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Research Article

Quantitative Accuracy Assessment of District Level Rainfall Forecast in Mizoram

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ABSTRACT

We evaluated the rainfall forecast accuracy using multiple indices (including bias factor and skill scores) for quantitative assessment of district-level rainfall forecast accuracy over past 12 years in Mizoram. Willmott index of agreement scored <0.5 across the seasonal variation with systematic error (SE) in rainfall forecast varied between 9.9 ± 1.56 to 17.02 ± 2.83 across all the studied raingauge stations in Mizoram. Limited skill scores and forecast bias downgraded district level seasonal rainfall forecast accuracy. Therefore, we recommended the adaptation of identified five indices *viz.* mean bias error (MBE), SKILL V, root mean square error (RMSE), mean absolute error (MAE)/ MAE skill score (MAESS) and index of agreement (IOA)/ correlation coefficient (CORR) for accounting 88.19% cumulative variance in quantitative district-level rainfall forecast in the subtropical humid regions of Mizoram.

Key words: Mizoram, rainfall forecast, accuracy evaluation, skill score, principal component analysis

Introduction

Weather information system plays a crucial role in resource-saving and increasing farming resiliency of Indian agriculture (Rathore *et al.*, 2011; Saha *et al.*, 2018). Since 2006-07, periodic dissemination of weather-based agro-advisory services prioritized the use of value-added products of medium-range weather forecast (rainfall) towards increasing the net farm profitability of small and marginal farmers across North East India (Sarmah *et al.*, 2015). The qualitative accuracy assessment of the rainfall forecast values often signified the superiority of ensemble models during the low rainfall receiving months and limited efficiency during major monsoon months across agro-climate conditions of India (Vashisth *et al.*, 2008; Rana *et al.*, 2012; Sridhara *et al.* 2014; Rajavel *et al.*, 2019; Sharma *et al.*, 2020). However, comprehensive quantitative assessment of accuracy of the multi-model ensemble (MME) generated weather forecasts are rarely reported against ground observations (Saha *et al.*, 2015). The rainfall and temperature forecast often gave good accuracy during post monsoon months, but the least accuracy for active monsoon months (Sharma *et al.*, 2020). In this context, we assessed the detailed estimates of quantitative accuracy for periodic district level India Meteorological Department (IMD)

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rainfall forecast. We also aimed for the identification of minimum number of forecast evaluation indices, essential for the quantitative rainfall forecast assessment across the sub-tropical humid regions of Mizoram.

Materials and Methods

We accessed the district-wise daily rainfall observation datasets periodically (2008-2020), from 26 rain gauge stations under the Department of Agriculture (RE), Government of Mizoram (Table 1). The area-weighted average of daily observed rainfall was calculated for the respective rain gauge stations within each district boundary. The representative average of 3 days district level rainfall forecast values were compared with the corresponding ground observations owing to its higher accuracy over the sub-temperate and sub-humid climate of western Himalayas (Rana *et al.*, 2012). The calculated values of 3 days district level rainfall forecast were further aggregated to fit within the standard seasonal boundaries *viz.* pre-monsoon/ summer (March-May), monsoon (June-September), post-monsoon (October-December) and winter (January-February) after IMD.

Error indices/ quantitative forecast accuracy estimators

The Pearson correlation coefficient between the IMD forecast (Pi) and rainfall observations (Oi) was assessed for studying their interdependence without accounting the forecast bias. The prediction skill of medium-range seasonal weather forecast was assessed using several other widely used skill score

Table 1. District-wise ground rainfall observation availability in Mizoram (2008-2020)

