Quantitative Precipitation Forecast by Deep Learning approaches

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ABSTRACT: Forecasting rainfall intensity and spatial distribution for varying time span is always a challenge to the professional meteorologist in spite of the rapid strides achieved in Numerical Weather Prediction (NWP) and the development of Multi-Model Ensemble (MME). The demand from various quarters for very precise rainfall forecast in terms of quantity and its duration is increasing rapidly. Agromet Advisory Services (AAS), aviation, surface transport operation, power transmission and trading, infrastructural projects, disaster management and defense operations etc., are a few to mention, the forecaster has to cater on a daily basis. A variety of NWP outputs from various models, advanced observational platforms and the knowledge acquired by the synoptic meteorologist over the years for a geographical region seldom help to predict an exceptionally heavy rainfall or extremely heavy rainfall event with confidence. The necessity of an objective tool to forecast the quantum of rainfall is felt for long to further increase the capability of the forecaster. In this paper, an attempt is made to reveal how the strength of pattern recognition and data mining in tandem with NWP products and rainfall databases can be leveraged to the advantage of the forecasting community to meet the challenges efficiently.

Key words: Deep learning, Pattern recognition, pattern matching, Image classification, image registration, vertical velocity (ω), Quantitative Precipitation Forecast (QPF).

1. Introduction

Shrinking acreage, burgeoning input cost and ever increasing demands for farm products are putting more pressure on the agricultural sector and farmers have to adopt effective management practices from day one of the crop calendar to deal with the challenges. Integrated Agricultural Advisory Services (IAAS) now renamed as Gramin Krishi Mausam Seva (GKMS) is one step in that direction to equip the farming community with knowledge input to deal with and aid agricultural practices. Improvement in the skill of medium range weather forecast made location specific quantitative forecast possible for a reasonable lead time. In many occasions during the past, the agro meteorological field units have reportedly saved the standing crop from unfavorable weather conditions by adopting suitable mitigation efforts based on advisories. GKMS for the farming community came into existence after the collaborative effort of India Meteorological Department (IMD), the National Centre for Medium Range Weather Forecasting (NCMRWF), the Indian Council of Agricultural Research (ICAR) and Agricultural Universities. The quantitative forecast for weather elements for district level for five days came into existence after its roll out. Since its inception to many other sectors are looking for a product to enhance their operational efficiency and add value in their chain of operation.

The crop specific advisories based on weather elements to the farming community in their own language at their door step were the motto of the service. On the basis of the ongoing effort client base has increased significantly and tens of thousands of registered farmers are in the network for receiving advisories in their local languages. The stake holders strived very hard to achieve the forecast accuracy by adopting a mix of strategy by consulting available NWP products, the MME output with value addition based on regional climate characteristics and knowledge inherited by the forecaster. Efforts are also on to disseminate the information up to block level to improve the usability of the product by the end users.

Elaborate study has been undertaken earlier to estimate the worthiness, if any and the economic value of the service to the farming community (Rathore *et al.* 2008). The case studies included estimates for both perfect and imperfect forecasts. From practical perspective, perfect forecasts are an unrealistic expectation, and on the other hand the less accurate forecasts also help farmers to determine farm management actions and add information for decision making. Reporting the effectiveness of advisories which are based on weather forecasts with lower skill levels is also helpful in determining the usefulness of the service and to further improve the quality of service. Our efforts are to narrow down the gap to improve the forecast a realistic expectation. Precise advisories at least up to five days ahead are at farmers' advantage to deal with any eventuality. The success of the service and popularity it earned among the farming community can be gauged by the increasing number of registered farmers and the number of hits in the farmers' portal. This product can be effectively used in other sectors as well to achieve economic benefit by adopting sector specific management practices provided we achieve more proficiency in rainfall quantum prediction.

An in-house verification method for the predicted elements to find out the effectiveness of the forecast and the degree up to which it was realized exists since beginning. This exercise ought to help the forecaster in fine tuning the products. Attempts are being made to narrow down the weakness, if at all exists, to strengthen the acceptance level among the user community. Elaborate deliberations are made on the subject in review meetings and brain storming sessions to exchange the ideas pertinent to each agro climatic regions. Still we are unable to break the ice as far as rainfall amount is concerned for certain geographical areas. The improvement in accuracy in those areas may go in hand with the development of a better objective method for value addition and improvement in the skill of NWP products.

