determine CI comprehensively and continuously. This is also reflected in outliers in the results, where machine learning methods struggle to estimate influences such as soil freezing or extreme drought accurately. This may be attributed to the limited number of measurements for these states, as measurements were minimized during these stages of the year compared to earlier data handling methods. Nevertheless, this is in light of recurring results confirming favorable passability conditions.

One solution to these limitations may involve more precise modeling of spatial relationships, where we can accurately estimate and cluster individual sites and soil conditions directly in relation to passability using correlations in static site properties. However, such advanced data processing will require significantly higher levels of spatial relationship modeling, which are provided by geographic information systems.

Our point-based model primarily failed in measurements with insufficient training data, especially in snow cover or frozen ground conditions (where soil hardness was high, even though other variables did not suggest it). The model would also theoretically fail in situations immediately after sudden and short-term precipitation events or when the soil has already been churned by other vehicles (e.g., agricultural machinery).

Given the limitations identified, we suggest future research directions. These may be mostly related to four factors:

1. geographical conditions and models,
2. meteorological conditions and models,
3. measurement method limitations, and
4. ML modeling methods limitations.

Given that this approach relies heavily on data-driven methods and no machine learning algorithm showed significant superiority over others, it is likely that most limitations stem from the quality of the input data.

Due to geographic inaccuracies, we suggest that further research concentrate on a more precise classification of sites. This entails refining the characteristics of individual locations. If meteorological data pertains to a homogeneous area, we can enhance our analysis by subdividing this locality using more detailed geographical data. Our aim is not only to confine ourselves to soil classification and making general statements about dry or waterlogged sites, but also to incorporate additional information such as slope gradient, soil horizon depth, cardinal orientation, and the size of the watershed feeding into the site.

In the realm of meteorological data analysis, the research scope is expansive. Considering rainfall analysis, it is imperative to incorporate a wider range of rainfall intervals based on geographical data, including longer durations of rainfall observation. While these additional intervals may seem redundant in broader contexts, they are crucial for specific location classes characterized by slow runoff and deep soil horizons. Similarly, parameters such as temperature and sunshine should be approached with comparable granularity.

While our method has prioritized developing a global model that could in future serve rather as a reference forecast, the future direction lies in the utilization of local models with significantly higher resolutions and more detailed soil characteristics. These local models will provide more accurate predictions tailored to specific geographical regions.

From the perspective of the measurement itself, limitations arise primarily in the extent of the dataset. The measurement process remains manual, so comparing the data volume, measured locations, or the entire range of conditions to continuous measurement methods is not feasible. However, any changes to the measurement method would disrupt the process of calculating passability characteristics. What can certainly be improved, though, is the extent of the measured dataset and its expansion, particularly regarding boundary conditions of passability.

Despite encountering some challenges, particularly in wetter regions and scenarios not covered by the training set, the developed Random Forest (RF) model demonstrates potential in estimating the impact of chernosols on the Cone Index (CI) by incorporating meteorological data from the global GFS model. Although the reliability of these estimates is limited, they can still be integrated into computational models of chernosols within geographical frameworks that model the area's trafficability. Consequently, these models, supported by additional geographic data, offer a more comprehensive foundation for decision support compared to throughput models that neglect soil influences. This research has thus yielded an initial approximation model that can be further refined in future endeavors. Notably, the significance of this model is amplified in regions lacking a functional station network providing detailed meteorological data or more refined national meteorological models.

While we have not pursued this variant extensively, some noteworthy findings have emerged. The selected features (predictors) can be enhanced through further refinement, incorporating not only additional soil characteristics but also aggregated values. For instance, the Haines index, commonly utilized in fire prediction and predominantly reflecting long-term drought conditions, exhibited high correlation values (about 0.4–0.5). Therefore, the development of aggregated values for forecasting purposes seems to hold promise.

In conclusion, although our research represents initial step in already developed area, there is ample opportunity for future research to build on our findings and develop more robust models for predicting soil permeability under different meteorological conditions. In particular, ML modelling of spatial patterns of predictors in GIS and classification of the problem or results based on static properties of areas. The final evaluation of the results marks the beginning of the next challenge: developing and refining prediction models. Assessing the quality of input data, understanding its impact, and evaluating the performance of the model itself will be crucial steps in this process. Moreover, considering the diverse needs of end-users and stakeholders, including both military and civilian sectors, adds another layer of complexity to model development. Therefore, collaboration within the research community will be essential to tackle these challenges effectively. By collectively addressing these tasks with careful consideration, we can advance the field and develop more robust and reliable prediction models for practical applications.

6. Conclusions

Our study highlights the potential of machine learning methods, particularly Random Forest, for predicting terrain passability using meteorological variables, with soil moisture, temperature, and precipitation identified as key predictors. While the models performed well under typical conditions, extreme scenarios like frozen ground or severe droughts revealed limitations stemming from low-resolution meteorological data, sparse manual measurements, and insufficient spatial modeling. These findings emphasize the need for higher-resolution geographical and meteorological models, expanded datasets, and refined site-specific features such as slope gradient and soil horizon depth.

Despite these challenges, the developed model offers a foundational framework for predicting soil passability, particularly in regions with limited meteorological data, and has applications across military and civilian sectors. Future research should focus on improving data quality, namely satellite-based soil-moisture measurements (Fan et al., 2025) and its verification through field measurements, enhancing spatial relationships through GIS, and addressing model limitations to develop more robust and reliable prediction systems tailored to diverse conditions and user needs.

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Measurement data can be provided by the authors upon request.

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SAŽETAK

Pristup modeliranju prohodnosti tla u GIS-u temeljenom na meteorološkim podacima korištenjem strojnog učenja

Lucie Marková, David Sládek, Martin Hubáček, Václav Talhofer i Petr Kolář

Mobilnost vozila po različitim terenima ovisi o mnoštvu geografskih i meteoroloških varijabli. Tradicionalni pristupi oslanjaju se na radno intenzivna ručna terenska mjerenja za procjenu uvjeta tla za prolazak vojnih ili humanitarnih vozila.

U ovoj studiji, cilj nam je bio istražiti nove metode za parametrizaciju indeksa stošca, temeljne metrike za procjenu izvedivosti prolaska, koristeći meteorološke podatke iz globalnog numeričkog modela The Global Forecast System. Usredotočujući se posebno na černosole, prvenstveno poljoprivredna tla koja se nalaze u ravnim, otvorenim regijama pogodnim za vojne operacije, upotrijebili smo metode strojnog učenja kako bismo procijenili kako uvjeti tla utječu na mobilnost vozila.

Kroz rigoroznu istraživačku analizu, istražili smo korelacije, metriku izvedbe modela i relativnu važnost prediktora u modeliranju stožastog indeksa. Naši nalazi naglašavaju komparativnu učinkovitost različitih pristupa modeliranju, posebno naglašavajući korisnost metode slučajnih šuma. Identificirali smo ključne uvjete okoline pod kojima model pouzdano predviđa indeks štošca. Ovo postavlja osnovu za prostorno modeliranje u GIS-u.

Unatoč ovim uvidima, naša je studija ograničena podacima i inherentnim ograničenjima rezolucije modela Globalnog sustava prognoze. Dobiveno rješenje postavlja početne temelje za implementaciju modela u GIS okruženju za predviđanje prometnosti černosola u široj europskoj regiji. Buduća istraživanja imat će za cilj proširiti skup podataka, prostorne odnose i koristiti modele s višom rezolucijom za robusnija i točnija predviđanja.

Ključne riječi: indeks stošca, prohodnost tla, strojno učenje, slučajna šuma, černosol

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