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Research Article

Verification of Ensembled Forecasting

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ABSTRACT

Ensemble based prediction systems over the years have proved their worthiness in providing better forecast guidance. The systems have evolved to regional scale from global scale since past twenty years. The objective of reducing error in forecast has led to ensemble approach applied at convective scale resolution. NCMRWF Regional Ensemble Prediction System (NEPS-R) is based on the regional version of Met Office Global and Regional Ensemble Prediction System (MOGREPS) with 12 members (1 control+11 perturbed). This regional ensemble prediction system having 4 km horizontal resolution and 80 vertical levels up to a height of 38.5 km is implemented in “Mihir HPCS”. NEPS-R uses boundary conditions and initial conditions generated from NEPS-G. Uncertainties of model are managed using Random Parameters (RP) scheme. NEPS-R is aimed at providing 3-day probabilistic forecasts using 12 members. Results of Bias and RMSE of the Global, Regional (1+11) have been compared and analyzed to understand the climate condition in India for the month of August 2019. NEPS-R predicted wind at U 850 and rainfall and compared with its global counterpart NEPS-G in predicting severe weather phenomena.

Keywords: Numerical weather prediction; Ensembled; Bias; RMSE

INTRODUCTION

Numerical Weather Prediction (NWP) is an initial value problem. A set of eqn. that represents atmospheric motion and includes parameterization of physical processes in the atmosphere is translated into computer code in an NWP model. The model is combined forward in time from best estimated initial state (or analysis) to forecast coming state of atmosphere. An advanced data taking in method combine observations of atmospheric condition to a short-range model prediction (usually 6 hours) to prepare the analysis. So, the factors that determine the accuracy of numerical weather forecast are:

- Accuracy in mentioning starting state of the atmosphere
- Accuracy in formulation of the model which is composed of a set of PDE representing laws of momentum, mass, and energy conservations

After the very first NWP introduced in starting of 1950s, a lot of work has been done in order to upgrade skill of NWP.

The improvement of NWP was done by using improved basic conditions which were generated using advanced observing systems and making of atmospheric data taking in methods. Many findings and research has led to improved numerical modeling along with advanced numerical methods, better and improved physical parameterization schemes. Again, atmosphere is a chaotic system. A small difference in the descriptions of initial state of a chaotic system often grows or amplifies very rapidly which leads to completely different predictions of the final state. Since we will never know every tiny detail of the initial condition of the atmosphere our prediction of the future state may become far from accurate even if we have a perfect model that exactly represents the atmospheric flow. Chaos thus means that there is always a finite limit to the predictability of a chaotic system. Ensemble Prediction System (EPS) provides a way of quantifying the uncertainty in forecasts using a stochastic dynamic prediction method. During the early stage of the forecast, error grows more or less linearly with time and the deterministic forecast shows good skill. During this period the small error in the initial condition remains small and trajectories of the model forecast and the ‘truth’ are close to each other in phase space [1]. Ensemble forecasting methods in different operational centers around the world mostly differ by the way in which initial condition perturbations are generated. However, it showed that the real analysis errors grow much faster than the random initial perturbations [2-4]. A second class of methods that takes care of growing errors in the initial perturbations were developed, tested and implemented at various operational centers around the world. “Breeding” and “singular vector” methods of

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perturbation generation lie in this class. Breeding Vectors (BVs) [5] are used to generate perturbations to the initial condition at NCEP and the Singular Vector (SV) approach is used at ECMWF [6,7]. In Met Office, UK, Ensemble Transform Kalman Filter (ETKF) is used in its Global and Regional Ensemble Prediction System (MOGREPS) to generate initial perturbations [8]. This method is similar to the error breeding method prescribed by Toth and Kalnay, 1993 with some differences [5]. In ETKF, the analysis perturbation of each member is the linear combination of the forecast perturbations. This mixing of forecast perturbations which produces mutually orthogonal analysis perturbations leads to improved performance of ETKF over the error breeding method (Figure 1) [6].

NCMRWF Global Ensemble Prediction System (NEPS-G)

National Centre for Medium Range Weather Forecasting (NCMRWF) has been running global ensemble prediction system (NEPS-G) based on Met Office Global and Regional Ensemble Prediction System (MOGREPS-G) since October, 2015. The horizontal resolution of the current operational NEPS-G is 12 km. The initial condition perturbations of this ensemble prediction system are also generated by Ensemble Transform Kalman Filter (ETKF) method. The uncertainties in the model are handelled by “RP” [9-10] and “Stochastic Kinetic Energy Backscatter” (SKEB) schemes [11]. RP scheme inherits uncertainties in empirical parameters of physical parameterization schemes. The forecast perturbations obtained from 6-hour short forecast run of 22 ensemble members are updated by ETKF four times a day (00, 06, 12 and 18 UTC). Perturbations of surface parameters such as sea-surface temperature, soil moisture content and soil temperature [12] are included in NEPS in order to address the problem of lack of ensemble spread near the surface. The NEPS-G aims to provide 10-day probabilistic forecasts using 23 members (22 perturbed+1 control) ensemble system. Out of 22 perturbed ensemble members, one set of eleven members run from 00 UTC of current day and the other set of 11 members run from 12 UTC of previous day to provide ensemble forecast of 10 days. The operational deterministic forecast running at 12 km resolution from 00 UTC is used as the control forecast. A technical report by Mamgain, et al., 2018 describes in detail the operational implementation of this high-resolution EPS at NCMRWF [13].

Regional ensemble prediction system

There is a greater need of an ensemble approach to account for uncertainty at kilometre-scale than at coarser resolutions. Keeping this in mind, many operational forecasting centres have moved on from short range EPSs to convective scale EPSs to handle the uncertainty in forecasts at a local scale. The phenomenal increase in computing power also has boosted the efforts of development of convective scale ensemble systems around the globe. Today convective scale ensemble systems are in operation at United Kingdom Meteorological Office (UKMO), Meteo France, and German Weather Service (GWS) and also at many other centres. NCMRWF has also implemented NEPS-R on the basis of MOGREPS-R developed at Met Office, UK. Parameterized physical processes include long- and short-wave radiation, mixed phase cloud microphysics, a boundary-layer turbulence scheme and a random parameters stochastic physics scheme [14, 15]. (Figures 2-5).

NWP refers to a numerical model which is used in meteorology for predicting weather. The designing and application of computer program in order to simulate any real system, which in our study is weather. Recognition by V. Bjerknes in 1904 that forecasting

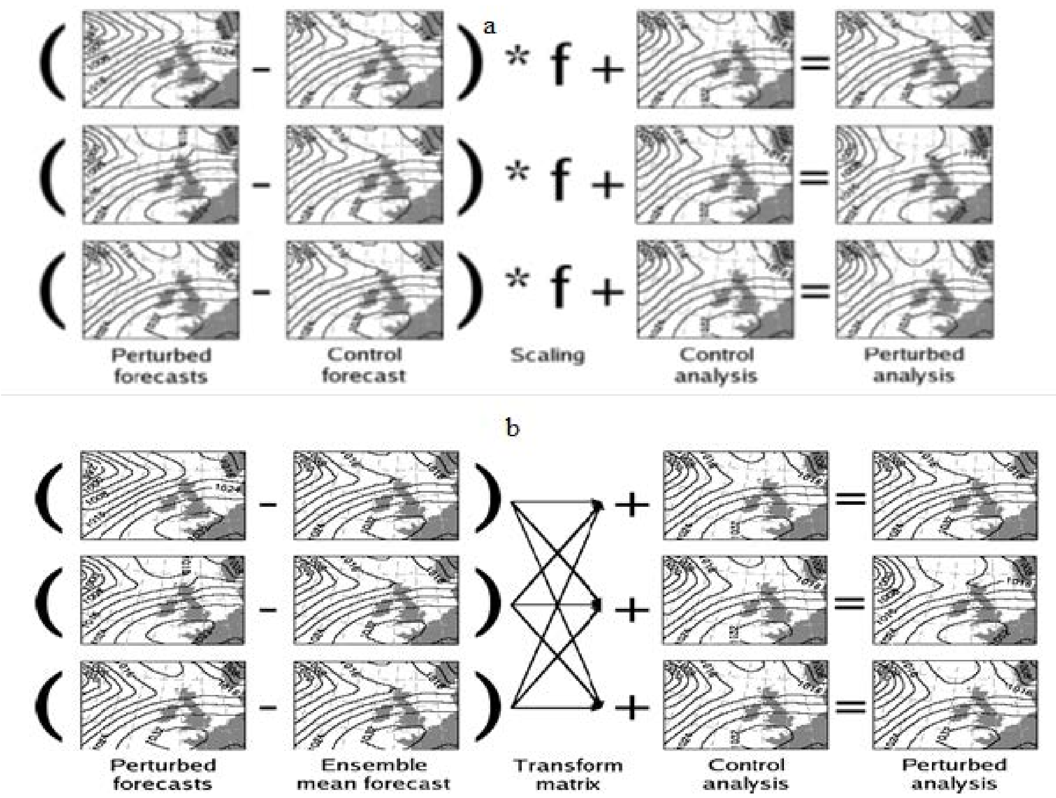

Figure 1: Graphical representation of the (a): error-breeding method; (b): ETKF [2].

