Short to Sub-Seasonal hydrologic forecast to manage water and agricultural resources in India

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Abstract.

Water resources and agriculture are often affected by the weather anomalies in India resulting in a disproportionate damage. While short to sub-seasonal prediction systems and forecast products are available, a skilful hydrologic forecast of runoff and root-zone soil moisture that can provide timely information has been lacking in India. Using precipitation and air temperature forecasts from the Climate Forecast System v2 (CFSv2), Global Ensemble Forecast System (GEFSv2) and four products from Indian Institute of Tropical Meteorology (IITM), here we show that the IITM ensemble mean (mean of all four products from IITM) can be used operationally to provide hydrologic forecast in India at 7-45 days accumulation period. The IITM ensemble mean forecast was further improved using bias correction for precipitation and air temperature. Bias corrected precipitation forecast showed an improvement of 2.1 mm(on all-India median MAE) while all-India median bias corrected temperature forecast was improved by 2.1°C for 45 days accumulation period. Moreover, the VIC simulated forecast of runoff and soil moisture successfully captured the observed anomalies during the severe drought years. The findings reported herein have strong implications for providing timely information that can help farmers and water managers in decision making in India.

1. Introduction

Droughts in India have enormous implications for water resources and agriculture (Mishra et al., 2014; Shah and Mishra, 2015). Many regions in India face drought risks due to lack of monsoon season rainfall. In 2015, a large part of India was under drought which affected agriculture and water resources (Mishra et al., 2016). Moreover, in 2015, about 33 million people were affected by the drought that covered 256 districts, 10 states, and caused an estimated loss of 650,000 crore Indian rupee (Indian Express, 11 May, 2016). The major driver of hydrological (based on runoff) or agricultural (based on soil moisture) droughts in India remains the Indian summer monsoon (Mishra et al., 2014; Shah and Mishra, 2015; Mishra et al., 2016),which accounts for about 80% of the mean annual rainfall and has 10% year-to-year variability (Rahman et al., 2009; Rajeevan et al., 2005, 2006). However, during the recent decades, increased air temperature has affected hydrologic and agricultural droughts in many regions of the World (Dai et al., 2004; Livneh and Hoerling, 2016; Park Williams et al., 2012; Shukla et al., 2015).

One of the relatively well known drivers of drought occurrence in India is the positive sea surface temperature anomaly in the Pacific Ocean (Kumar et al., 1999, 2006) and in the Indian Ocean (Mishra et al., 2012; Roxy et al., 2015). However, in the absence of hydrologic forecast at appropriate lead time, planning of agricultural and water resources sectors are often adversely affected. For instance, many times the cost of seeds, field preparation, and transplantation cannot be recovered due to prolonged anomalies of soil moisture or rainfall. Furthermore, water resources, reservoir operations, and irrigation planning is affected in the absence of a skilful forecast at sufficient lead time. Prediction of anomalies in meteorological and hydrological conditions well in advance can assist timely decision-making to minimize impact on agricultural and water resources sectors. Shah and Mishra (2016b)showed potential of the Global Ensemble Forecast System (GEFS; Hamill et al., 2013) for hydrologic prediction in India with a lead time up to 7 days. They reported that up to 7-days lead time, major skill in hydrologic prediction is derived from initial hydrologic conditions (i.e. initial soil moisture content) as shown in Shukla and Lettenmaier (2011). Yuan et al.(2011) reported that soil moisture forecast from the CFSv2 (CFSv2; Saha et al., 2014) provides useful information to predict droughts in the tropical region. Moreover, Yuan et al (2012a) showed that the CFSv2 can provide a better seasonal hydroclimatic forecast than ensemble streamflow prediction in the USA.

Despite the utility of the various forecast products that can provide useful skill in hydrologic predictions, efforts have largely been limited to evaluate the potential of these products to provide forecast at 7-45 days accumulation period that can be used for agricultural and water resources planning in India. Here we provide an assessment of skill in hydrologic forecast that can be utilized for drought forecast at 7-45 days accumulation period using data from GEFSv2, CFSv2, and IITM to improve management of water and agricultural resources in India.

2. Data and Methodology

2.1 Observed data

Forecast products were evaluated against observed data from India Meteorological Department (IMD). We used the 0.25º daily gridded precipitation product from IMD which was developed based on ground observations from 6995 stations across India using an inverse distance weighing scheme (Shepard, 1984) and is available for the period of 1901-2015 (Pai et al., 2015). The IMD precipitation captures spatial variability of the monsoon season rainfall and features related to orographic rainfall in the Western Ghats and foothills of Himalaya. We used 0.5º daily observed maximum and minimum temperatures from IMD, which were developed based on 395 stations across India (Srivastava et al., 2009). Gridded air temperature dataset is available for 1951-2013 and have been used in many previous studies (Mishra et al., 2014; Shah and Mishra, 2015, 2016b, 2014; Mishra et al. 2016).

