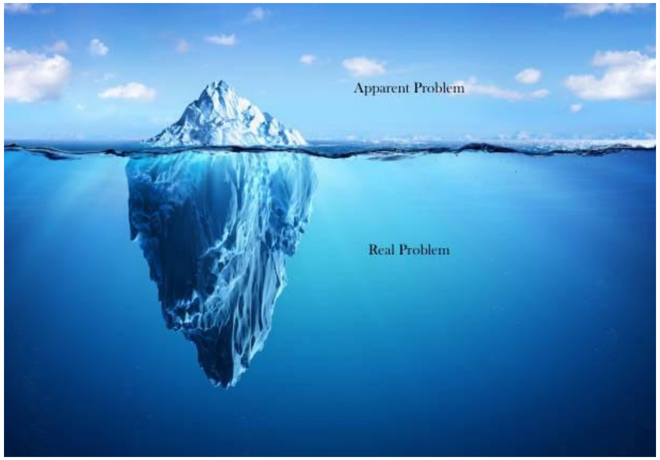
NCMRWF Model Based Probabilistic Forecast Products

Raghavendra Ashrit
NCMRWF

Deterministic Forecasts

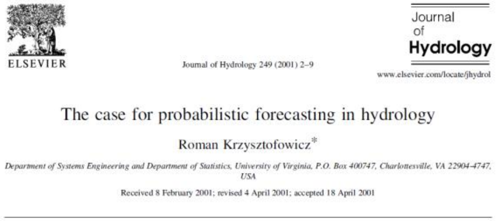
- Our models cannot predict the future perfectly.
  - so we optimize them to push the prediction error down as far as we can go.
  - Better models, hopefully, lead to smaller errors.

- building a model for the uncertainty part of the problem (the area of the iceberg) we cannot see.
  - Quantifying the uncertainty will allow us to amend the point predictions (= best guesses) with deviation estimates and, ultimately, will lead to better and more robust models



Why Probabilistic forecasts?

- Deterministc forecast: Specifies a point estimate of a predictand.
  - Forces the forecaster to suppress information on uncertainty.
  - Creates an illusion of certainty in users mind.
  - Leading to suboptimal action
  - Wrong forecasts can cause economic losses
- Probabilistic forecast: specifies a probability distribution function(pdf) of predictand.
- Probabilistic forecasts decouple
  - Forecasting : which might involve principles of Science
  - Decision making: which involve decision maker’s evaluation of consequences of alternative actions and events
- Probabilistic predictions, unify point prediction and uncertainty modeling in one consistent framework.
- Using probabilistic prediction models we can calculate best-guess predictions and derive the “safety buffers” that, together, result in well informed decisions



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The case for probabilistic forecasting in hydrology

Roman Krzysztofowicz*

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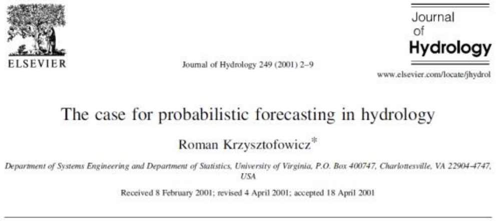
Received 8 February 2001; revised 4 April 2001; accepted 18 April 2001

Benefits of Probabilistic forecasts

- There are four potential benefits:
  - Probabilistic forecasts are scientifically honest since they allow the forecaster to admit the uncertainty and express the degree of certainty/uncertainty
  - Enable an authority to set risk-based monitoring and warning and emergenct response.
  - They apprise the user of uncertainty (necessary evil) for making rational decision, enabling the user to take risk into account.
  - Potential for economic benefits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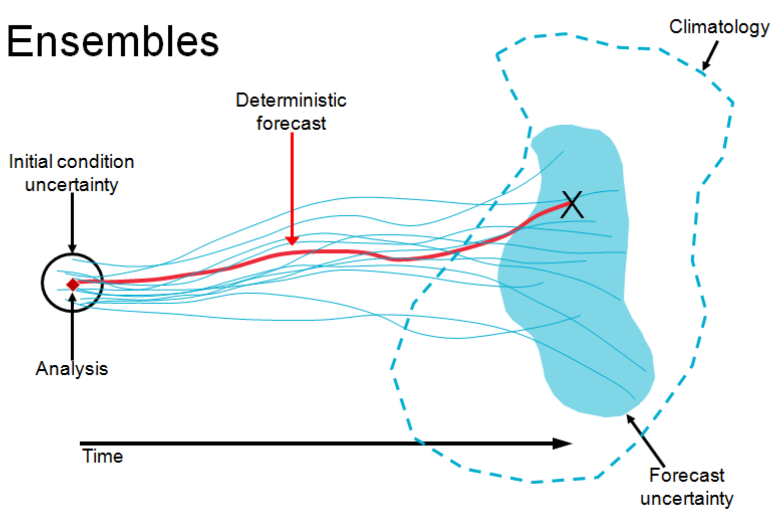
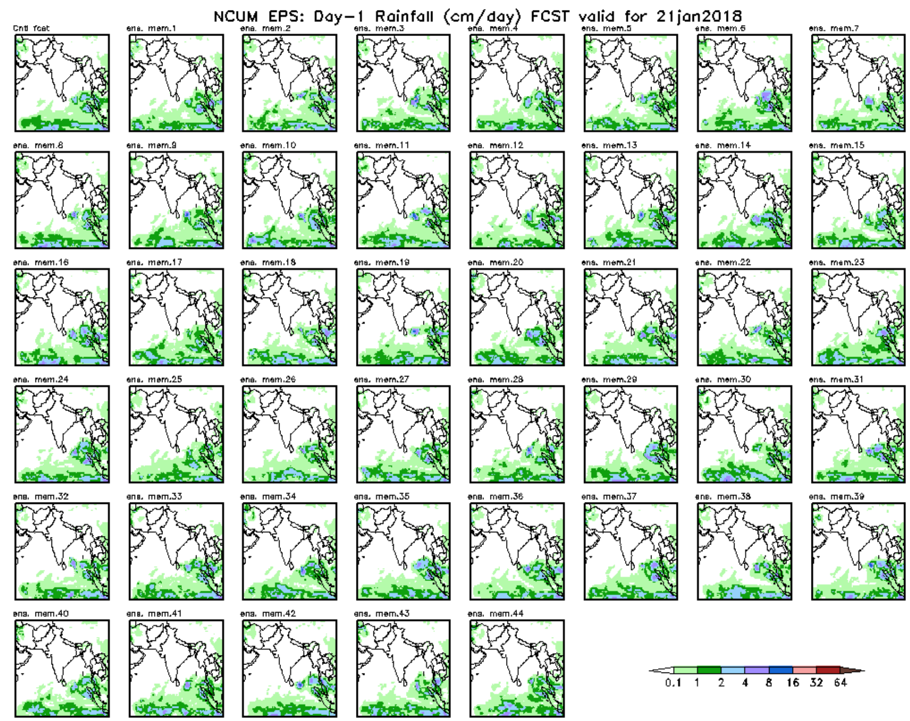
NCMRWF Ensemble Forecasting System (NEPS)

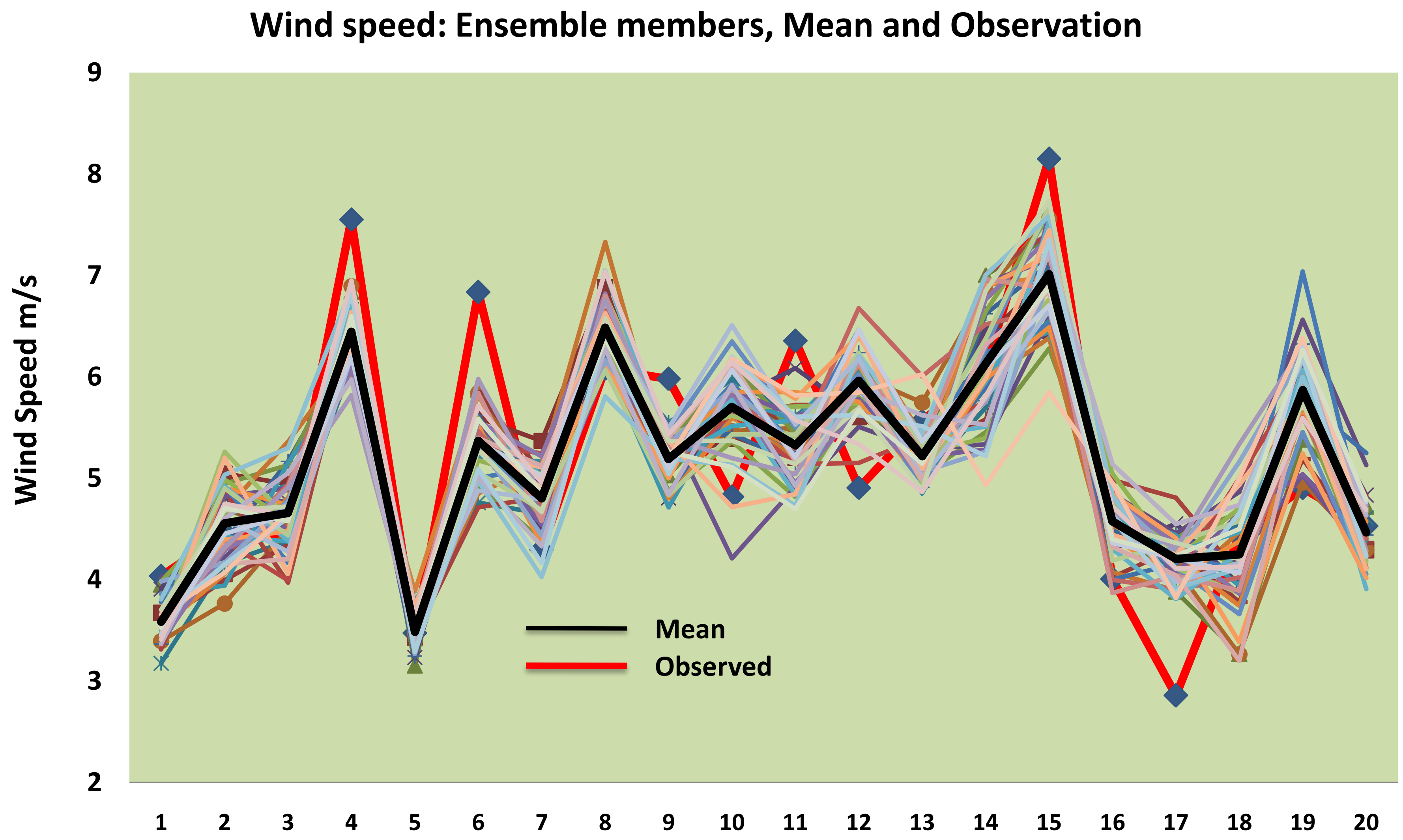
- What is an ensemble forecast?
  - Instead of running just a single forecast, the computer model is run a number of times from slightly different starting conditions. The complete set of forecasts is referred to as the ensemble, and individual forecasts within it as ensemble members.
  - Ensemble forecast systems are designed so that each member should be equally likely.