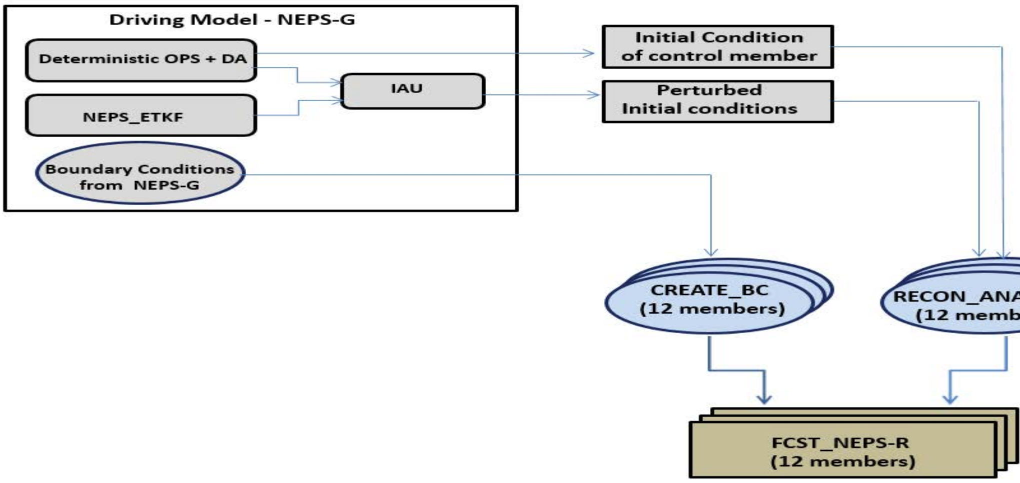

Figure 2: Flow chart of processes involved in NEPS-R.

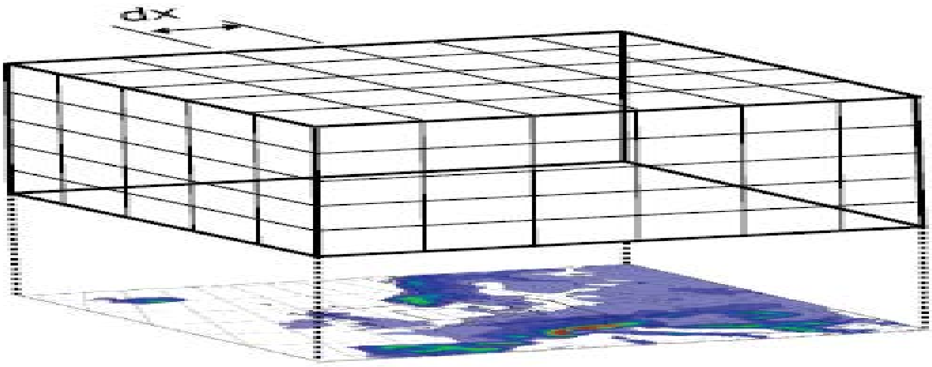

Figure 3: Is grid point model the model domain is broken down into discrete regions called "grid boxes".

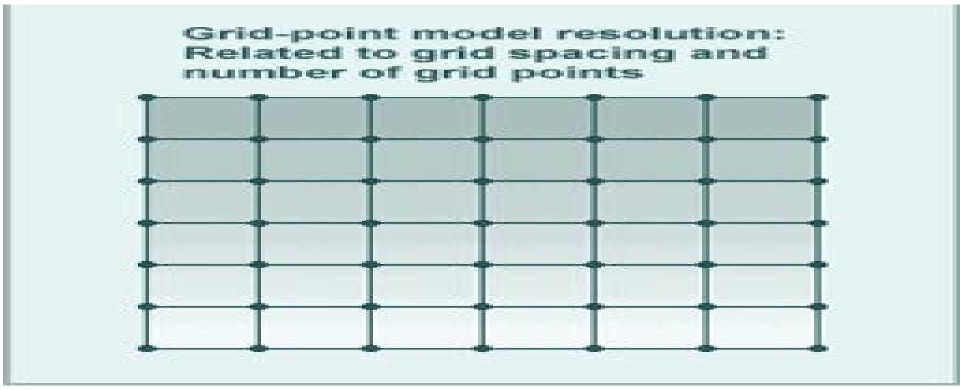

Figure 4: Is grid point model the model domain is broken down into discrete regions called "grid boxes."

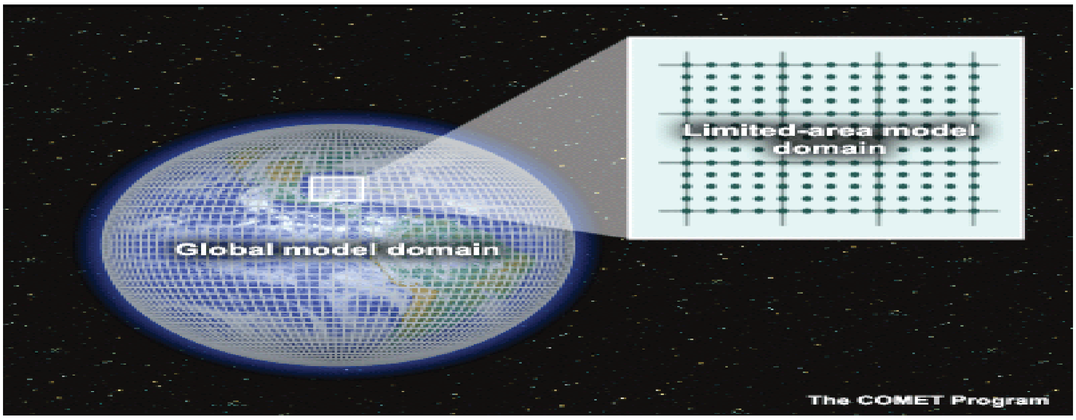

Figure 5: Is grid point model the model domain is broken down into discrete regions called "grid boxes."

is fundamentally an initial-value problem and basic system of equations already known L. F. Richardson's first attempt at practical NWP. Radiosonde invention in 1930s made upper-air data available Late 1940s: First successful dynamical-numerical forecast made by Charney, von Neumann and others. The horizontal resolution of an NWP model is related to the spacing between grid points for grid point models or the number of waves that can be resolved for spectral models [16]. Durai, et al. 2010, studied a concise and synthesized documentation of the current level of skill of the NCEP GFS day-1 to day-5 precipitation forecasts during Indian summer monsoon of 2008, making detailed inter-comparison with daily rainfall analysis from the use of rain gauge observations and satellite (KALPANA-1) derived Quantitative Precipitation Estimates (QPE) obtained from IMD, further the model predicted rainfall is comparatively higher than the observed rainfall over most parts of the country during the season [17]. Metri, et al. 2010, studied the rainfall features at different rain gauge stations of Goa state have been studied for the period of 30 years, it also came out from the study that the orography of Goa plays an important role in rainfall distribution, hence, Valpoi receives maximum rainfall due to its orographic effect [18].