2. Data and Methodology

Numerical weather prediction models are important tools for understanding of atmospheric phenomena as well as for weather forecasts. The predictability provided by these numerical models shows a strong dependence on initial conditions and has been widely discussed since 1960s. In this sense, a knowledge of systematic errors is of paramount importance in the realization of improvements in the forecasting system. The technique of combining forecasts made by numerical models has been well explored by researchers with an objective of minimizing the errors and helping meteorologists in the preparation of accurate weather forecasts. Most of the articles on this subject agree that a combination of different model forecasts provides significant improvement in quality. The concept of using the combination of a set of model forecast, MME for the enhancement of its quality was first discussed (Krishnamurti *et al.* 1999, 2000a, 2000b). Many studies in that field confirmed that the combination of various types of model outputs could produce forecasts of greater reliability (Johnson and Swinbank 2009; Roy Bhowmik and Durai 2008, 2010, 2012). In other recent studies (Krishnamurti *et al.* 2009, Mitra *et al.* 2011 and Kumar *et al.* 2012) addressing the monsoons of India assert that when predictions are generated from a set of numerical models their quality was improved and their mean square errors reduced. Also (Rathore *et al.* 2011) demonstrated that MME have better capability (compared to member models) to capture large scale rainfall features of summer monsoon, such as heavy rainfall belt along the west coast, over the domain of monsoon trough and along the hills of Himalayas. Wong et. al., (2016) presents a novel technique of precipitation nowcasting using the machine learning approach. The precipitation nowcasting is formulated as a spatio-temporal sequence forecast of radar reflectivity using the convolutional long short-term memory (ConvLSTM) network. Compared to another deep-learning approach, namely the fully connected LSTM (FC-LSTM), the convolutional structures in ConvLSTM contribute favourably in capturing the spatio-temporal correlations of radar sequences. Experiments and verification of quantitative precipitation forecast (QPF) using several years of data reveal that ConvLSTM outperforms FC-LSTM as well as the operational radar-based QPF using optical flow echo-tracking and semi-Lagrangian advection method. Extension of the framework of ConvLSTM to consider the uncertainty in forecasting the spatio-temporal sequence of radar QPF, as well as merging with other sources of meteorological data such as NWP model to improve the performance of QPF and to predict other high impact weather processes will also be discussed. Aditya et. al., (2015) studied specifically the power of making predictions via a hybrid approach that combines discriminatively trained predictive models with a deep neural network that models the joint statistics of a set of weather-related variables. They show how the base model can be enhanced with spatial interpolation that uses learned long-range spatial dependencies. They also derive an efficient learning and inference procedure that allows for large scale optimization of the model parameters. They evaluate the methods with experiments on real-world meteorological data that highlight the promise of the approach. Xingjian Shi et. al., (2016) formulate precipitation nowcasting as a spatiotemporal sequence forecasting problem in which both the input and the prediction target are spatiotemporal sequences. By extending the fully connected LSTM (FC-LSTM) to have convolutional structures in both the input-to-state and state-to-state transitions. They propose the convolutional LSTM (ConvLSTM) and use it to build an end-to-end trainable model for the precipitation nowcasting problem. Experiments show that ConvLSTM network captures spatio-temporal correlations better and consistently outperforms FC-LSTM and the state-of-the art operational ROVER algorithm for precipitation nowcasting.

Observations revealed that the ensemble forecast was able to provide more realistic spatial distribution of rainfall over the Indian monsoon region by taking the strength of each constituent model. However, the MME's skill of forecasting moderate to heavy rainfall suffered during the initial years (Lal *et al.* 2006) and is depicted in figure 1. Since then a lot of efforts by many groups had taken place to minimize this deficiency. By adopting efficient strategies they formulated superior ensemble forecast than the forecasts of constituent models. IMD implemented MME based district level quantitative forecasts in the operational mode since 1 June 2008, as mandated by IAAS of India.

At present (i) IMD run GFS T574, (ii) ECMWF T799, (iii) JMA T899, (iv) UKMO and (v) NCEP GFS are used for development of MME forecast. As the model outputs available at different resolutions, in the first step, model outputs of the constituent models are interpolated at the uniform grid resolution of 0.25^o X 0.25^o lat/long. The ensemble forecast fields are then used to generate district level forecasts by taking average value of all grid points falling in a particular district.

The state agromet advisory units are issuing district level forecast for five days since 2008. The system has generated a lot of forecast products as well as database of realized weather. At the national level 0.25^o X 0.25^o rainfall model forecast are verified with 0.25^o X 0.25^o gridded realized data for Indian domain 0^o N to 40^o N and 60^o E to 100^o E. At the state level the district level forecast are put to different verification methods to ascertain the degree of accuracy and to identify the skill and weaknesses of the model outputs and the final value added products passed to the farming community. Following are the skill scores used for verification of rainfall forecast. Skill scores for Yes/No rain fall forecast as

A = Number of hits (predicted and observed)

B= Number of false alarm (predicted but not observed)

C= Number of misses (observed but not predicted)

D= Number of correct predictions of no rain (neither predicted nor observed)

N=Total number of forecast

1) Forecasrt accuracy (ACC) or Ratio Score (RS) is the ratio of correct forecast to the total number of forecast, RS = $\frac{A+D}{N}$

2) Hanssen and Kuipers Scores or true Skill Score (HK Score) is the ratio of economic saving over climatology due to the forecast to that of a set of perfect forecasts

$$HK = ACC_{events} + ACC_{non\text{-}events} - 1 = \frac{AD-BC}{(A+C)(B+D)}$$

Range : -1 to +1 and the perfect score is :1

3) Probability of Detection (POD)= $\frac{\text{Correct rain forecast}}{\text{rain observation}} = \frac{A}{A+C}$

Range: 0 to 1 and the perfect score is: 1

4) False Alarm Ratio = FAR = $\frac{\text{False alarms}}{\text{Hits+ False alarms}} = \frac{B}{A+B}$

5) Skill scores for quantitative precipitation.

