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Usability assessment of district level rainfall forecast in Mizoram

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सार – भारत मौसम विज्ञान विभाग (आईएमडी) ने पिछले बारह वर्षों में मिजोरम में आवधिक जिला स्तरीय वर्षा का पूर्वानुमान जारी किया।हमने कई सूचकांक आधारित दृष्टिकोणों का उपयोग करके पूर्वानुमान की सटीकता और उपयोगिता का मूल्यांकन किया। प्रमुख वर्षा वाले महीनों में गैर-वर्षा वाले महीनों के दौरान सीमित पूर्वानुमान के साथ सटीकता अधिक थी।प्रमुख घटक विश्लेषण ने चार सूचकांकों की पहचान की, जैसे विषम अनुपात कौशल स्कोर (ORSS), संसूचनकी संभावना (PoD), विषम अनुपात (OR) और अभिनति पूर्वाग्रह (BIAS), जो न्यूनतम वर्षा डेटासेट का उपयोग करके सटीक पूर्वानुमान मूल्यांकन के लिए आवश्यक हैं। सापेक्षप्रचालन विशेषता (ROC) वक्र ने संकेत दिया कि ग्रामीण कृषि मौसम सेवा (GKMS) नेटवर्क के तहत मल्टी मॉडल-एंसेम्बल (MME) अंशांकन के माध्यम से पूर्वानुमान सटीकता बढ़ाने की काफी गुंजाइश थी।

ABSTRACT. India Meteorological Department (IMD) issued periodic district level rainfall forecast in Mizoram over past twelve years. We evaluated the accuracy and usability of forecast using several index based approaches. The accuracy was more but with limited forecast skills during non-rainy over major rain-receiving months. Principal component analysis identified four indices, *viz*., Odds ratio skill score (ORSS), Probability of Detection (PoD), Odds ratio (OR) and Frequency bias (BIAS); essential for forecast accuracy evaluation using minimum rainfall datasets. Relative operating characteristic (ROC) curve signified that there was considerable scope for increaseing forecast accuracy through multi model-ensemble (MME) calibration under Gramin Krishi Mausam Seva (GKMS) network.

Key words –Mizoram, Rainfall forecast, Usability, Accuracy assessment, Principal component analysis.

1. Introduction

Spatiotemporal variability in regional rainfall dynamics determined the magnitude of observed variation in *rainfed* (*jhum*) agro-ecosystem productivity of North East Indian hills (Chakraborty *et al*., 2017; Saha *et al*., 2018). Successful crop production still remained under the leniency of periodic seasonal weather aberrations in Mizoram (Saha *et al*., 2015). Irregular pattern of monsoon onset and heavy to extreme rainfall during major rainfall receiving months often resulted seasonal crop failure and increased farmers' grievances in this region (Rana *et al*., 2013; Sarmah *et al*., 2015; Saha *et al*., 2016). Prior dissemination of weather forecast and associated farming advisories has provided some narrow opportunity windows for their source poor tribal farmers, in order to minimize the magnitude of crop loss through timely manipulation of regular crop management practices, especially at critical crop growth stages. Thus, adaptation of regular weather forecast based Agro-meteorological advisories among the tribal Mizo farmers unveiled the potential to narrow down yield gap, reduce cost of cultivation, increase resource use efficiency and improved farming resiliency in Mizo Agriculture.

Since early 2007, India Meteorological Department (IMD) issued district level agro-advisory bulletins based on medium range weather forecast (5 days forecast on every Tuesday and Friday) for periodic manipulation of regular crop and livestock management strategies towards resource efficient sustainable crop production. The district level rainfall forecast was generated through multi model-ensemble techniques (MME; Rathore *et al*., 2011). The seasonal accuracy of weather forecasts determined the overall quality and relative efficacy of agro-advisory bulletins (Chattopadhyay *et al*., 2016). Any successful rainfall forecast system remained fragmentary without such systemic forecast accuracy evaluation, in terms of seasonal usability at local scale in determining crop specific schedules on agronomical operations starting from land preparation to final harvest (Rathore *et al*., 2001). Our literature survey revealed the previous reporting on the least usability of MME generated in active monsoon months and maximum usability for winter months across different agro-climatic regions of India, *viz*., subtropical to cold arid zones of Jammu and Kashmir hills (Hasan, 1999), semi-arid environment of Delhi (Vashisth *et al*., 2008), sub-tropical semi-arid region of Anand in Middle Gujarat Agroclimatic Zone (2005-2008; Singh *et al*., 2008 and Lunagaria *et al*., 2009), southern Saurashtra agro climatic zone of Junagadh, Gujarat (1996 to 2009; Sahu *et al*., 2011), sub-humid and sub-temperate of Kangra district, Himachal Pradesh (1994-2010; Rana *et al*., 2012), North bank plain zone of Assam (Sonitpur, Udalguri, Darrag, Dhemaji and Lakhimpur district during 2009-2014; Sarmah *et al*., 2015) and Kalimpong hills of Darjeeling, West Bengal (Mani and Mukherjee, 2016). The net usability of MME generated district level rainfall forecast was rarely reported over North East Indian hills (NEH). Hence, we evaluated the accuracy and usability of the medium range rainfall forecast over Lusai hills (Mizoram) of Indian NEH region.