2.2 Forecast Products

We evaluated prediction skill of precipitation, maximum and minimum temperatures from the CFSv2 reforecast (Saha et al., 2014), GEFSv2 reforecast (Hamill et al., 2013) and forecast products from IITM. Reforecast from the CFSv2 are based on a dynamical coupled model and are available at every 5th day from the start of year from the National Centre of Environmental Prediction (NCEP). Moreover, 6-hourly forecasts at every 5th day from CFSv2 are available with up to nine months lead time and at 1º resolution for 1982-2009. Climate forecast System (CFS) model's atmospheric component is operational at T126 spectral truncation (~100 Km horizontal resolution) and 64 sigma-pressure hybrid vertical resolution. Shukla and Lettenmaier (2011) using CFSv2 reported that initial hydrologic conditions dominate skill of hydrologic prediction in the continental United States (CONUS) up to 1-month lead time, beyond which skill from meteorological forcing dominated. McEvoy et al. (2016) recently demonstrated higher skill for potential evapotranspiration than precipitation using the CFSv2. Moreover, Yuan et al. (2011) reported that CFSv2 performs better than CFSv1 for prediction of precipitation and air temperature in the United States. Mo and Lettenmaier (2014) found that for shorter lead times (about 1 month), CFSv2 forecast has higher skill for soil moisture prediction than the benchmark forecast (climatological mean). Moreover, Tian et al. (2016) evaluated CFSv2 for the CONUS and found that extreme indices based on temperature were better predicted than that of precipitation.

Other than CFSv2, we compared precipitation and temperature forecast from GEFSv2 reforecast (Hamill et al., 2013), which is based on the Global Forecast System (GFS) model, for 7 and 15 days lead time. Ensemble members are generated in GEFS by making perturbations in initial atmospheric conditions which lead to 11 ensemble members. The GEFS model runs at T254L42 resolution (~40 Km horizontal resolution) for the first 8 days lead time and at T190 (~54 km) for lead time beyond 7.5 days. The GEFS reforecast are available at 1º resolution for lead time up to 16 days and at 0.5° for 8 days lead from 1985 to present. Shah and Mishra (2016b) evaluated skill of GEFSv2 reforecast for drought prediction in India for accumulation period of7 days and found that the GEFS reforecast showed correlation of more than 0.5 against drought estimates from the observed data.

We obtained four forecast products from IITM. The forecast products of IITM are generated from the same CFSv2 model that has been described above. Abhilash et. al. (2014) developed an ensemble prediction system using CFSv2 at T126 horizontal resolution (~100km) [hereafter: IITM-CFST126] for prediction of monsoon intraseasonal oscillations (MISO) over the Indian monsoon region 15-20 days in advance. They found that though the skill was reasonable, there was a significant dry bias over the Indian land. Sharmilaet.al.(2013) reported that CFSv2 simulates the northward propagating MISO reasonably well but it has cold bias in SST and tropospheric temperatures. Thus, Abhilash et al.(2013) implemented a lead time dependent SST bias correction and forced the GFS (Atmospheric component of CFSv2) with slightly different physics and showed that it has improved skill over India compared to the CFSv2 (hereafter: IITM-GFST126). Subsequently, Sahai et. al. (2015a) implemented a high resolution version of CFSv2 (at T382 horizontal resolution ~35km; hereafter: IITM-CFST382) and showed that it has better skills in steep orographic regions. Although these three individual models show similar prediction skill and their errors saturate at about the same lead time of around 25 days, there are many instances where the three models disagree in predicting particular events, such as the amplitude and phase of monsoon intraseasonal oscillation (MISO) propagation. Considering these facts, Abhilash et al. (2015) proposed a CFS based multimodel ensemble mean (MME), which improved the spread error relationship and added value to both the deterministic and probabilistic forecasts. Real time skill for these models has been reported in the previous studies(Borah et al., 2015; Joseph et al., 2015b, 2015a, Sahai et al., 2013, 2015b). Subsequently, bias corrected SST forced GFS was also run at T382 resolution (hereafter: IITM-GFST382). Thus IITM's forecasts are available for four models, named IITM-CFST126, IITM-GFST126, IITM-CFST382, and IITM-GFST382. Model integrations for the year starting since 2001 to 2015 are carried out from 16th May and continued up to 28th September at every 5 day interval (16th May, 21st May, 26th May,..., 23rd Sep, 28th Sep) for the next 45 days period. Forecast ensemble members from IITM are available at 1° resolution. Ensemble mean of all four IITM products (hereafter: IITM-ensemble) and individual products were compared with CFSv2 and GEFSv2 to evaluate the hydrologic prediction skill. The aim of this comparison was to evaluate if IITM forecast products provide better prediction skill than CFSv2 and GEFSv2. Moreover, the product that provide the best hydrologic prediction skill in India can be used operationally to forecast hydrologic conditions and rainfall and temperature anomalies that can help in decision making in agricultural and water resources.