Mohanty, et al. 2019, reviewed the recent developments related to land surface processes and their application to ISM process studies, the evolution of land surface models, state-of-art Land Data Assimilation Systems (LDAS) and their applications in NWP models were discussed [19]. Kaur, et al. 2019, studied usability analysis for the weather parameters was done using skill scores and critical values for the error structure for the different seasons, further ratio scores derived between the forecasted and observed values during post-monsoon and winter seasons were observed to be relatively higher as compared to those for the monsoon seasons, indicating the performance of forecast models to be better in post-monsoon and winter seasons than in the summer and monsoon seasons, forecasting of wind speed plays an important role in saving the crop from lodging especially in the Rabi crop season and it was observed that in this season (2017 years-2018 years) the wind speed prediction was 74% correct. Hence, the accuracy of forecast of weather parameters in advance is found to be useful for farmers for doing appropriate field operations and crop management practices [23]. 'Resolution' can be understood as space between grids or number of waves and represents average area included in one grid point in an grid point model or else as number of waves used in spectral model. The smallest area that can be shown by any model is much larger than grid 'resolution'. In fact, phenomena with dimensions on same scale as grid spacing are unlikely to be depicted or predicted within a model. Global models, they do forecasting for all the parts of surface of Earth. Regional models, they do forecasting of few fixed sections on surface of Earth (e.g. North America or continental US).

Lateral boundary condition is about relation which explains values of forecast variable on horizontal edges of model's domain. As we know that G-Model covers Earth's entire surface, hence there is no requirement of lateral boundary conditions. As R-Model covers only limited area, hence makes it important that initial conditions are added. This is important in order to make R-Model understand and hence generate beneficial forecast.

The calculation of Bias and RMSE has been done in order to see the deviation in the error values of the actual values and forecasted values of the weather parameters. Further it is done because it brings out the more predictable elements by smoothing out the relatively unpredictable features on a smaller scale, thus providing good forecast guidance. The ensemble prediction system provides a measure of uncertainty in the forecast which is not possible to determine with a control forecast alone. RMSE of different variables calculated from the ensemble forecasts is a way to assess the future weather scenarios. RMSE of the values of the meteorological variable predicted by all the ensemble members, which gives us the most likely outcome on an average and is normally better than forecast of individual members.

METHODOLOGY

The initial conditions for control and perturbed ensemble members are obtained from the high resolution (12 km) NEPS-G which is operational since June 2018. The unperturbed initial conditions or analyses fields of NEPS-G are provided by Hybrid 4D-VAR data assimilation system. ETKF generates initial condition perturbation for NEPS-G [14]. Using Incremental Analysis Update (IAU) analysis perturbations are added to analysis fields (Clayton, 2011) to generate 11 sets of perturbed initial conditions for NEPS-G. These initial conditions (both perturbed and unperturbed) from NEPS-G are reconfigured to prepare the initial conditions for NEPS-R. The boundary conditions for NEPS-R are also provided by NEPS-G. So NEPS-R essentially runs with initial and boundary conditions from a global ensemble. NEPS-G is running operationally at NCMRWF at 12 km resolution, so the initial and boundary conditions for the control and 11 perturbed members are obtained from NEPS-G for the operational run. The NEPS-G is based on Unified Model version 10.8 (UM10.8), which is a part of 'Operational Parallel Suite', PS40, developed at Met Office, UK. It operates with a total of 23 ensembles members (1 control+22 perturbed forecasts). The Ensemble Transform Kalman Filter (ETKF) system generates the 22 analysis perturbations of horizontal wind speed components (U and V), potential temperature (T), specific humidity (q) and exner pressure (π) at all 70 model levels [20-23]. The ensemble mean is arithmetic mean of the values of the meteorological variable predicted by all the ensemble members, which gives us the most likely outcome on an average and is normally better than forecast of individual members.

Ensemble mean and spread

The ensemble prediction system provides a measure of uncertainty in the forecast which is not possible to determine with a control forecast alone. The ensemble mean and spread of different variables calculated from the ensemble forecasts is a way to assess the future weather scenarios. The ensemble mean is arithmetic mean of the values of the meteorological variable predicted by all the ensemble members, which gives us the most likely outcome on an average and is normally better than forecast of individual members. This is because it brings out the more predictable elements by smoothing out the relatively unpredictable features on a smaller scale, thus providing good forecast guidance. A model variable, which when large indicates greater uncertainty in the forecast and is generally displayed along with ensemble mean.

Root mean square error

The ensemble prediction system provides a measure of uncertainty in the forecast which is not possible to determine with a control forecast alone. RMSE of different variables calculated from the ensemble forecasts is a way to assess the future weather scenarios. RMSE of the values of the meteorological variable predicted by all the ensemble members, which gives us the most likely outcome on an average and is normally better than forecast of individual members.

Hence, Bias and RSME helps to see the deviation in the values of actual and predicted values of weather.

RESULTS

Ensemble based prediction systems have been successful in providing better forecast guidance and have evolved in the past few decades starting with Global EPS focusing on uncertainties.

The Day-1, Day-2, Day-3 bias of Ensemble models**,** of regional model and global model has been calculated and compared for control and 11 perturbed models and difference plot has been made.

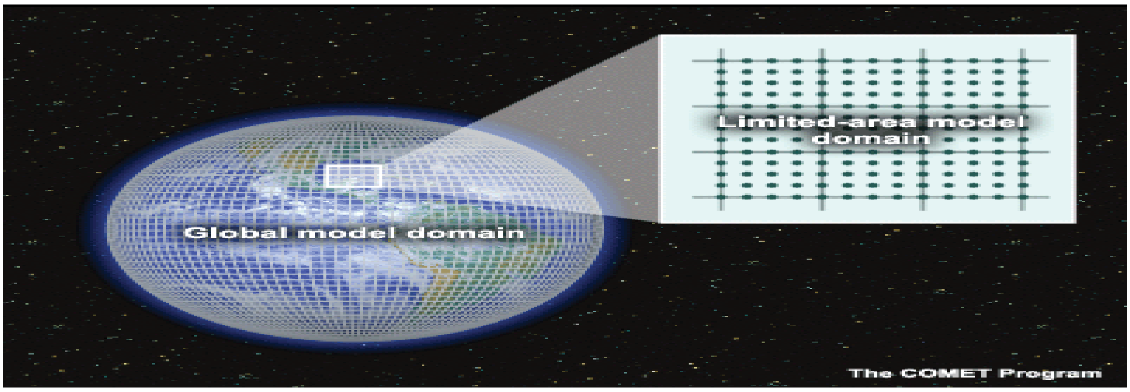

Figure 6: Bias of wind at U850 at 00 UTC for day-1, day-2, and day-3.

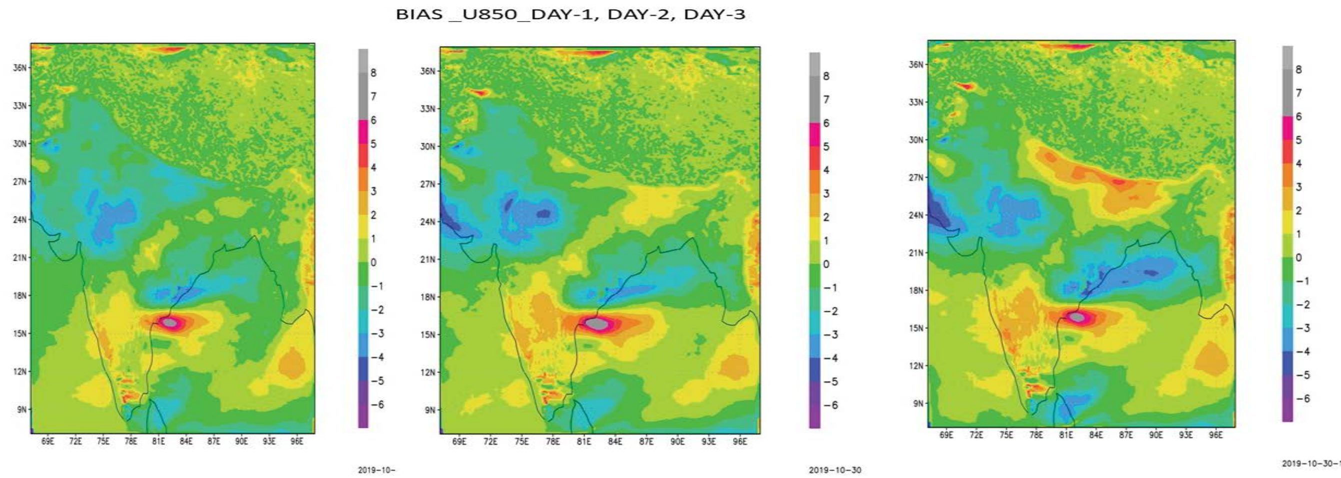

Figure 7: Bias of wind at U850 at 00 UTC for day-1, day-2 and day-3 (control).