2. Data and Methodology

The climatologically district and biodiversity enriched region of Lusai hills were categorized under humid to per-humid climate (Annual rainfall>2500 mm). The undulated topography (>95% of total geographical area) of hill agro ecosystems in north east India often poses a serious challenge for accounting the micro scale localized weather variability. Since 1999, Department of Agriculture (RE) maintained 26 rain gauge stations for recording daily rainfall observations in the distant locations of Mizoram (Fig. 1). We accessed the ground rainfall observations (June 2008 - June 2020) of all the raingauge stations and assigned area weighted average for determining representative district level daily rainfall observations. Furthermore, the value added district level rainfall forecasts received from Regional Meteorological

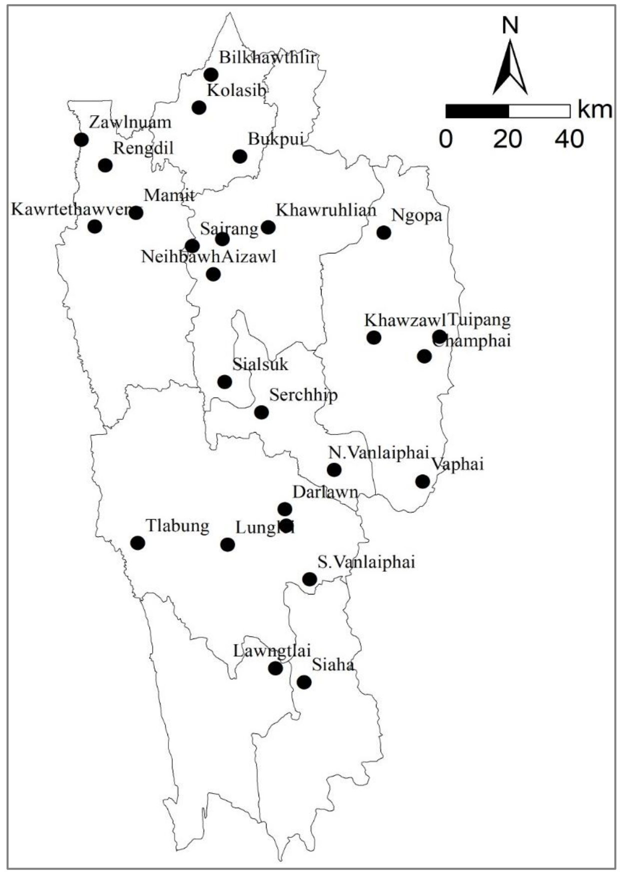


Fig. 1. The details of ground observations recorded in different raingauge station (2008-2020)

Centre (RMC Guwahati, IMD) were evaluated against the derived district level ground observations, with the fixed lead time of first 3 days from initial 5 days forecast issued over past 12 years (Chattopadhyay *et al*., 2016).

Our present rainfall forecast evaluation relied on multiple verification quality attributes of district level rainfall operational forecast in Mizoram (Purvanchal; D3A6). We adapted the standard delineated seasonal boundaries over North east Indian subdivisions as adapted by IMD likely, Pre-monsoon/ summer, (March-May), monsoon (June-September), Post monsoon (October-December) and winter (January-February). We measured the aspects of forecast quality based on rainfall forecasts and observations (as discrete variables) that was related to the marginal distributions of, *i.e*., probability of forecast that disregards the probability of observations. The critical value (threshold) for error structure were categorized as Success (Correct; ± 10% & Usable; ± 20%) and Failure

TABLE 1(a)

2 × 2 contingency table

		Observed class		Total
		Yes	No	
Forecast class	Yes	a	b	a+b
	No	c	d	c+d
Total		**a+c**	**b+d**	**a+b+c+d = n**

TABLE 1(b)