6) The quantity of precipitation is divided in to four classes namely (O_1, F_1) for no rain or less than 0.1 mm rainfall, (O_2, F_2) light to moderate rain (0.1 mm to less than 3.5 cm), (O_3, F_3) rainfall between 3.5 cm and upto12.5 cm and (O_4, F_4) greater than 12.5 cm and a 4x4 contingency table (table 1) is prepared for the number of occasions the forecast (F_i) is Observed (O_i) for all $i = 1,4$.

Then hit rate HR = $\frac{n_{11}+n_{22}+n_{33}+n_{44}}{n_{TT}}$

and the Root Mean Square Error (RMSE) = $\sqrt{\frac{\sum_{i=1}^{n}\left(X_{obs,i}-X_{model,i}\right)^2}{n}}$

At the state level, the strategies adopted for rainfall forecast verification are based on the following error structure. The forecast is correct when the absolute difference between observed rainfall value and forecast value is less than or equal to 25% of the observed rainfall value. It is usable, if the absolute difference lies between 25% of the observed and 50% of the observed and is unusable otherwise.

The national level verification result pertaining to Kerala from report (Ashok Kumar *et al.* 2014) and result of state level verification on the value added products are given in table 2, table 3 and table 4. It was revealed from verification of value added forecast that the quality of district level weather forecast after value addition improved significantly (table 4) except for rainfall quantity as in table 2. However, the skill score shows the rainfall events are captured well both by MME as well as the value added one as depicted as POD in table 3. The Percentage correctness of MME and value added forecasts for Kerala is given in figure 2. The report on block level weather forecast 2014 correctly brought out the quality of quantitative rainfall forecast for the entire country and highlighted the difficulties it encounters on oceanic islands and high terrain regions including Kerala. Incidentally the whole part of Kerala state lies in the problem area and pose great challenge to the forecaster to value add the rainfall quantity. The challenge will further multiply if we step into the block level. These challenges highlight the need for an objective method for QPF until NWP models are improved to address the problem areas.

The conventional weather forecasting was actually a pattern recognition problem and the synoptic forecasters do the analysis on different weather charts and look for the patterns and issue forecast based on the character and behavior of the patterns during the previous hours and its future projection. His theoretical knowledge and experience in that geographical area often guides him to issue a spatial forecast as well as a quantitative range forecast at least for a short term period with fairly good accuracy. Many times the acquired knowledge base and experience gained and memory of resultant weather of a particular pattern often produced excellent quantitative forecast for short term in that age of meager technological support. At present we have excellent NWP forecast products of the same patterns for many days, and if anybody having the ability to reproduce the resultant weather, say quantum of rainfall pertaining to a particular pattern for a day on that period of the year by memorizing, can produce good forecast. The authors moot the idea of using artificial intelligence as the human brain cannot recollect exactly what happened in that particular year when pattern was the same or whether any pattern of that sort existed at all any time in the past with same behavior. Here the technology of pattern recognition and matching can be leveraged to create an environment for objective QPF and a tool for value addition in the problem zones.

We have reanalysis fields of the past and NWP forecast products of the same parameter for any time step up to next ten days and the rainfall database to robustly meet this challenge. It is in our advantage that we have inherited a fairly good database of district wise rainfall from Daily Rainfall Monitoring Scheme (DRMS) and rain gauge stations under Hydrology Project on one hand and reanalysis products of NCEP or any NWP centre for many years and also have forecast fields of same parameters for different time step. Also intelligent pattern recognition softwares are also available or can be developed in-house. Care should be taken while selecting the domain of pattern as a large area may result in no match on many occasions. A 15^o Lat x 15^o Long domain or a still smaller one centered around the area of interest is sufficiently enough to have a worthwhile search. The forecast product and the stored patterns must be in uniform format and had been created using same analytical tools. It is assumed that a pattern will perform the same way in that period of the season and no pattern will perform the same way throughout the year. Keeping in view of this the authors restrict the period for match to 31 days centered around the forecast day (Date ± 15) of stored patterns of all the available years from the database. This will not only reduce the labour of machine matching but also help create an environment of uniform physical process and atmospheric conditions including radiation to prevail for the forecast and archived fields. The pattern matching in this case is relatively simple compared to other machine matching problems were images are matched with already registered images taken at different orientations, sampling environment, with different sensors and photogrammetric conditions. Here, once we fix the domain of the pattern and forecast field, an environment is created for going directly into pattern recognition and matching without any preprocessing of the images (forecast fields). The process of matching and data mapping is shown in figure 3a and figure 3b. Out of all the available fields Omega fields are relatively simple and have direct physical significance as it stands for vertical velocity. Two sample composite omega fields, one for a normal monsoon (table 5 and figure 4) and another for vigorous monsoon condition (table 6 and figure 5) and realized rain for those patterns are given in table 7 and table 8.