We used ensemble mean (of all available ensemble members) of individual forecast products for evaluation. We selected forecasts at every 15th day, which was evaluated for 7, 15, 30, and 45 day accumulation period using accumulated precipitation and average temperature. We use the term accumulation period instead of lead time as forecast evaluation was performed for accumulated precipitation and mean temperature for 7, 15, 30, and 45 days. We selected forecasts starting from 16th May till end of September as currently IITM provides forecast during the monsoon season. However, IITM will extend forecast to the non-monsoon season in near future. We aggregated all the observed and forecast variables (precipitation, maximum and minimum air temperatures) to daily-scale (if they were available at sub-daily time period) and regridded to 0.25° horizontal resolution to make them consistent with the spatial resolution of observed data. We regridded precipitation and air temperature using Maurer et al.(2002) which uses the Synergraphic Mapping System (SYMAP) algorithm (Shepard, 1984) for precipitation and lapse rate based on elevation data for air temperature. We, however, carefully evaluated all the products at their original spatial resolution and at 0.25° to make sure that datasets are consistent at both resolutions for spatial and temporal variability. We found that the bias in the forecast products at coarser and higher resolution was consistent.

We considered a common period of 2001-2009 for comparison and evaluation of different forecast products against the observed gridded data from IMD.

2.3 Forecast Evaluation

For evaluation of the forecast from each product against the observations, we prepared yearly time-series of precipitation and temperature forecast for each forecast date by accumulating precipitation and averaging temperature for a given lead time (7-45 days). For instance, if the date of forecast was 1st June and lead time 15 days, accumulated precipitation and mean temperature for 15 days from June 1st for each of the products were estimated for the period 2001-2009. As the period for evaluation was 2001-2009, sample size was 10, and we acknowledge that a larger sample size with data for a longer retrospective record will help us to better categorize uncertainty in forecast skill. We used coefficient of correlation, mean absolute error (MAE), and critical success index (CSI) to evaluate performance of the forecast products. A non-parametric Spearman Rank Correlation coefficient (Wilks, 2006) was used to evaluate performance of forecast products in capturing temporal relationship with OBS. For this the forecast product and corresponding OBS are assigned ranks and then correlation was estimated using following equation (2.1)

$$r_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \qquad (2.1)$$

Where r_s is Spearman Rank Correlation coefficient; d_i is difference in rank between paired forecast and OBS; and n is sample size (here 10). Significance of correlation was tested using the exact permutation distribution test (Robson, 2002). Observed samples were permuted and rank correlations were estimated. Estimated correlation is significant if it rejects the null hypothesis at 5% significance level.

Mean absolute error (MAE) was used to estimate error in the forecast products as compared to OBS. Absolute error was estimated in all the forecast products for each year as compared to OBS and then mean of all years was taken to estimate MAE. Critical success index (CSI; (Wilks, 2006)) was used to evaluate anomalies predicted using forecast products as compared to OBS similar to (AghaKouchak and Mehran, 2013). CSI is ratio of hit events and sum of hit and miss, and false events (hit+miss+false).

2.4 The Variable Infiltration Capacity (VIC) model

We used the Variable Infiltration Capacity (VIC, version 4.1.2) (Liang et al., 1994, 1996) model to simulate hydrologic variables (total runoff and root-zone soil moisture) using meteorological forcing (daily precipitation, and maximum and minimum temperatures) from IMD and the forecast products. Soil moisture and runoff predicted using forecast products were evaluated against soil moisture and runoff simulated using the observed forcing from IMD. The VIC model simulates water and energy fluxes at each grid cell and sub-grid variability of precipitation, elevation, soil, and vegetation is well represented (Gao et al., 2010). The soil parameters used were developed based on Harmonized World Soil Database (HWSD) v1.2. The vegetation parameters used in this study were developed using 1-km Advanced Very High Resolution

Radiometer (AVHRR) global land cover information. We used vegetation library that was developed at University of Washington. The vegetation parameters were not specifically developed to incorporate crops that are grown in India. However, the existing parameters were successfully used in the model application over India (Shah and Mishra, 2015; Shah and Mishra, 2016).The VIC model's version that was used in this study does not explicitly represent groundwater, rather it only accounts for baseflow. We acknowledge that India specific soil and vegetation parameters along with the representation of irrigation, reservoir, and groundwater can improve the water budget; however, these were not considered in the present study due to unavailability of either observations or the model version that has the representation of human interventions. The VIC model setup used in this study is well calibrated and evaluated against observed streamflow and satellite based evapotranspiration and soil moisture in Shah and Mishra (2016a) and Shah and Mishra (2016b). The VIC model has been widely used for hydrologic prediction at watershed and regional scales (Mo and Lettenmaier, 2014; Shah and Mishra, 2016b; Shukla and Lettenmaier, 2011; Yuan and Wood, 2012b).