District	Site details	Latitude (N)	Longitude (E)	Altitude (a.m.s.l.)
Champhai	Champhai	23° 28' 40"	93° 19' 44"	1678
	Vaphai	23° 05' 54"	93° 19' 27"	1733
	Ngopa	23°51' 11"	93°12' 40"	1127
	Khawzawl	23° 32' 05"	93° 10' 58"	1187
Serchhip	Serchhip	23° 18' 29"	92° 51' 24"	1281
	N. Vanlaiphai	23° 07' 60"	93° 04' 02"	1354
Kolasib	Bilkhawthlir	24° 19' 53"	92° 42' 38"	594
	Kolasib	24° 13' 54"	92° 40' 33"	722
	Bukpui	24° 05' 02"	92° 47' 39"	723
Aizawl	Aizawl	23° 43' 37"	92° 43' 03"	1231
	Sialsuk	23° 24' 01"	92° 44' 59"	1488
	Neihbawh	23° 49' 59"	92° 44' 37"	1123
	Sairang	23° 48' 44"	92° 39' 23"	457
	Darlawn	23° 00' 51"	92° 55' 28"	1256
	Khawruhlian	23° 52' 08"	92° 52' 34"	1069
Lunglei	Lunglei	22° 54' 25"	92° 45' 30"	1128
	Tlabung	22° 54' 43"	92° 29' 53"	21
	Hnahthial	22° 57' 51"	92° 55' 42"	883
	S. Vanlaiphai	22° 48' 07"	92° 59' 46"	1372
Lawngtlai	Lawngtlai	22° 31' 56"	92° 53' 50"	847
Siaha	Siaha	22° 29' 24"	92° 58' 50"	1226
	Tuipang	22° 92' 13"	93° 22' 23"	1079
Mamit	Mamit	23° 54' 47"	92° 29' 35"	901
	Kawrtethaw veng	23° 52' 16"	92° 22' 26"	48
	Zawlnuam	24° 08' 05"	92° 20' 04"	35
	Rengdil	24° 03' 23"	92° 24' 14"	160

measures namely Willmott index of agreement (IOA; Willmott *et al.*, 2011), mean absolute error (MAE), MAE skill score (MAESS; for comparing the forecast across the delineated diverse bioclimatic condition), bias factor, mean bias error (MBE) and its other normalized estimates, and Skill V (proximity between standard deviation of predictions and observations) as follows:

Correlation coefficient (r) =

$$\frac{\sum(P_i - \overline{P})(O_i - \overline{O})}{\sqrt{\sum(P_i - \overline{P})^2}\sqrt{\sum(O_i - \overline{O})^2}} \text{-}1 \geq r \geq +1 \; (+1 = \text{perfect}) \quad \ldots(1)$$

Index of agreement (IOA)=

$$1 - \frac{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2}{\frac{1}{n}\sum_{i=1}^{n}(|P_i - \overline{O}| + |O_i - \overline{O}|)^2} \; 0 \text{ (least)} \geq IOA \geq +1 \text{ (perfect)} \quad \ldots(2)$$

Mean absolute error (MAE)=

$$\frac{1}{n}\sum_{i=1}^{n}|P_i - O_i| \; 0 \geq MAE \geq +\infty \; (0 = \text{perfect}) \quad \ldots(3)$$

$$MAEc = \frac{1}{n}\sum_{i=1}^{n}|\overline{O} - O_i| \quad \ldots(4)$$

MAE skill score (MAESS) =

$$1 - \frac{MAE}{MAE_c} \text{-}\infty \geq MAESS \geq +\infty \; (+1 = \text{perfect}) \quad \ldots(5)$$

$$\text{Bias Factor (BF)} = \frac{1}{n}\left(\frac{\sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} O_i}\right) \text{-}\infty \geq BF \geq +\infty \; (+1 = \text{perfect}) \quad \ldots(6)$$

Mean bias error (MBE) =

$$\frac{1}{n}\sum_{i=1}^{n}|P_i - O_i| \text{-}\infty \geq MBE \geq +\infty \; (0 = \text{perfect}) \quad \ldots(7)$$

$$\text{Normalized mean bias error (NMBE)} = \frac{\sum_{i=1}^{n}(P_i - O_i)}{\sum_{i=1}^{n} O_i} \quad \ldots(8)$$

$$\text{SkillV} = \frac{SD_p}{SD_o} \text{-}\infty \geq \text{SkillV} \geq +\infty \; (+1 = \text{perfect}) \quad \ldots(9)$$

Where, SD_p and SD_o is the standard deviation (SD) of predictions to that of respective observations for their model predicted mean ($\overline{P}$) and observed mean values ($\overline{O}$). The relative magnitude of mean square error (MSE = $RMSE^2$) for the district level rainfall time series (predicted and observed) was calculated for acquiring periodic rainfall variability during our present study period.

Root mean square error (RMSE) =

$$\sqrt{\frac{1}{n}\sum_{k=0}^{n}(O_i - P_i)^2} \; 0 \geq RMSE \geq +\infty \; (0 = \text{perfect}) \quad \ldots(10)$$

$$\text{Normalized RMSE} = \frac{RMSE}{\text{Max}(O_i) - \text{Min}(O_i)} \quad \ldots(11)$$

$$\text{Relative error (RE \%)} = \frac{RMSE}{\overline{O}} \times 100 \quad \ldots(12)$$