Rosenfeld (1984) has discussed different approaches for pattern recognition problem. Since the fields are created under uniform conditions a simple matching algorithm for a one to one match or a match with a mean pattern with in a pre-calibrated tolerance structure is sufficient. The patterns from database and the forecast field are given as discrete two-dimensional matrices A_{ij} and B_{ij} respectively. In a one to one match (Scheme A) the system picks a forecast field from NWP output and search for a match from the database of the same field of all stored data of Date ± 15 from forecast date of all available years. The flowchart of the Scheme is shown in Figure 3a. A match is (ideally) established if all the elements of A_{ij} match with corresponding elements of B_{ij}, a direct match and the resultant rainfall can be mapped for the date of the matched pattern.

An ideal match may be difficult to achieve as the elements to be matched are of dimension 7x6. If no match is established the process may be subjected to scheme B, which uses an archived mean pattern and respective derived tolerance structure T_{ij}. The mean patterns $\overline{A_{ij}}$ are created for each day by averaging the patterns with in thirty one day's centered around that date (Date ± 15) of all the years by grouping the patterns which produced same sub-division wise rainfall ranges (1) greater than 20.5 cm (2) rainfall between 12.5 cm and up to 20.4 cm (3) rainfall between 6.5 cm and up to 12.4 cm (4) rainfall between 3.5 cm and up to 6.4 cm (5) rainfall between 7.5 mm and up to 34.4 mm (6) light rain between 2.5 mm and 7.4 mm (7) very light rain between 0.1 mm and 2.4 mm), (8) for no rain or less than 0.1 mm rainfall. After image classification procedure as described above the respective element's of patterns are averaged $\overline{A_{ij}}$ and its standard deviation (tolerance structure T_{ij}) generated and archived. This completes the procedure of image registration. A maximum of eight patterns of basic filed and eight tolerance structure fields may be registered for a day. After image registration, a maximum of 365 x 8 such fields and equal number of tolerance structure fields will be available in the database. The system downloads the forecast fields of a Date and match for a pattern from the archived mean pattern of Date ± 15 with in the respective tolerance structure ($\overline{A_{ij}} \pm T_{ij} = B_{ij}$). The scheme is shown in Figure 3b. Once a match is found it will print out the rainfall range for that subdivision.

3. Conclusion

The success of any service depends upon the popularity it earned among the user community. In spite of the advancement in observation, data communication, numerical models, physics and computing technology, we have a long way to go to improve the quality and reliability of quantitative rainfall forecast, as it is the most sought after element for various activities. The challenge will multiply many folds once we narrow it down to block level. The proposed methodology can be fine-tuned by adopting suitable pattern matching algorithms, selection of domain size and analysis of patterns and respective rainfall yields for image classification and image registration. Image registration can also be downscaled by considering a cluster of districts based on homogeneity in rainfall patterns.

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Tables

Table 1: 4x4 contingency table for the number of occasions the forecast (F_i) and Observed (O_i)

Forecast	Observed				
	O_1	O_2	O_3	O_4	Total
F_1	n_{11}	n_{12}	n_{13}	n_{14}	n_{1T}
F_2	n_{21}	n_{22}	n_{23}	n_{24}	n_{2T}
F_3	n_{31}	n_{32}	n_{33}	n_{34}	n_{3T}
F_4	n_{41}	n_{42}	n_{43}	n_{44}	n_{4T}
Total	n_{T1}	n_{T2}	n_{T3}	n_{T4}	n_{TT}

Table 2: Skill scores for rainfall quantity

Element		Correct	Usable	Unusable
Skill score for rainfall quantity (Extracted from report)	Day 1	29	16	55
	Day 2	28	16	56
	Day 3	24	16	60
	Day 4	24	16	60
	Day 5	25	15	60
Skill score for rainfall quantity (at SAMC Thiruvananthapuram)	Day 1	39	9	52
	Day 2	40	9	51
	Day 3	42	5	53
	Day 4	40	8	52
	Day 5	37	10	53

Table 3: Skill scores for Yes/No rainfall

Element		RS	HK	POD	FAR
Skill score for Yes/No rainfall (Extracted from report)	Day 1	81.48	0.26	0.91	0.14
	Day 2	78.46	0.22	0.87	0.15
	Day 3	76.37	0.13	0.86	0.17
	Day 4	75.5	0.11	0.85	0.17
	Day 5	78.02	0.21	0.86	0.15
Skill score for Yes/No rainfall (at SAMC Thiruvananthapuram)	Day 1	81.45	0.34	0.79	0.36
	Day 2	79.57	0.30	0.72	0.36
	Day 3	79.98	0.29	0.73	0.40
	Day 4	79.60	0.31	0.71	0.33
	Day 5	78.01	0.31	0.67	0.38