Indices adapted for qualitative evaluation of daily rainfall forecast accuracy

Error structure indices	Expression	Range (significance)
False Alarm Ratio (FAR)	$\frac{b}{(a+b)}$	0 (=perfect end) to +1 (= poor end)
Missing Rate (MR)	$\frac{c}{(a+c)}$	0 (=perfect end) to +1 (= poor end)
Success Ratio (SR)	$\frac{a}{a+b}$	0 (= poor end) to +1 (=perfect end)
Correct Non-occurrence (C-NON)	$\frac{d}{(b+d)}$	0 (= poor end) to +1 (=perfect end)
Probability of Detection (PoD)/ Hit rate (H)	$\frac{a}{(a+c)}$	0 (=poor end) to +1 (=perfect end)
Probability of False Detection (PoFD)	$\frac{b}{b+d}$	0 (=perfect end) to +1 (= poor end)
Odds ratio (OR)	$\frac{\left[\frac{\text{PoD}}{(1-\text{PoD})}\right]}{\left(\frac{\text{PoFD}}{1-\text{PoFD}}\right)}$	0 (=poor end) to +∞ (=perfect end), +1= no skill
Ratio Score (RS) or Forecast Accuracy (ACC) or Percent Correct (PC)	$\frac{a+d}{(a+b+c+d)}$	0 (= no correct forecast) to +1 (= all correct forecasts)
Frequency bias (BIAS)	$\frac{(a+b)}{(a+c)}$	B=1(unbiased), B> +1(over-forecast; false alarm), B < +1 (under-forecast; missing the event completely)
Critical Success score (CS score) (Threat Score; independent of d)	$\frac{a}{(a+b+c)}$	0 (= poor end) to +1 (=perfect end)
Equitable threat score (ETS; Gilbert skill score)	$\frac{a-A}{a+b+c-A}; \text{where} A=\frac{(a+c)(a+b)}{n}$	-1/3 (=poor end) to +1 (= perfect end), 0 = no skill
Heidke Skill Score (HSS; independent of n)	$\frac{2(ad-bc)}{[(a+c)(c+d)+(a+b)(b+d)]}$	. HSS = 1 (perfect forecast); HSS = 0 (no skill). HSS < 0, (worse than reference forecast)
Hanseen and Kuipers Scores or True Skill Score (HKS)	$\frac{(ad-bc)}{(a+c)(b+d)}$	-1 (= poor end)to +1 (=perfect end), 0 = no skill
Odds ratio skill score (ORSS; Yule's Q)	$\frac{(ad-bc)}{(ad+bc)}$	0 (= poor end) to +1 (=perfect end)

TABLE 1(c)

Indices adapted for accuracy evaluation of extreme rainfall events

Base rate (p)	$\frac{a+c}{n}$
Relative frequency of forecasted events (q)	$\frac{a+b}{n}$
Extreme Dependency Score (EDS)	$\frac{\log p - \log \text{PoD}}{\log p + \log \text{PoD}}$
Stable Extreme Dependency Score (SEDS; forecast frequency)	$\frac{\log q - \log \text{PoD}}{\log p + \log \text{PoD}}$
Extremal Dependency Index (EDI)	$\frac{\log \text{PoFD} - \log \text{PoD}}{\log \text{PoFD} + \log \text{PoD}}$
Symmetric Extremal Dependency Index (SEDI)	$\frac{\log \text{PoFD} - \log \text{PoD} - \log(1-\text{PoFD}) + \log(1-\text{PoD})}{\log \text{PoFD} + \log \text{PoD} + \log(1-\text{PoFD}) + \log(1-\text{PoD})}$

(F; otherwise) for verification of predicted district wise rainfall. The qualitative assessment was determined using 2 × 2 contingency table [Table 1(a)] with one degree of freedom. Such operational evaluation methods often relied on the qualitative evaluation of probabilistic *dichotomous* (*yes/no*) forecasts, as further characterized into four major categories like hits (a), false alarms (b), misses (c) and correct negative (d). The independence between forecasted and observed values was tested by $\chi 2$ statistics with Yate's correction (wherever necessary),

$$\chi 2 = \sum_i \sum_j \frac{(O_i - P_i)^2}{P_i}$$

where, O_i and P_i is the observed and predicted values for the i^{th} sample recorded at any specific location respectively. The relative intensity of association between forecasted and observed rainfall values were tested by means of Yules co-efficient of association (Y). The degree of associations or dissociations of the 2 × 2 contingency tables were assessed using Tschuprow' sco-efficient (T) expressed as:

