



# Development of a NWP based Integrated Block Level Forecast System (IBL-FS) using statistical post-processing technique for the state Jharkhand (India)

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A statistical post-processing forecast system for medium range predictions using the GFS model has been developed for Jharkhand (India) with the aim of improving rainfall and temperature predictions for agricultural applications. The basis of the integrated block level forecast system (IBL-FS) build includes (i) Decaying weighted mean (DWM) bias correction technique, (ii) Value addition and (iii) Inverse distance squared weighted (IDSW) interpolation. In the first step, model bias corrected district level forecast for 24 districts of Jharkhand is generated from the output of numerical GFS model (T1534L64) by applying DWM bias correction technique. In the second step, these bias corrected forecasts are value-added using forecast from various NWP models and synoptic methods. Finally in the third step, the IDSW interpolation method is used to generate the forecast at an unmeasured block from the value-added district level forecast of the surrounding districts. The value-added forecast for 263 blocks for the state Jharkhand is prepared up to medium range time scale (120 h). The performance skill of IBL-FS is evaluated for rainfall during monsoon season 2018 and 2019, for minimum temperature during winter season 2019, and for maximum temperature during summer season 2019 using different statistical metrics. The skill of IBL-FS is found to be higher than the direct model forecast (DMFC) by 15% to 43% for minimum temperature, by 18% to 41% for maximum temperature, and by 22% to 30% for rainfall forecast for day1 to day5 forecasts. This study concludes that the integrated approach is more skillful than DMFC for real time forecasts and useful for farming for the blocks of Jharkhand.

*Keywords:* block level forecast, district level forecast, Global Forecast System (GFS), statistical post processing, decaying weighted mean (DWM), inverse distance squared weighted (IDSW) interpolation

## 1. Introduction

Jharkhand is a state in the eastern part of India and is surrounded by the state Bihar to the northern side, West Bengal to the eastern side, Odisha to the

southern part and Chhattisgarh and Uttar Pradesh to the western side (shown in Fig. 1). The main seasons are summer, rainy and winter. The summer is characterized by mean maximum temperature around 35 °C. The southwest monsoon brings nearly all the state's annual rainfall which is about 1092 mm. Nearly half of the annual precipitation falls in July and August. The winter season is characterized by mean minimum temperature around 11 °C. Agriculture is important sector in the economy of Jharkhand. Farmers produce several crops such as rice, wheat, maize, pulses, potatoes, and vegetables such as tomato, carrots, cabbage, brinjal, pumpkin, and papaya.

Growth and yield of crops under normal environment are mainly determined by weather during the growing season. In case of wheat yield, average temperature during flowering time, minimum rainfall during planting time were effective while maximum humidity in harvest time was effective on barley yield (Ozkan and Akcaoz, 2002). Agarwal and Sinha (1993) showed that increase of temperature would decrease wheat yield. It is possible to minimize the effects of unfavourable weather by suitable use of fertilization, nutrient, and appropriate selection of variety of crops.

In view of the impact of short to medium range weather variability on yield of crops, venturing into generation of Agro Meteorological Services (AMS) from district level quantitative weather forecasts to block level in the medium range time scale is a challenging task to the operational forecasters. Numerical Weather Prediction (NWP) is the only state-of-the-art tool to provide quantitative weather forecast in real time. Significant improvement in accuracy and reliability of NWP products has occurred due to development of sophisticated numerical



**Figure 1.** Map of India and the state Jharkhand.

techniques, significant enhancement of computational power, and phenomenal increase in the number of surface, upper air, radar and satellite observations. But accurate forecasting for surface parameters is a very challenging task due to complex terrain having different altitudes, orientations and also various model constraints. Further, the NWP model forecasts contain systematic bias due to imperfect initial conditions, model physics, and boundary conditions (Mass et al., 2002; Hart et al., 2004; Krishnamurti et al., 2004). The systematic bias in the NWP model also arises due to inability of the NWP models to handle subgrid scale phenomena correctly. The local weather dominated by small scale effects may be represented poorly or may not be represented in the model as NWP models generally homogenize the orographic and land surface characteristics. In real-time, there is variation in model outputs from various models (viz. WRF, NCUM, GEFS, ECMWF, NCEP GFS) and also it is not achievable to generate forecast up to medium range scale by subjective synoptic method considering the chaotic nature of atmosphere. Therefore, combination of both has become the mainstay of operational weather forecasting, which is known as value-added official forecast. Operational forecasters widely use the value addition by combination of objective and subjective methods as it can add skill to the dynamical forecast and can generate a consensus forecast under the scenario of wide variation of different model forecasts. Previous studies (Wilson et al., 2004, 2010) also showed that skill of NWP models is inconsistent and automated forecasting techniques are less skilful than human-machine blended forecasts. Experienced forecasters, assisted by statistics, are able to give best interpretation to a machine-produced forecast by exercising proper weighting and judgment. Kumar et al. (2017) proposed a simple downscaling from NWP model output at block level but because of various constraint of direct model output as discussed above, it has a limitation for real time use and they suggested for value addition. Durai and Bhardwaj (2014) and Kumar et al. (2018) used decaying weighted mean (DWM) bias correction technique for minimizing the model bias of daily maximum and minimum temperature forecast.

The importance and efficacy of statistical post-processing has long been recognized in weather forecasting (Glahn et al., 2009). Statistical post-processing methods are applied to quantify and reduce the uncertainties in the raw model forecasts. Early studies included analog method (AM) (Lorenz, 1969; Van Den Dool, 1994), analog ensemble (AnEn)(Delle Monache et al., 2013), perfect prognosis (PP) (Klein et al., 1959), and model output statistics (MOS) (Glahn and Lowry, 1972). The AM essentially uses past forecast datasets that are similar to the current forecasts and forms calibrated forecasts from the observations. In the AnEn, the probability distribution of the future state of the atmosphere is estimated using past observations. The PP and MOS post-processing tools are mainly regression-based methods. Regression-based methods are used for statistical correlation between the predictand (the observation) and the predictors (the model forecasts). The MOS approach (Glahn and Lowry, 1972) has been

successfully used to provide location-specific (may not be at grid point) forecasts from model through bias removal and interpolation. In this approach, Mao et al. (1999) proposed a technique that updates bias using the most recent 2–4 weeks of model and observational data. Stensrud and Skindlov (1996) showed that previous 7-day running mean bias correction method can improve the direct model forecasts. Steed and Mass (2004) showed that removal of bias using a 2-week running bias produce least amount of error compared to periods of 1, 3, 4, and 6 weeks. Over the recent years, many other post-processing methods have been proposed including quantile regression (QR) (Bremnes, 2004; Friederichs and Hense, 2007), quantile mapping (QM) (Hashino et al., 2007; Piani et al., 2010), standardized anomaly MOS (SAMOS) (Scheuerer et al., 2014) and ensemble model output statistics (EMOS) (Stauffer et al., 2017). Kleiber et al. (2011) developed the GMA (Geo-statistical Model Averaging) for precipitation forecasts. Skoien et al. (2016) developed the top kriging based EMOS method to interpolate EMOS parameters at unknown locations.

In view of implementation of various new schemes for the benefit of farming community at the block level, improved model forecast by post-processing has been widely used by many operational centres. India Meteorological Department (IMD) has implemented ‘Gramin Krishi Mausam Sewa (GKMS)’ scheme at Krishi Vigyan Kendras (KVKs) for the benefit of farming community at district level across the country. Presently, district Agromet Advisory Service (AAS) bulletins are issued bi-weekly (Tuesday and Friday) by Agro Meteorological Field Units (AMFUs) of each state to minimize the impact of adverse weather on crops and to boost agriculture production.

There are three AMFUs in Jharkhand namely Ranchi, Dumka and Darisai. The list of AFMUs and their area of responsibility based on Agricultural climate area for the State of Jharkhand is given in Tab. 1. There is an operational need and growing demand from the AMFUs of Jharkhand to provide weather forecast objectively in the medium scale range to enhance the service at block level to satisfy the farmers and for other services. In view of this, in this study a three stage integrated approach has been developed to generate value-added bias corrected forecast of three surface parameters (maximum temperatures, minimum

*Table 1. The AFMU and Agriculture Climate area for the State of Jharkhand.*

S. No.	AMFU	Agriculture climate area	Area of responsibility (Districts)
1	Ranchi	Central and Western Plateau	Ranchi, Khunti, Bokaro, Hazaribagh, Ramgarh, Chatra, Garhwa, Palamau, Latehar, Lohardaga, Gumla and Simdega
2	Dumka	Central and North-Eastern Plateau	Dumka, Sahebganj, Godda, Pakur, Deoghar, Giridih, Dhanbad, Jamtara and Koderma
3	Darisai	South-Eastern Plateau	West-Singhbhum, East-Singhbhum and Saraikela-Kharsawan

temperatures, and rainfall,) up to five days (24 h, 48 h, 72 h, 96 h, 120 h) for all the 263 blocks of Jharkhand. The paper is organized as follows. Qualitative assessment in weather forecasting is briefly described in section 2. The data used in this study is described in Section 3. Three step integrated approach is described in section 4. Statistical metrics used in this study are described in section 5. Results and summary are discussed in section 6 and section 7, respectively.