Table 4: State level verification of MME and value added products

Element	Verification of MME forecast (Extracted from report)					Verification after value addition (at SAMC Thiruvananthapuram)			
		RMSE	Correct	Usable	Unusable	RMSE	Correct	Usable	Unusable
Skill score for Maximum temperature	Day 1	2.85	19.33	23.52	57.14	1.06	70	22	8
	Day 2	2.90	18.35	23.71	57.92	1.39	68	20	12
	Day 3	3.01	15.32	16.02	68.65	1.37	62	28	10
	Day 4	3.09	14.34	15.62	70.02	1.36	65	22	13
	Day 5	3.11	14.44	14.94	70.61	1.60	59	25	16
Skill score for Minimum temperature	Day 1	1.92	33.85	29.64	36.49	1.16	78	18	4
	Day 2	1.91	34.80	28.80	36.20	1.10	79	17	4
	Day 3	2.29	18.10	32.50	49.31	1.06	68	22	10
	Day 4	2.26	20.30	30.60	49.01	1.26	66	24	10
	Day 5	2.23	19.70	31.80	48.41	1.20	70	23	7
Skill score for cloud amount	Day 1	1.57	88.10	9.12	2.76	1.67	86	10	4
	Day 2	1.47	87.44	9.22	3.33	1.75	83	14	3
	Day 3	1.70	87.30	8.21	4.39	1.71	79	15	6
	Day 4	1.80	85.40	8.68	5.87	1.68	76	19	5
	Day 5	1.79	84.70	9.61	5.68	1.86	79	16	5
Skill score for Maximum Relative Humidity	Day 1	7.39	82.51	17.18	0.29	2.74	81	19	0
	Day 2	7.48	81.97	17.72	0.29	2.49	78	20	2
	Day 3	9.42	67.72	31.78	0.48	2.47	80	19	1
	Day 4	9.33	68.13	31.47	0.38	2.56	76	22	2
	Day5	9.52	65.88	33.33	0.78	2.55	82	17	1
Skill score for Minimum Relative Humidity	Day 1	10.52	67.77	26.76	5.46	2.66	82	17	1
	Day 2	10.24	67.30	29.01	3.67	2.64	83	16	1
	Day 3	13.01	56.21	31.71	12.06	2.69	82	15	3
	Day 4	13.31	54.89	30.44	14.66	2.67	82	15	3
	Day 5	13.36	55.89	29.19	14.91	2.78	83	14	3
Skill score for wind speed	Day 1	10.62	49.12	30.99	19.88	4.93	62	38	0
	Day 2	9.77	52.63	31.67	15.69	5.85	60	40	0
	Day 3	12.55	35.47	31.77	32.74	5.94	64	36	0
	Day 4	12.47	37.13	31.28	31.57	5.95	62	38	0
	Day5	12.07	38.40	31.09	30.50	5.91	67	33	0
Skill score for wind direction	Day 1	79.51	32.64	7.36	59.98	43.08	64	10	26
	Day 2	85.36	28.57	7.93	63.48	47.49	65	5	30
	Day 3	57.20	45.89	10.63	43.47	50.55	67	3	30
	Day 4	59.33	45.30	10.80	43.89	49.37	62	9	29
	Day 5	57.83	45.81	9.89	44.28	49.51	64	7	29

Table 5: NCEP composite mean Omega (Pa/s) at 850mb on 1st July 2014

Omega (Pa/s) at 850 hPa		Longitude (Degree East)					
		70.0-72.5	72.5-75.0	75.0-77.5	77.5-80.0	80.0-82.5	82.5-85.0
Latitude (Degree North)	18.5-21.0	-0.065	-0.033	0.009	0.006	-0.031	-0.051
	16.0-18.5	-0.054	-0.023	0.018	0.013	-0.031	-0.062
	13.6-16.0	-0.027	-0.012	0.026	0.033	0.000	-0.031
	11.1-13.6	-0.014	-0.024	0.004	0.028	0.026	0.018
	08.6-11.1	-0.020	-0.048	-0.039	-0.012	0.011	0.035
	06.2-08.6	-0.012	-0.039	-0.050	-0.043	-0.016	0.026
	03.7-06.2	0.007	-0.007	-0.031	-0.046	-0.028	0.021

Table.6: NCEP composite mean Omega (Pa/s) at 850mb on 31st July 2014

Omega (Pa/s) at 850 hPa		Longitude (Degree East)					
		70.0-72.5	72.5-75.0	75.0-77.5	77.5-80.0	80.0-82.5	82.5-85.0
Latitude (Degree North)	18.5-21.0	-0.172	-0.197	-0.161	-0.071	0.004	0.018
	16.0-18.5	-0.237	-0.261	-0.180	-0.040	0.033	-0.013
	13.6-16.0	-0.167	-0.198	-0.104	0.046	0.089	-0.017
	11.1-13.6	-0.067	-0.123	-0.053	0.075	0.097	-0.014
	08.6-11.1	-0.022	-0.096	-0.066	0.025	0.041	-0.036
	06.2-08.6	-0.004	-0.068	-0.065	-0.014	-0.006	-0.053
	03.7-06.2	0.023	-0.009	-0.019	-0.003	-0.002	-0.033

Table 7: Forecast for 1st July 2014 and its realized rain fall (mm).