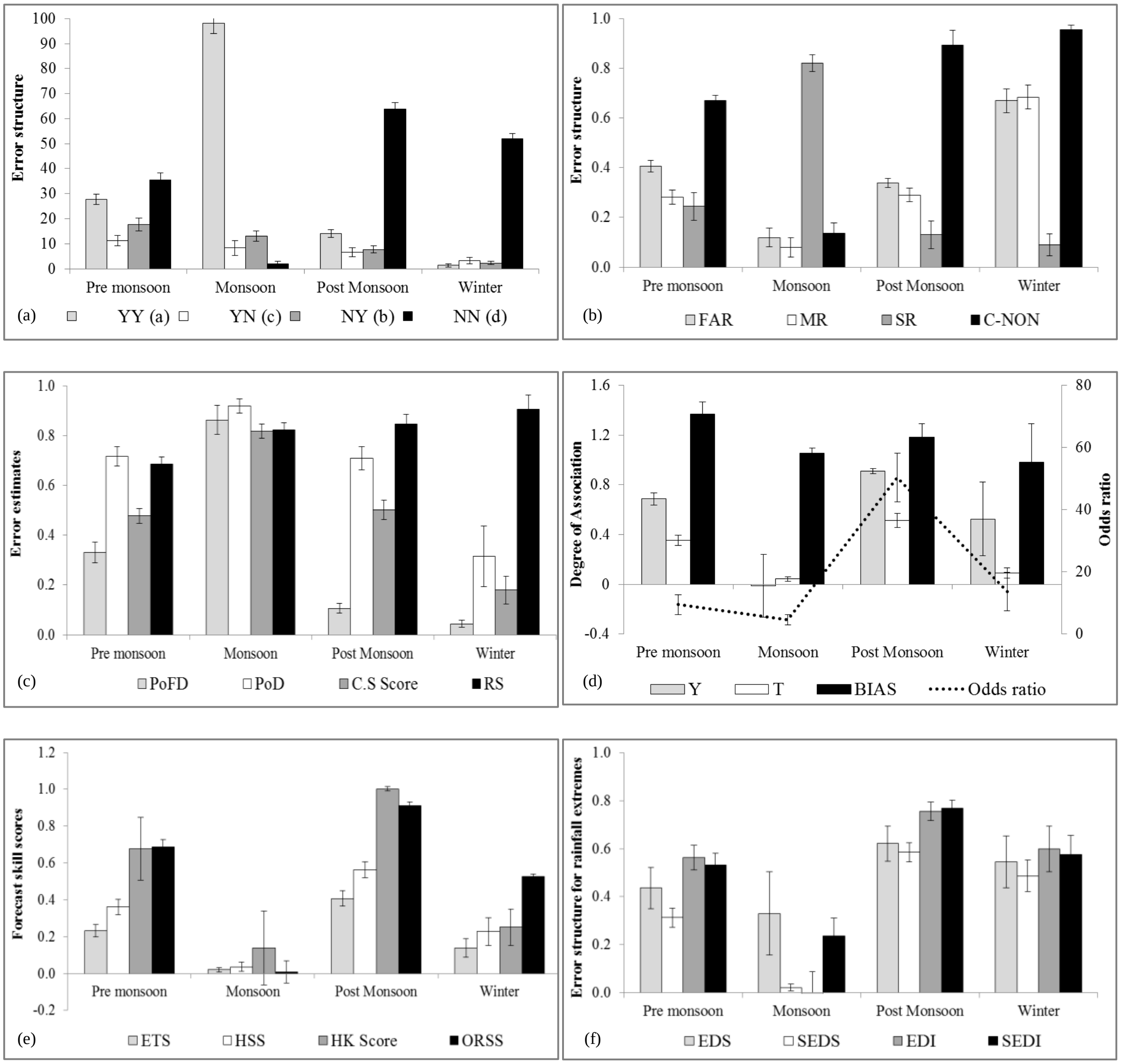
(*i*) Yules co-efficient $(\text{Y}) = \frac{\text{ad} - \text{bc}}{\text{ad} + \text{bc}}$

(*ii*) Tschuprow'sco-efficient $(\text{T}) = \left(\frac{\chi^2}{n}\right)^{1/2}$

Yule-Y ranged between -1 (=complete dissociation) to +1 (=complete association). The forecast accuracy and subsequent skill scores were determined using different error structure estimates as mentioned in Table 1(b). In order to verification of the forecast values for the extreme (rare/infrequent), high-impact weather, *i.e.*, heavy to extreme heavy rainfall events (0.95th percentile criteria), we adapted deterministic limit approach. It accounted a pre-defined rare extreme rainfall event (seasonal scale) for 'the lead time (T) at which number of hits (a) equals the sum of misses (c) and false alarms (b) for entire forecast sample dataset analyzed in our present study. The advent of rare events was independent of base values with the minimal dataset approach of assigning standard scores [base rate or event frequency based; Table 1(c)].