## 2. Qualitative assessment in weather forecasting

Prediction of chaotic nature of atmosphere is very challenging task to the forecasters. Forecasters have greatly benefited from the objective guidance by NWP models. Different NWP models rarely can generate similar forecasts, *i.e.* sophisticated numerical models can not reproduce consensus forecasts as each model has its own configuration and limitation. Under such scenario, it is a challenge to the operational forecasters to generate a consensus single and more skilful official forecast. Forecasters execute it by considering various factors (discussed in section 4.2). The official forecasts generated by various centres are the final forecast for a region and found to be more skilful. Karstens et al. (2018) also showed benefit of human-machine mix forecast for both user and forecaster. Furthermore, a satellite based scientific method known as “Dvorak technique” (SDT), (Dvorak, 1975) used to determine intensity and forecast of tropical cyclones by analyzing satellite image patterns. Regional Specialized Meteorological Centre (RSMC), New Delhi entrusted by the World Meteorological Organization (WMO) and Joint Typhoon Warning Center (JTWC) use the SDT to determine intensity of tropical cyclones over the north Indian Ocean (NIO) but there are discrepancies (Kotal et al., 2018). Similarly, there are discrepancies for other ocean basins also (Yu et al., 2007; Song et al., 2010). In the SDT (Dvorak, 1975), the technique proposed various stages for tropical cyclone intensity analysis and forecasting from satellite imagery qualitatively. The operational scientific tool SDT is subjective and the success of this technique largely depends on the skill of the forecasters. Nevertheless, the SDT has become an important operational tool, widely used by the cyclone centers for ocean basins all over the globe. As no method is perfect in weather forecasting, therefore, analysis and forecast of chaotic nature of atmosphere has been the best assessment by combination of both objective and subjective methods for operational use in real-time.

## 3. Data

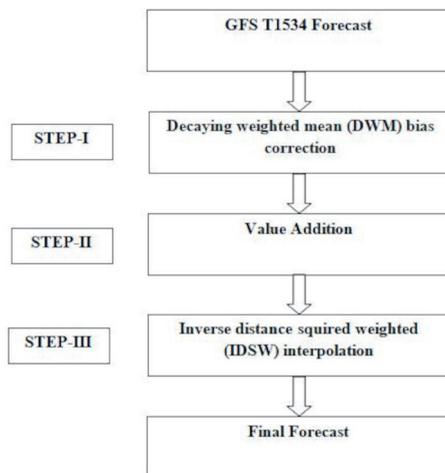
There are number of surface and upper air observatories available at various locations in India. These observatories are equipped with meteorological instruments and observations are taken both manually (eye-reading) by the observers and by self-recording instruments. Regular observations of meteorological parameters are taken at three-hour interval (00 UTC, 03 UTC, 06 UTC, 09 UTC,

12 UTC, 15 UTC, 18 UTC, 21 UTC) daily. Observational data are stored in standard WMO (World Meteorological Organization) coded format and disseminated to the users. These data are also used in the data assimilation of numerical models. The Global Forecast System (GFS), adopted from National Centre for Environmental Prediction (NCEP) has been operational at IMD, New Delhi at T1534 (~ 12 km in horizontal over the tropics) resolution. Ensemble Kalman Filter (ENKF) based Grid point Statistical Interpolation (GSI) scheme is used for global data assimilation for the forecast up to 10 days. The model is run four times in a day (00 UTC, 06 UTC, 12 UTC, and 18 UTC). The real-time outputs are made available to the national web site of IMD. In addition to GFS forecasts, for the day-to-day weather forecasting, IMD also use NWP products prepared by some other operational NWP Centers like, NCMRWF (National Centre for Medium Range Weather Forecast, India), ECMWF (European Centre for Medium-Range Weather Forecasts), NCEP Global Forecast System (NCEP GFS). The GFS model forecast data of 00 UTC are used as input to generate block level forecast using IBL-FS for AAS bulletins, issued bi-weekly (Tuesday and Friday). In this study, the minimum temperature forecast and maximum temperature forecast is verified for the winter season 2019 (January and February) and for the summer season 2019 (March, April and May), respectively. Rainfall forecast is verified for the monsoon season 2018 and 2019 (June, July, August, September). Verification has been carried out up to five-day forecast.

The state Jharkhand has 24 districts, and each district has some number of blocks which altogether constitutes the district. On average, each district has about 11 blocks. There is total 263 blocks in the 24 districts. The state Jharkhand has an area of 79,710 km<sup>2</sup>. Out of 24 districts, West Singhbhum is the biggest district in the state with an area of 7,224 km<sup>2</sup> and Ramgarh is the smallest district with an area of 1,341 km<sup>2</sup>. The Capital of Jharkhand is Ranchi with an area of 5,097 km<sup>2</sup>. Average area of one district is about 3,321 km<sup>2</sup>, and average area of one block is about 303 km<sup>2</sup>.

#### 4. Methodology

There are various commonly used statistical post-processing methods to reduce model forecast uncertainties. Model Output Statistics (MOS) is a type of statistical post-processing technique used to improve NWP model forecasts by relating model outputs to observational or additional model data. MOS post-processing tools used in weather forecasting are mostly based on regression methods. Artificial neural networks (ANNs), support vector machines, multivariable regression models, and fuzzy reasoning techniques are major technologies used for a MOS application. Statistical post-processing techniques in MOS approach, like decaying weighted mean and interpolation have been used in the IBS-FS to improve model forecasts. The three step IBL-FS for real time forecasts at block level for the state Jharkhand is briefly described below. The three steps are: (i) Decaying



**Figure 2.** Flow diagram of Integrated Block Level Forecast System (IBL-FS)

weighted mean (DWM) bias correction technique, (ii) Value addition, and (iii) Inverse distance squared weighted (IDSW) interpolation. The flow diagram of IBL-FS is shown in Fig. 2. An Excel program is developed for the IBL-FS for real time application.

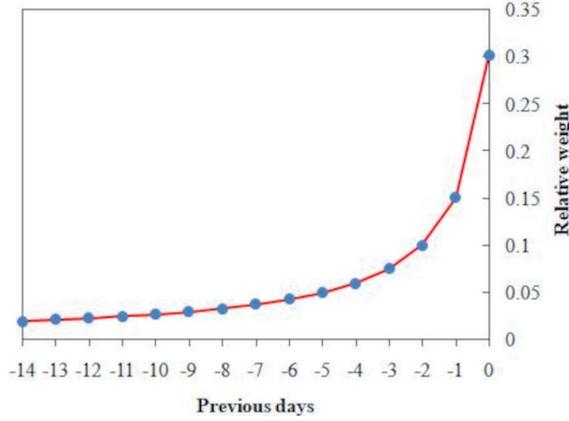
*4.1. STEP-I: Decaying weighted mean (DWM) bias correction technique*

District level forecast are generated from the operational GFS model. In this district level forecasts, a statistical algorithm is used to minimize the model bias by applying decaying weighted mean (DWM) bias correction technique to the forecasts for different lead time (24 h, 48 h, 72 h, 96 h, 120 h). In DWM bias correction method (Durai and Bhardwaj, 2014), the model forecast bias  $b_{kl}(i) = f_{kl}(i) - O_{kl}(i)$  for lead time  $l$  is defined as the difference between the forecast  $f_{kl}(i)$  and observation  $O_{kl}(i)$  at time  $l$  for a location ( $k$ ). The bias at each observatory and each forecast hour is computed from the previous 14 days forecast error starting from the forecast issue day ( $l = 0$ ) using decreasing weight so that the nearest recent data has the largest weight which ranges from 0.3 to 0.02. The DWM with the weight coefficient  $w_{kl}(i)$  is computed as:

$$w_{kl}(i) = \frac{w_k(i)}{\sum_{i=0}^{-14} w_k(l)}, \tag{1}$$

where  $w_k(i) = \frac{1}{1-i}$  and  $i = 0, -1, -2, -3, \dots, -14$ .