2.5 Bias-correction of Precipitation and Temperature Forecast

Improvements in hydrologic predictioncan be achieved by post-processing the forecast of meteorological variables (precipitation, maximum and minimum temperatures).We corrected precipitation forecast using linear scaling approach as described in Shah and Mishra (2015, 2016b). For each forecast date, we corrected precipitation for the selected (7, 15, 30 and 45 days) accumulation period. We first corrected accumulated precipitation due to extreme events (above 90th percentile) for each forecast date in the training period and a scaling factor was obtained for each forecast dates based on ratio of precipitation for 45 days accumulation period due to extreme events in the observed and forecast products. In the second step, after the correction for extreme precipitation, scaling factors were obtained based on precipitation for 45 days accumulation period, for each forecast dates from the forecast products and OBS for the entire training period. Scaling factors were estimated for the training period (Nine years), which were evaluated in the testing period (One year). More detailed information on this method can be obtained from Shah and Mishra (2016b).

To correct daily mean (of maximum and minimum) temperature from the forecast, we performed Quantile-Quantile (Q-Q) mapping (Wood, 2002). Initially, we prepared yearly time-series of 45-days accumulation period average temperature forecast for all the forecast dates along with corresponding observed time-series. For each forecast date and for each grid cell, we estimated quantiles of mean temperature for 45 days accumulation period for each year using the climatology of the entire period. To estimate quantiles, cumulative distribution functions (CDF) were fitted. Weibull plotting position was used to map cumulative distribution function when percentiles fall between 1/(N+1) and N/(N+1); where N is number of climatological years during the training period. In case when percentiles fall beyond these limits, normal distribution was fitted and values were extrapolated. More details on the Q-Q mapping can be obtained from Shah and Mishra (2016b). Similarly, quantiles were estimated for OBS temperature for corresponding time-series. Based on estimated quantiles, Q-Q mapping was done and forecast was replaced with corresponding value based on OBS. We estimated bias corrected mean temperature using Q-Q mapping. Bias (difference between corrected and uncorrected 45-day average mean temperature) was then added equally to daily raw Tmax and Tmin to get the corrected values of daily maximum and minimum temperatures. We did not bias correct Tmax and Tmin individually as that will affect the diurnal temperature range (Tmax-Tmin). We adopted multifold validation approach leaving-one-year out for testing both precipitation and mean temperature (Shah and Mishra, 2016b).

Forecast of soil moisture and runoff is essential for planning and decision making in agriculture and water resources (Asoka and Mishra, 2015). Hence, we evaluated forecast skill of soil moisture and runoff simulated using meteorological variables from IITM-ensemble. Using the raw and bias corrected forecasts (precipitation, maximum, and minimum temperatures), the Variable Infiltration Capacity (VIC) model was run to obtain soil moisture and total runoff (surface runoff+baseflow) forecast. We evaluated improvements in correlation of runoff and soil moisture predicted using the bias-corrected precipitation and temperatures from the IITM ensemble (IITM-ensemble-bc) against uncorrected (raw) precipitation and temperatures from the IITM ensemble mean (IITM-ensemble) and CFSv2 (Supplemental Fig.S14). For simulating runoff and soil moisture, forcings from all the three products were used to run the VIC model at 0.25º and daily resolution while initial hydrologic conditions were generated using the observed forcing from the IMD. Forecast skill in hydrologic prediction was evaluated for mean total runoff and soil moisture for 7-45 day accumulation period. We considered 45 day accumulation period to evaluate the hydrologic prediction skill as for shorter lead times forecast skill are generally higher owing to persistence in initial hydrologic condition.