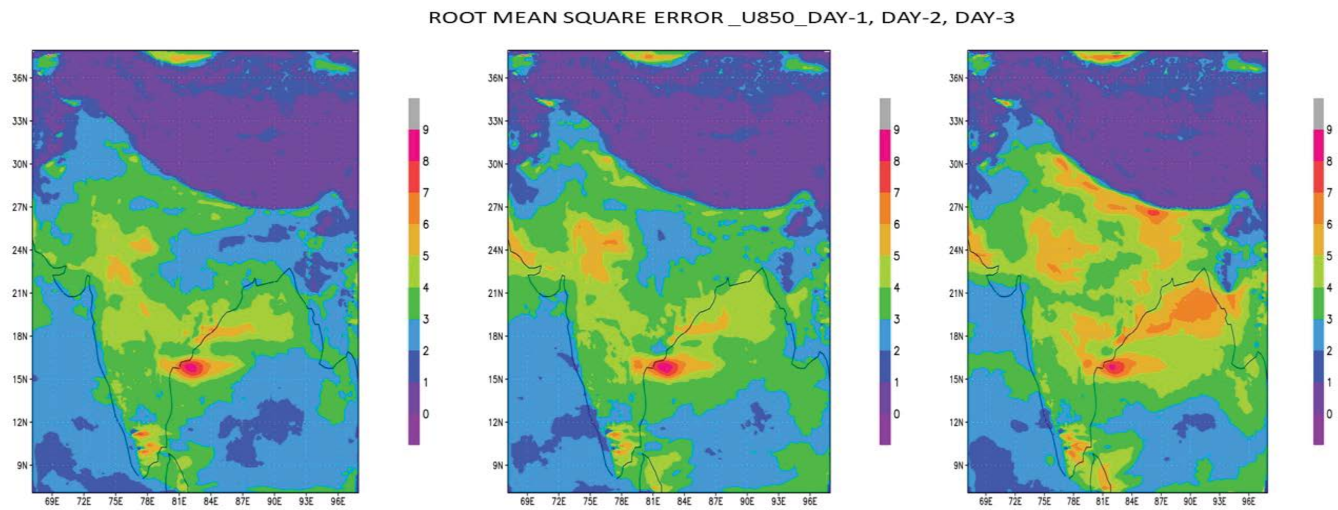

Figure 8: Difference plot of bias of wind at U850 at 00 UTC for day-1, day-2, and day-3.

Similarly, RMSE has been calculated for Day-1, Day-2, and Day-3. Here (Figures 6-22) shows the results.

Above all the Figures 6-22 are the resulting plots of calculated Bias and RMSE for Wind at U850 and Rainfall for day 1, 2 and 3 by taking values of actual and forecasted values.

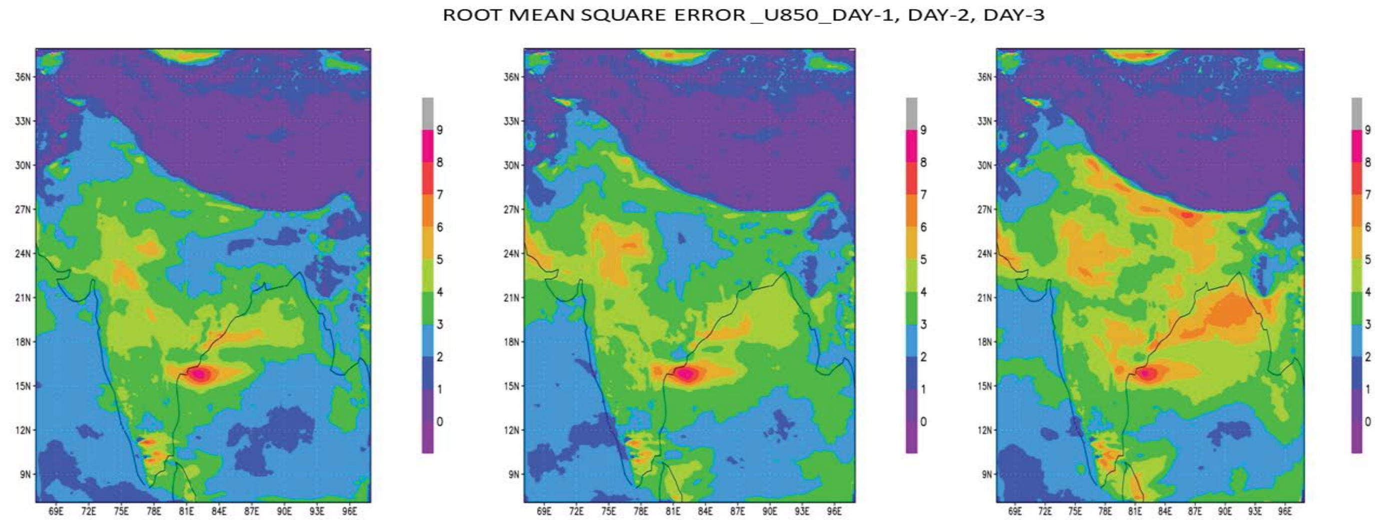

Figure 9: RMSE of wind at U850 at 00 UTC for day-1, day-2, and day-3.

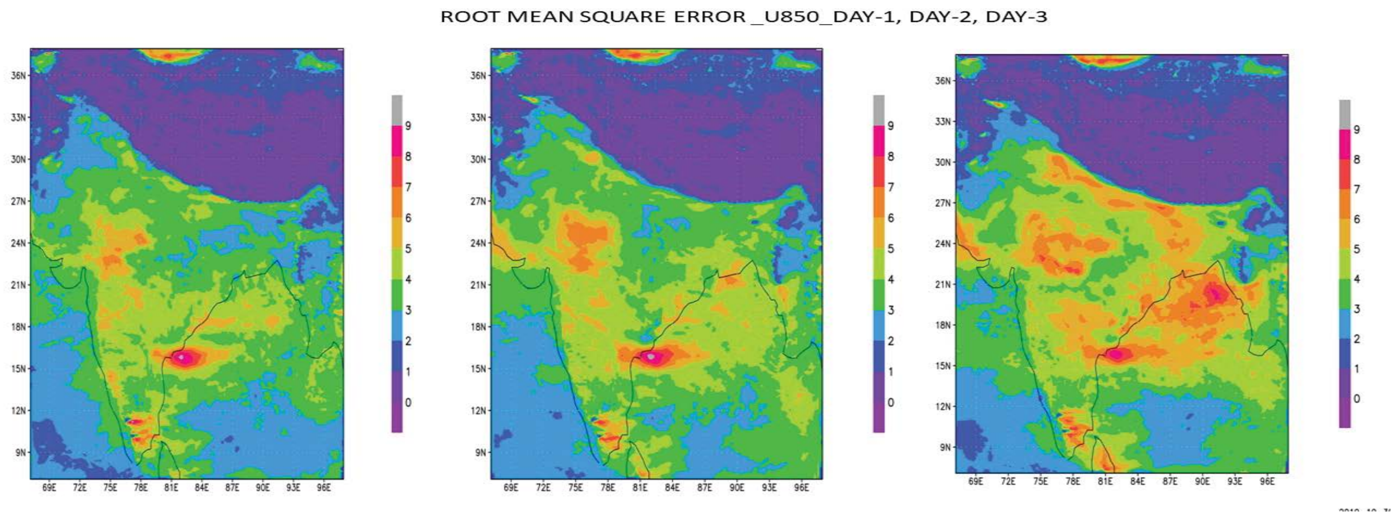

Figure 10: RMSE of wind at U850 at 00 UTC for day-1, day-2 and day-3 (control).