The weight  $w_{kl}(i)$  considered for computing model bias from its past performance starting from the forecast issue day ( $l = 0$ ) and successively previous first 14 days is illustrated in Fig. 3.



**Figure 3.** Illustration of weights used in the decaying weighted mean bias correction with previous 14 days for computing daily model bias.

The bias  $B_{kl}$  at each observatory is computed daily by applying the weight coefficient  $w_{kl}(i)$  at each forecast hour as:

$$B_{kl} = \sum_{i=0}^{-14} w_{kl}(i) \cdot b_{kl}(i). \quad (2)$$

This bias  $B_{kl}$  is subtracted from the model forecasts to produce the bias corrected forecast, which is defined as:

$$F_{kl} = f_{kl} - B_{kl}, \quad (3)$$

where  $f_{kl}$  is the direct model forecasts.

The DWM bias is computed at each observatory and used for the districts having observatory, whereas interpolated values from the nearest observatories are used for the other districts. The advantage of this technique is that it takes into account the day-to-day changes in forecast bias and gives more weight to recent model forecast error and less to older error. The bias correction is done to eliminate the common systematic errors in the GFS model forecasts. This step is not applied for rainfall, considering the discrete nature of occurrence of rainfall (unlike the temperature).

#### 4.2. STEP-II: Value addition

The model bias corrected (by DWM) district level forecast generated from GFS model is value-added. Value addition is done by considering initial model forecast differences from observations, and model outputs from various models (WRF, NCUM, GEFS) including models from other countries (ECMWF, NCEP GFS). Thereafter subjective corrections are made based on official forecasts issued by Meteorological Centers and Regional Meteorological Centers. Value addition

Table 2. Eighteen surrounding districts of neighboring five states of Jharkhand.

S. No.	Neighboring five states	Districts
1.	Odisha	Sundergarh, Kendujhar, Mayurbhanj
2.	Chhattisgarh	Jashpur, Surguja
3.	Uttar Pradesh	Sonbhadra
4.	Bihar	Bhabua, Orangabad, Gaya, Nawada, Jamui, Banka, Bhagalpur, Katihar
5.	West Bengal	West Medinipur, Purulia, Birbhumi, Malda

is done for 24 districts of Jharkhand and 18 surrounding districts of neighboring five states (Tab. 2). Twenty-four districts of Jharkhand and 18 surrounding districts neighboring states (Bihar, West Bengal, Odisha, Chhattisgarh, Uttar Pradesh) are shown in Fig. 4 and the 263 numbers of blocks are shown in Fig. 5.

The step I and step III are objective techniques and are based on sophisticated statistical methods. But in Step II, the value addition component is done operationally by experienced forecasters. Guidelines combining objective and subjective procedures have been followed to generate more accurate value-added official forecasts for 24 districts. These are:

(i) Initial bias correction: In this correction, initial difference (ID) of model analysis and observation (if any) is removed. After application of interpolated DWM bias correction, if any district has significant difference (beyond usable range) from the nearest observation at the initial time (lead time = 0) then the

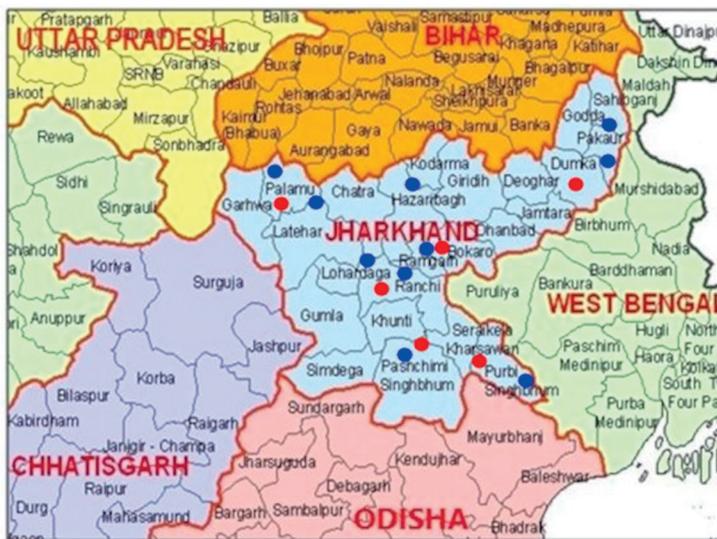


Figure 4. Districts of Jharkhand and surrounding states (solid red circles for temperature and solid blue circles for rainfall indicate location of observational points).



**Figure 5.** Blocks of Jharkhand state.

difference (initial bias) is removed at the initial time. Similarly, value for district at any forecast lead time can also be modified if larger deviation of forecasts from the surrounding districts is noticed, thus improving spatial consistency. As observation for all districts are not available, the difference at the available obser-

*Table 3. Observatories in Jharkhand and nearest surrounding districts (applied for correction).*

S. No.	Observatories	Surrounding districts (value within parenthesis indicates distance from the observatory in km)
1.	Ranchi	Ranchi (0), Ramgarh (35.8), Lohardaga (67.7), Gumla (84.8), Purulia (WB) (143.3)
2.	Jamshedpur	East-Singhbhum (0), Saraikela-Kharsawan (37), Medinipur (WB) (129.5), Mayurbhanj (OD) (77.7)
3.	Chaibasa	West-Singhbhum (0), Simdega (136.7), Khunti (73.8), Jaspur (CH) (177.1), Sundergarh (OD) (189.4), Kendujhar (OD) (89.5)
4.	Bokaro	Bokaro (0), Hazaribagh (86.8), Dhanbad (31.7), Giridih (50.7), Koderma (95.1), Nawada (120)
5.	Dumka(AWS)	Sahibganj (100.6), Godda (53.6), Dumka (0), Pakur (72.7), Deoghar (60.8), Jamtara (52.2), Katihar (BR) (122.8), Banka (BR) (67.9), Bhagalpur (BR) (95.9), Birbhum (WB) (55.9), Mushirdabad (WB) (108.5), Malda (WB) (117.1), Jamui (BR) (122.8)
6.	Daltonganj	Chatra (81.9), Garhwa (33.6), Latehar (49.3), Palamu (24.4), Bhabhua (BR) (108.5), Aurangabad (BR) (68.9), Surguja (CH) (140.6), Gaya (BR) (102.8), Sonbhadra (UP) (123.8)

(OD: Odisha, CH: Chhattisgarh, UP: Uttar Pradesh, BR: Bihar, WB: West Bengal)

vatories is applied at nearest surrounding districts assuming the homogeneity for these districts. There are six observatories in the Jharkhand (Ranchi, Jamshedpur, Chaibasa, Bokaro, Dumka and Daltonganj). The observatory Dumka is an automatic weather station (AWS). The surrounding districts where IDs of the six observatories are applied are shown in Tab. 3.

(ii) Model guidance: Output of all available models is consulted. Digital data of some models available in real time are also considered for simple ensemble and used to generate objective value of the parameters.

(iii) Subjective value addition: Finally, a subjective correction is made by the forecasters of Meteorological Centers.

Therefore, the final weather forecast is issued by the professional forecaster, using or discarding the guidance of information provided from all sources as mentioned in Step-I and II. Step-I is used for statistical bias correction and Step-II is all about human-machine blending. The value-added official forecast is prepared based on statistical bias correction and human-machine blending for all the districts, where human (forecaster) modify the machine (model) generated forecast (for all lead time). Value addition is done by considering the facts of consistency of different NWP model forecasts, synoptic features, past performance of models, persistency of evolution and movement of weather phenomenon, and forecaster's skill, experience, and geographical and climatological knowledge over the region.

The modified GFS forecast after step-II is the actual operational official forecast, routinely generated by forecasters of the Meteorological Centre of the state. Value-added official forecasts are generated for all 24 districts of the state Jharkhand, but there is requirement to generate such forecasts for blocks also for agrometeorological and other services. It can be mentioned that it is practically near impossible to generate such value-added official forecasts for all 263 blocks in real-time. Therefore, in this study, a mathematical approach (inverse distance weighted (IDW) interpolation method) is proposed (presented below) to augment the official forecast from district level to block level.