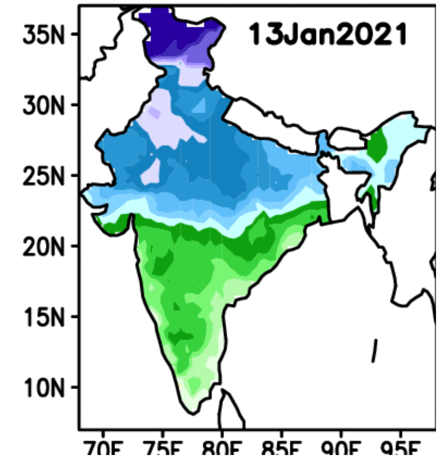


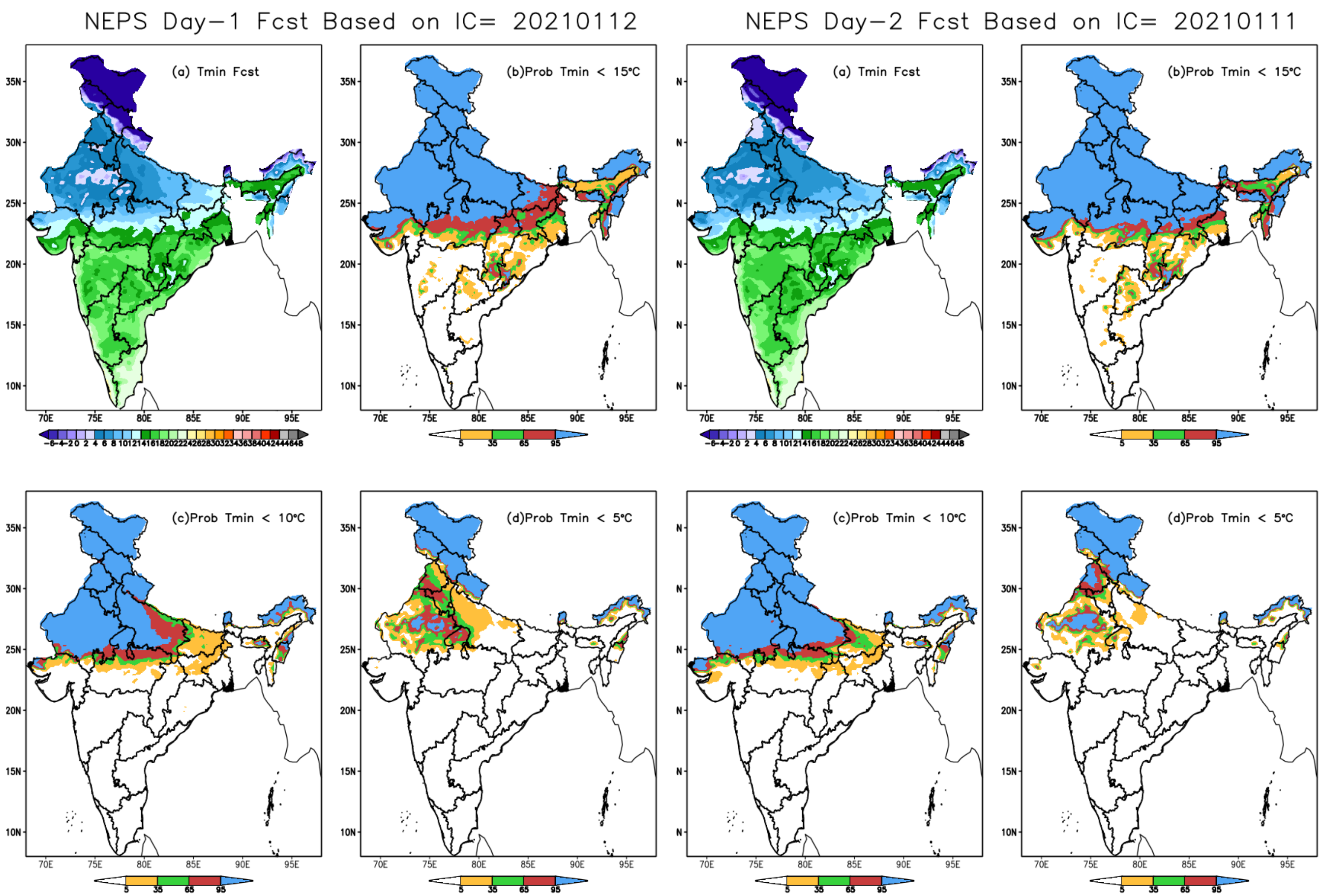
Ensemble Prediction System

Ensemble Members forecast at 6 hour interval



Probabilistic Forecast of recent cold wave





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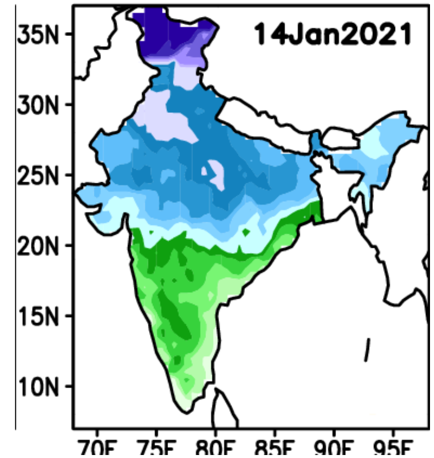
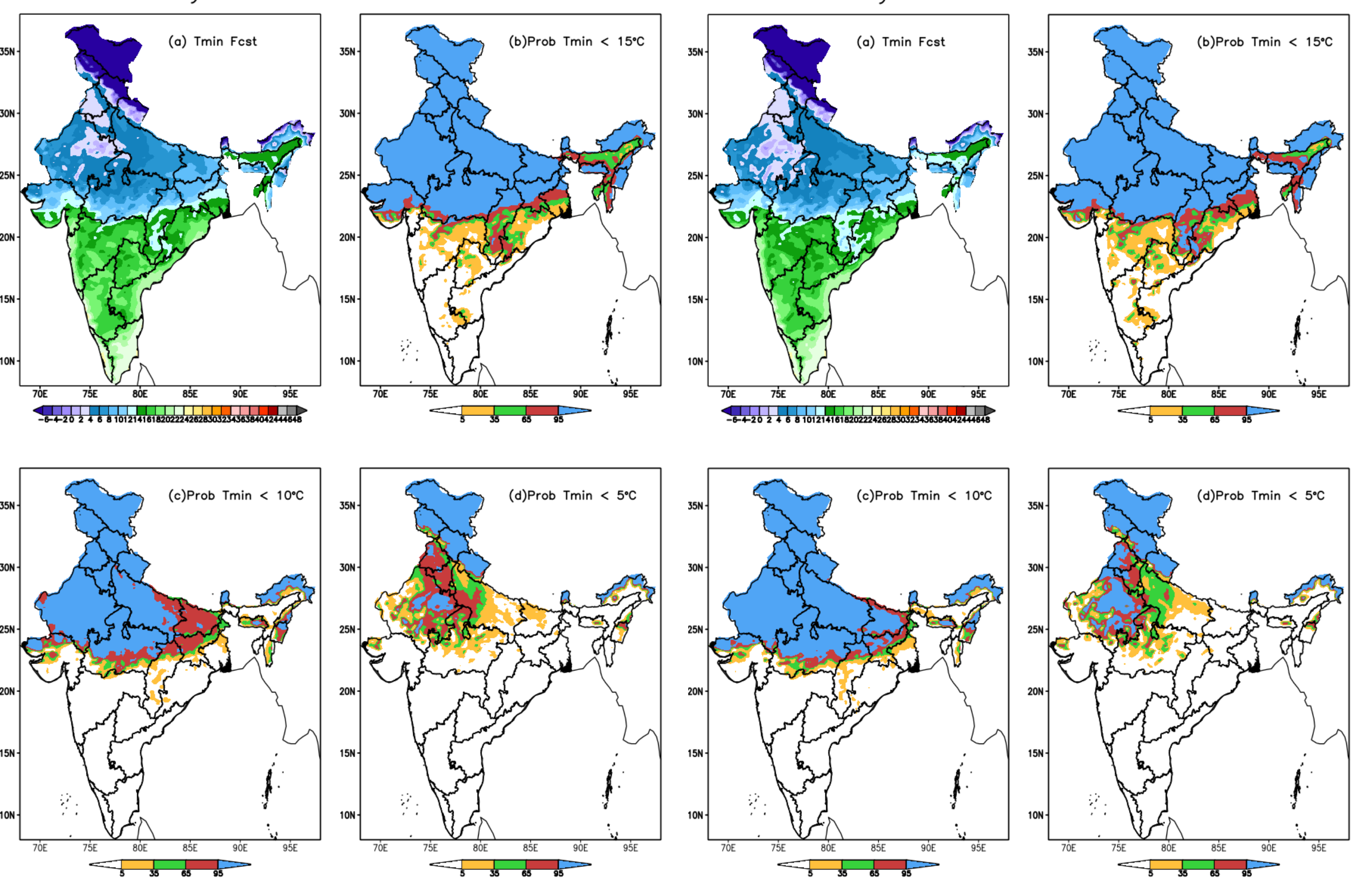
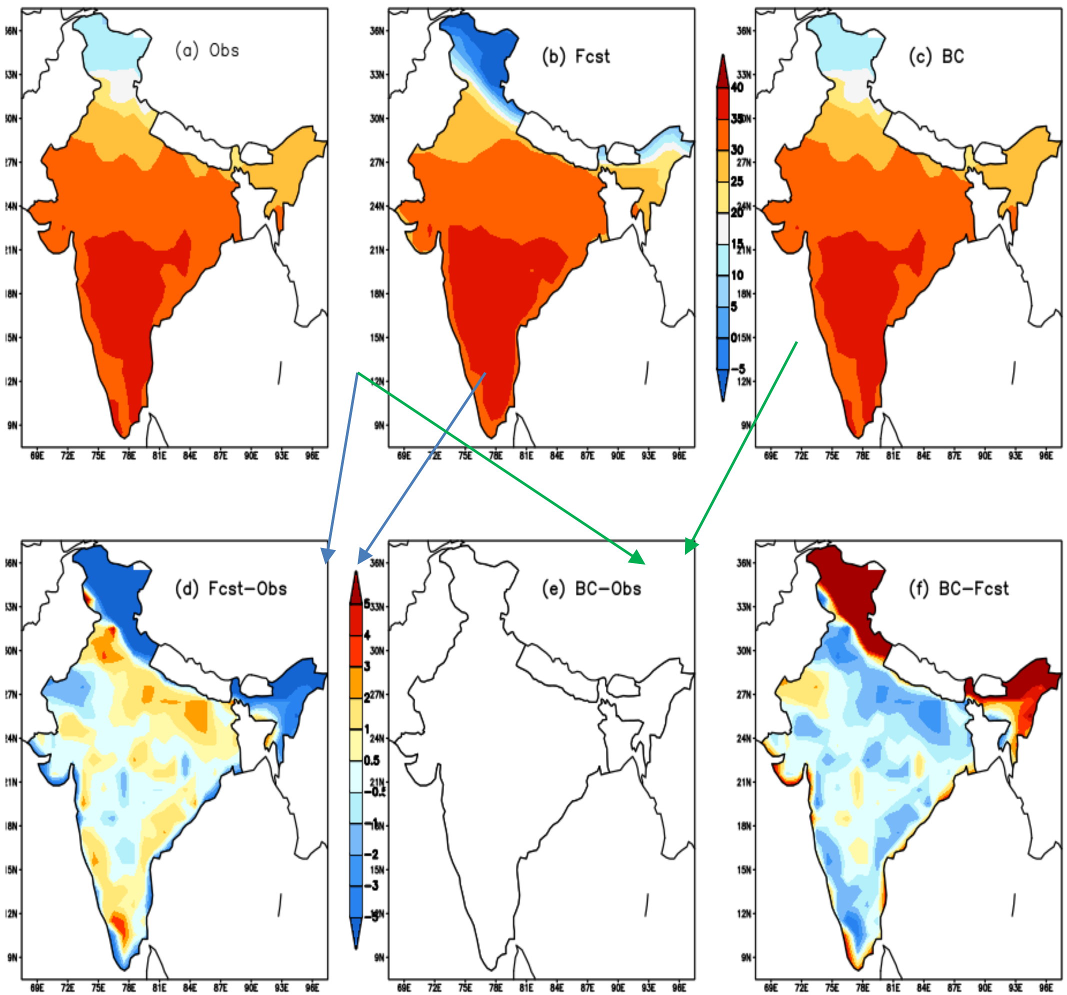