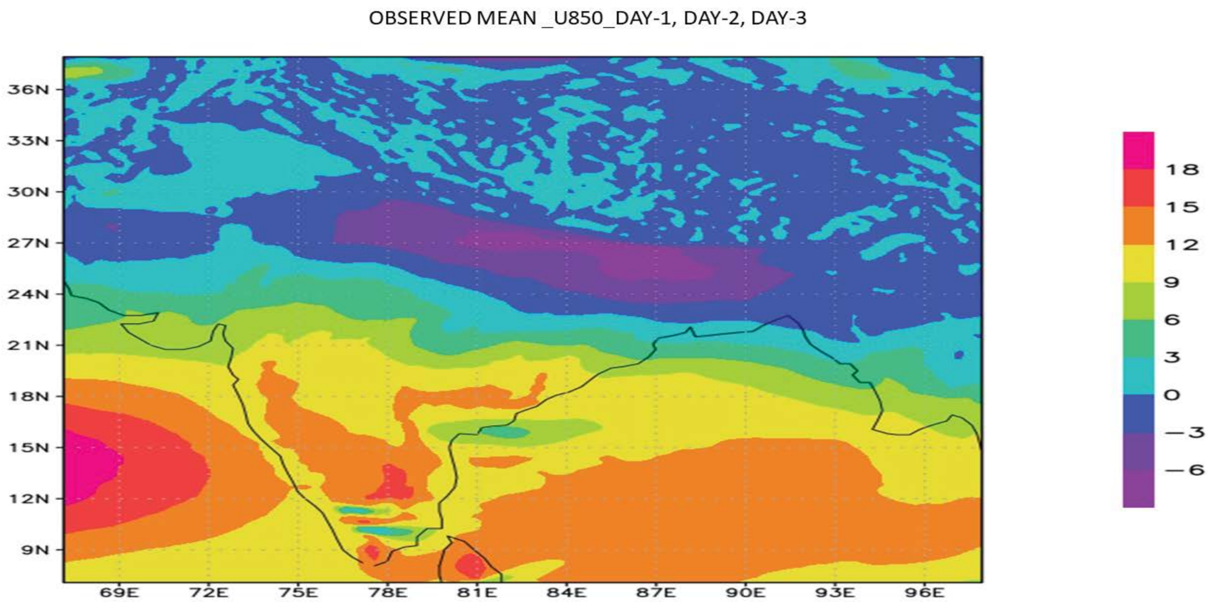

Figure 11: Mean of observed of wind at U850 at 00 UTC for day-1, day-2 and day-3.

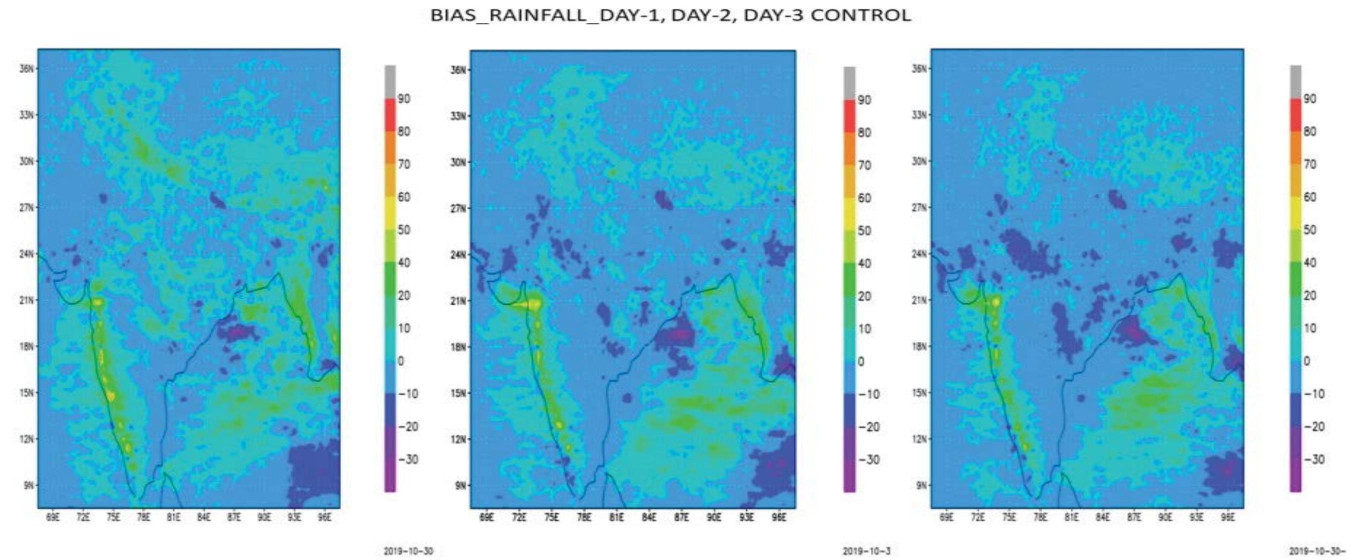

Figure 12: Bias of rainfall for day-1, day-2 and day-3.

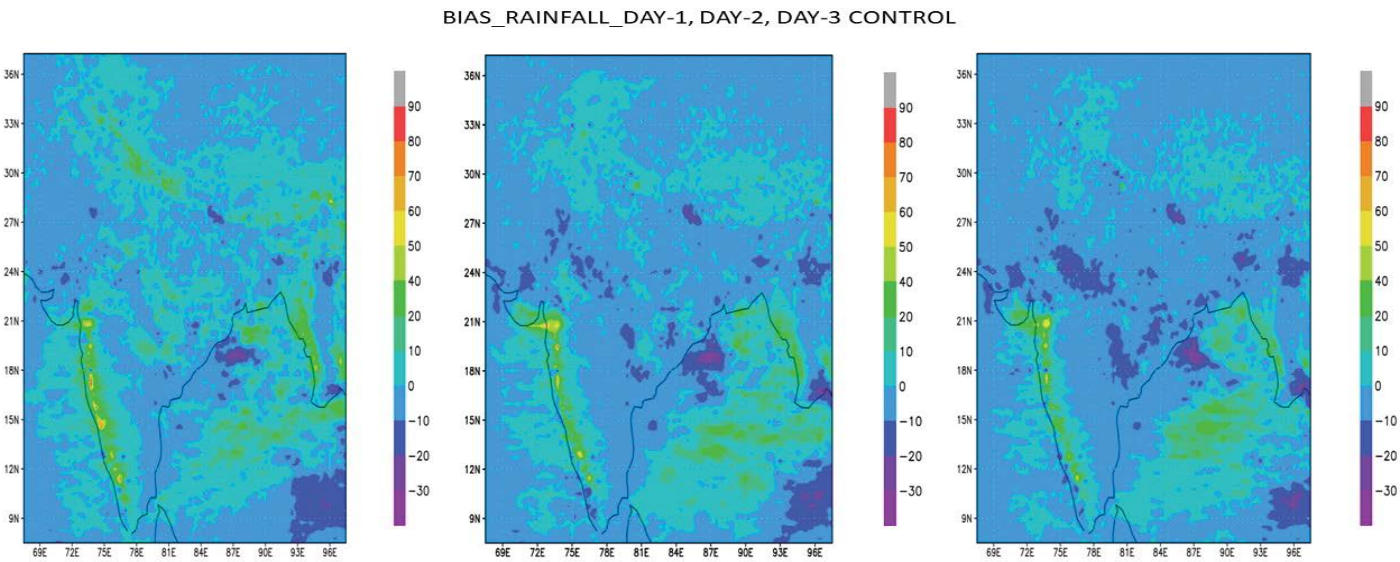

Figure 13: Bias of rainfall for day-1, day-2 and day-3 (control).