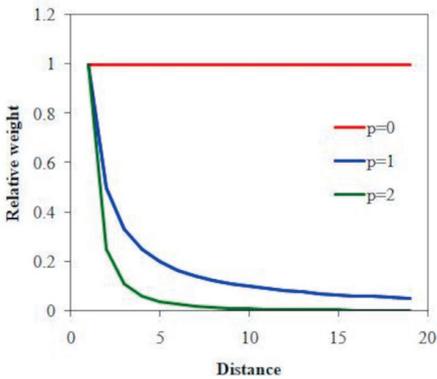
#### *4.3. STEP-III: Inverse distance squared weighted (IDSW) interpolation*

After step-II, the deterministic inverse distance weighted (IDW) interpolation method is used to generate the final forecast at an unmeasured block from the value-added district level forecast of the surrounding districts. Districts of surrounding states are also used for IDW interpolation (for the blocks in a district of Jharkhand attached to the district of neighboring states).

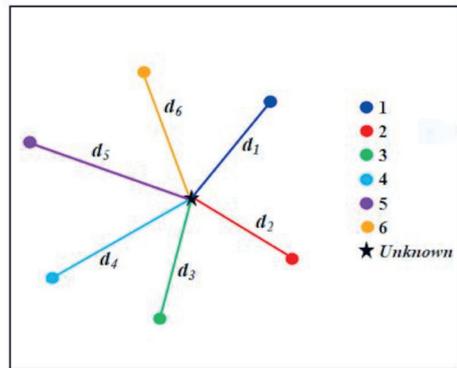
Several studies have been conducted on the post-processing forecasts for locations without observatories. The most common interpolation techniques estimate a parameter at an unknown location by a weighted average of nearby data. Among statistical methods, variants of kriging are often proposed as statistical techniques with superior mathematical properties (Journel, 1986;

Cressie, 1993; Deutsch, 2002). Among deterministic methods, the IDW interpolation method (Franke, 1982; Nalder and Wein, 1998) has been often used for spatial analysis. There are several reasons why IDW technique may be preferred over the kriging-based techniques. It is simple and easy applicable to any number of dimensions. Besides these, it does not suffer from the string effect of kriging (Deutsch, 1993, 1994), screening effect due negative weights (Deutsch and Journel, 1998), and does not require solving system of equations for the weights. Moreover, it is robust in estimation and provides reasonable estimates. Many comparative studies have also shown that the IDW technique is even better than kriging-based techniques (Weber and Englund, 1992). For that reason, IDW interpolation method has been used in this study. In the IDW interpolation, the assumption is made explicitly that values that are closer to required location are more alike and have more influence on the required location than those that are farther apart, that is, local influence decreases with distance. Therefore, IDW uses the known values surrounding the required location and gives more weights to values closest to the required location (same value for co-location) and the weight diminishes as a function of distance ( $d$ ). The weights are inversely proportional to the distance between the data point and the required location, and to the power value  $p$  of the distance. As the distance increases, the weights decrease rapidly. The rate at which the weights decrease is dependent on the value of  $p$  as demonstrated in Fig. 6. The figure shows that if  $p = 0$ , there is no decrease with distance, and if the  $p$  value is very high, only the immediate surrounding points will influence the value of the required location and other values will have little relationship to the value of the required location.

The preferred default value  $p = 2$  (no theoretical justification) is used in this study and the method is known as the inverse distance squared weighted (IDSW) interpolation. The unknown value is computed using following equation:



**Figure 6.** Illustration of decrease of weight with distance.



**Figure 7.** Illustration of known (six districts) points and unknown (block) point.

$$Z_p = \frac{\sum_{i=1}^n \left( \frac{z_i}{d_i^p} \right)}{\sum_{i=1}^n \left( \frac{1}{d_i^p} \right)}, \tag{4}$$

where  $z$  is the required value at unknown point,  $d$  is distance,  $p$  is the power of the distance,  $n$  is the number of known points and  $i = 1, \dots, n$ .

In this study, a set of 6 ( $n = 6$ ) known points of surrounding districts including the same district point of the block within which it belongs are considered to estimate the value for the unknown block as demonstrated in Fig. 7.

### 5. Statistical metrics used for verification

#### a. Statistical metrics for evaluation of temperature (maximum and minimum) forecasts

Various statistical metrics are used to evaluate the performance of IBL-FS. Five statistical metrics are used for evaluation of temperature (maximum and minimum) forecasts. These are: (i) Forecast error ( $E$ ), (ii) Absolute error ( $AE$ ), (iii) Mean absolute error ( $MAE$ ), (iv) Root mean square error ( $RMSE$ ). Details of the metrics are given in the *Appendix*. In addition, the forecast skill of IBL-FS is also computed and defined as

$$Skill(\%) = \frac{MAE_{DMFC} - MAE_{IBL-FS}}{MAE_{DMFC}} \times 100, \tag{5}$$

where  $MAE_{DMFC}$  and  $MAE_{IBL-FS}$  are the MAE of direct model forecast (DMFC) and MAE of IBL-FS forecast, respectively.

#### b. Metrics for rainfall verification

In addition to MAE, and RMSE various skill score (given in *Appendix*) for dichotomous categorical forecasts are also computed using the contingency table (Tab. 4). These are: Bias ( $B$ ), Probability of Detection ( $POD$ ), False Alarm Ratio ( $FAR$ ), Critical Success Index ( $CSI$ ), and Percentage Correction ( $PC$ ).

Table 4. Contingency table for rainfall forecast.

		Event observed →		
		Yes	No	Marginal total
← Event forecast	Yes	YY (Hit) a	YN (False alarm) b	Forecast Yes (a+b)
	No	NY (Miss) c	NN (Correct non-event) d	Forecast No (c+d)
	Marginal total	Observe Yes (a+c)	Observe No (b+d)	Sum total (n = a+b+c+d)

Table 5. Classification of usability of rainfall and temperature (maximum and minimum).

Parameter	Category	Possible outcome from contingency table (Tab. 4)	Criteria
Rainfall	Correct	NN	Always
		YY	If $AE \leq 0.25$ of observed rain
	Usable	YY	If $0.25$ of observed rain $< AE \leq 0.5$ of observed rain
		YN	If $AE \leq 0.5$ of upper limit of light rainfall category (Tab. 6)
		NY	If $AE > 0.5$ of observed rain
	Unusable	YN	If $AE > 0.5$ of upper limit of light rainfall category (Tab. 6)
NY			
Temperature	Correct	–	$AE \leq 1.0$ °C
	Usable	–	$1$ °C $< AE \leq 2.0$ °C
	Unusable	–	$AE > 2.0$ °C

\**AE*: Absolute error

Table 6. Classification of 24-hour accumulated rainfall.

S. No.	Terminology	Rainfall range [mm]
1	Very light rainfall	Trace–2.4
2	Light rainfall	2.5–15.5
3	Moderate rainfall	15.6–64.4
4	Heavy rainfall	64.5–115.5
5	Very heavy rainfall	115.6–204.4
6	Extremely heavy rainfall	$\geq 204.5$
7	Exceptionally heavy rainfall	When the amount is a value near about the highest recorded rainfall at or near the station for the month or season. However, this term will be used only when the actual rainfall amount exceeds 12 cm.

In view of usability of rainfall and temperature forecast, a conditional table (Tab. 5) has been prepared (Kumar et al., 2018) to evaluate the usability of forecast in agrometeorological services. Classification of 24-hour accumulated rainfall as per IMD convention is given in Tab. 6. Total number of usable forecasts is considered as sum of correct forecasts and usable forecasts as shown in Tab. 5. Overall usability in terms of percentage is defined as total number of correct and usable forecasts divided by total number of forecasts. Mathematically it is defined as:

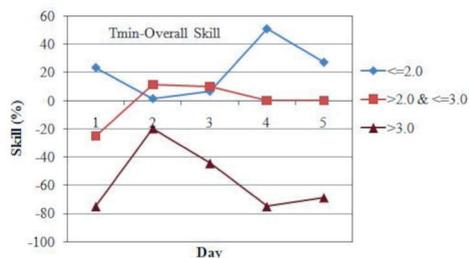
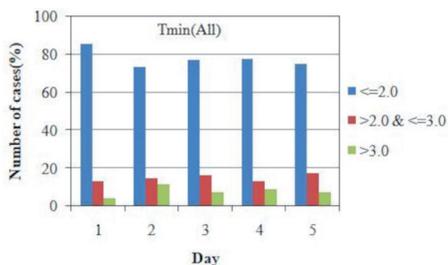
$$Usability(\%) = \frac{Number(correct + usable)}{Number(correct + usable + unusable)} \times 100. \quad (6)$$

## 6. Result and discussions

The main purpose of the analysis of forecast errors was to bring out a numerical measure of the quality of forecasts and also to assess the improvement of the value-added forecast generated by IBL-FS compared to DMFC. A quantitative evaluation of IBL-FS forecast errors of maximum and minimum temperature and inter-comparison of error statistics between DMFC and IBL-FS forecast for all the five regular observatories (Ranchi, Daltonganj, Jamshedpur, Bokaro and Chaibasa) over Jharkhand are discussed. Ten rainfall observatories are also considered for rainfall verification. In this study, the closest grid point values of GFS from the observational points are used for forecast verification and all the official forecasts (issued in real time) are verified for forecast lead times 24 h, 48 h, 72 h, 96 h, and 120 h.