Relative operating characteristic (ROC curve) - Good quality forecast was accounted for maximum PoD and minimum PoFD. Reduction in probability threshold often increased both PoD and PoFD. Minimizing PoFD though modifying probability threshold should be carried with minimum expense of PoD reduction. The ROC curve accounted the relative plot actual sensitivity versus false positivity for a sequence of PoD and PoFD pairs under variable probability threshold (0 to 1). ROC curve measured resolution (independent of forecast bias), *i.e.*, the ability of the forecast to discriminate between events and non-events, in order to make the yes/no decision. The area under the ROC curve varied between 0 (poor) to 1 (perfect end). The diagonal line between (0, 0) and (1, 1) locus indicated no skill (Area = 0.5; no skill).

For instantaneous forecast quality evaluation, identification of dominant error structure variables is essential for large scale adaptability in MME generated



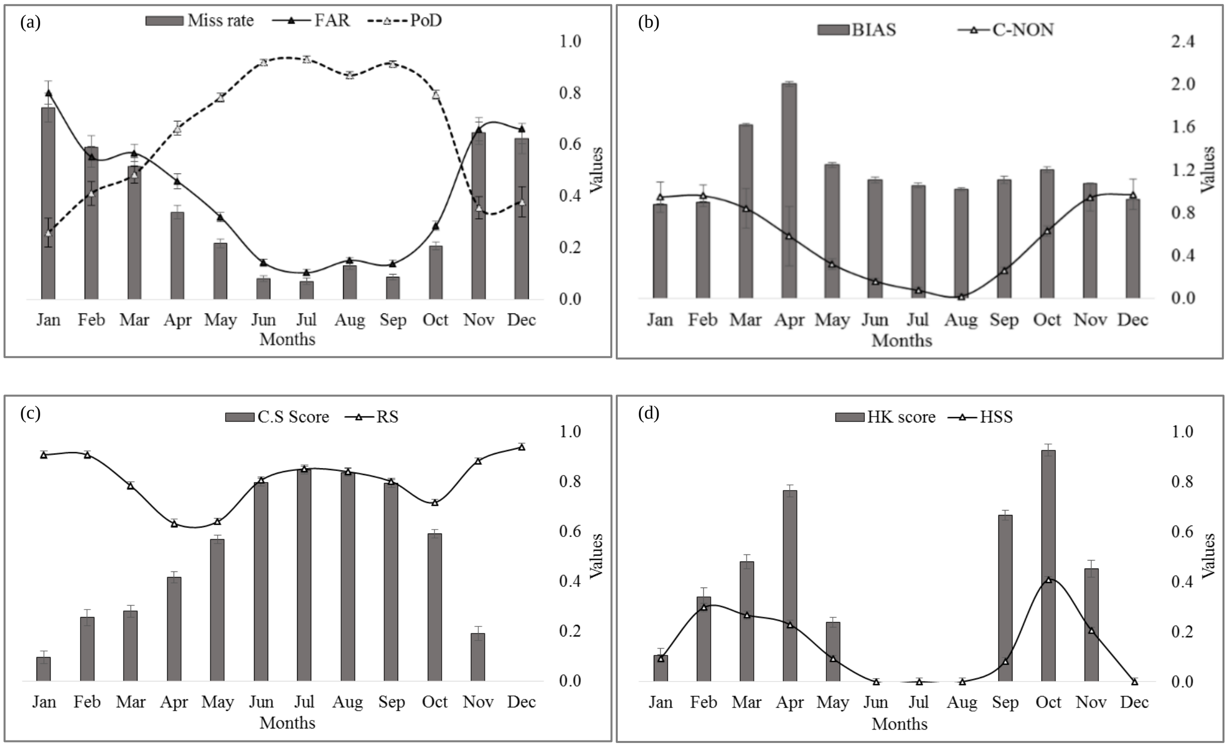
Figs. 2(a-f). Structural error estimates for operational evaluation of seasonal district level rainfall forecast

rainfall forecast accuracy assessment studies. In order to minimize the dimensionality while retaining the largest variance in the calculated qualitative error estimates, we adapted Principal Component Analysis (PCA). The first PC explained maximum variability followed by the rest expressed lion share of residual variability. The important underlying variables were identified for each PC based on factor loadings values within 10% threshold limit over the maximum weighted factor, retained under each PC. The subsequent correlation was verified for the identified minimum number of dominant forecast quality error estimates in our present dataset.