NEPS Day−1 Fcst Based on IC= 20210113

NEPS Day−2 Fcst Based on IC= 20210112



Bias Correction in NEPS Tmax
Mean Error in Tmax (Day-3) Mar 2019



$$F_{bc}(t) = F(t) - Bias(t)$$

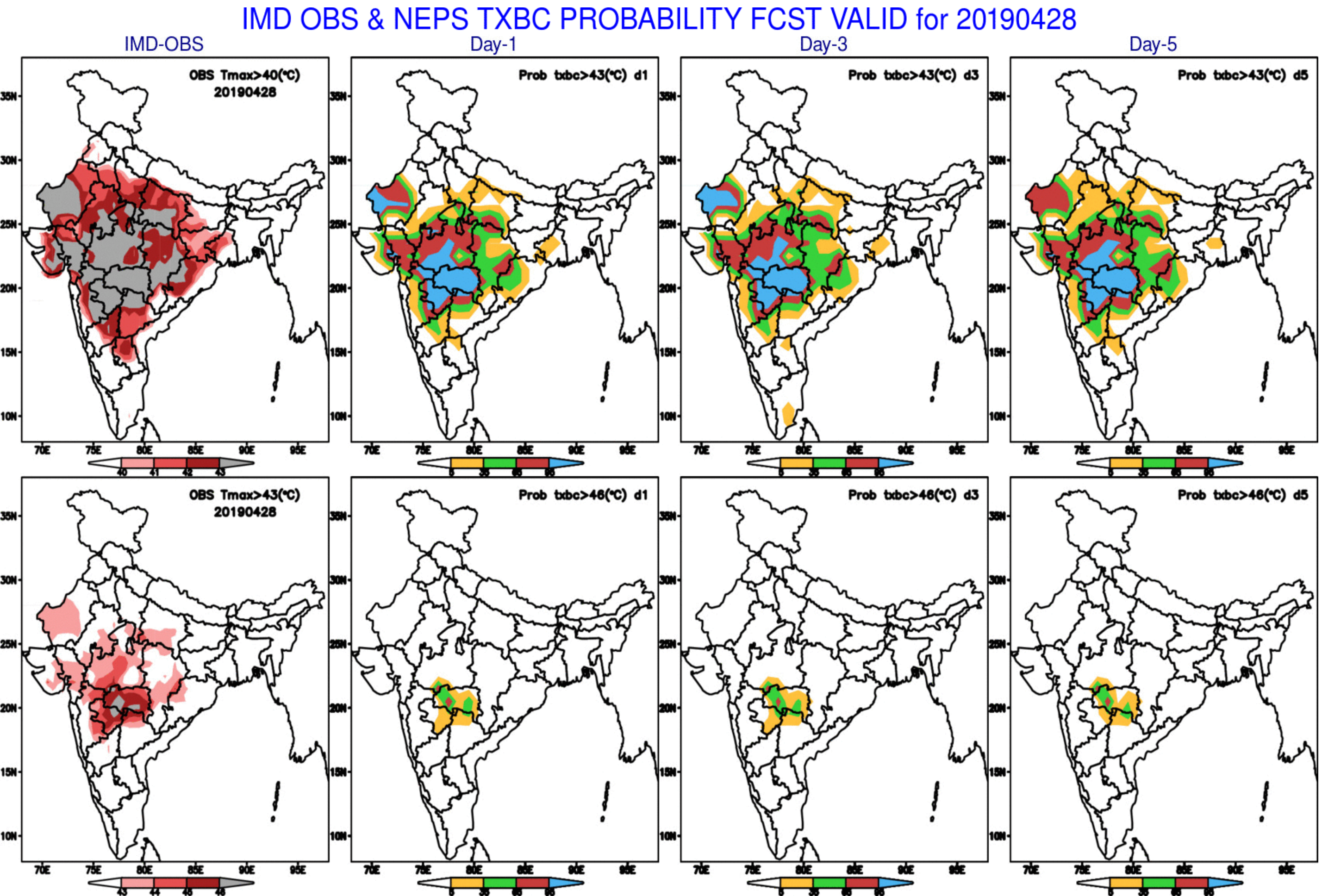
$$BIAS(t) = (1 - w) \times b(t-1) + B$$

$$B = \frac{1}{N}\sum_{1}^{30}(F_i - O_i)$$

- adaptive [Kalman filter type (KF)] algorithm to accumulate the decaying averaging bias
- This method allows the incorporation of the most recent behaviour of the system into the estimation of the bias [Cui et al., 2012; Glahn, 2012]

NEPS: Bias Corrected ProbTx

28th Apr-4th May Western & Central India

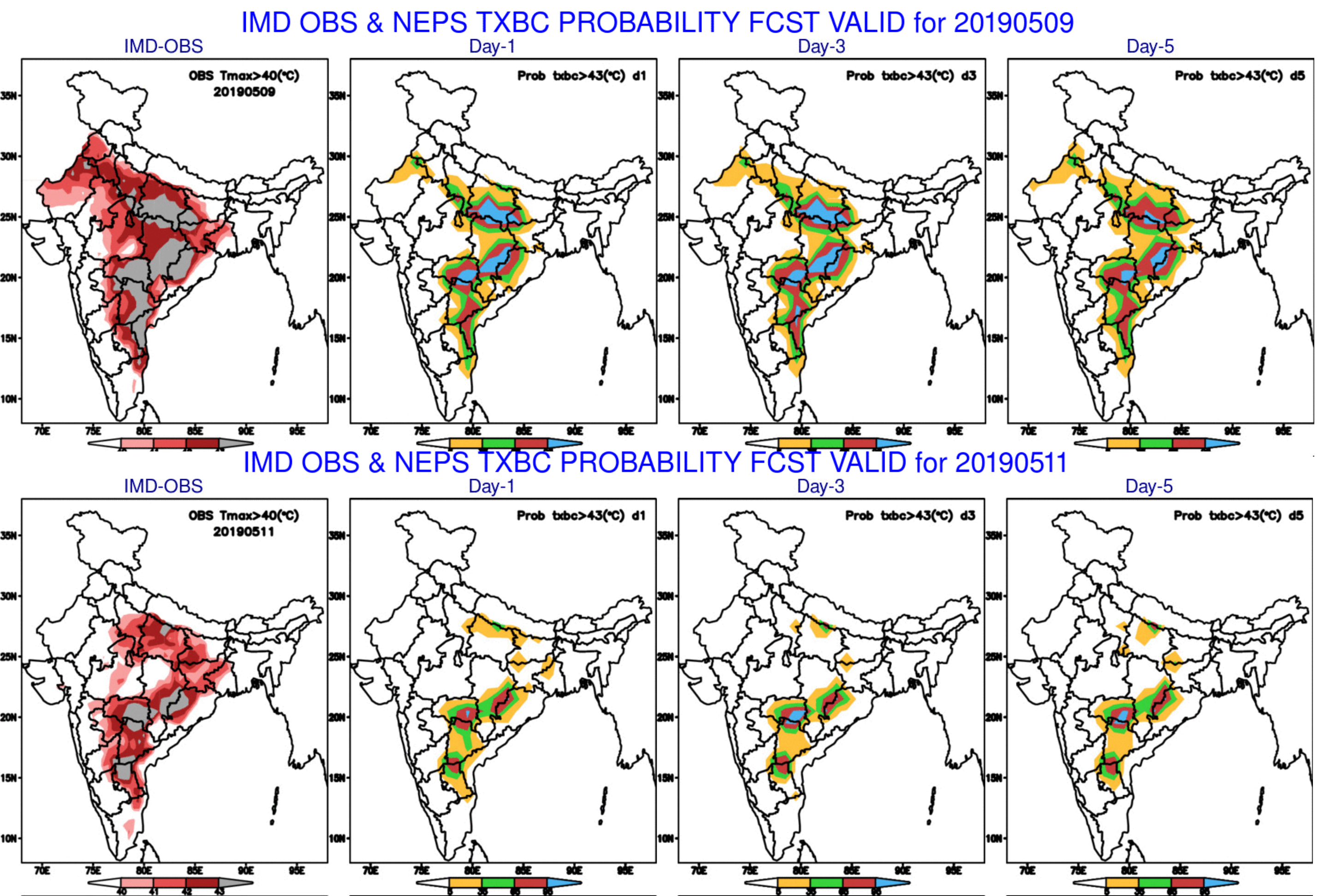


Tmax >43 over large area of western and central India
Forecast probability > 65% and 95%

Tmax >46 over central peninsula
Forecast probability > 35%

NEPS: Bias Corrected ProbTx

9-11th May N India and Eastern



Tmax >43 over Northern and eastern India
Forecast probability > 65% and 95%

Tmax >43 reduced over Northern India
Limited to eastern India
Forecast probability > 65% and 95%