Districts	Rainfall Realized	MME Forecast	SAMC Forecast
Thiruvananthapuram	3	18	18
Kollam	8	17	17
Pathanamthitta	23	22	22
Alappuzha	5	19	19
Kottayam	19	30	30
Idukki	13	44	44
Ernakulam	26	25	25
Thrissur	22	20	20
Palakkad	3	15	15
Malappuram	8	12	12
Kozhikode	23	15	15
Wayanad	5	19	19
Kannur	19	17	17
Kasaragod	13	14	14

Table 8: Forecast for 31st July 2014 and its realized rain fall (mm).

Districts	Rainfall Realized	MME Forecast	SAMC Forecast
Thiruvananthapuram	49	25	25
Kollam	40	32	32
Pathanamthitta	83	34	34
Alappuzha	67	30	30
Kottayam	114	33	33
Idukki	87	38	38
Ernakulam	95	31	31
Thrissur	99	27	27
Palakkad	93	23	23
Malappuram	83	35	35
Kozhikode	75	42	42
Wayanad	77	56	56
Kannur	132	45	45
Kasaragod	152	22	22

Figures

Figure Legends

Figure 1: Performance of district level rainfall forecasts for some selective states

Figure 2: Percentage correctness of MME and value added forecasts for Kerala.

Figure 3a: Scheme A for QPF.

Figure 3b: Scheme B for QPF.

Figure 4: NCEP composite mean Omega (Pa/s) at 850mb for 1st July 2014

Figure 5: NCEP composite mean Omega (Pa/s) at 850mb for 31st July 2014

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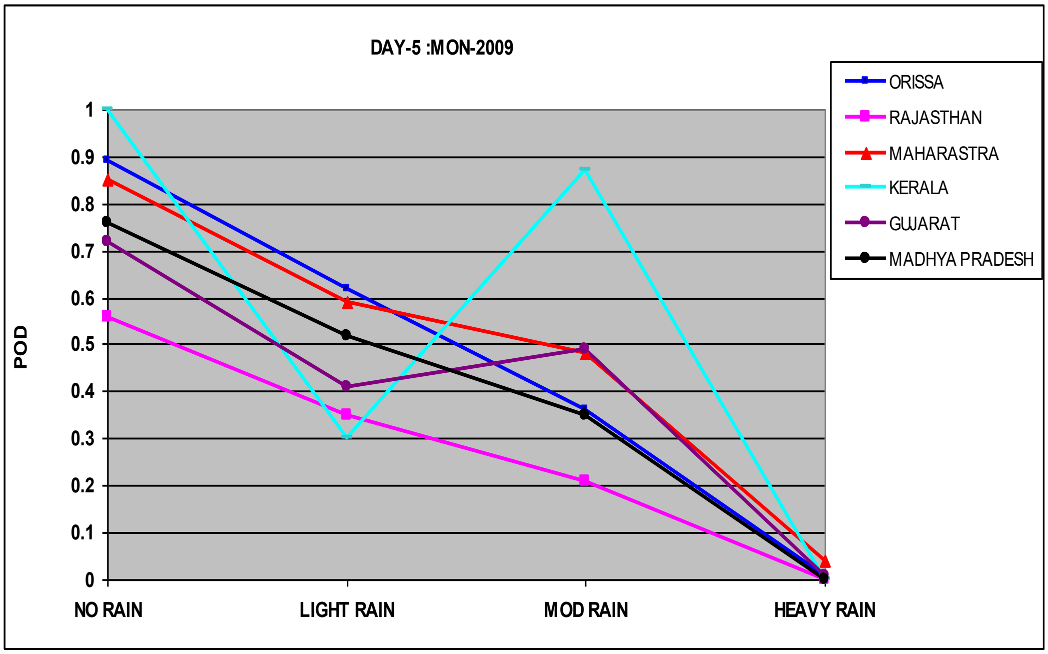

Figure 1: Performance of district level rainfall forecasts for some selective states