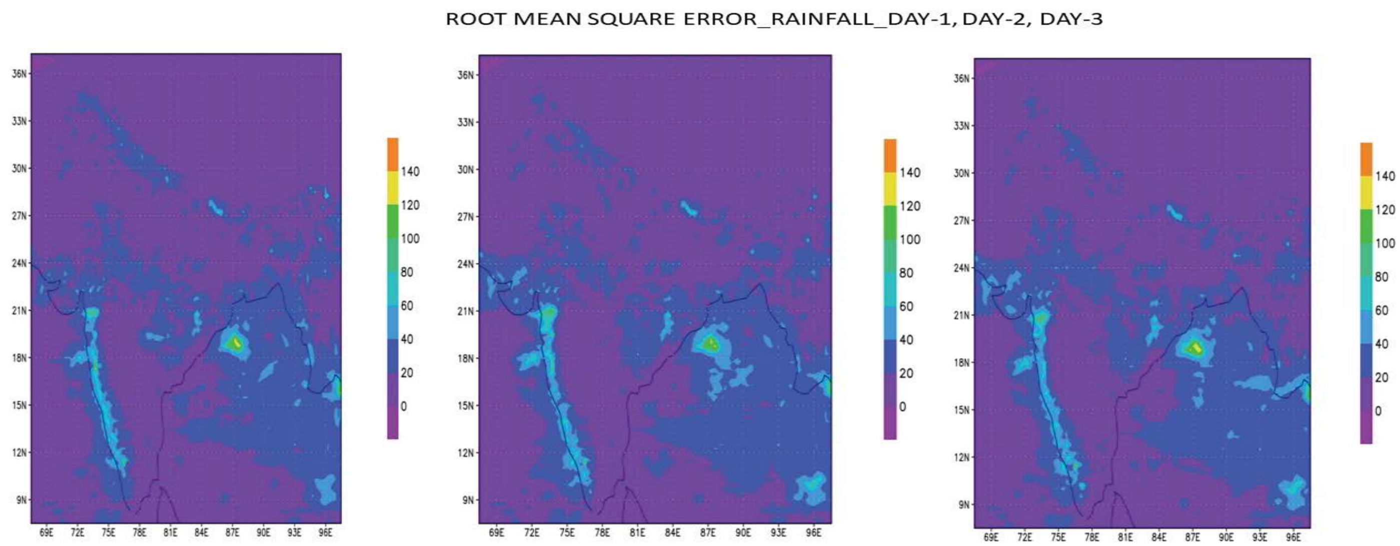

Figure 14: RMSE of rainfall for day-1, day-2 and day-3.

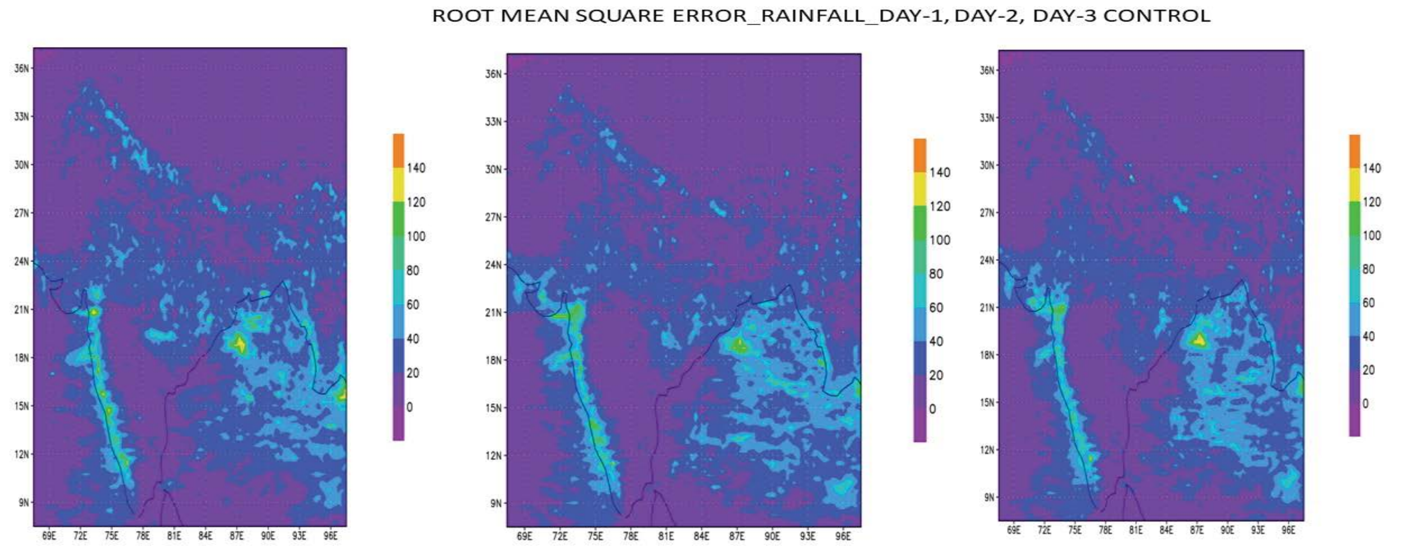

Figure 15: RMSE of rainfall for day-1, day-2 and day-3 (control).

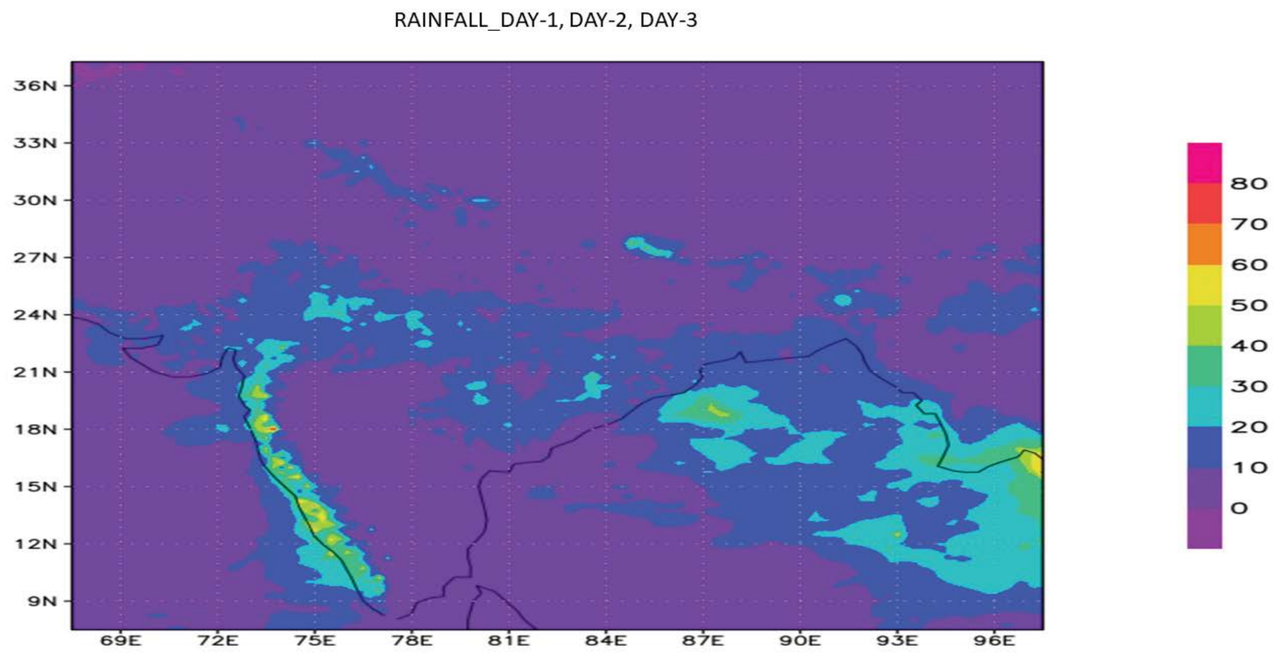

Figure 16: Mean of observed rainfall for day-1, day-2, day-3.