Extreme Forecast Index (EFI)

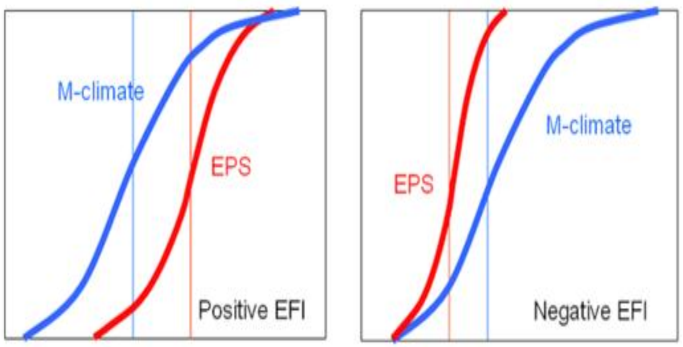
- At the ECMWF, one tool that condenses the forecast information from the Integrated Forecasting System ensemble (ENS) is the extreme forecast index (EFI)
- EFI is an index that highlights regions that are forecast to have potentially anomalous weather conditions

Calculating the Extreme Forecast Index (EFI)

The Extreme Forecast Index is calculated according to the formula:

$$EFI = \frac{2}{\pi}\int_0^1 \frac{p-F_f(p)}{\sqrt{p(1-p)}}\mathrm{dp}$$

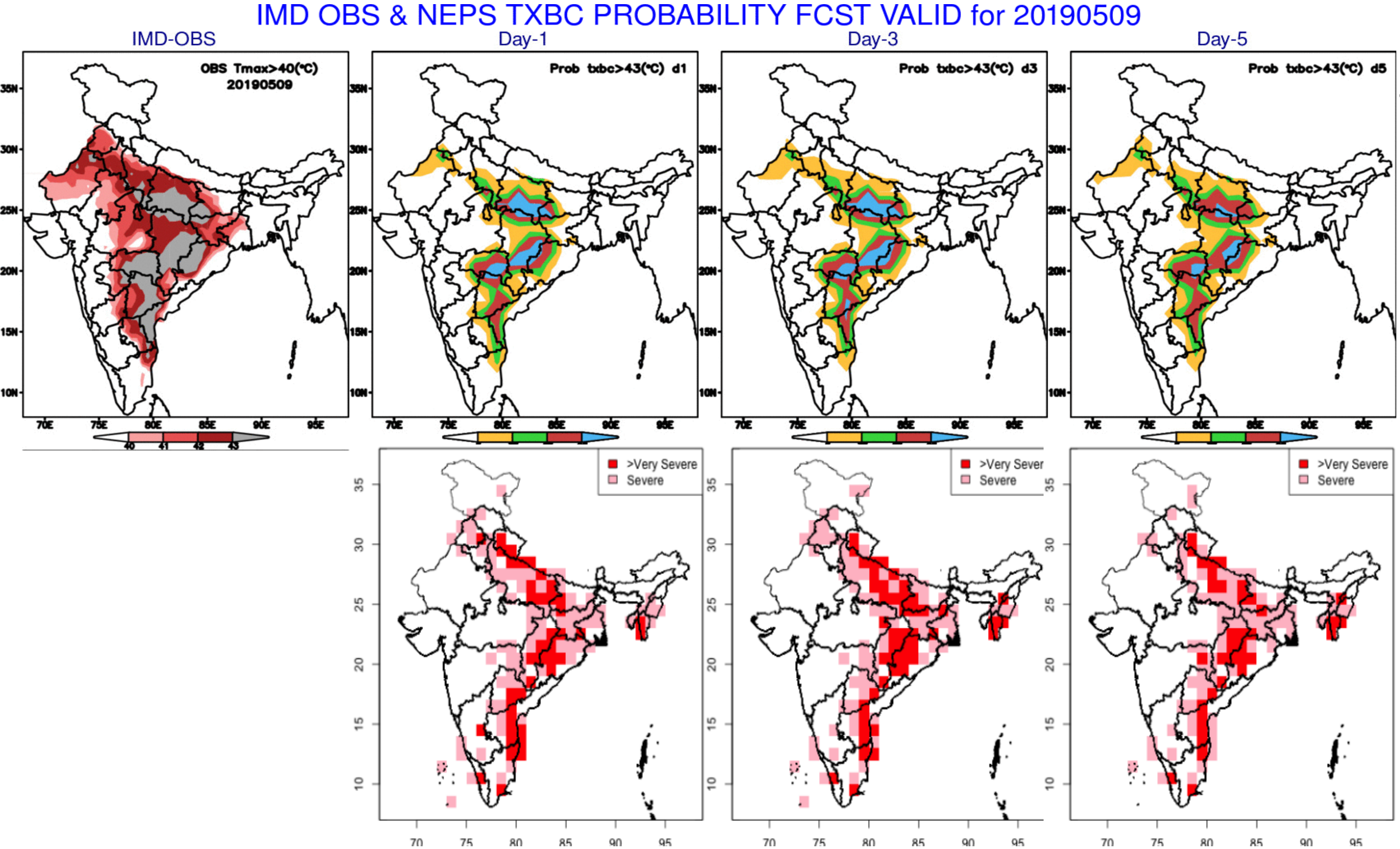
where Ff(p) denotes the proportion of EPS (ensemble prediction system) members lying below the p quantile of the climate record. The EFI is computed for many weather parameters, for different forecast ranges and accumulation periods.



- **EFI=0:**
  - **The probability distribution agrees with the M-climate distribution.**
- **If the probability distribution (mean, spread and asymmetry) does not agree with the climate probability distribution, the EFI takes non-zero values.**
- **EFI=+1:**
  - **all the members forecast values above the absolute maximum in the M-climate,**
- **EFI = -1:**
  - **all forecast values below the absolute minimum in the M-climate**

Extreme Forecast Index (EFI)