### 6.1. Minimum temperature forecasts

In this section, performance of the IBL-FS has been analyzed for all 85 forecasts of minimum temperature (including all five observatories) for each lead time, issued in winter season 2019 (January and February). The frequency distribution analysis (Fig. 8) of MAE shows that in 73% to 86% cases the MAE was less or equal to 2 °C (usable), for about 13%–18% cases the MAE was greater than 2 °C but less or equal to 3 °C and in about 4% to 12% cases MAE was greater than 3 °C. Figure 9 shows the IBL-FS forecast frequency skill over DMFC, where frequency refers to the number of cases with MAE within one out of three different ranges that describe usability (as shown in Fig. 8). The exact number is thus used as metric in Eq. (5). In other words, the increased frequency of usable cases (MAE < 2 °C), compared to DMFC, leads to positive frequency skill, which is a desirable outcome. On the other hand, the number of unusable cases (MAE > 3 °C) is reduced when frequency skill is negative, which is also preferable. The results suggest that IBL-FS improves usability in terms that the

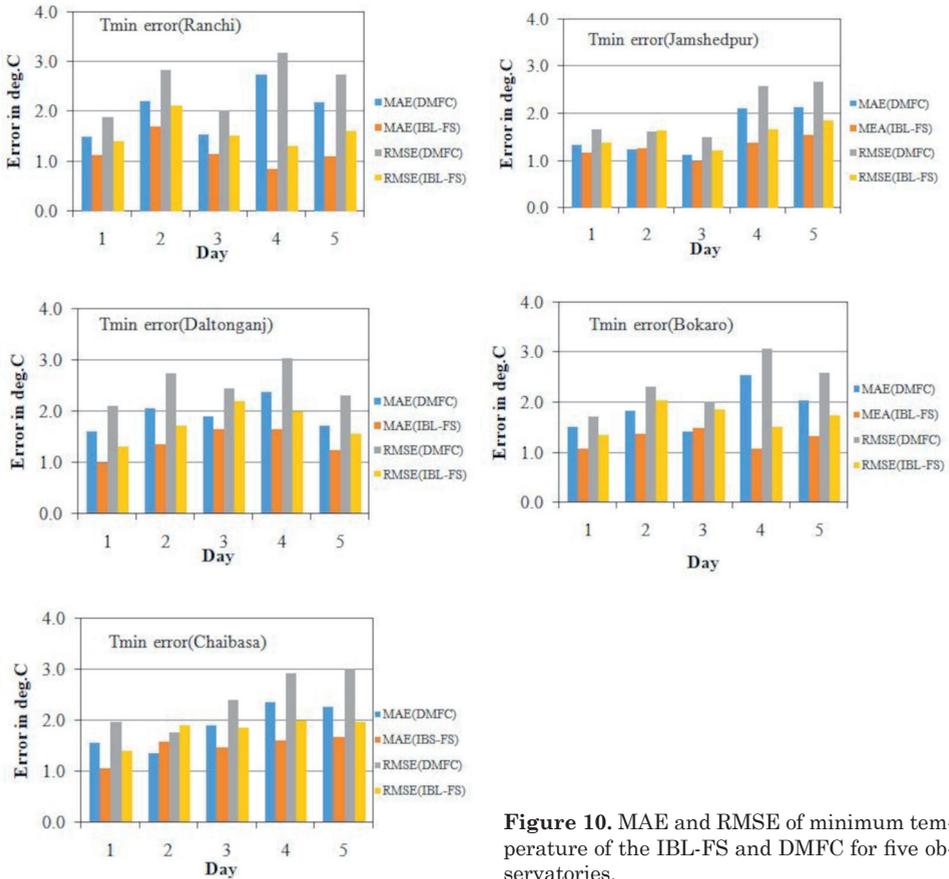


**Figure 8.** Frequency distribution of MAE for minimum temperature of IBL-FS.

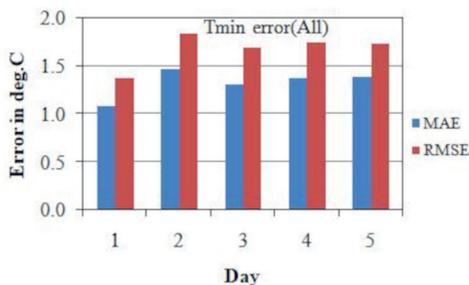
**Figure 9.** The frequency skill of IBL-FS over DMFC for minimum temperature in terms of usability.

frequency of MAE below 2 °C is increased if compared to DMFC, up to 51% for day4. The improvement over DMFC is also supported by the fact that the frequency of higher error range (MAE above 3 °C) is reduced.

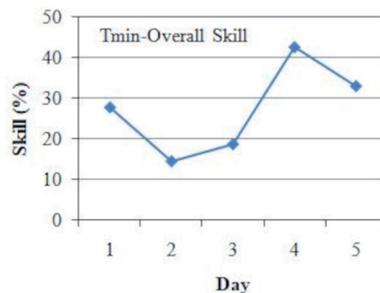
Figures 10a-e depict the forecast errors of minimum temperature of the IBL-FS and DMFC for five observatories. The IBL-FS forecast error (MAE) for Ranchi (Fig. 10a) ranged from 1.1 °C to 1.7 °C during day1 to day5 with maximum error of 1.7 °C on day2, while RMSE ranged from 1.3 °C to 2.1 °C during day1 to day5 with maximum error of 2.1 °C on day2. Figure 10b for Jamshedpur shows that the MAE ranged from 1.2 °C to 1.5 °C during day1 to day5 and RMSE ranged from 1.2 °C to 1.9 °C during day1 to day5. The MAE ranged from 1.0 °C to 1.7 °C and corresponding RMSE ranged from 1.3 °C to 2.2 °C for Daltonganj (Fig. 10c), MAE ranged from 1.1 °C to 1.5 °C and corresponding RMSE ranged from 1.3 °C to 2.0 °C for Bokaro (Fig. 10d). For Chaibasa (Fig. 10e) the MAE ranged from 1.1 °C to 1.7 °C and corresponding RMSE ranged from 1.4 °C to 2.0 °C during



**Figure 10.** MAE and RMSE of minimum temperature of the IBL-FS and DMFC for five observatories.



**Figure 11.** Average error for minimum temperature of the IBL-FS for all five observatories.



**Figure 12.** Skill in terms of MAE of IBL-FS over DMFC for minimum temperature for all the five observatories.

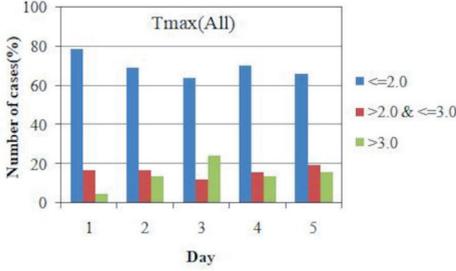
day1 to day5. Figure 10(a-e) shows there were improvements for all stations and for all forecast hours except for Jamshedpur and Chaibasa on day2.

The above analysis shows that for all the stations and for all the forecast hours, lowest MAE ranged from 1.0 °C to 1.2 °C and highest MAE ranged from 1.5 °C to 1.7 °C. This error range also demonstrates that error characteristics for all the stations were near similar. On average, the MAE of IBL-FS for all the five stations (Fig. 11) ranged from 1.1 °C to 1.5 °C and RMSE ranged from 1.4 °C to 1.8 °C during day1 to day5. The inter-comparison has been carried out by computing the skill (Eq. 5) using MAE metric. The inter-comparison of MAE (Fig. 12) reveals that IBL-FS has positive skill over DMFC and the skill of IBL-FS was higher by about 15% to 43% than DMFC during day1 to day5 and an overall improvement of RMSE ranged from 18% to 40% (not shown).