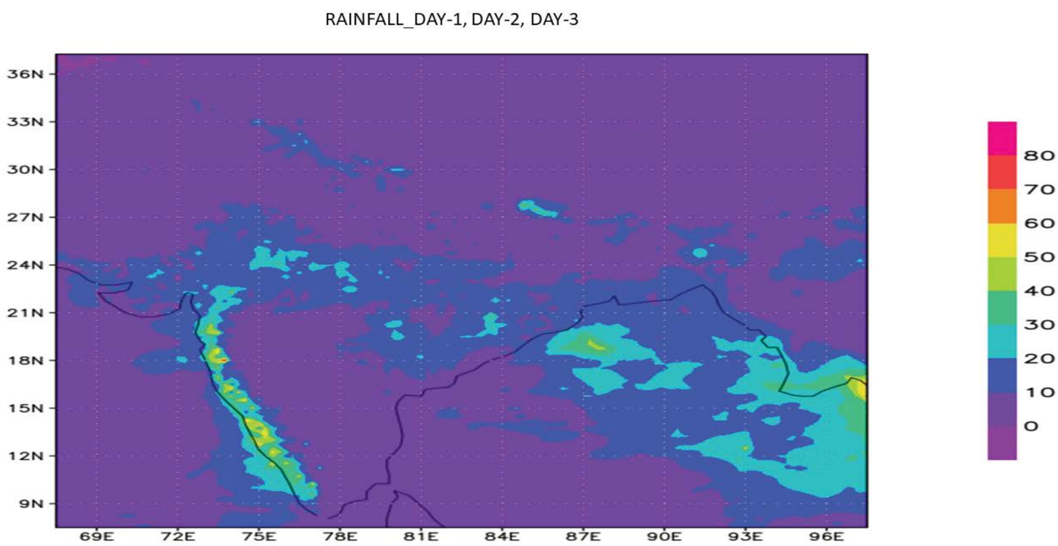

Figure 17: Bias of global rainfall for day-1, day-2, and day-3.

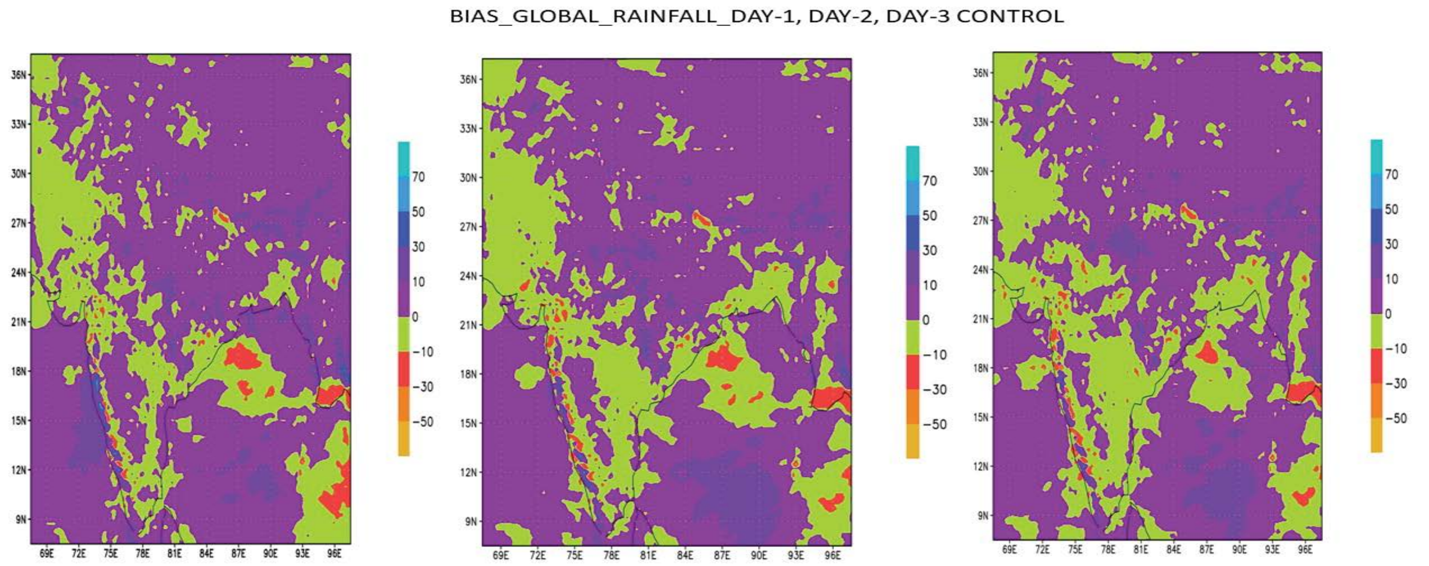

Figure 18: Bias of global rainfall for day-1, day-2, and day-3 (control).

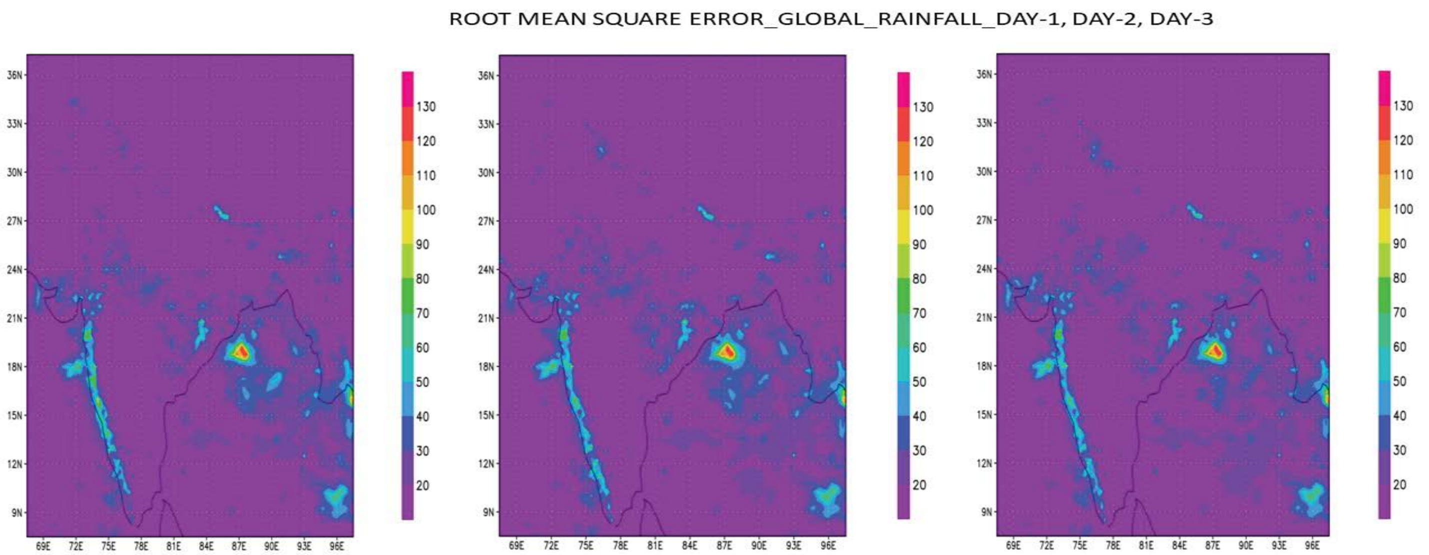

Figure 19: RMSE of global rainfall for day-1, day-2, and day-3.

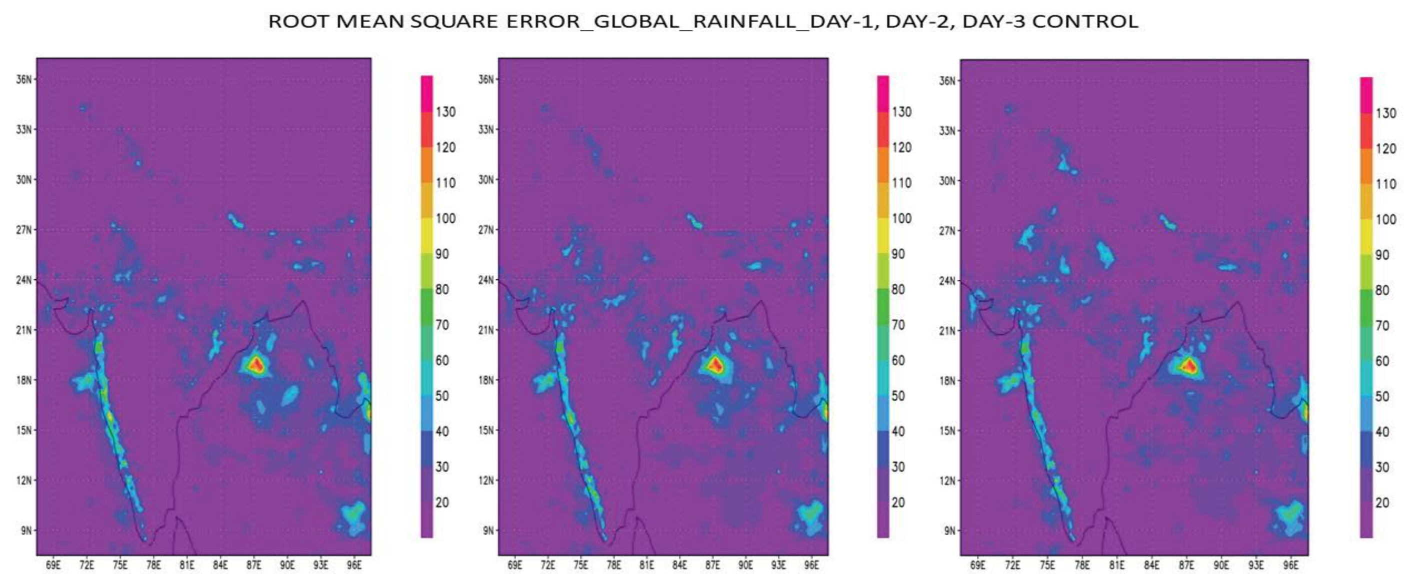

Figure 20: RMSE of global rainfall for day-1, day-2, and day-3 (control).