3. Results and discussion

3.1 Comparison of Forecast Skill for Precipitation and Temperature forecast:

3.1.1 Lead time 7 and 15-days

We estimated forecast skill (against observations, OBS hereafter) in precipitation and air temperature from all the forecast products for 7, 15, 30, and 45 day accumulation period. Hydrologic forecast at these accumulation periods can be used for planning (field preparation, sowing, irrigation, water management, and reservoir operations) and decision making in water resources and agriculture. All the forecast products showed significantly high (more than 0.75) Spearman Rank correlation (Fig. 1a-n) in the majority of India for accumulation period of 7 days indicating higher skill for shorter lead time. We noticed that correlation declines as accumulation period was increased from 7 to 15-days especially in the central region (Fig. 1). Moreover, we find that GEFSv2 and IITM-ensemble (correlation more than 0.6 for majority of India) perform better than CFSv2 for 15 day accumulation period. Correlations between observed and forecast were generally lower for forecast initiated during the months of July and August (Fig.1o-p). Among all the forecast products, IITM products and their IITM-ensemble mean (mean of all four IITM forecast products) showed better correlations with OBS as compared to GEFSv2 and

CFSv2 for 7 and 15 day accumulation period (Fig. 1 and Supplementary Table S1). Among the IITM products, products with the atmospheric model operating at higher resolution (IITM-CFST382 and IITM-GFST382) showed relatively better performance as compared to the other two IITM products, which demonstrates that the models operating at higher resolution provide a better forecast skill (Duffy et al., 2003; Roebber et al., 2004).

We estimated MAE in precipitation forecast from all the products as compared to OBS for accumulation period of 7 and 15 days (Fig. S1). We find that MAE is proportional to the magnitude of precipitation as the monsoon season precipitation is higher in the core monsoon, northeastern, and Western Ghats regions (Fig. S1). Moreover, all the products showed a lower MAE in the arid and semi-arid regions of the western India during the monsoon season and MAE was higher during the months of July-September (Fig. S1o,p). MAE, however, decreases as forecast accumulation period was increased from 7 to 15 days, which is due to longer accumulation period for precipitation. We noticed that all India median MAE (median of all the grids) in the forecast products vary with the date of forecast, however, both CFSv2 and IITM ensemble mean showed comparable MAE at all India scale for 7 day accumulation period (Fig S1o and Table S1). However, for 15 day accumulation period, and for most of the forecast dates (Fig S1p), the IITM-ensemble showed lower error compared to the other products. Overall, based on correlation and MAE, we find that the IITM ensemble performs better than the other forecast products for 7 and 15 day accumulation period for precipitation prediction.

Lower skill in precipitation forecast in July and August can be attributed to high intraseasonal variability as a large fraction of total precipitation in the monsoon season occurs during these months. Intraseasonal variability can be characterized by spells of active-break periods of length 3-5 days (Rajeevan et al., 2010). Active-break spells are dominated by SST, wind pattern, Maiden-Julian Oscillation (MJO), and ITCZ (Goswami and Ajayamohan, 2000; Rajeevan et al., 2010; Woolnough et al., 2007). Predictability of precipitation in India depends on the ability of models to capture intraseaonal and interannual variability in precipitation (Webster et al., 1998). Improvements in spatial resolution of the atmospheric model and bias corrected SST in the IITM forecast products lead to enhancement in forecast skill, which potentially can be used for decision making in water resources and agriculture in India.

Similar to precipitation for 7 and 15-days accumulation period, we evaluated skill in maximum (Tmax) and minimum (Tmin) temperatures from all the forecast products against observed air temperatures from IMD (Fig. S2). Tmax averaged for 7 day accumulation period from all the forecast products showed a good correlation with OBS over the most of India (Fig. S2a-g). Similar to precipitation from the IITM-ensemble, Tmax showed the highest correlation with OBS (0.78; Table S1). However, correlation for 15 days accumulation period was lower than that of 7 days accumulation period (Fig S2h-n,p; Table S1). The IITM-ensemble showed correlation above 0.8 over most of the regions in India and generally skill in Tmax forecast are better than that of precipitation. However, all the forecast products showed a negative correlation (OBS and forecast) in the Northern Himalayan region, which can be partially attributed to sparse gage stations in the complex regions of Himalayas (Mishra, 2015).

At 7 days accumulation period, the forecast products showed higher MAE in the Northwestern arid region, Himalayan range, and Western Ghats (Fig. S3). The IITM products and ensemble mean showed improvement in MAE, which was contributed by enhancements in spatial resolution and bias corrected inputs (SST) in IITM models (Fig. S3a-g,o and Table S1). Overall, the IITM-ensemble showed lower MAE for most of the forecast dates during the monsoon season (Fig S3o and Table S1). Moreover, the IITM-ensemble showed lower all-India median MAE (1.2 ºC) as compared to the GEFSv2 (2.0 ºC) and CFSv2 (1.7 ºC) for 15 days accumulation period (Fig. S3h-n,p). Similar to 7 day accumulation period, all India median MAE in Tmax was the lowest in IITM ensemble for 15 days accumulation period. CFSv2 models showed better skill in Tmax than GEFSv2, which is consistent with the findings of Shah and Mishra (2016b).