9-11th May N India and Eastern

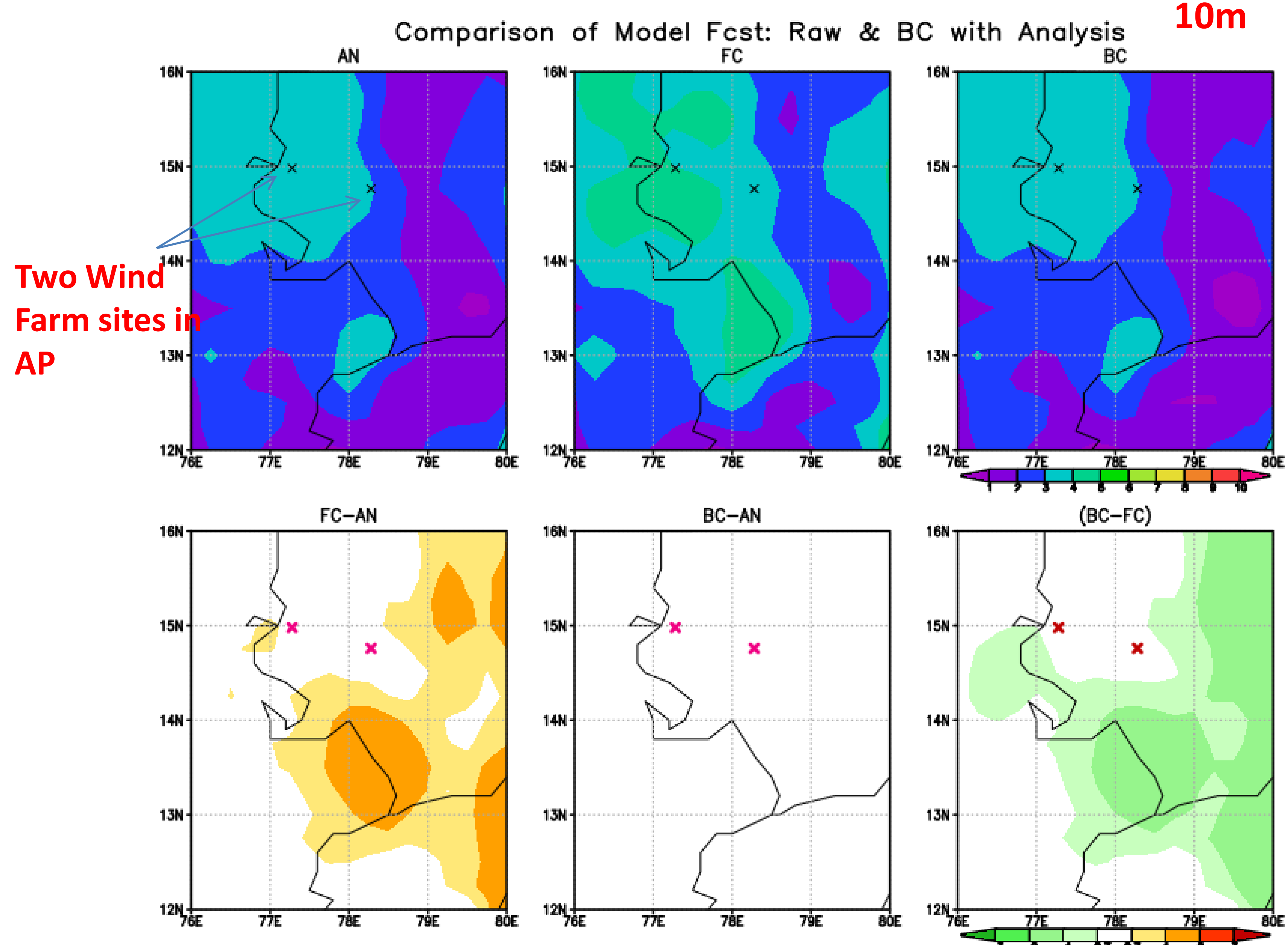


Tmax >43 over Northern and eastern India Forecast probability > 65% and 95%

NCMRWF Forecast 10m and 925 hPa WS over S India

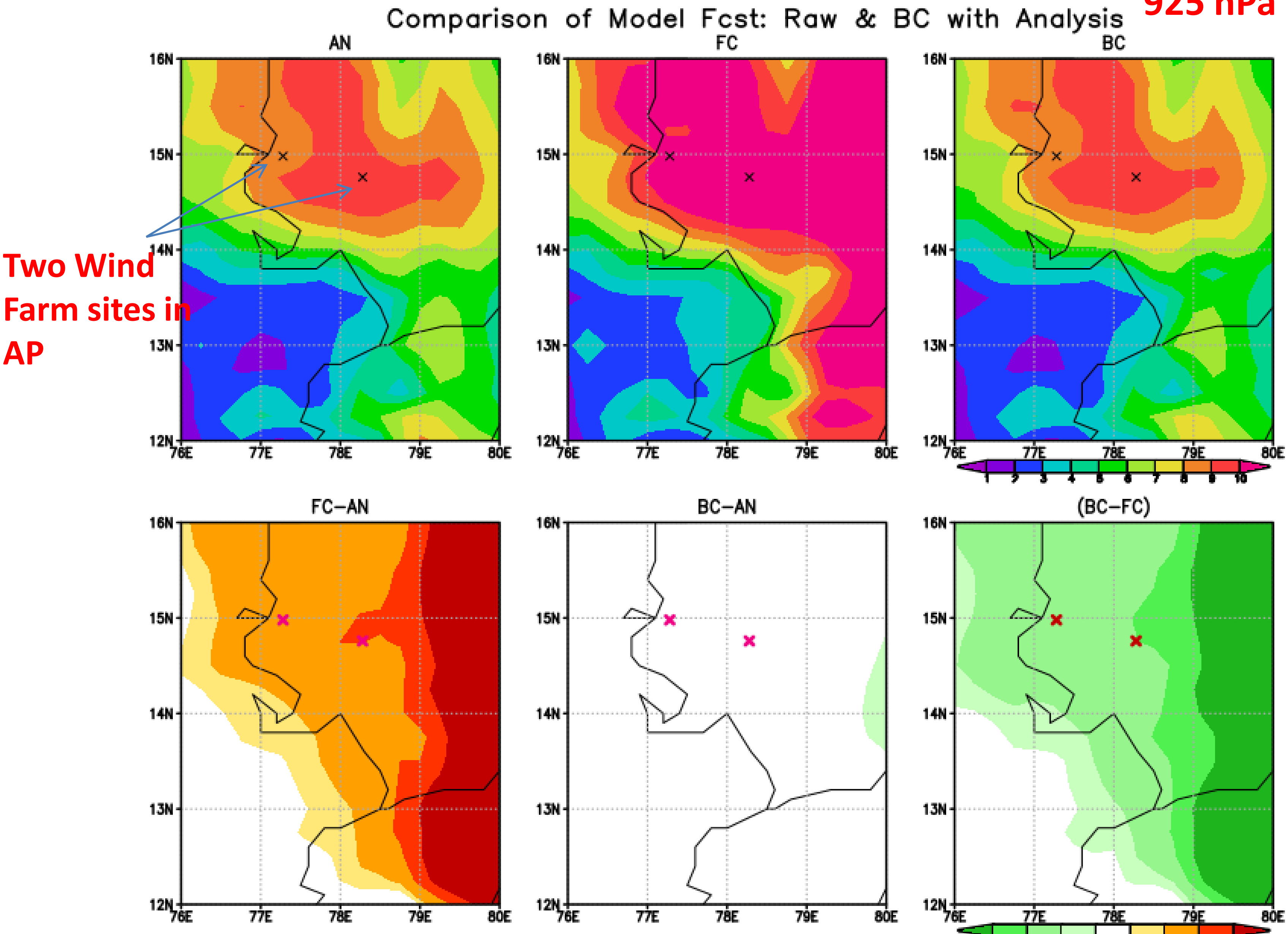
Analysis, Raw and Bias Corrected Forecasts

Wind Speed 10m



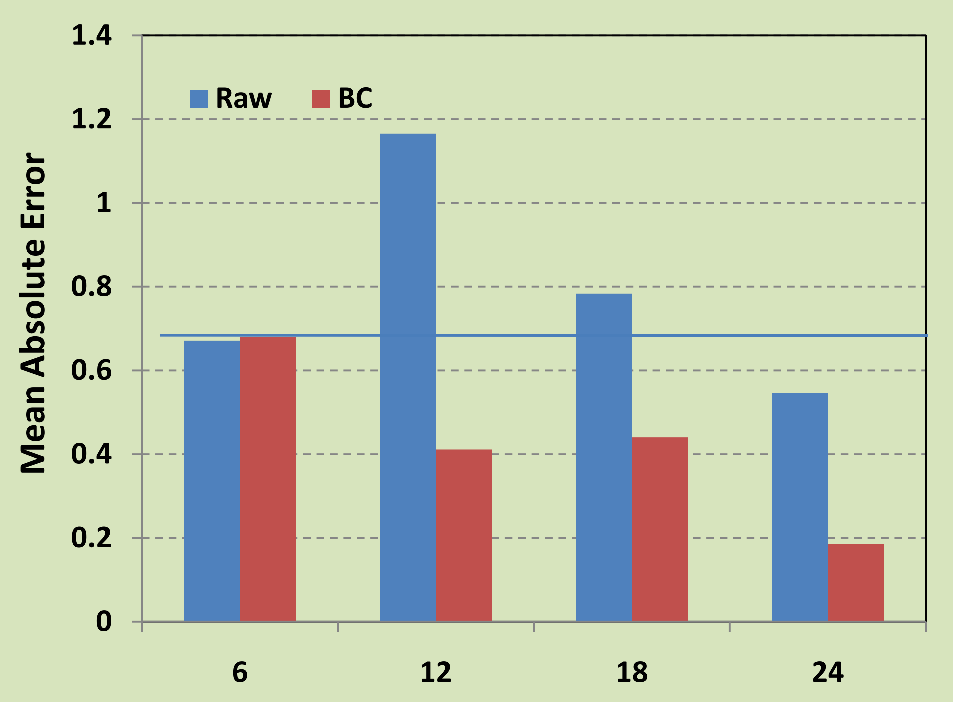
NCUM Analysis and 24h FCST Mean (Apr-Jun)

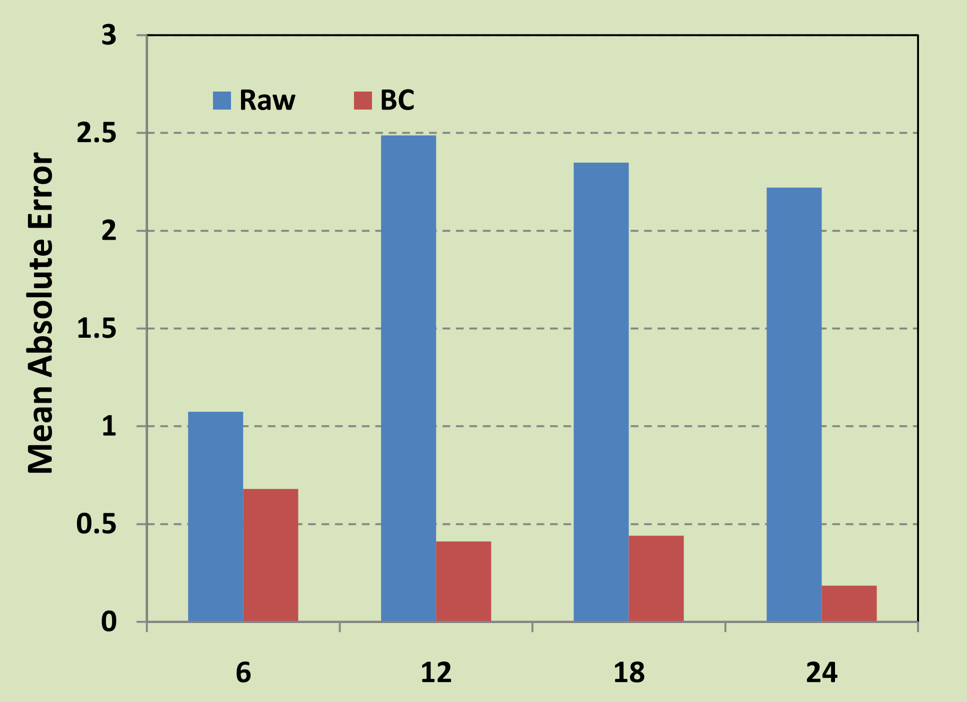
Wind Speed
925 hPa



NCUM Analysis and 24h FCST Mean (Apr-Jun)

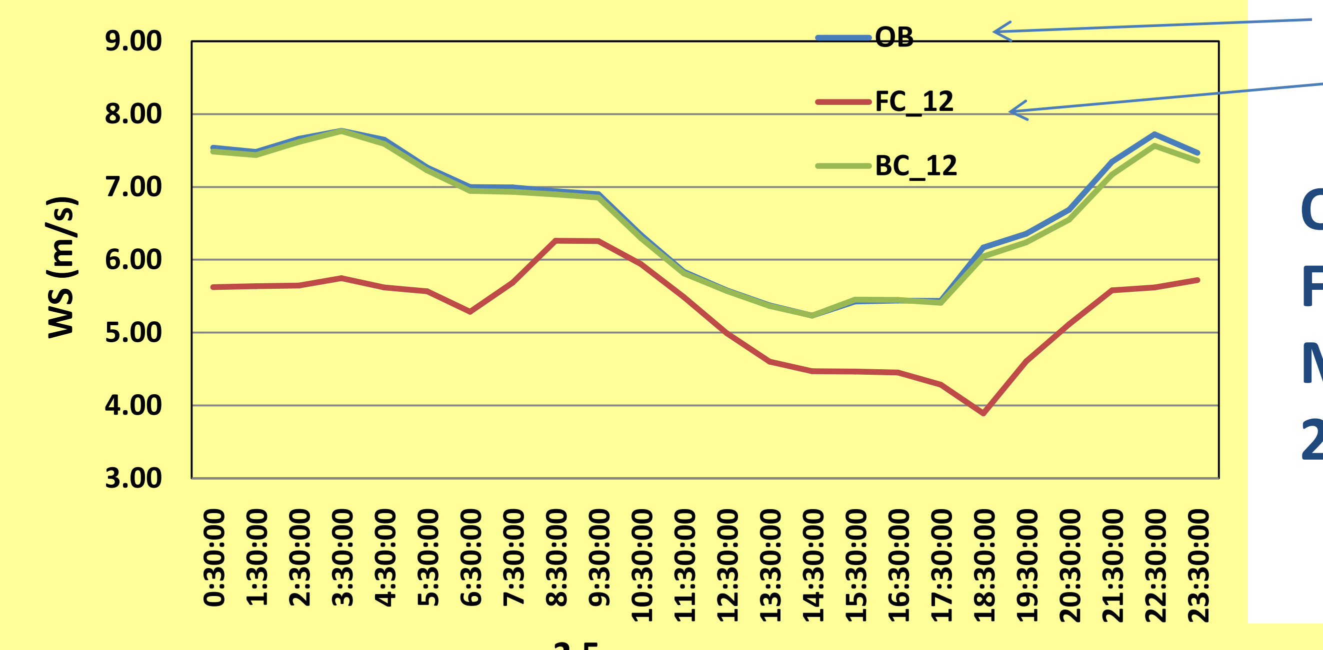
Impact of BC : Reduced MAE in the 10m (L) & 925 hPa (R) Wind Speed