The disintegrated version of RMSE is comprised of bias and standard deviation of error (error variance) as follows (Hou *et al.*, 2001):

$$RMSE = bias^2 + sde^2 = mnbias^2 + sdbias^2 + dispersion^2 \quad \ldots(13)$$

The systematic components accounted for the bias of the mean (mnbias; έ) and standard deviation (sdbias). The mnbias signified the simplest measure expressed as the difference between predicted mean ($\overline{P}$) and observed mean ($\overline{O}$) of rainfall timeseries. The sdbias referred to the difference between standard deviations (σ) of P and O. The mnbias and sdbias together quantified the total amplitude errors (i.e. average tendency of predicted values for overestimating or underestimating the observed rainfall). Moreover, the dispersion component (D) solely accounted for the contribution from phase error (in terms of cross-correlation coefficient). The representative mathematical expression for the abovementioned error components are as follows:

$$mnbias = \overline{P} - \overline{O} \quad \ldots(14)$$

$$sdbias = \sigma\overline{P} - \sigma\overline{O} \quad \ldots(15)$$

$$\text{Dispersion (D)} = \sqrt{2}\,\sigma(\overline{P})\,\sigma(\overline{O})\,(1 - r_c) \quad \ldots(16)$$

Where, r_c= cross-correlation coefficient between the observed and predicted time series.

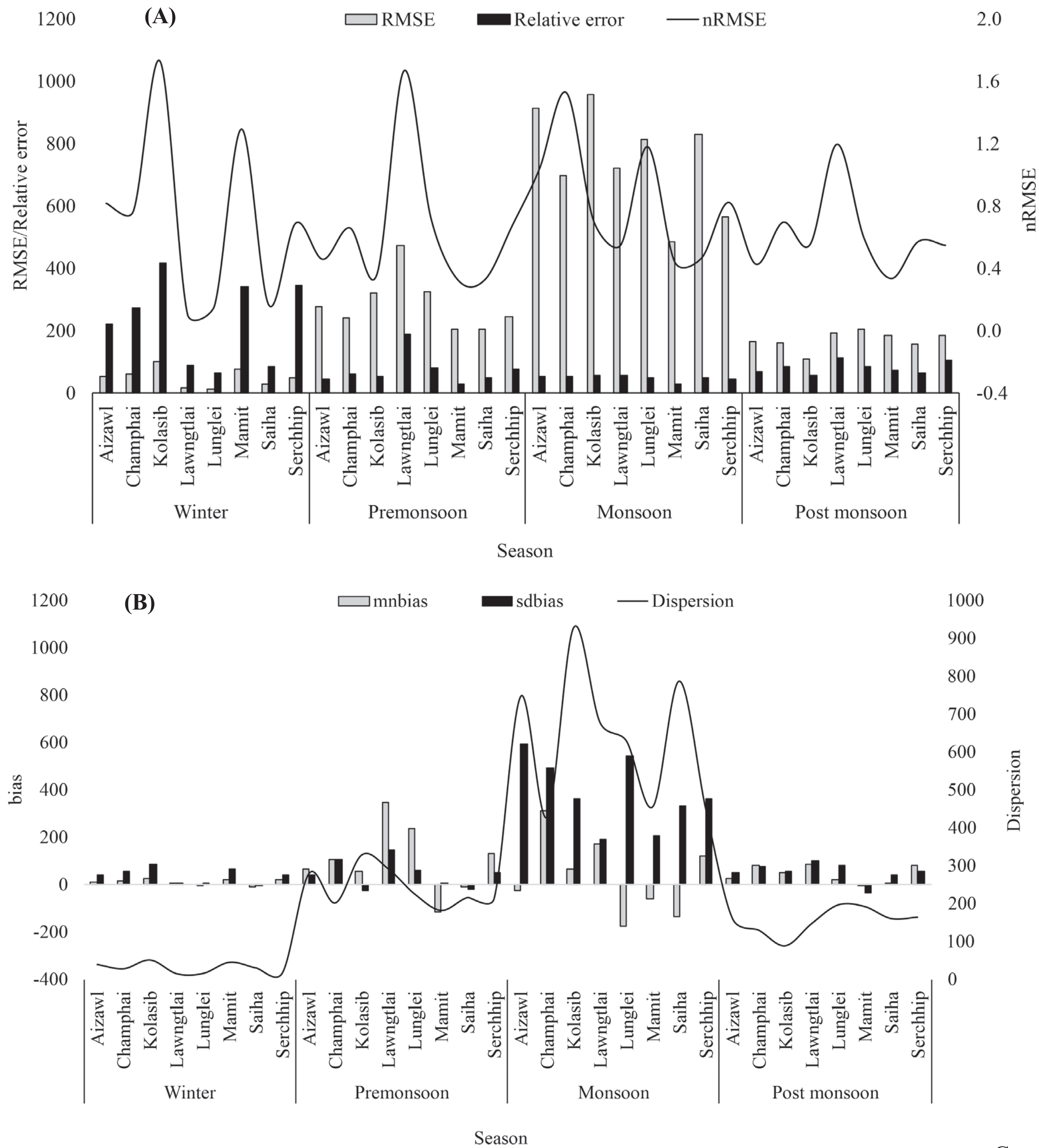
RMSE and MAE indicated the magnitude of average error but provide no information on the relative magnitude of average difference between forecasts and observations. MAE measured mean magnitude of forecast errors, while RMSE gave more weightage to the largest errors. MBE accounted for the direction of error bias. Negative (positive) MBE values signified underestimation (overestimation) i.e. predicted values are smaller (higher) than observations. Therefore, the systematic error (SE) in MME rainfall forecast is as follows,