Similar to precipitation and Tmax, forecast skill was estimated based on correlation and MAE for minimum temperature (Tmin). Tmin from all the forecast products showed lower correlation with OBS as compared to precipitation and Tmax in July-August (Fig. S4). For Tmin, GEFSv2 (correlations for accumulation period of7 day: 0.55 and accumulation period of15 day: 0.52) and the IITM-ensemble (correlation 0.52 and 0.48 for 7 and 15 day) showed comparable skill (Table S1). For Tmax and Tmin forecasts, the IITM-ensemble showed lower all-India median MAE as compared to GEFSv2 (Figs. S3,S5 and Table S1). Predictions of Tmin from all the products showed weaker performance than Tmax, which was also reported in Shah and Mishra (2016b). The difference in the performance of Tmax and Tmin can be explained as Tmax is mostly governed by partitioning of energy budget which can be simulated by land surface models) whereas Tmin depends on night time boundary conditions and presence of clouds on infrared losses (which may be difficult to simulate) (Pattantyus-Abraham et al., 2004; Pitman and Perkins, 2009). Overall, predictions of Tmin from all the forecast products showed higher errors in the Northwest and Himalayan range and for the most cases, the IITM ensemble outperformed the other forecast products (Fig. S5).

3.1.2 Lead time 30 & 45 -days

Since GEFSv2 reforecast is available only up to lead time16 days, our comparison for the accumulation period of 30 and 45 days was limited to the forecast products from the IITM and CFSv2. The four IITM products and their ensemble mean showed comparatively better (though not significant) correlations with OBS as compared to CFSv2 (Fig. S6, Table S1). We found that the correlations were higher than 0.5 in the majority of western and central India indicating a reasonable skill at 30 day accumulation period in the IITM ensemble. However, at 45-day accumulation period, satisfactory forecast skill can only be seen in the arid and semi-arid regions where precipitation amount is substantially lower than the other regions in India (Fig. S6). These results indicate that based on correlations, a reasonable skill can be obtained in the precipitation forecast from the IITM products. Precipitation forecast at accumulation period of 30 and 45 days showed spatial patterns similar to that of MAE as were observed for the accumulation period of 7 and 15 days (Fig. S7).The IITM ensemble showed an improvement in error over CFSv2 in the majority of India (Fig. S7). The IITM ensemble mean showed lower error for accumulation period of 30 and 45 days (Fig. S7m,n). This improvement in correlation and MAE can be attributed to finer resolution of the models and bias corrected SSTs, as shown by the IITM-CFST382, and IITM-GFST382 in comparison to IITM-GFST126, IITM-CFST126, GEFSv2, and CFSv2.

Prediction of Tmax from the IITM ensemble showed significant and higher correlation with OBS at 30 day accumulation period, with major contribution from the IITM-GFST382 product (Fig. S8). We notice that the IITM ensemble showed correlations more than 0.6 for the majority of India between OBS and predicted Tmax at 30 day accumulation period. At 45 day accumulation period, correlation decreases (in comparison to 30 day accumulation period), however, predictions of Tmax from the IITM ensemble mean showed better skill than CFSv2 with OBS. Spatial patterns of MAE in Tmax prediction for accumulation period of 30 and 45 days were consistent with spatial patterns for accumulation period of 7 and 15 days indicating larger errors in predicted Tmax in the northern and western parts of the country (Fig S9). Predictions of Tmin showed lower correlation as compared to Tmax (similar to shorter lead times), especially in the Northwest region, where correlations were negative (Fig S10). Predictions of Tmin from the IITM-GFST126 and GFST382 showed better correlation in the southern peninsula. Spatial patterns of MAE in Tmin predictions at accumulation period of 30 and 45 days were consistent with spatial pattern for 7 and 15 days accumulation period (Fig S11). Predictions from IITM-CFST382 product showed lower errors as compared to the all other products (Table S1). Predictions of Tmin from the IITM-ensemble mean showed lower error (30 day accumulation period: 0.9 and 45 day accumulation period: 1.1 ºC) as compared to CFSv2 (1.2 and 1.2 ºC for 30 and 45 days accumulation periods) [Table S1]. Overall, the IITM ensemble performs better than GEFSv2 and CFSv2 for all the accumulation periods (7-45 days). Moreover, the IITM ensemble mean also outperforms other products from the IITM in most of the cases in terms of their individual performance.