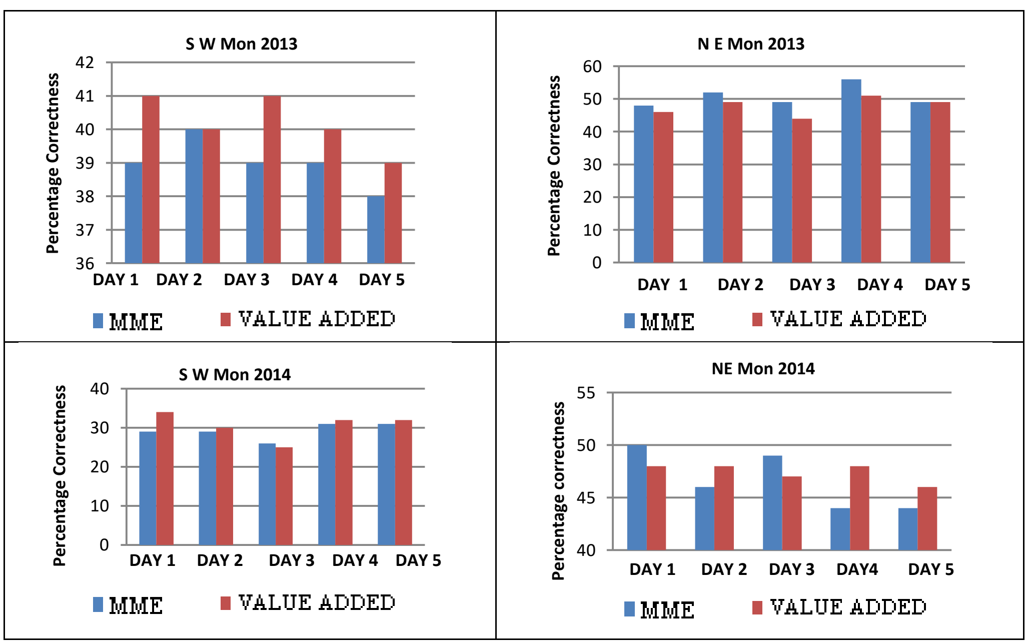

Figure 2: Percentage correctness of MME and value added forecasts for Kerala.