SE = $(RMSE^2\text{-}MBE^2)^{1/2}$ (If, MBE = 0, then RMSE = SE) …(17)

Principal component analysis (PCA): Principal component analysis extracted the respective principal components (PCs) using varimax rotation with Kaiser Normalization method, variance explained criteria, mean eigenvalues using SPSS 16.0 software. The error indices with factor loading/eigenvalue within 10% of the highest factor loading were identified as the key parameters from each PC.

Results and Discussion

District-wise quantitative analysis showed high spatio-temporal variation in the calculated forecast



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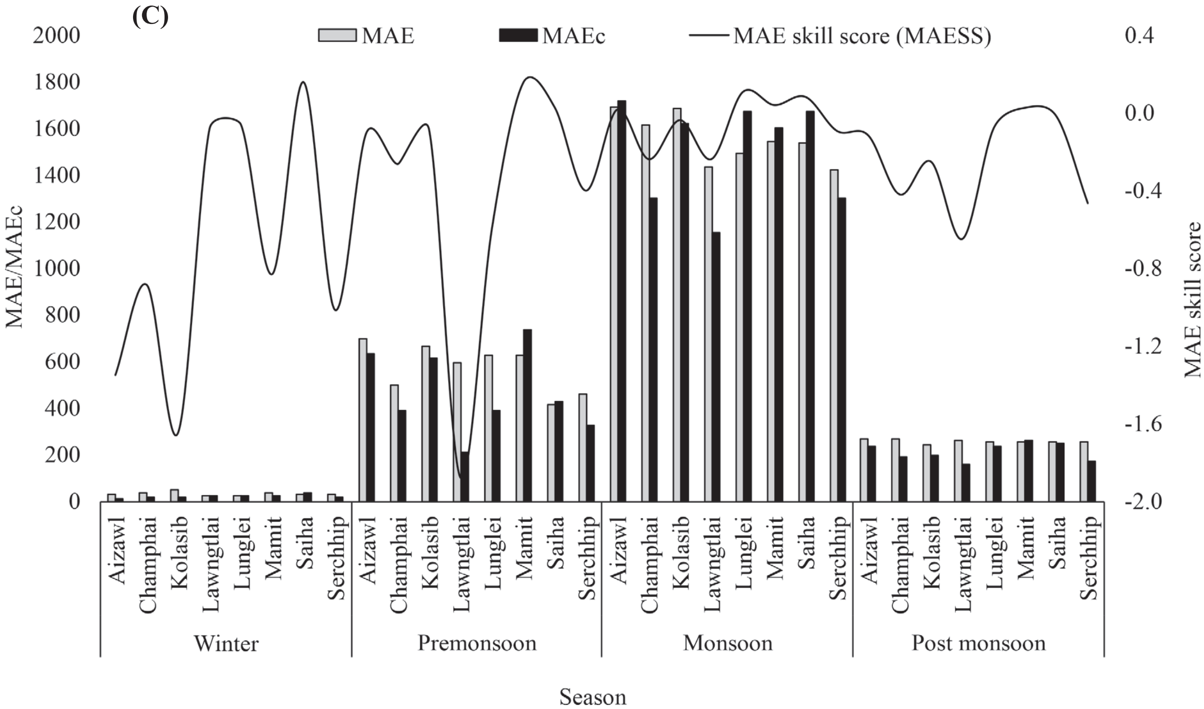
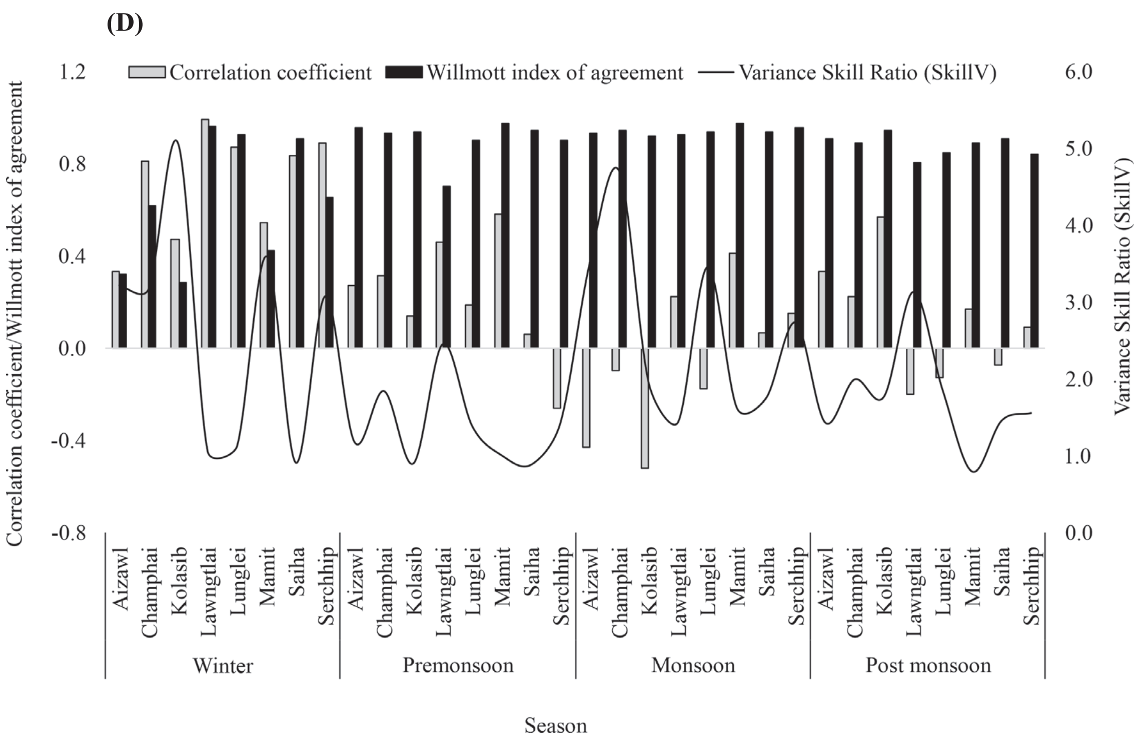