Since the IITM ensemble performed better than the other forecast products from IITM, the performance of the IITM ensemble was compared against CFSv2 for 7-45 days accumulation periods (Fig.2). Since the forecast skill declines with the lead time, we discuss forecast skill at 45 day accumulation period in details and results for the other leads are presented in supplemental Fig. S12. At 45 day accumulation period, correlation in precipitation forecast from CFSv2 is more than 0.2 only in a few regions (mainly centred in northern and western India) [Fig.2a]. The IITM-ensemble showed correlation (~0.3) higher than CFSv2 (Fig 2b) in most of the regions, especially during July-August months (Fig 2c). For Tmax and Tmin forecasts, the IITM-ensemble showed higher correlations than CFSv2 in majority of India (Fig 2d,e,g,h).We found that the difference in forecast skill from the IITM-ensemble and CFSv2 is higher for longer accumulation periods. At 7 day accumulation period, precipitation forecast from CFSv2 and IITM-ensemble showed correlation more than 0.6 in most regions in India, therefore, for shorter accumulation periods, difference in the forecast skill of CFSv2 and IITM-ensemble is moderate (Fig S12a). For 15 and 30 day accumulation period, difference in correlations shown by CFSv2 and IITM ensemble was higher than for 45 days accumulation period (Fig S13 and S14). These results show that the IITM ensemble forecast of precipitation, Tmax, and Tmin have better skill than CFSv2 for the majority of India, which can be used for hydrologic prediction of runoff and soil moisture that can be valuable for decision making of water resources and agriculture. Moreover, for 30 and 45 day accumulation periods, the IITM-ensemble showed relatively better forecast skill than that of CFSv2.

3.2 Performance of bias-corrected IITM-ensemble

Our results show that the bias correction resulted in reduction in all-India median MAE in precipitation predictions for all the forecast dates during the monsoon season months (Fig. 3c) especially in the Himalayan range and Northeast region (Fig 3a,b). We find substantial improvements in MAE of maximum and minimum temperatures after the bias correction (Figs 3d,e). For instance, all India median MAE was reduced for all the forecast dates after the bias correction (Fig. 3f). Median reduction in MAE for all dates was observed as 2.1 ºC. We find that the bias correction substantially improved temperature forecast from the IITM ensemble. This improvement in temperature forecast can be valuable for hydrologic applications. For instance, air temperature influences energy budget in hydrologic models and therefore can affect the partitioning of evapotranspiration and runoff. Due to high intraseasonal variability in the monsoon season precipitation, bias correction resulted in only marginal improvements in the precipitation forecast.

We find that linear scaling improved negative bias in precipitation forecast in central India and Western Ghats and positive bias in the Himalayan range and Southern peninsula. During the testing period (one year), improvement in bias is consistent with the training period (Nine year; Fig S15c,d). Improvements in correlation of all-India average precipitation predictions from the IITM-ensemble before and after bias-correction can be noticed (Fig. S16). At 45 days accumulation period a substantial improvement was noticed as compare to other accumulation periods (Fig. S16d). Overall, we noticed that the IITM ensemble mean showed improved forecast skill after the bias correction for most of the regions.We bias corrected the forecast products for the accumulation period of 45 days. However, the bias in the forecast products may have temporal variability and may not be constant for the entire period of 45 days. Therefore, bias correction approaches based on the variable lead time (Stockdale, 1997) need to be evaluated in future when IITM forecast for long-term retrospective period is available. However, the bias correction approach that we presented can be applied to evaluate seasonal forecast skill

3.3 Prediction of Soil moisture and total runoff

The VIC model was calibrated and evaluated using observed streamflow and satellite soil moisture and evapotranspiration (Shah and Mishra,2016a and Shah and Mishra,2016b). In this study, we used calibrated VIC model forced with observed IMD data to simulate soil moisture and runoff, which was considered as a reference to evaluate the forecast of soil moisture and runoff. Forecast of root-zone soil moisture and runoff was simulated using the VIC model forced with the forecast products (IITM-ensemble-bc, IITM-ensemble, and CFSv2), which were evaluated against the soil moisture/runoff obtained from the VIC model simulation using the observed forcing from IMD (Fig. S17). For all the forecast dates predicted root-zone soil moisture (top 60 cm soil moisture; Fig. S14) showed higher correlation than total runoff (Fig S17), which is due to higher persistence in soil moisture as compared to runoff (Shah and Mishra, 2016b). The bias-corrected IITM-ensemble showed higher correlations than the uncorrected IITM-ensemble and CFSv2. CSI of predicting dry anomaly in precipitation using the IITM-ensemble were higher in the Northwestern region whereas lower in Himalayan range and southern peninsula as compared to CFSv2, which is consistent with the results based on correlation and MAE (Fig. 4). Bias corrected IITM-ensemble showed an improved CSI in comparison to the raw forecast from the IITM-ensemble and CFSv2 for the majority of regions in India. However, CSI of predicting warm temperature anomalies was lower than that of CSI of predicting dry precipitation anomalies (Fig. 4), especially in Himalayan ranges. This can be due to higher uncertainty among observations in this region (Mishra, 2015). CSI in runoff and soil moisture is higher as compared to precipitation and temperature due to persistence in initial hydrologic conditions (Fig. 4). For 7, 15 and 30 day accumulation periods CSI is higher than that of 45 day accumulation period (Fig S18). We observed that as accumulation period was increased from 7 to 45 days, CSI of runoff declines in the arid and semi-arid regions of northwest. Overall, we found that the bias correction of forecast improves CSI of precipitation, temperature, total runoff, and soil moisture anomalies in India.