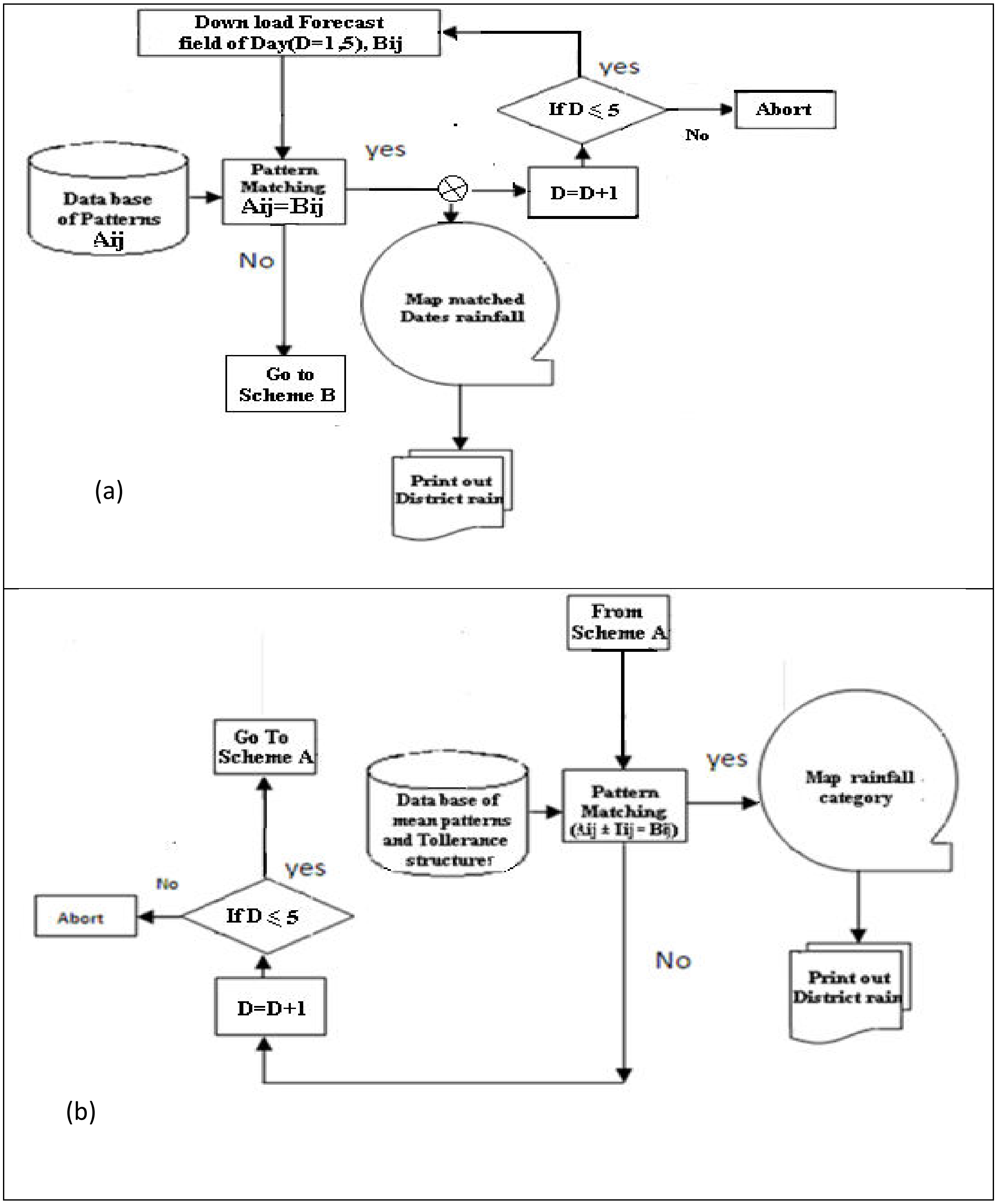

Figure 3: (a) Scheme A for QPF (b) Scheme B for QPF

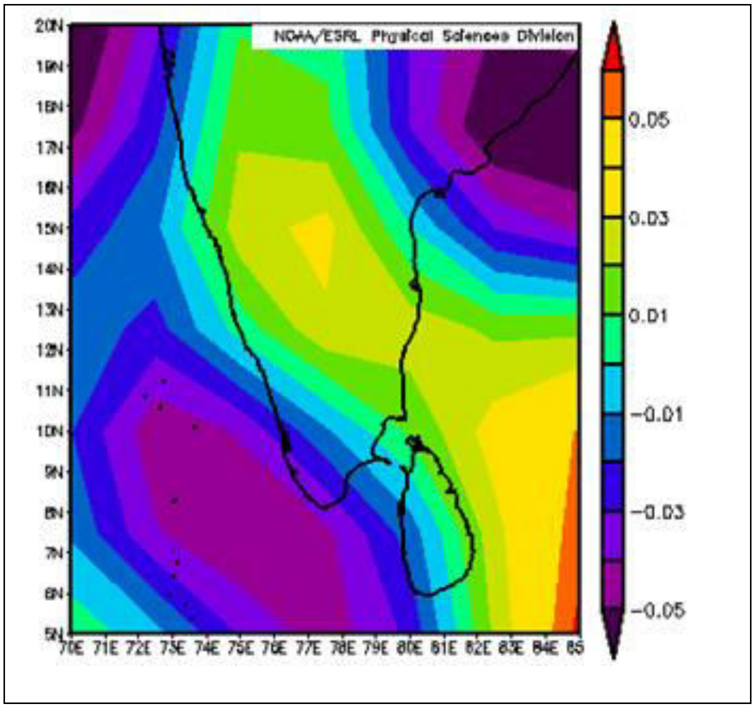

Figure 4: NCEP composite mean Omega (Pa/s) at 850mb for 1st July 2014

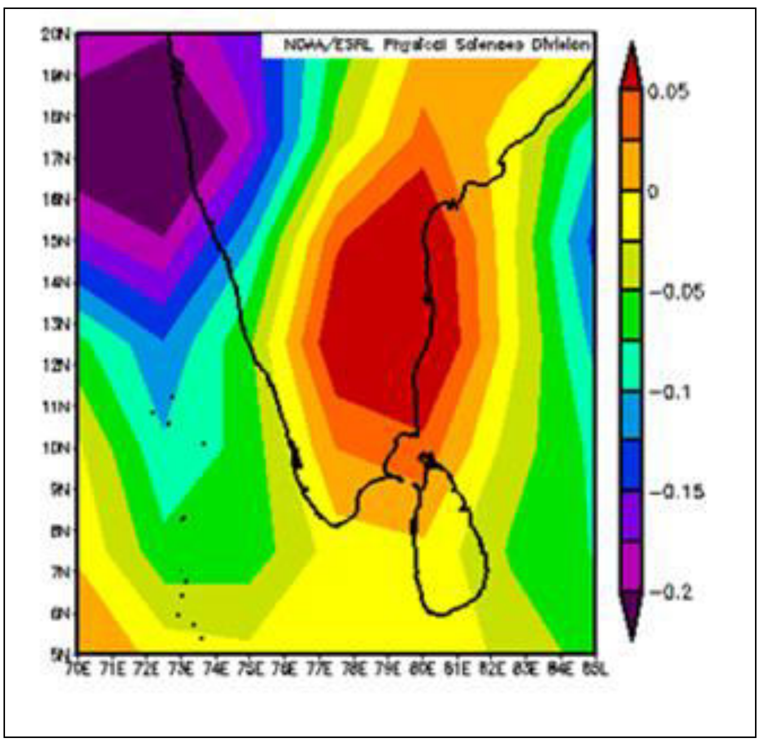

Figure 5: NCEP composite mean Omega (Pa/s) at 850mb for 31st July 2014