3. Results and discussion

3.1. *Seasonal pattern*

The daily rainfall forecast were verified for their applicability using dichotomous approach (yes/no based) against the ground observations using multiple index based approaches derived from their marginal distribution, in comprehensive manner. Initially, we characterized the correct forecast as summation of counts for YY (a) and NN (d) calculated over seasonal to annual scale; rest two remaining categories were summed up to the failure, *i.e.*,



Figs. 3(a-d). Monthly error estimates for operational evaluation of district level rainfall forecast

NY (b) and YN (c). The detailed account of seasonally averaged qualitative rainfall forecast accuracy counts across all the rain gauge stations confirmed maximum hits (80.7%) for monsoon rainfall forecast values with the least occurrences for correct negatives (1.6%) [Fig. 2(A)]. In contrast, winter rainfall forecast experienced the highest (88.5%) correct negatives [C-NON; Fig. 2(B)] and RS score [0.91±0.015; Fig. 2(C)] with the least PoFD values followed by post monsoon season. The overall annual correct forecast was accounted ~80.8% of total forecast issued and their intra annual (seasonal) percentage distribution varied likewise: winter (90.7) > post monsoon (84.6) > monsoon (82.4) > pre monsoon (68.54). Pre-monsoon rainfall forecast experienced maximum average counts for both false alarm (b) and miss (c) events that resulted more significant BIAS (> +1) of over- forecast [Figs. 2(A&D)]. However, the least occurrence of reported average hit events (a) resulted the reported high values of FAR and MR in winter rainfall forecast.

The seasonal forecast assessment confirmed higher SR and CS score, with their greater PoFD values during monsoon months [Figs. 2(B&C)]. The minimal values of Yule's Coefficient (Y = -0.013± 0.04) and Tschuprow's co efficient (T= 0.25± 0.02) further confirmed the conspicuous degree of disassociation between daily monsoon forecast and supportive ground observations with the least Odds ratio values (4.55 ± 1.58) during our present entire study period. In courtesy, the post monsoon forecast was highly inclusive towards subsequent daily rain-gauge observations (Y= 0.91± 0.05; T= 0.51± 0.05 and Odds Ratio = 50.3± 7.79). The results of forecast skill score assessment evaluation using ETS, HSS, HKS and ORSS yielded almost similar pattern. The rainfall forecast had almost no skill (ETS/ HSS ~ 0) during monsoon, but with the highest skill and reliability (HK score = +1) during post monsoon season [Fig. 2(E)]. All the four indices (EDS, SEDS, EDI and SEDI) used for seasonal extreme heavy rainfall events prediction accuracy assessment also gave in the similar pattern. The mean forecast frequency expressed in terms of SEDS varied 0.022±0.01 (monsoon) to 0.585±003 (post monsoon). The lower values of 0.022 signified that out of every 1000 cases of extreme rainfall event only 22 events would be forecasted during monsoon season though the present MME output for Mizoram. However, the net count got increased to 585 for every 1000 observed extreme rainfall events during the post monsoon months. The EDI and SEDI indices were independent of the base rate calculation; thus considered to be the most promising estimates of forecast accuracy on rare rainfall events towards perfection. The largest post-monsoon SEDI values (0.76 ± 0.03) indicated the highest vicinity of subsequent rainfall forecast values towards ground observations but the least proximity (0.23 ± 0.07) for periodic monsoonal rainfall prediction [Fig. 2(F)].

3.2. *Monthly pattern*

Seasonal pattern often over shadowed the month wise intra-annual variation of forecast accuracy. Hence, any precise assessment of rainfall forecast accuracy should be aseesed with downscaled time resolution from seasonal to monthly time domain. Unlike rest part of mainland India, premonsoon and monsoon season accounted ~35% and ~60% of annual rainfall in Mizoram. It also provided a good scope for extended season for growing diverse long duration agricultural and horticultural crops (local varieties) over > 6 months time period (April to October), after adapting their 'Good Friday sowing' under *rainfed* (*jhum*) agro-ecosystem. We downscaled the seasonal analysis for focusing the precise need for improvement of rainfall forecast during major rainy months in Mizoram. It was quite clear that with the advent of the premonsoon shower during April, the PoD and CS score increased with sharp decline in MR and FAR; the prominent pattern continued up to the monsoon withdrawal phase in October [Figs. 3(A&C)]. Therefore, the apparent usablity of MME forecast was satisfactory during the major crop growth (*jhum)*season. The average forecast BIAS was extremely higher (over-forecast) during March (+1.62) – May (+ 1.25) with it's highest peak during April (+2.01) [Fig. 3(B)]. In courtsey, the lower BIAS values (under-forecast) were prominent during December (+0.92) - February (+0.90) with its least value during January (0.87). The limited ability of MME rainfall forecast for predicting correct negative (d) events were also prominent at the time of initiation (April-May) and termination (September-October) of *jhum* season [Fig. 3(C)]. The forecast skill score was remarkably higher during the initiation (February-May; highest in April) and terminating (September-November; highest in October) phase of the extended rainy season in Mizoram [Fig. 3(D)]. On the either side of these two peak period, we identified the drastic reduction in both HK score and HSS score, *i.e*., May-August and December-January. The lower forcast skill (almost no skill) involved in rainfall forecast during these two identified time period was consistant for all of our studied locations in Mizoram [Fig. 3(D)]. Thus, our study clearly signified that higher number of rainy days during May-August increased the liklihood of higher hit counts (a) during rainfall receiving months. After the elimination of probablity factor of rainfall occuerance (bias), the effective control of forecast skill factor was very limited on the MME rainfall forecast during the major rainfall receiving months (May-August) in Mizoram. Conversly, very lessforcast skills during non rainy months (December-January) having very few rainy days manifested the poor forecast quality, partcularly during December.