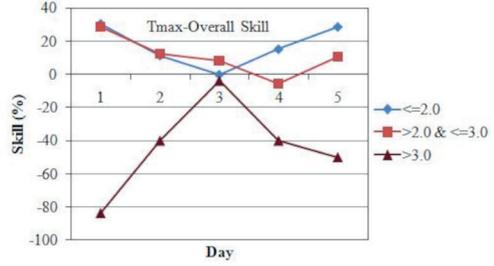
## 6.2. Maximum temperature forecasts

In this section, performance of the IBL-FS has been analyzed for all 135 forecasts of maximum temperature for each lead time (including all five observatories), issued in summer season 2019 (March, April and May). The frequency distribution analysis (Fig. 13) of MAE shows that 64% to 79% cases the MAE was less or equal to 2 °C (usable), about 12%–19% cases the MAE was greater than 2 °C but less or equal to 3 °C and about 5% to 24% cases MAE was greater than 3 °C. The comparison with DMFC (Fig. 14) also suggests that the number of usable maximum temperature forecasts (number of cases of  $MAE \leq 2$  °C) for IBL-FS has increased in all forecast hours up to 31% at day1 and 29% at day5. Similar like for minimum temperature, the results suggest the improvement in maximum temperature is also noticeable for higher error range ( $> 3$  °C), in terms of reducing the cases with high error. The improvement in skill in terms of usability measured by frequency is somewhat less pronounced for day3 than for other lead times.

The IBL-FS forecast error (MAE) for maximum temperature of Ranchi (Fig. 15a) ranged from 1.1 °C on day1 to 1.5 °C on day5 with maximum error of 1.9 °C



**Figure 13.** Frequency distribution of MAE for maximum temperature of IBL-FS.

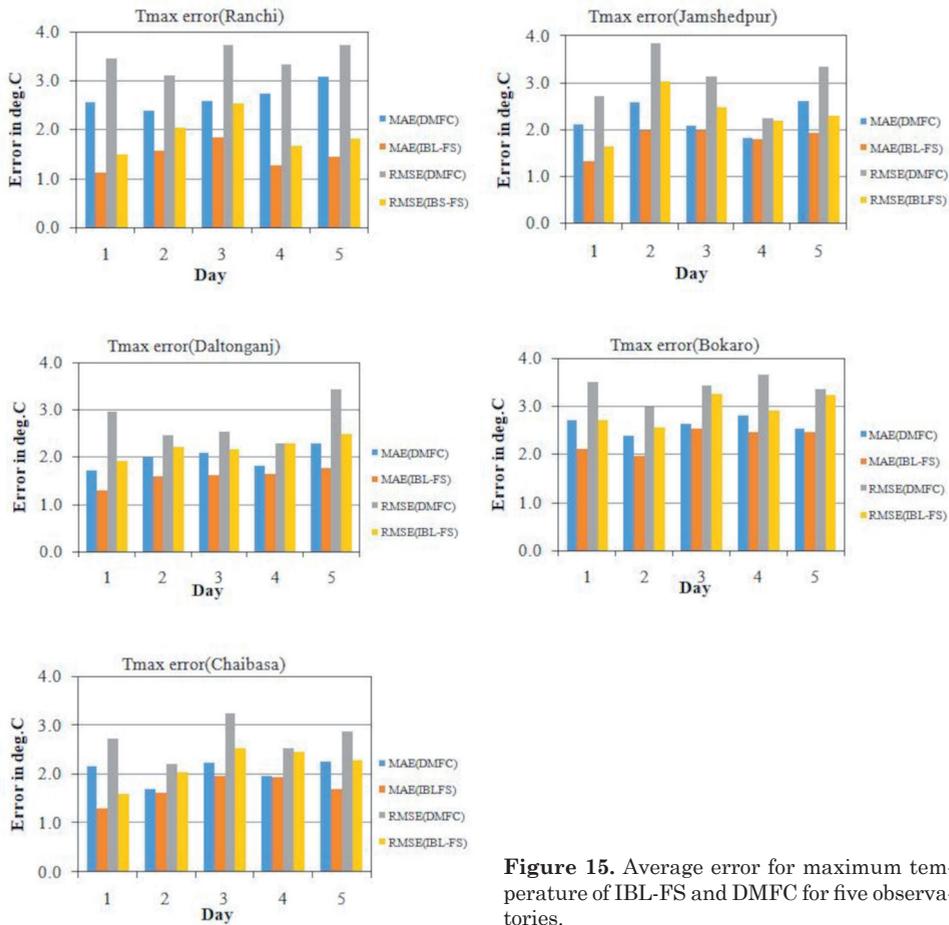


**Figure 14.** The frequency skill of IBL-FS over DMFC for minimum temperature in terms of usability.

on day3, while RMSE ranged from 1.5 °C on day1 to 1.8 °C on day5 with maximum error of 2.5 °C on day3. Figure 15b for Jamshedpur shows that the MAE ranged from 1.3 °C to 2.0 °C and RMSE ranged from 1.5 °C to 1.8 °C during day1 to day5. The MAE ranged from 1.3 °C to 1.8 °C and RMSE ranged from 1.9 °C to 2.5 °C for Daltonganj (Fig. 15c), while MAE ranged from 2.0 °C to 2.5 °C and RMSE ranged from 2.6 °C to 3.3 °C for Bokaro (Fig. 15d). For Chaibasa (Fig. 15e) the MAE and RMSE ranged from 1.3 °C to 2.0 °C and 1.6 °C to 2.5 °C, respectively. Figures 15a-e show there was improvement for all stations and for all forecast hours.

Previously discussed frequency analysis of MAE shows that the number of cases (73% to 86%) of minimum temperature forecast error within the usable range (MAE ≤ 2 °C) was higher than the number of usable maximum temperature (64% to 79%) forecasts. Additionally, the analysis also shows that for all the stations and for all the forecast hours, the lowest MAE for maximum temperature ranged from 1.1 °C to 2.0 °C and the highest MAE ranged from 1.8 °C to 2.5 °C. These error ranges are higher than for the minimum temperature, which also demonstrates that the error characteristics of maximum temperature for all the stations were not like minimum temperature. It needs to be mentioned that the summer season in the area is mainly dominated by the convective type of weather such as thunderstorms, dust storms, hailstorms, and associated rainfall. The frequency of convective activity (62.5%) is the highest during the 0630 UTC to 1230 UTC time (Kotal et al., 2021) when maximum temperature of a day attains. Wide variation of maximum temperature (22.6 °C to 46.7 °C) during the season and relatively unpredictable (beyond a few hours) convective weather events in the medium range forecast scale (Clerk et al., 2009) may be the plausible reason for larger variation of maximum temperature error.

On average, the MAE for all the five stations (Fig. 16) ranged from 1.3 °C to 1.9 °C and RMSE ranged from 1.7 °C to 2.4 °C during day1 to day5. Figure 17 shows the inter-comparison (using Eq. 5) of the MAE of IBL-FS with the DMFC



**Figure 15.** Average error for maximum temperature of IBL-FS and DMFC for five observatories.

for the forecast period day1 to day5. The inter-comparison of error reveals that IBL-FS has higher accuracy (smaller error) than DMFC for maximum temperature forecast for about 18% to 41% during day1 to day5. Similarly, the improvement of RMSE is found to be from 17% to 44% (not shown).

It is also to be noted that the skill is higher (Figs. 12 and 17) at short and long lead time and comparatively less in between. A similar trend is noticed in the error distribution of DMFC. Previous studies showed that in the short-range scale, convective predictability decreases with forecast lead time (Golding, 1998) and synoptic-scale flows can support the predictability at medium-range forecasts (Richardson et al., 2020). Predictability is also higher during strong synoptic scale forcing than during weak forcing (Christian Keil et al., 2014). The variations in the predictability may have affected the forecast skill.



Figure 16. Average error of maximum temperature of IBL-FS for all the five observatories.

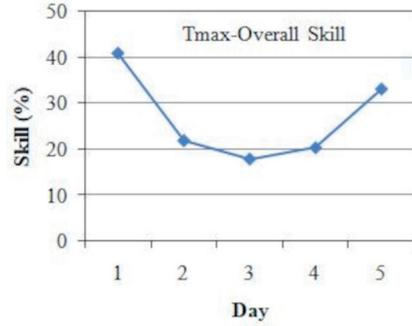


Figure 17. Skill in terms of MAE of IBL-FS over DMFC for maximum temperature for all the five observatories.