(C)
MAE
MAEc
MAE skill score (MAESS)
MAE/MAEc
MAE skill score
Aizawl
Champhai
Kolasib
Lawngtlai
Lunglei
Mamit
Saiha
Serchhip
Winter
Premonsoon
Monsoon
Post monsoon
Season


(D)
Correlation coefficient
Willmott index of agreement
Variance Skill Ratio (SkillV)
Correlation coefficient/Willmott index of agreement
Variance Skill Ratio (SkillV)
Aizawl
Champhai
Kolasib
Lawngtlai
Lunglei
Mamit
Saiha
Serchhip
Winter
Premonsoon
Monsoon
Post monsoon
Season

Contd...

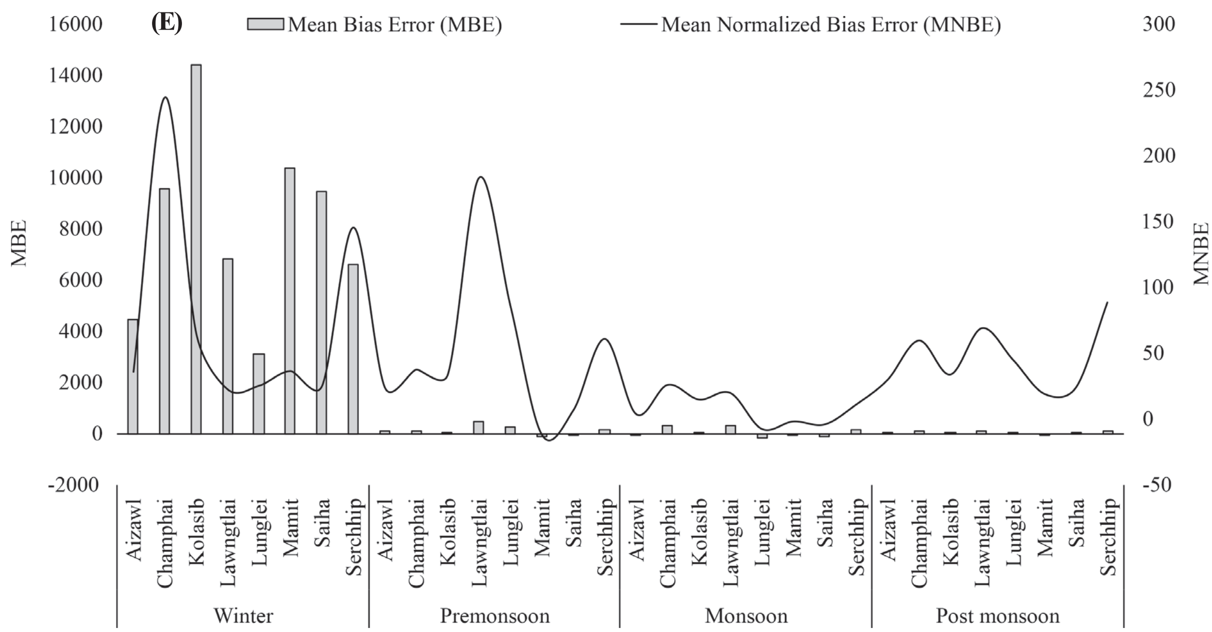


Fig. 1. Variation in error estimates for district level seasonal rainfall forecast values in Mizoram

error estimates (Fig. 1 A to E). On seasonal time scale, maximum dispersion was observed during high rainfall receiving monsoon season with higher values of RMSE (Fig. 1 A). The least deviation was recorded for non-rainy winter months (Vashisth *et al.*, 2008; Rana *et al.*, 2012). However, the n-RMSE showed no clear seasonal pattern. Positive mnbias indicated the overestimation tendency of forecast values during the majority of our study period (except some facets during monsoon months) (Fig. 1B). In courtesy, the sdbias and dispersion values were peaked during monsoon months. The highest values of MAE were observed during active monsoon season followed by pre-monsoon months (Fig. 1C). The least values of MAE were evident during winter with very poor skill score around the year. The higher MAE values with limited skill score suggested the poor precision of district-level rainfall forecast during major rain receiving months in Mizoram. However, high IOA and correlation coefficient indicated higher degree of apparent association between forecast and observed values (Fig. 1D; Willmott *et al.*, 2011). Therefore, likelihood factor dominated over forecast skills in the district level rainfall during monsoon months. The higher MBE values further supported the findings indicating more bias with apparently accurate predictions during winter months (Fig. 1E).

The systematic error (SE) in MME generated monthly rainfall forecast signified more error proneness during rainfall receiving months i.e. April to October at Mizoram (Fig. 2). It was quite evident that with the initiation of seasonal rainfall the SE values increased peak during June-July and diminished gradually with the cessation of monsoon shower (Vashisth *et al.*, 2008; Sridhara *et al.*, 2014). The periodic variation of RMSE domineered over MBE for determining the monthly SE pattern in IMD rainfall forecast. Efficient MME calibration and value addition should aim towards the minimization of periodic RE values and further improvement of IMD rainfall forecasts. Such initiatives will be one of the most effective tools to minimize the observed impact of climate variability on the agriculture sector in Mizoram (Saha *et al.*, 2015).

For operation scale quantitative rainfall forecast evaluation at district level, the cumbersome practice of calculating such huge number of error estimates may be avoided with adaptation of suitable data reduction techniques. Therefore, we aimed for the identification of most effective and prominent error structure evaluation parameters. Hierarchical clustering identified the distinctness of RE from other quantitative error estimates but had failed to discriminate among the mean square error, bias and