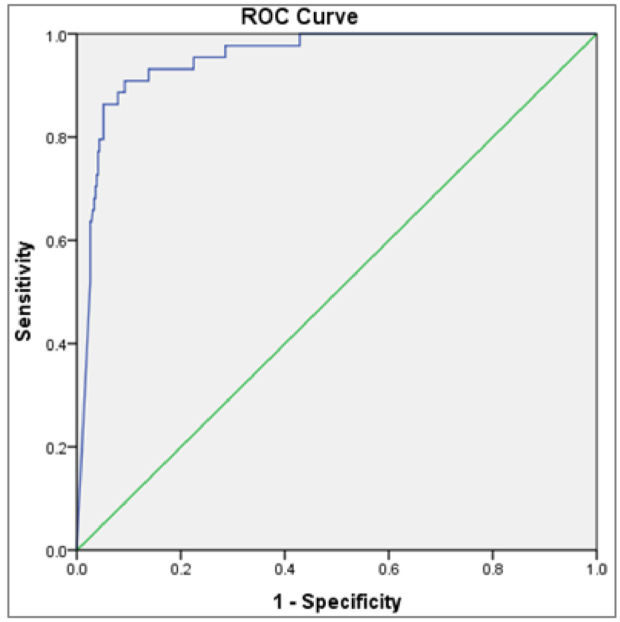


Fig. 4. ROC curve of IMD-MME district level rainfall forecast in Mizoram (Period: 2008-2020)

3.3. *ROC curve*

The ROC Curve of IMD MME rainfall forecast traveled from the bottom left to top left, then move across to top right of diagram (Fig. 4). The two extreme end points signified the best (0, 1) and worst (1, 0) forecast model, respectively. The diagonal line indicated no skill. The area was estimated about 0.953±0.14 (p<0.001). In spite of having considerable BIAS and our result confirmed the good resolution of the MME generated seasonal rainfall forecasts. The close proximity of curve area towards 1.0 unveiled the excellent potential for future improvement in the current MME generated seasonal rainfall forecast skills with minimum bias through proper model calibration measures in Mizoram.

3.4. *Derivation of minimum parameter sets for qualitative rainfall forecast error evaluation:*

Principal Component analysis extracted four prominent Principal components (PCs) accounting 86.49% of cumulative variance within our present dataset [Table 2(A)& Fig. 5(A)]. We evaluated the respective factor loadings for each identified PC for determining weightage with 10% threshold over maximum and minimum loading. Finally, we identified four forecast quality evaluation parameters, *viz*., ORSS (PC-1), PoD (PC - 2), Odds ratio (PC - 3) and BIAS (PC- 4) as the

TABLE 2(A)