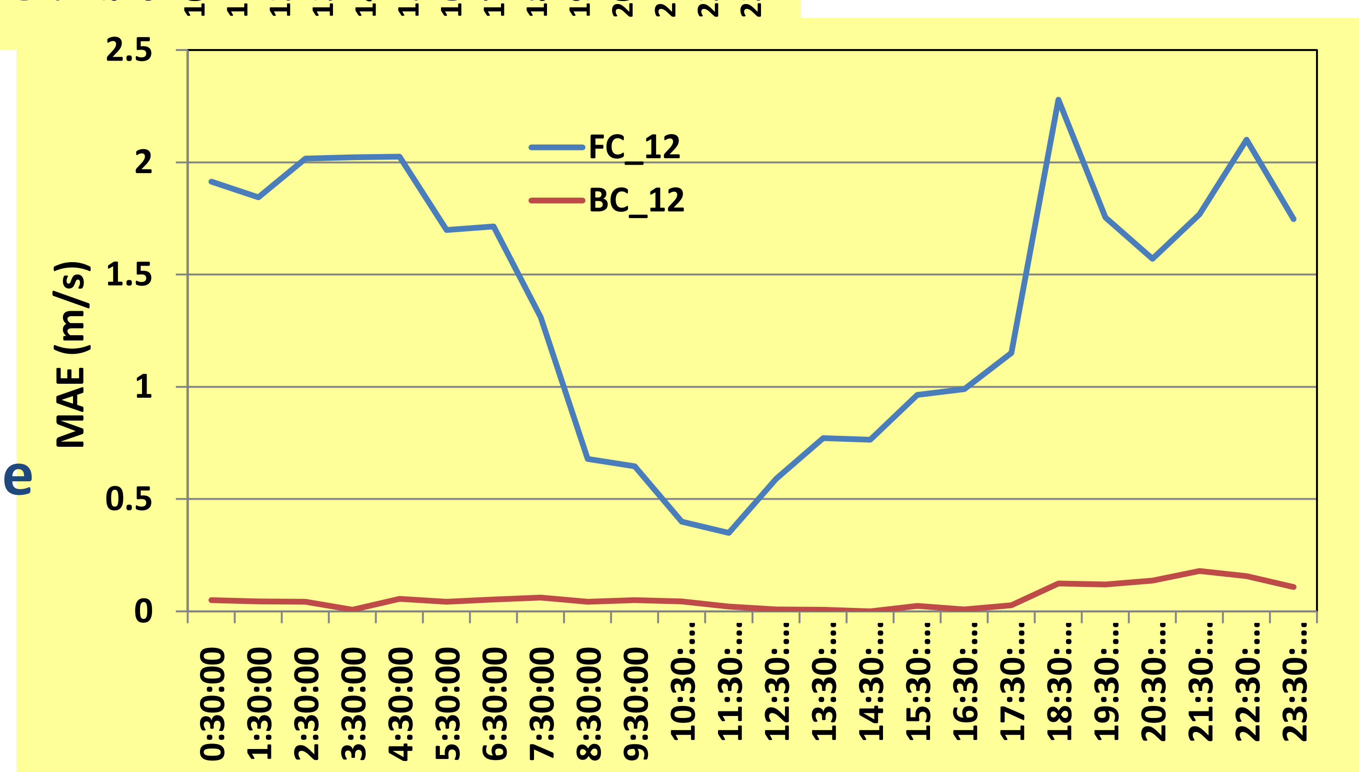


•MEA Reduction by-
•65%, 44% and 66% in 12h, 18h and 24h forecasts

•MEA Reduction by-
•75%, 79% and 79% in 12h, 18h and 24h forecasts

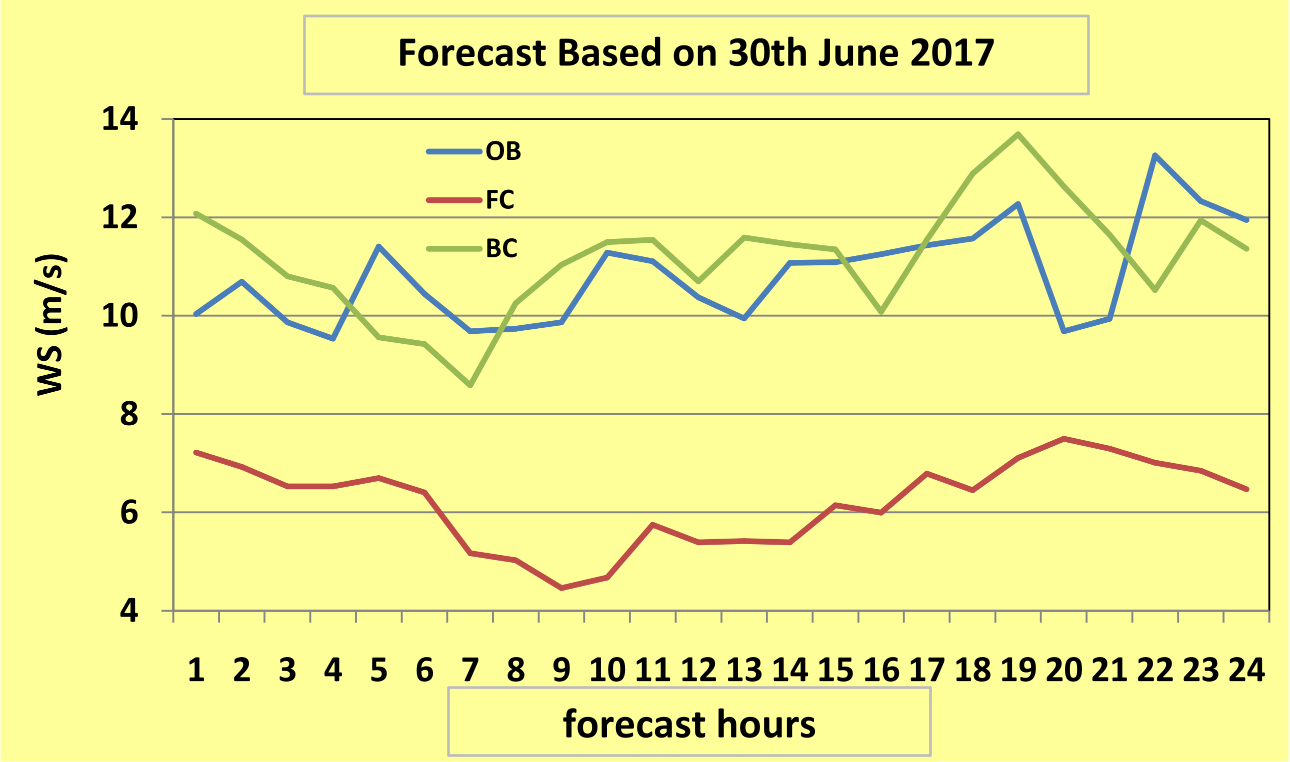


Observed and Forecast Wind: Mean (Apr-Jun 2017) Diurnal Cycle



Observed and Forecast Wind: MAE (Apr-Jun 2017) Diurnal Cycle

Forecast on a Typical day (South India : AP)



PQPF for Different FMOs

Based on NEPS

Ensemble Forecast Product for Flood Advisory

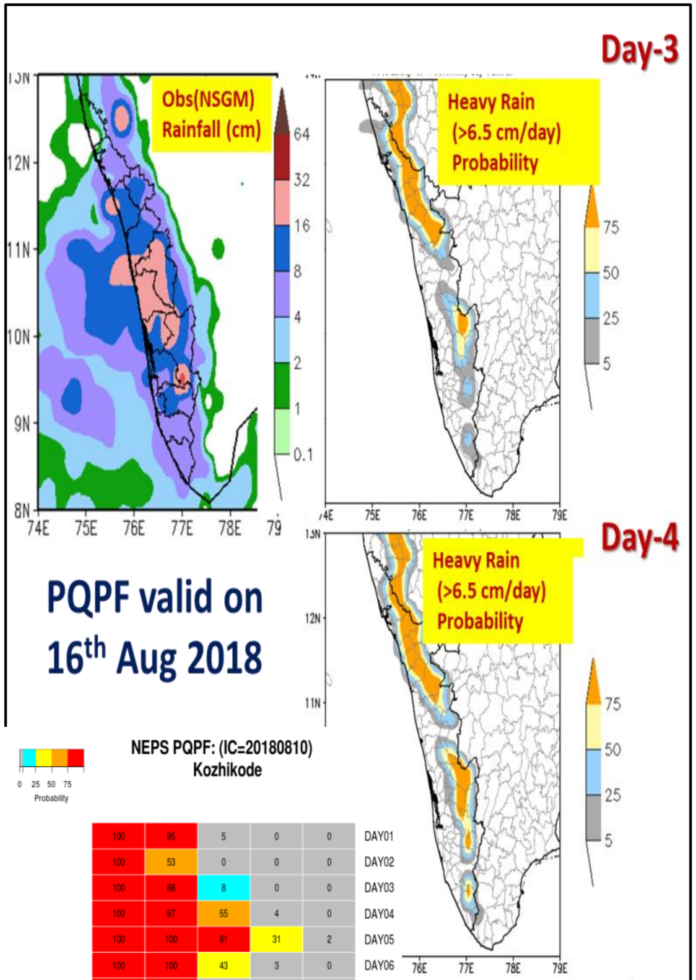
- Rainfall forecast from NCMRWF Ensemble Prediction System
- 23 members (22 + 1 Control)
- 4D Var Hybrid Data Assimilation System
- 12 km x 12 km Grid with global coverage (spatial resolution)
- High temporal resolution for specific applications
- Forecast lead time: 10 days

Probabilistic Forecast for Different FMO

- Methodology: Rainfall probability for a river sub-basins is calculated using neighborhood post processing
- All rainy grid points from all the ensemble members falling inside a sub-basin is considered in probability calculation
- Rainfall threshold (mm) 0.1-10, 10-25, 25-50, 50-100 and > 100
- Probability band 0-5, 5-25, 25-50, 50-75 and 75-100
- 13 FMOs
- Presented in Graphical Format and shared with IMD
- (http://hydro.imd.gov.in/hydrometweb/(S(a53rq3vchakjvx55nedd33zw))/PRODUCTS/QPF/neps_00.html)