### 6.3. Rainfall forecasts

In this section, performance of the IBL-FS has been analyzed for all 350 forecasts of rainfall for each lead time (including all ten observatories), issued in each monsoon season 2018 and 2019 (June, July, August, September). Ten rainfall observatories at block level (Panki, Bishrampur, Chaibasa, Ghatsila, Gomia, Mahespur, Mandar, Ormanjhi, Barhi and Pakuria) chosen from all parts of the state are considered for rainfall verification. These stations are also under the scheme of daily rainfall monitoring system (DRMS) of Meteorological Centre, Ranchi. Therefore, the site of the observatories is as per WMO defined criteria and regularly maintained. The daily rainfall data are also available for these stations.

Figure 18, prepared using contingency table (as in Tab. 4), shows that there was a trend of over forecast (higher BIAS) for all forecast hours. The POD was found to be between 0.93 to 0.98, FAR between 0.45 to 0.61, PC between 0.48 to 0.62 and CSI between 0.38 to 0.48 during day1 to day5 forecasts for monsoon season 2018 (Figure 18a). For the monsoon season 2019, the BIAS was higher,

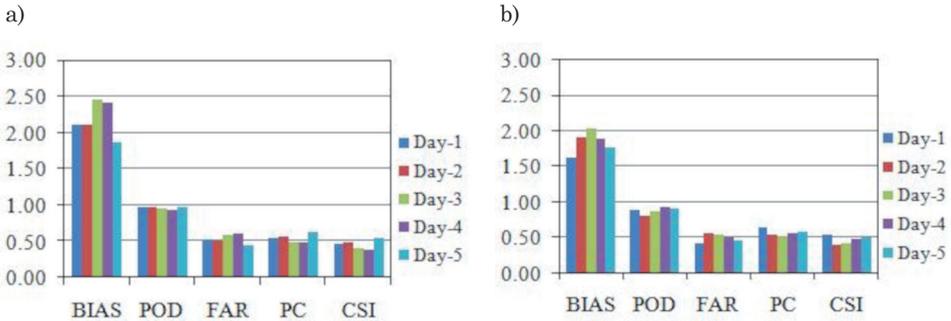


Figure 18. Statistical metrics for rainfall forecast: (a) for 2018, (b) for 2019.

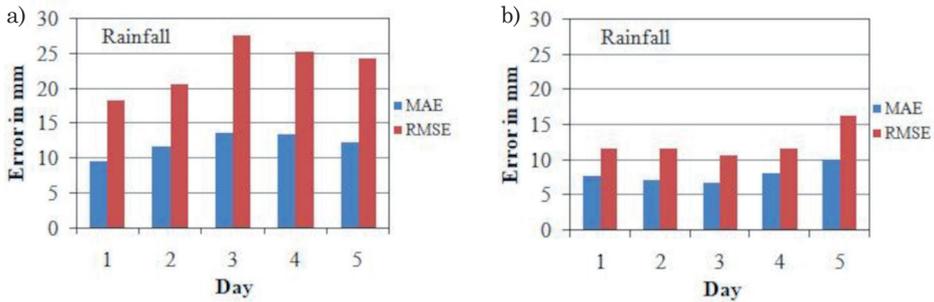


Figure 19. Rainfall forecast errors: (a) for 2018, (b) for 2019.

POD was found to be between 0.82 to 0.93, FAR was between 0.43 to 0.56, PC was between 0.52 to 0.65 and CSI was between 0.40 to 0.54 during day1 to day5 forecasts (Fig. 18b). The MAE for all ten stations ranged from 9.5 mm to 13.7 mm for IBL-FS forecast and it ranged from 13.7 mm to 19.5 mm for DMFC for monsoon season 2018 (Fig. 19a). For the monsoon season 2019, the MAE for all ten stations ranged from 7.7 mm to 10.0 mm for IBL-FS forecast and it ranged from 7.8 mm to 13.6 mm for DMFC (Fig. 19b). The RMSE of IBL-FS and DMFC ranged from 13.2 mm to 18.9 mm and 18.3 mm to 27.7 mm, respectively, during day1 to day5 forecast for the monsoon season 2018 and these were 10.6 mm to 16.3 mm and 14.1 mm to 21.0 mm, respectively, for 2019. The skill of IBL-FS was found to be higher than DMFC by 24% to 30% at all forecast hours for 2018 (Fig. 20a) and by about 22% to 29% at all forecast hours (except on day2 where it was 9%) for 2019 (Fig. 20b). The improvement of RMSE is found to be from 18% to 35% for 2018 and from 17% to 32% for 2019. Rainfall verification results for all the locations show no trend of errors for the forecast lead time from day1 to day5 due to higher variability of rainfall. Usability of rainfall (Fig. 21a) based on Tab. 5 suggests that the usability (correct plus usable) of IBL-FS was higher than DMFC at all forecast hours for 2018, but for 2019 the usability of IBL-FS was higher at day1, day3, day4 and comparable at day2 and day5 (Fig. 21b).

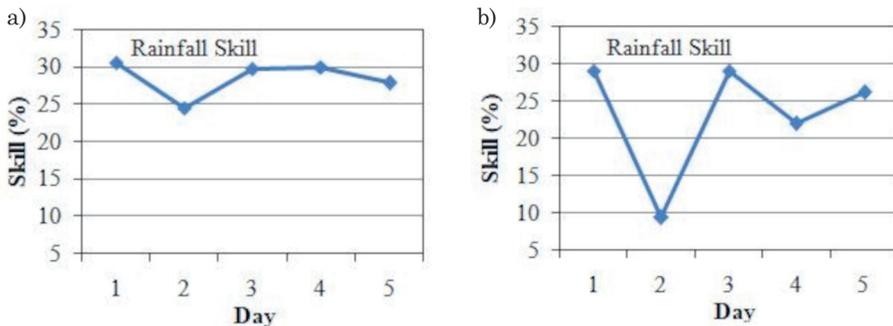
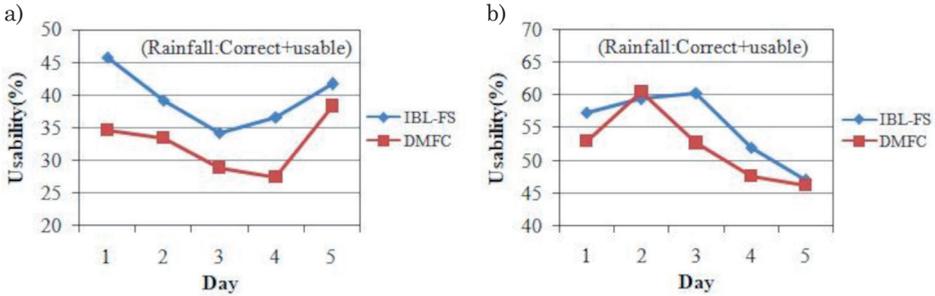


Figure 20. Rainfall forecast skill: (a) for 2018, (b) for 2019.



**Figure 21.** Usability (correct plus usable) of rainfall forecast: (a) for 2018, (b) for 2019.

Overall usability (based on equation 6) in 2019 (47%–60%) was higher than 2018 (34%–45%). The characteristics of the monsoon of 2018 and 2019 may have impact on the forecast performances. Monsoon rainfall over the state Jharkhand was deficient in 2018 and was normal in 2019. District wise rainfall distribution was also different for the two seasons. In 2018, out of the total 24 districts of the state, 7 districts received normal rainfall (departure from normal  $-19\%$  to  $+19\%$ ) and 17 districts received deficient (departure from normal  $-20\%$  to  $-59\%$ ) seasonal rainfall. Overall seasonal departure was  $-28\%$ . In 2019, out of the total 24 districts of the state, 1 district received excess (departure from normal  $+20\%$  to  $+59\%$ ), 13 districts normal (departure  $-19\%$  to  $+19\%$ ) and remaining 10 districts received deficient (departure  $-20\%$  to  $-59\%$ ) seasonal rainfall. Overall seasonal departure was  $-19\%$ . There was also difference in monthly distribution of rainfall. During the monsoon season 2018, the rainfall departure was  $-35\%$  in June,  $-18\%$  in July,  $-26\%$  in August and  $-40\%$  in September. During the monsoon season 2019, the monthly departure of rainfall was  $-55\%$  in June,  $-25\%$  in August,  $-13\%$  in August, and  $+13\%$  in the month of September. Therefore, the skill is found to be higher for normal rainfall season than deficient rainfall season. Such seasonal and district wise variability of rainfall may have affected the results.