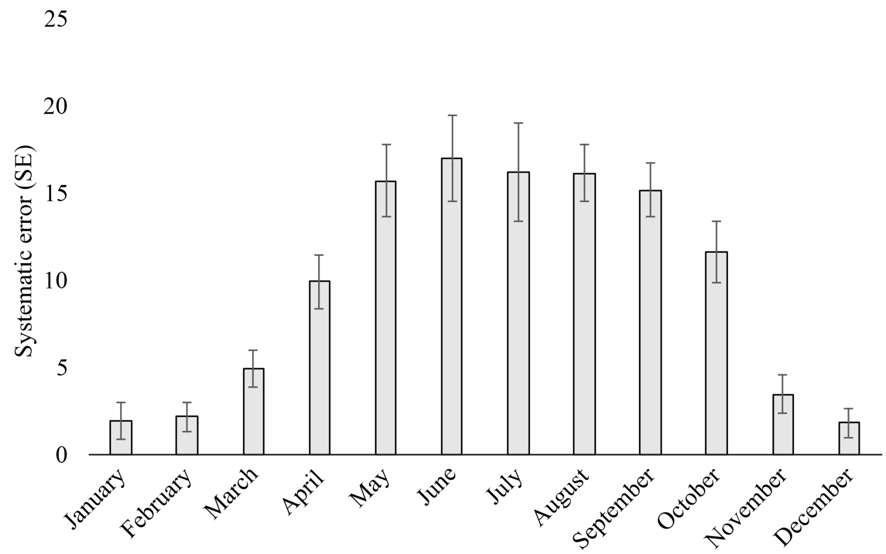


Fig. 2. Systematic error (SE) estimated for district level monthly rainfall forecasts in Mizoram

relative association between observed and forecasted values of district-level rainfall (Fig. 3A). Data reduction techniques using principal component analysis (PCA) identified five principal components for our present dataset accounting 87.9% cumulative variance (Table 2a and Fig. 3B). With 10% threshold, we identified five prominent parameters viz. MBE (PC-1), Skill V (PC-2), RMSE (PC-3), MAE/ MAESS (PC-4) and IOA/CORR (PC-5). These five indices are the most essential distinct indices for quantitative evaluation of periodic IMD rainfall forecast for the sub-tropical humid regions of

Table 2a. Detailed variablity accountated by the respective PCs for quantitative error estimates

Principal component	Eigen value	% of Variance	Cumulative variance %
PC1	4.51	28.16	28.16
PC2	4.22	26.36	54.52
PC3	2.79	17.47	71.99
PC4	1.32	8.26	80.25
PC5	1.27	7.94	88.19

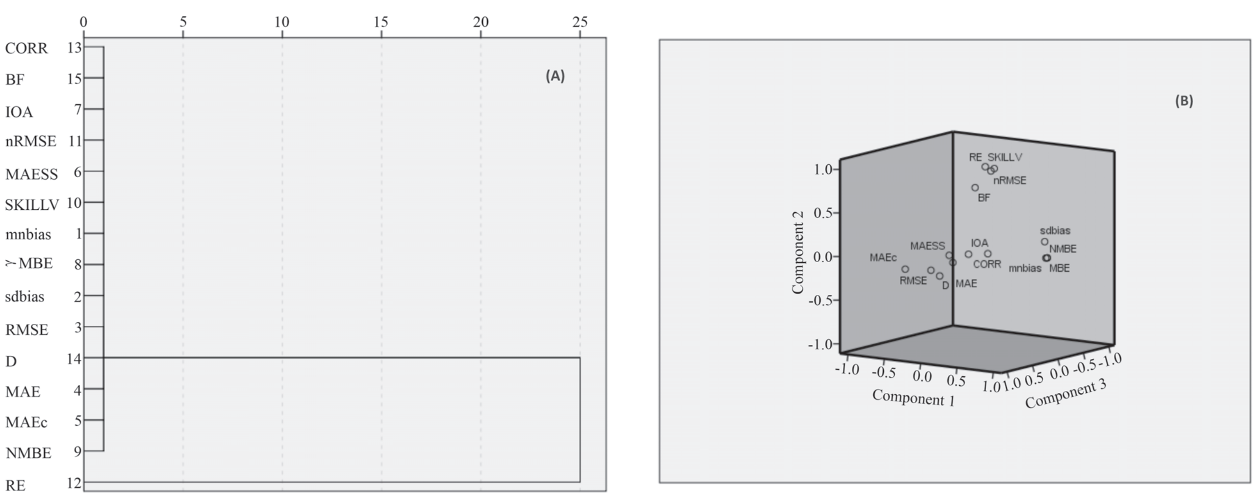


Fig. 3. (A) Hierachial clustering (B) placement of error estimates in 3-D space for the quantitative error estimates in district level rainfall forecasts in Mizoram

Table 2b. Factor loading of quantitative error estimates for respective PCs in rotated component matrix