Probabilistic Forecasts of High Impact/Extreme Rainfall Events

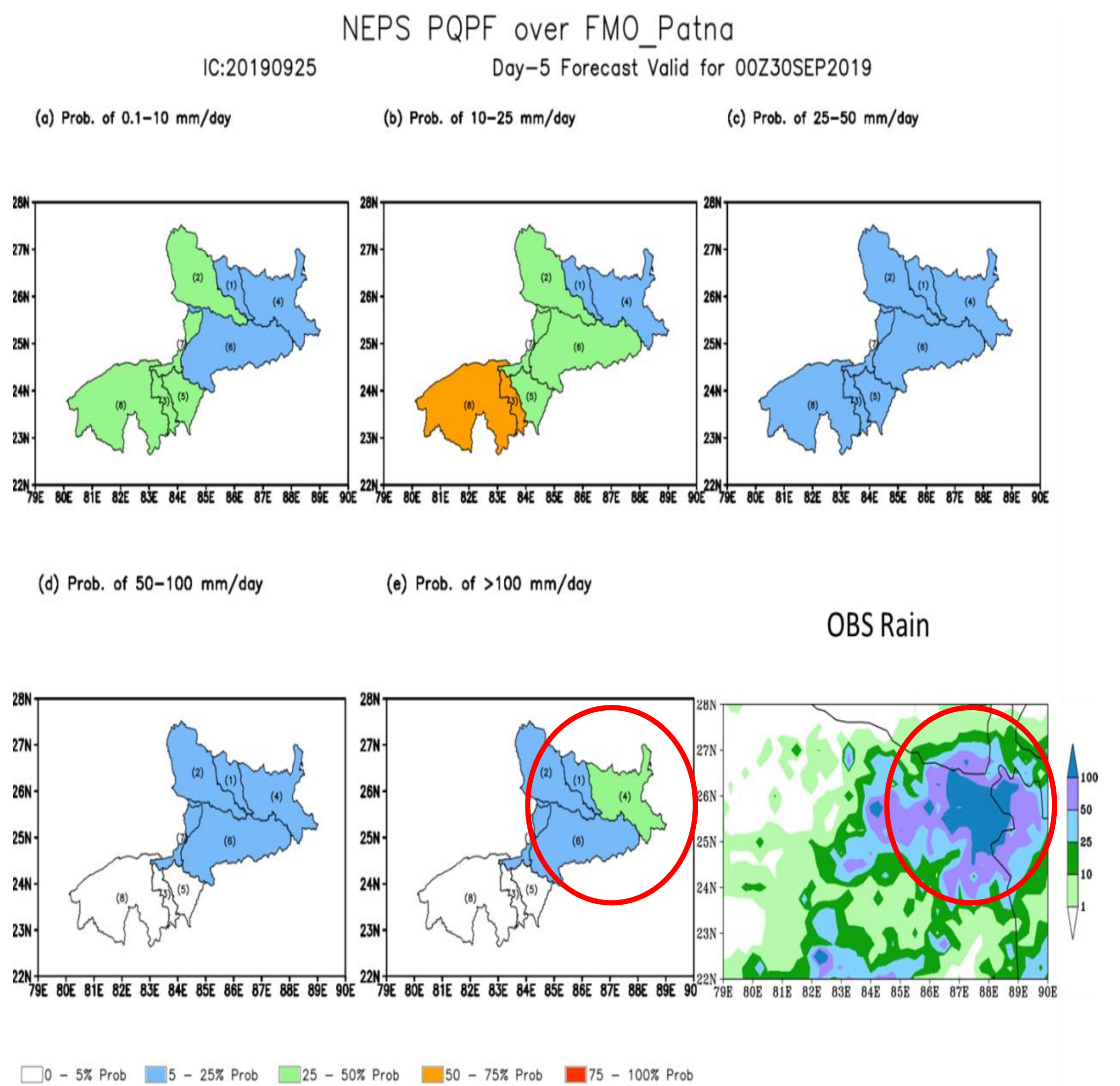
PQPF at district level



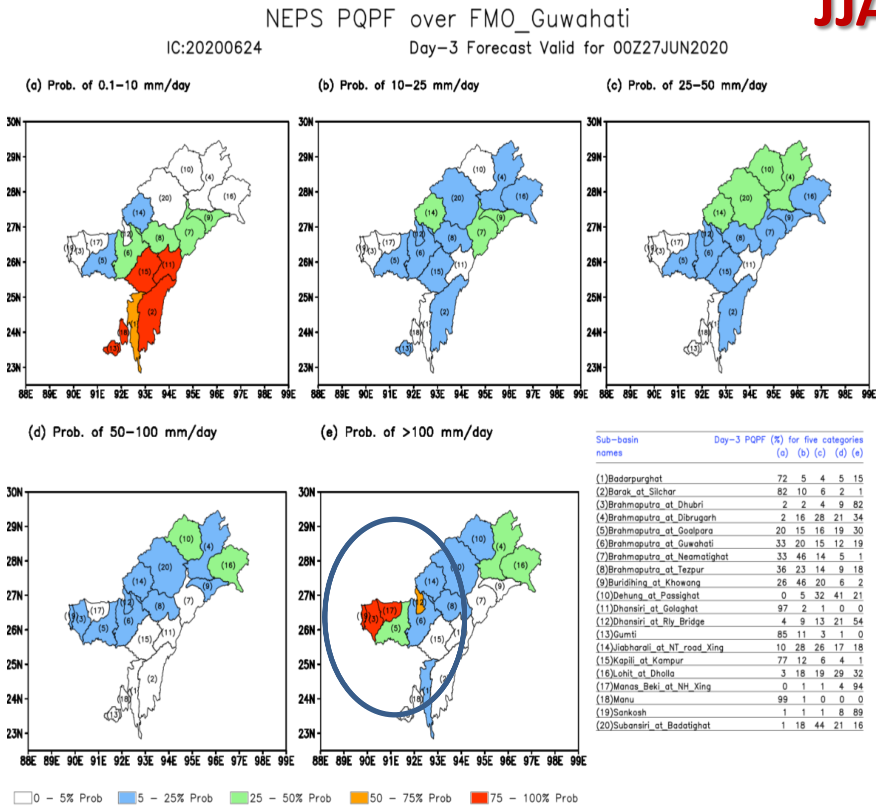
NEPS PQPF: (IC=20180810)
Kozhikode

	>2.5mm	>15.6mm	>65.5mm	>115mm	>195mm
DAY01	100	95	5	0	0
DAY02	100	53	0	0	0
DAY03	100	88	8	0	0
DAY04	100	97	55	4	0
DAY05	100	100	81	31	2
DAY06	100	100	43	3	0
DAY07	96	78	0	0	0
DAY08	100	74	0	0	0
DAY09	100	43	0	0	0
DAY10	100	39	0	0	0

PQPF at River-Sub basins level



Verification of PQPF over River Basins during JJAS 2020



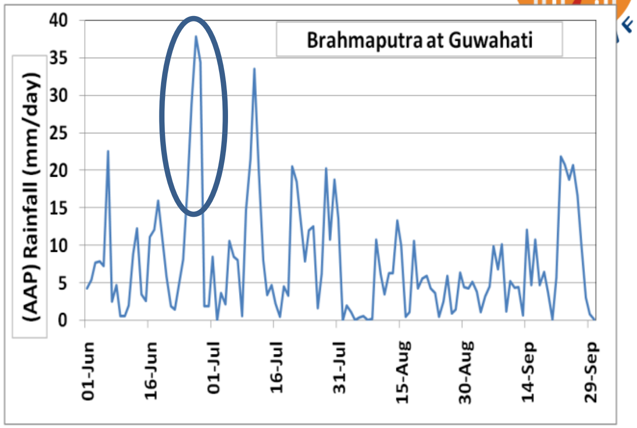
Sub-basin names	Day−3 PQPF (%) for five categories (a)	(b)	(c)	(d)	(e)
(1)Badarpurghat	72	5	4	5	15
(2)Barak_at_Silchar	82	10	6	2	1
(3)Brahmaputra_at_Dhubri	2	2	4	9	82
(4)Brahmaputra_at_Dibrugarh	2	16	28	21	34
(5)Brahmaputra_at_Goalpara	20	15	16	19	30
(6)Brahmaputra_at_Guwahati	33	20	15	12	19
(7)Brahmaputra_at_Neamatighat	33	46	14	5	1
(8)Brahmaputra_at_Tezpur	36	23	14	9	18
(9)Buridihing_at_Khowang	26	46	20	6	2
(10)Dehung_at_Passighat	0	5	32	41	21
(11)Dhansiri_at_Golaghat	97	2	1	0	0
(12)Dhansiri_at_Rly_Bridge	4	9	13	21	54
(13)Gumti	85	11	3	1	0
(14)Jiabharali_at_NT_road_Xing	10	28	26	17	18
(15)Kapili_at_Kampur	77	12	6	4	1
(16)Lohit_at_Dholla	3	18	19	29	32
(17)Manas_Beki_at_NH_Xing	0	1	1	4	94
(18)Manu	99	1	0	0	0
(19)Sankosh	1	1	1	8	89
(20)Subansiri_at_Badatighat	1	18	44	21	16

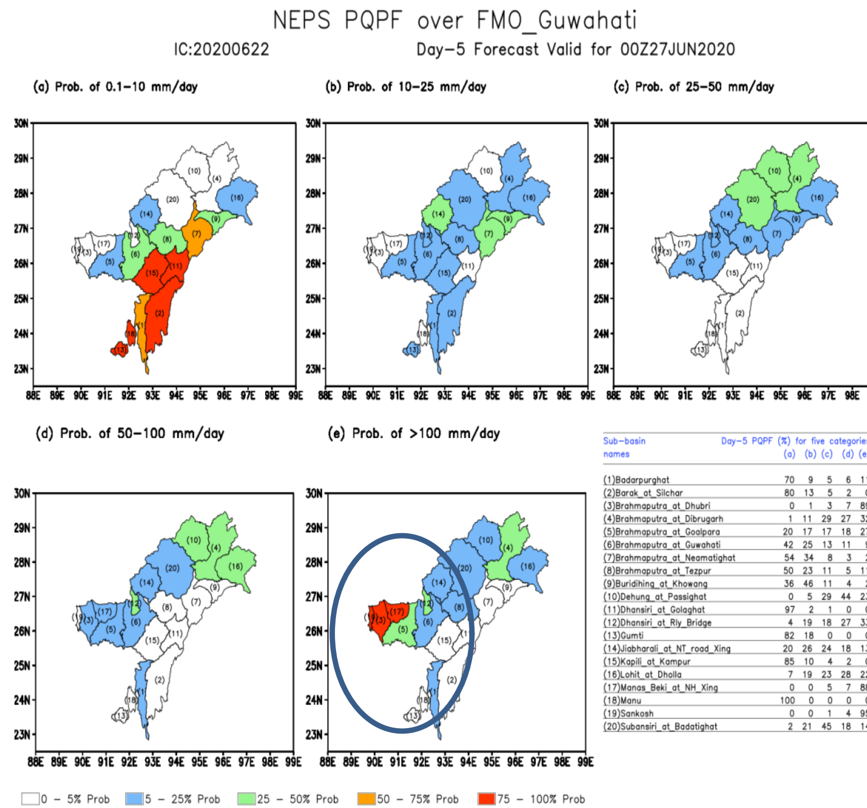
Observed Rainfall :