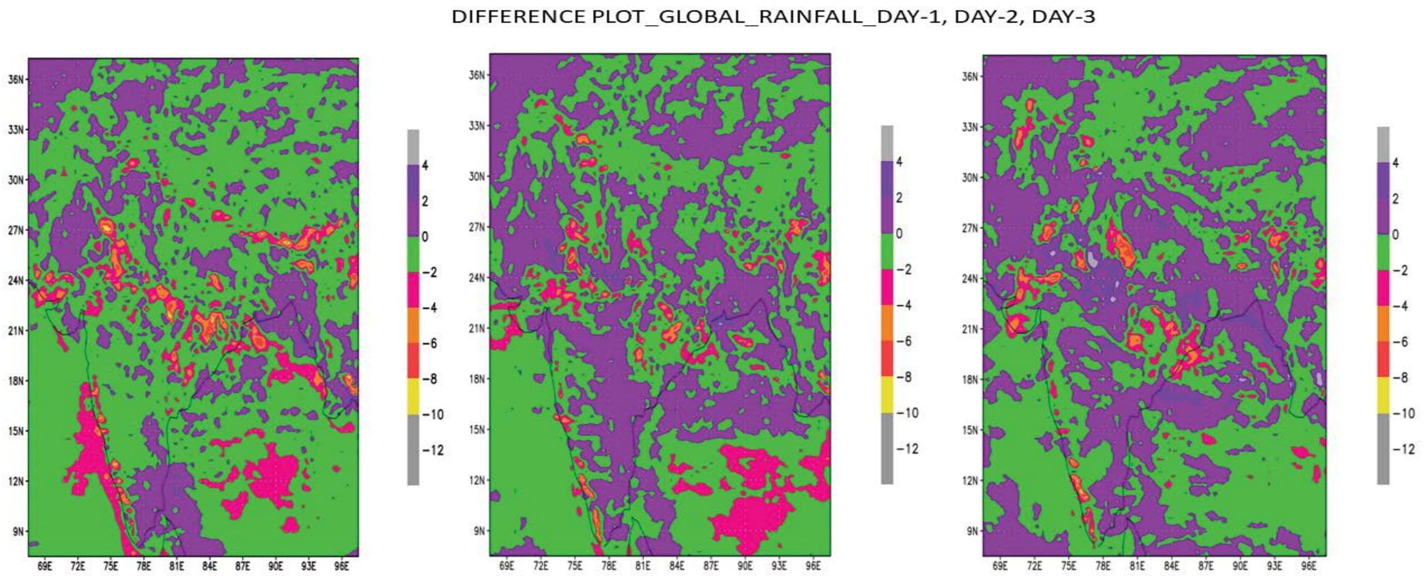

Figure 21: Difference plot of global rainfall for day-1, day-2, and day-3.

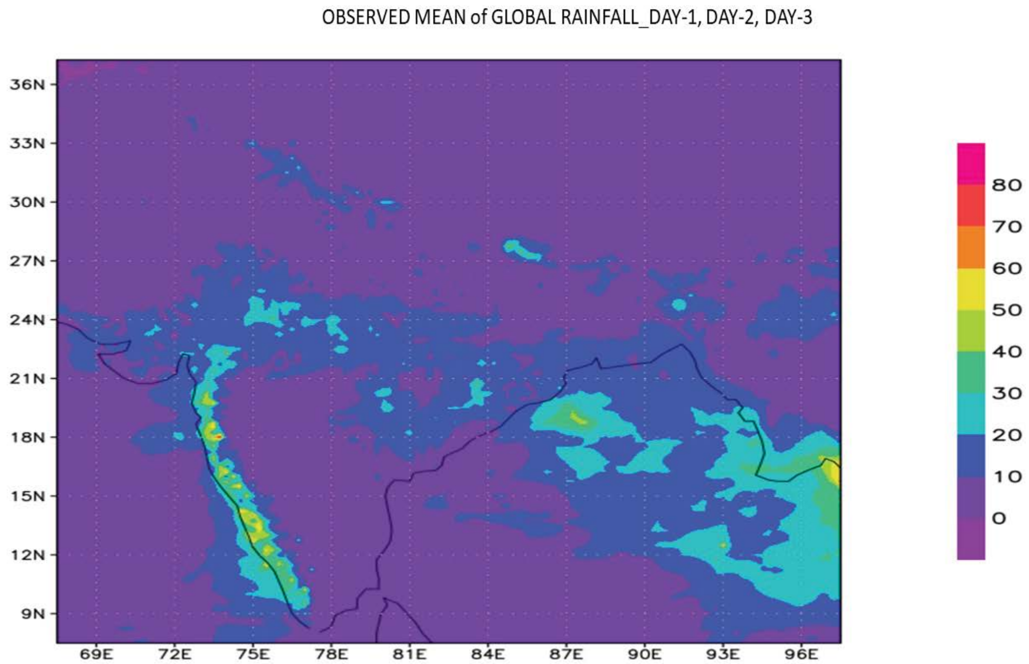

Figure 22: Mean of observed global rainfall for day-1, day-2, and day-3.

SUMMARY

Ensemble based prediction systems have been successful in providing better forecast guidance and have evolved in the past few decades starting with Global EPS focusing on uncertainties. With rise in computing capacity, short range EPS has been developed and operationally implemented at many meteorological centres around the world to address the significant uncertainty on shorter time and length scales. The convective scale ensemble is very much essential in order to handle the uncertainty in forecasts at a kilometre scale. Unified Model based convective scale regional ensemble prediction system has been implemented at NCMRWF using MOGREPS. The initial and boundary conditions for the control and 11 perturbed members are obtained from the operational runs of NEPS-G. NEPS-R has its own Random Parameters (RP) scheme to take care of model uncertainties. Several sensitivity experiments were carried out to arrive at an operationally feasible model setup and configuration to save computational time and resources. With reference to the reports 9, 10 and 11 of NCMRWF the following results could be concluded. On August 6, a depression formed over north-west Bay of Bengal, with IMD giving the storm the identifier BOB 03. Soon after the system intensified into a deep depression, it started approaching the north Odisha coastline. On August 7, the deep depression made land fall along the north Odisha-west Bengal Coastline, on August 11 it dissipated. Haryana, Delhi and Chandigarh had deficit of rainfall of about 42%, hence, received deficit or scanty rainfall. Monsoon rainfall during August was 115% of its Long Period Average. After 1996 (119% of LPA) this is the highest recorded rainfall in August (115% of LPA). After 2010, this is the first-time rainfall during August is above LPA. The highest cumulative rainfall during August (13%) has been recorded in August 2019 after 1983 (142%). Heavy Rain battered much of Odisha, with accumulation peaking at 382.6 mm. Preliminary evaluation of rainfall forecast of NEPS-G and NEPS-R for the

Kerala heavy rain event on 15 August, 2019 and tropical cyclone 'Titli' indicate that NEPS-R has performed better than NEPS-G. NEPS-R was able to predict the heavy rainfall of 16 cm-32 cm for the Kerala heavy rain event at different lead times, whereas NEPS-G was able to predict a maximum of 8 cm-16 cm at different lead times. The models indicate that NEPS-R predicted higher probability of rainfall for different thresholds over comparatively larger area than NEPS-G.

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