Parameters	PC1	PC2	PC3	PC4	PC5
mnbias	0.965	0.037	0.032	0.147	-0.012
sdbias	0.761	0.162	-0.241	-0.012	-0.029
RMSE	-0.02	-0.081	0.911	0.402	0.196
MAE	0.054	-0.027	0.425	0.874	0.021
MAEc	-0.394	-0.106	0.853	0.169	-0.117
MAESS	-0.406	-0.077	0.141	-0.811	-0.186
IOA	-0.101	-0.033	-0.039	0.292	0.883
MBE	0.977	0.039	0.022	0.119	-0.003
NMBE	0.977	0.039	0.021	0.12	-0.003
SKILLV	0.144	0.964	-0.141	0.019	-0.009
nRMSE	0.148	0.839	-0.082	0.112	0.09
RE	0.016	0.856	-0.132	-0.041	-0.003
CORR	-0.065	-0.071	-0.391	0.134	-0.747
D	0.107	-0.131	0.835	0.11	0.214
BF	-0.015	0.746	0.046	-0.063	-0.034
Maximum	0.977	0.964	0.911	0.874	0.883
10% threshold	0.098	0.096	0.091	0.087	0.088
Minimum	-0.406	-0.131	-0.391	-0.811	-0.747
10% threshold	-0.041	-0.013	-0.039	-0.081	-0.075
Identified parameters	MBE	SKILLV	RMSE	MAE/ MAESS	IOA/CORR

Mizoram (Table 2b). For other humid to per humid regions, rainfall forecast accuracy assessment studies should focus on these five identified accuracy indices from our present study.

Conclusion

The quantitative accuracy of district-level MME generated rainfall forecast had limited skill score over the year. The probability factor primarily dominated for determining the observed higher apparent accuracy of rainfall forecast during non-rainy months in Mizoram. Therefore, quantitative rainfall forecast assessment studies should include the bias and skill score through adaptation of the identified five quantitative accuracy indices viz. MBE, SKILLV, RMSE, MAE/ MAESS and IOA/CORR. rather than relying only on RMSE or MBE values as widely reported in literature, particularly under subtropical humid environment in Mizoram. Our proposed methodology will be useful to improve the accuracy assessment process of location-specific weather prediction values towards improved quality of periodic agro-advisory bulletin, issued by the respective agrometeological field units (AMFUs) located in other North East Indian hill states also.

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Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

References

Hou, D., Kalnay, E. and Droegemeier, K.K. 2001. Objective verification of the SAMEX ’98 ensemble forecasts. *Monthly Weather Review* **129**: 73-91.

Rajavel, M., Khare, P., Sahu, M.L. and Prasad, J.R. 2019. District level weather forecast verification in Chhattisgarh, *Mausam* **70**(4): 841-852.

Rana, R.S., Singh, M.M., Sood, R., Aditya, Sood, K. and Sharma, R. 2012. Status of medium range weather forecast in sub-temperate and sub-humid climate of western Himalayas *Journal of Agrometeorology* **14**(Special Issue): 213-221.

Rathore, L.S., Roy Bhowmik, S.K., Chattopadhyay, N. 2011. Integrated agrometeorological advisory services in India. *In*: Challenges and Opportunities in Agrometeorology, pp. 195-205.

Rathore, L.S. 2013. Weather information for sustainable agriculture in India. *Journal of Agricultural Physics* **13**(2): 89-105.

Saha, S., Chakraborty, D., Choudhury, B.U., Singh, S.B., Chinza, N., Lalzarliana, C., Dutta, S.K., Chowdhury, S., Boopathi, T., Lungmuana, Singh, A.R. and Ngachan, S.V. 2015. Spatial variability in temporal trends of precipitation and its impact on the agricultural scenario of Mizoram, *Current Science* **109**(2): 2278–2282.

Saha, S., Chakraborty, D., Paul, R.K., Samanta, S. and Singh, S.B. 2018. Disparity in rainfall trend and patterns among different regions: analysis of 158 years' time series of rainfall dataset across India. *Theoretical and Applied Climatology* **134**(1-2): 381-395.

Sarmah, K., Neog, P., Rajbongshi, R. and Sarma, A. 2015. Verification and usability of medium range weather forecast for north bank plain zone of Assam, India. *Mausam* **66**(3): 585-594.

Sharma, B., Gill, K.K. and Bhatt K. (2020) Decadal variation in weather forecast accuracy at Ludhiana, Punjab. *Journal of Agricultural Physics* **20**(1): 125-131

Sridhara, S., Gopakkali, P., Somashekarappa, P.R., Pradeep, S. and Agnihotri, G. 2014. Validation, usability and assessment of economic impact of agro advisories for southern transitional zone of Karnataka. *Journal of Agrometeorology* **16**(Special Issue-I): 214-218.

Vashisth, A., Das, D.K., Bhagawati, G., Sharma, P.K. 2008. Accuracy of weather forecast for semi-arid climate of Delhi for agricultural management practices. *Journal of Agricultural Physics* **8**: 51-58.

Willmott, C.J., Robeson, S.M. and Matsuura, K. 2011. A refined index of model performance. *International Journal of Climatology* **32**(13). DOI: 10.1002/joc.2419

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