28.8 mm on 26Jun

37.8 mm on 27Jun

34.4 mm on 28Jun





Sub-basin names	Day−5 PQPF (%) for five categories (a)	(b)	(c)	(d)	(e)
(1)Badarpurghat	70	9	5	6	11
(2)Barak_at_Silchar	80	13	5	2	0
(3)Brahmaputra_at_Dhubri	0	1	3	7	89
(4)Brahmaputra_at_Dibrugarh	1	11	29	27	32
(5)Brahmaputra_at_Goalpara	20	17	17	18	27
(6)Brahmaputra_at_Guwahati	42	25	13	11	9
(7)Brahmaputra_at_Neamatighat	54	34	8	3	2
(8)Brahmaputra_at_Tezpur	50	23	11	5	11
(9)Buridihing_at_Khowang	36	46	11	4	2
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(15)Kapili_at_Kampur	85	10	4	2	0
(16)Lohit_at_Dholla	7	19	23	28	22
(17)Manas_Beki_at_NH_Xing	0	0	5	7	88
(18)Manu	100	0	0	0	0
(19)Sankosh	0	0	1	4	95
(20)Subansiri_at_Badatighat	2	21	45	18	14

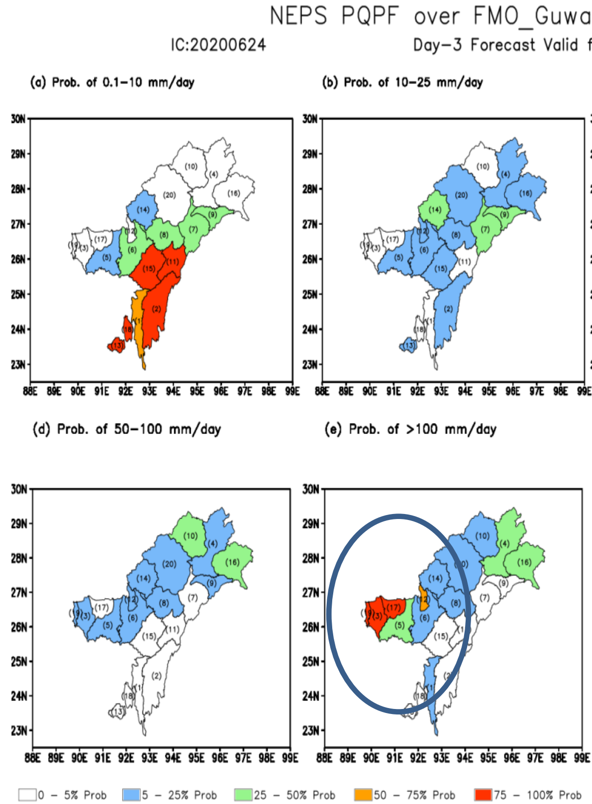
NCMRWF Ensemble Rainfall: PQPF over River Basins

Post-processing for RB:

- PQPF is based on all members and all grids in a sub-basin
- Accounting for displacement errors in rainfall forecasts
- Improved estimate of PQPF compared to point rainfall

Above example:

Verification of PQPF over River Basins during JJAS 2020



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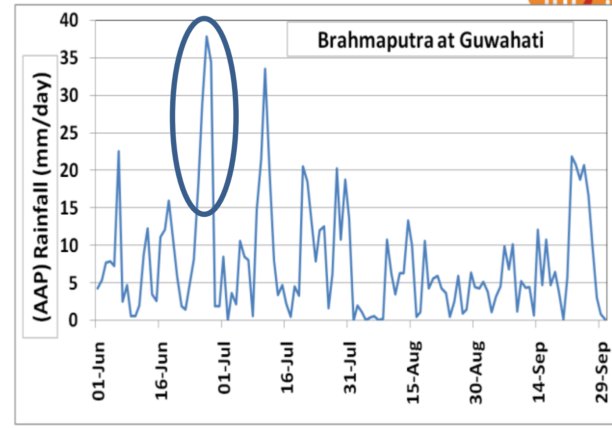

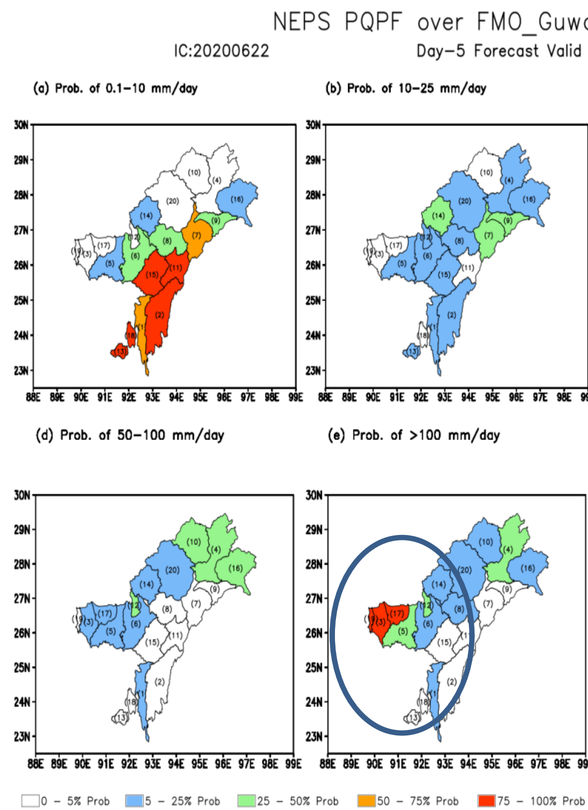

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(9)Buridihing_at_Khowang	36	46	11	4	2
(10)Dehung_at_Passighat	0	5	29	44	23
(11)Dhansiri_at_Golaghat	97	2	1	0	0
(12)Dhansiri_at_Rly_Bridge	4	19	18	27	33
(13)Gumti	82	18	0	0	0
(14)Jiabharali_at_NT_road_Xing	20	26	24	18	13
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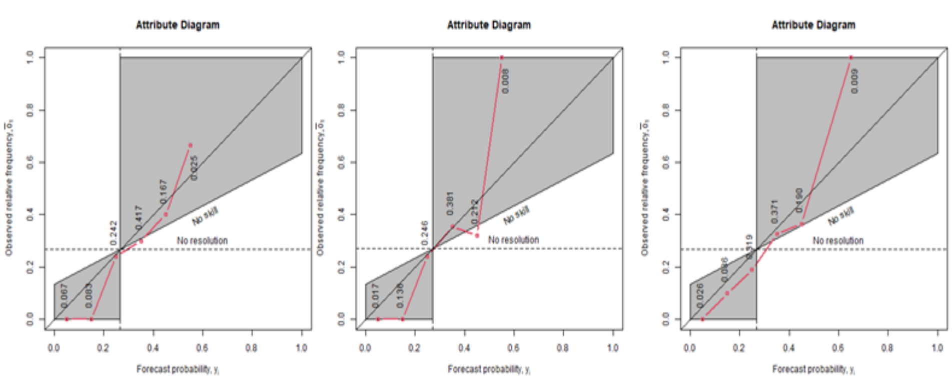
JJAS 2020 Reliability Diagram (20-25mm/day)

Day-1 **Day-3** **Day-5**



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Review on probabilistic forecasting of wind power generation

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A B S T R A C T

The randomness and intermittence of wind resources is the biggest challenge in the integration of wind power into the power system. Accurate forecasting of wind power generation is an efficient tool to deal with such problem. Conventional wind power forecasting produces a value, or the conditional expectation of wind power output at a time point in the future. However, any prediction involves inherent uncertainty. In recent years, several probabilistic forecasting approaches have been reported in wind power forecasting studies. Compared to currently wide-used point forecasts, probabilistic forecasts could provide additional quantitative information on the uncertainty associated with wind power generation. For decision-makings in the uncertainty environment, probabilistic forecasts are optimal inputs. A review of state-of-the-art methods and new developments in wind power probabilistic forecasting is presented in this paper. Firstly, three different representations of wind power uncertainty are briefly introduced. Then, different forecasting methods are discussed. These methods are classified into three categories in terms of uncertainty representation, i.e. probabilistic forecasts (parametric and non-parametric), risk index forecasts and space-time scenario forecasts. Finally, requirements and the overall framework of the uncertainty forecasting evaluation are summarized. In addition, this article also describes current challenges and future developments associated with wind power probabilistic prediction.

9. Discussion

With the rapid development of the uncertainty forecasting method, the application of uncertainty forecasting in power system engineering might happen in the future. Today, forecasts end-users may still prefer to get wind power single-value forecasts because point forecasts are more easily to be understood and accepted. It is much expensive to generate uncertainty forecasts, and is hard to verify. Nowadays, probabilistic information coming from uncertainty forecasts is still difficult to be appreciated by users. However, after integrating more and more stochastic power generation in power system, traditional point forecasts cannot satisfy the requirement of uncertainty information in decision-making problems. Therefore, methodologies of wind power forecasts should be developed in the probabilistic framework. The development of uncertainty forecasting would be of great benefit to increase the penetration of wind power generation. However, the study on wind power uncertainty forecasting is still in the early stage. Much problem and challenge still exists in this field.

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HYSPLIT SREF Dispersion Forecast

HYSPLIT SREF Dispersion Forecast

EXPERIMENTAL - information may not be current.

Over the past few years, the use of dispersion model ensembles has been an increasingly attractive approach to predict atmospheric transport. The ensembles are generally constructed by combining multiple numerical weather prediction simulations or output from different dispersion models, by introducing variations in a particular model's physics parameterizations, or by different combinations of these variations. In addition, the source term and height distribution can be varied to create dispersion ensembles.

For this application, we create a HYSPLIT ensemble simulation using the 26 meteorological model members from the National Weather Service (NWS) operational Sort Range Ensemble Forecast (SREF). The HYSPLIT model runs are generated by using the Transfer Coefficient Matrix procedure that is updated with the most recent meteorological data at 03, 09, 15 and 21Z.

The figures below show each of the simulation ensemble members as well as a series of statistical measures that describe the ensemble properties such as:

EM FOR ENSEMBLE DISPERSION FORECAST IN CASE OF NUCLEAR EMERGENCIES

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Potential Use of Transport and Dispersion Model Ensembles for Forecasting Applications

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Ensemble dispersion forecasting—Part I: concept, approach and indicators

Improving SCIPUFF Dispersion Forecasts with NWP Ensembles

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- **Data can be imperfect, incomplete, or uncertain. There is often more than one explanation for why things happened the way they did; and by examining those alternative explanations using probability.**
- **However, thinking probabilistically takes some getting used to, as the human mind is naturally deterministic. We generally believe that something is true or false. Either you like someone or you don't.**
- **For make good decisions in complex, unpredictable environments one of the best ways to embrace uncertainty and be more probabilistic in approach is to learn to think like a professional gambler.**
- **Developing a probabilistic mindset allows you to be better prepared for the uncertainties and complexities of the Algorithmic Age. Even when events are determined by an infinitely complex set of factors, probabilistic thinking can help us identify the most likely outcomes and the best decisions to make.**

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