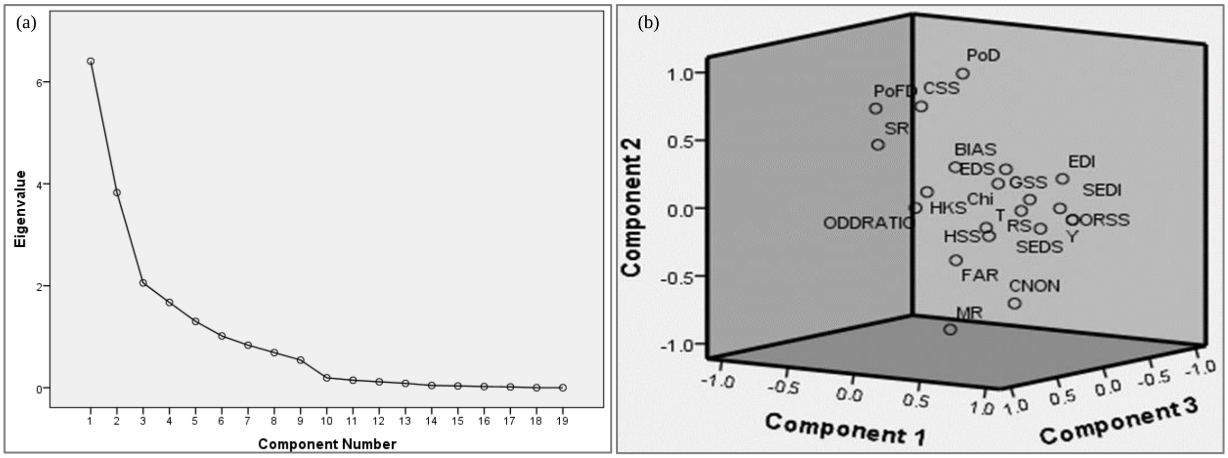
Detailed variablity accountated by the respective PCs for qualitative forecast error estimates

Principal Component	Eigen value	% of Variance	Cumulative variance%
PC1	10.293	49.013	49.013
PC2	4.256	20.267	69.28
PC3	2.595	12.355	81.635
PC4	1.021	4.861	86.496

TABLE 2(B)

Factor loading of error structure estimates for respective PCs in rotated component matrix

Parameters	PC 1	PC 2	PC 3	PC 4
Chi	0.591	0.248	0.393	-0.095
Y	0.958	-0.021	0.113	0.024
T	0.661	-0.036	0.623	0.037
FAR	-0.142	-0.476	-0.198	0.802
MR	-0.122	-0.771	-0.106	-0.118
SR	-0.665	0.337	-0.111	-0.463
CNON	0.645	-0.644	0.293	0.116
PoFD	-0.761	0.579	-0.211	0.019
PoD	0.122	0.971	0.106	0.118
Odd ratio	0.262	0.097	0.817	-0.009
CSS	-0.033	0.746	0.335	-0.523
RS	0.652	0.031	0.231	-0.295
BIAS	-0.083	0.229	-0.107	0.893
GSS	0.844	0.161	0.412	-0.063
HSS	0.671	-0.099	0.608	0.014
HKS	0.297	0.208	0.744	-0.307
ORSS	0.958	-0.021	0.113	0.024
EDS	0.503	0.316	0.184	0.671
SEDS	0.896	-0.056	0.372	0.051
EDI	0.913	0.282	0.156	0.065
SEDI	0.948	0.079	0.235	0.058
Maximum	0.958	0.971	0.817	0.893
10% threshold	0.096	0.097	0.082	0.089
Minimum	-0.761	-0.971	-0.211	-0.523
10% threshold	-0.076	-0.097	-0.021	-0.052
Identified parameters	**ORSS**	**PoD**	**Odd ratio**	**BIAS**



Figs.5 (a&b). (A) Scee pot of eigen values accounting cumulative variablity in the identified PCs and (B) placement of parameters in 3D space for qualitative error estimates in district level rainfall forecasts

representative of variablity accounted in our present dataset [Table 2(B)]. The distrinctiness of the identified indices were prominant in their threedimension plot of respective PC co-ordinates [Fig. 5(B)]; as the minimally required parameters for periodic rainfall forecast accuracy assessment under the subtropical humid climate conditions of Mizoram.

4. Conclusion

The over all qualitative performance of IMD operated MME forecasting model output was better during non-rainy (post-monsoon and winter seasons) than rainy (monsoon and pre monsoon) seasons. At present, the highly erratic accurate rainfall prediction pattern during the major during rainfall reciving months (premonsoon and monsoon months) limited its effective usablity and subsequent adaptation of supportive agro-advisory services among the *rainfed jhum* farming communities in Mizoram. However, the relatively higher accuracy of qualitative forecast with limited forecast skills during non rainy post monsoon and wintermonths ensured the higher apparent usability of seasonal forecast for determing periodic farm operations designed for *rabi* agriculture; practiced in some scattered patches of low lying rice fallows in the state. Our result in sighted the huge scope for future improvement in qualitative regular rainfall forecast skills for the higher sensitivity of MME forecast throgh calibration. The associated improvement in extreme rainfall event forecast skills with lower frequency bias is essential to increase the net usability of periodic MME generated rainfall forecast for the *jhum* farmers in Mizoram. It will increase the actual quality of periodical agro-advisories issued under Gramin Krishi Mausam Seva (GKMS) programme in Mizoram.

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