## 7. Summary and conclusions

There is operational need for prediction of surface meteorological parameters in the medium range scale (120 h) at block level to augment the Agro Meteorological services (AMS). The present paper describes development of a NWP based three steps integrated block level forecast system (IBL-FS) for improvement of rainfall and temperature predictions for the state Jharkhand. The three components of IBL-FS are: (i) Decaying weighted mean (DWM) bias correction, (ii) Value addition and (iii) Inverse distance squared weighted (IDSW) interpolation. All the three steps are applied on the GFS (T1534L64) model forecasts (operational at IMD) to generate the forecast for all 263 blocks of Jharkhand. Forecasts of three surface parameters (maximum and minimum temperature, and rainfall) are generated for five days in the medium range time scale (24 h, 48 h, 72 h, 96

h, 120 h). Verification of performance of IBL-FS has been made to identify the quality of forecasts in terms of numerical measures. Awareness of the biases would also aid concerned AMFUs to issue Agro advisories for farmers.

The performance skill of IBL-FS has been evaluated for rainfall during monsoon season 2018 and 2019 (June, July, August, September), for minimum temperature during winter season 2019 (January, February), and for maximum temperature during summer season 2019 (March, April, May). The inter-comparison of the MAE between IBL-FS with the DMFC reveals that IBL-FS has positive skill over DMFC and skill of IBL-FS was higher by about 15% to 43% and 18% to 41% than DMFC for minimum temperature and maximum temperature, respectively, for day1 to day5 forecasts. Analysis of forecast error shows that although there was improvement of MAE in IBL-FS for all forecast lead times but in some cases it, unexpectedly, reaches the maximum for medium lead times due to similar inconsistency in MAE of direct model forecasts. The different ranges of errors in minimum and maximum temperature for all the forecast hours demonstrate that error characteristics for all the stations, even though similar for minimum temperature, are inconsistent and higher for maximum than minimum temperature. Domination of more unpredictable (beyond few hours) convective weather systems during the summer season may have impacted the maximum temperature error. Further, the reduction of error in both maximum temperature and minimum temperature is more pronounced for the higher error range of MAE ( $> 3\text{ }^{\circ}\text{C}$ ) than lower error ranges, in general. Inverse distance squared weighted (IDSW) interpolation technique is applicable over a smaller region and shows skillful results for rainfall also in both monsoon seasons (2018 and 2019). The skill of IBL-FS was found to be higher than DMFC by 24% to 30% and 22 % to 29% for 2018 and 2019, respectively, at all forecast hours. Overall usability in 2019 (47%–60%) and 2018 (34%–45%) suggests that the skill was higher for normal rainfall season (2019) than deficient rainfall season (2018). The characteristics of monsoon rainfall in 2018 (deficient) and 2019 (normal), and district wise variability of rainfall (more rain-deficient districts in 2018) may have affected the forecast performances.

Finally, the integrated approach by combination of both subjective (human-machine blending) and objective methods used for official forecasting for the state Jharkhand was found to be more skillful than direct model forecast for both maximum and minimum temperature, and for rainfall at all forecast hours (24 h, 48 h, 72 h, 96 h, 120 h). Regional Meteorological Centre of the state generates the bulletin and disseminates to the AMFUs for the guidance to the farming community. However, separate study is needed to evaluate the impact of subjective correction only without applying any objective correction. The integrated block level forecast system is implemented from 01 June 2019 for real time forecasting for the 263 blocks of Jharkhand. An Excel based program has been developed to make the system more user friendly for real time application. In view of the encouraging result, by applying similar technique, it would be possible to develop separate systems for all other states also.

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## SAŽETAK

### **Razvoj numeričke prognoze vremena na temelju združenog više-stupanjskog prognostičkog sustava (IBL-FS) uz korištenje naknadne statističke korekcije pristranosti modela za državu Jharkhand (Indija)**

*Shyam Das Kotal i Radheshyam Sharma*

Za državu Jharkhand (Indija) razvijen je prognostički sustav na temelju statističkog pristupa za srednjoročnu prognozu pomoću GFS modela s ciljem poboljšanja prognoze količine oborine i temperature za primjenu u poljoprivredi. Osnova formiranja združenog više-stupanjskog prognostičkog sustava (IBL-FS) uključuje (i) tehniku korekcije pristra-

nosti ponderirane srednje vrijednosti (DWM), (ii) zbrajanje vrijednosti i (iii) ponderiranu interpolaciju temeljenu na obrnuto-proporcionalnom kvadratu udaljenosti (IDSW). U prvom koraku, modelska pristranost u prognozi na razini okruga se ispravlja za 24 okruga Jharkhanda koja su dobivena iz rezultata numeričkog GFS modela (T1534L64) primjenom DWM tehnike korekcije pristranosti. U drugom koraku, prognozi kojoj je uklonjena pristranost dodaje se rasap vrijednosti iz različitih prognostičkih modela za numeričku prognozu vremena i sinoptičkih metoda. Konačno, u trećem koraku, IDSW metoda interpolacije koristi se za generiranje prognoze na područjima bez mjerenja, na temelju korigiranih vrijednosti prognoze drugih okolnih područja (blokova). Prognoza korigirana dodanom vrijednošću za 263 bloka za državu Jharkhand radi se u vremenskom okviru srednjoročne prognoze (120 h). Uspješnost prognoza sustava IBL-FS radio se za oborinu tijekom sezone monsuna 2018. i 2019., za minimalnu temperaturu tijekom zimske sezone 2019. i za maksimalnu temperaturu tijekom ljetne sezone 2019. koristeći različite statističke metrike. Utvrđeno je da je uspješnost prognoze IBL-FS bolja od same nekorrigirane prognoze modela (DMFC) za 15% do 43% za minimalnu temperaturu, za 18% do 41% za maksimalnu temperaturu i za 22% do 30% za prognozu količine oborine za prognoze od dana 1 do 5. Ova studija zaključuje da je prikazani združeni više-stupanjski prognostički sustav uspješniji od DMFC za svakodnevnu prognozu u realnom vremenu i da je koristan za poljoprivredu u državi Jharkhand.

*Keywords:* prognoza na razini bloka, prognoza na razini okruga, globalni sustav prognoze (GFS), statistička naknadna obrada, opadajući ponderirani prosjek (DWM), interpolacija s obrnuto proporcionalnim kvadratom udaljenosti (IDSW)

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## Appendix

### *Statistical Metrics*

*a. Statistical metrics used for evaluation of temperature (maximum and minimum) forecasts*

(i) Forecast error,  $E$ , is defined as,

$$E = (F_i - O_i), \quad (i)$$

(ii) Absolute error,  $AE$ , is defined as,

$$AE = |(F_i - O_i)|, \quad (ii)$$

(iii) Mean absolute error,  $MAE$ , is defined as,

$$MAE = \frac{1}{N} \sum_{i=1}^N |(F_i - O_i)|, \quad (iii)$$

(iv) Root mean square error,  $RMSE$ , is defined as,

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (F_i - O_i)^2}, \quad (iv)$$

where  $F_i$  and  $O_i$  are forecast and observed value of the verification parameter and  $N$  is the total number of observation.

*b. Metrics for rainfall verification*

(i) Mean absolute error ( $MAE$ ) and root mean square error ( $RMSE$ ) as defined above are computed.

(ii) For dichotomous categorical forecasts, having only two possible outcomes (Yes or No), a contingency table (Tab. 4) is used to compute following five skill score.

*Bias (B)*: For categorical forecasts, bias (also known as frequency bias) is equal to the total number of forecast events divided by the total number of observed events.

$$B = (a+b)/(a+c). \text{ Perfect score: } 1 \text{ (unbiased),}$$

if  $B > 1$  (over forecast), the event was forecast more than it was observed,

if  $B < 1$  (under forecast), the event was forecast less than if was observed.

*Probability of detection (POD)*: A measure of discrimination, POD is defined as the number of hits divided by the total number of observed events.

$$POD = a/(a+c). \text{ Range: } 0 \text{ to } 1. \text{ Perfect score: } 1.$$

*False Alarm Ratio (FAR):* A measure of reliability, FAR is defined as the number of false alarms divided by the total number of forecast events.

$$FAR = b/(a+b). \text{ Range: 0 to 1. Perfect score: 0.}$$

*Critical Success Index (CSI):* A value of warnings combines Hit Rate and False Alarm Ratio into one score. It is calculated as follows:

$$CSI = a/(a+b+c). \text{ Range: 0 to 1. Perfect score: 1.}$$

*Percent Correct (PC):* The percent correct is the percent of forecasts that are correct.

$$PC = (a+d)/n. \text{ Range: 0 to 1. Perfect score: 1.}$$