To show the utility of bias corrected forecast in hydrologic prediction in India, we analyzed the forecast for one of the recent drought years in India. Anomalies of total runoff and root-zone soil moisture predicted on 15thJuly 2009 for 45 day accumulation period using the VIC model with the bias corrected IITM-ensemble forecast were compared against the observed anomalies (Fig. 5). Forecast of these hydroclimatic anomalies at sufficient lead time can be helpful in decision making related to water resources and agriculture. We found that the IITM-ensemble-bc successfully captured spatial pattern of observed anomalies, which demonstrates the utility of hydroclimatic forecast for various applications. Persistence in initial hydrologic conditions simulated using the observed forcing and ability of the IITM-ensemble-bc to capture anomalies in precipitation and temperature (Fig S19) resulted in an improved forecast of total runoff and root-zone soil moisture in the majority of regions in India. However, some overestimation in the areal extent and severity of hydroclimatic anomalies can be noted in central India. These results show that the framework developed using the IITM-ensemble-bc forecast and the VIC model can be used to predict runoff and soil moisture up to 45 day accumulation period of forecast. Early-warning based on predictions can be helpful in decision making in water resources and agricultural sector so as to minimize risk.

4. Summary and Conclusions

Hydrologic forecast at 7-45 day accumulation period is essential for decision making in agriculture and water resources. Considering the importance of hydrologic prediction in India, we evaluated CFSv2, GEFSv2, and forecast products from the IITM. We found that meteorological variables predicted using the IITM products, especially the IITM-ensemble showed better forecast skill than the other two (CFSv2 and GEFSv2) products for all the accumulation periods (7,15, 30, and 45 days) during the monsoon season. We observed improved skills for the accumulation period 30 and 45 days by using the IITM-ensemble in comparison to CFSv2, which may be associated with the improvement in model resolution and initial condition used at IITM. For instance, Roxy et al. (Roxy et al., 2015) reported that CFSv2 has cold bias of 2-3°C in SSTs which may lead to dry bias in the monsoon season in India. Abhilash et al.(2014a) showed that forcings from GFS and CFS models with bias-corrected SSTs lead to improvement in predictability over the Indian region and that is due to improvement in ability to capture active and break spells. The IITM-ensemble performs better than individual IITM products for most of the selected forecast dates. This is consistent with findings of Palmer et al.(2004) and Kirtman et al. (2014), where they reported that multimodel ensemble outperforms individual model. One of the limitations of evaluation of the forecast products in this study is small sample size. The evaluation of all the forecast products was based on 10 common years between all products and 9 forecast dates during the monsoon season. Increasing the sample size in future based on the availability of forecasts for longer period may further improve evaluation and the bias correction. Our results showed higher forecast skill in the IITM ensemble, which might be associated with its ability to capture intraseasonal variability of rainfall during the monsoon season. The major factors that might have contributed in the improvements in the IITM forecast are:

i. Ensemble members of IITM forecast are generated by perturbing initial atmospheric conditions to improvesimulation of northward propagation
ii. Improvements in the boundary conditions with bias corrected SSTresult in improved precipitation prediction
iii. Higher spatial resolution of the IITM forecast can better resolve orographic rainfall

We evaluated the performance of bias corrected forecast from the IITM-ensemble for accumulation periods up to 45 days. Linear-scaling of precipitation forecast and Q-Q mapping of temperature forecast resulted in reduced errors and bias in forecast in India. Linear scaling precipitation with multifold validation showed an improvement in the Himalayan range and south central region. Bias correction of precipitation and air temperatures resulted in an improvement of about 2.1 mm and 2.1°C, respectively in all-India median of mean absolute error. Total runoff and root-zone soil moisture forecasts obtained using the corrected IITM-ensemble showed higher skill as compared to CFSv2 and raw IITM-ensemble for accumulation period up to 45 days. We found that all-India median CSI forrunoff forecast was improved from 0.63 to 0.71 after bias-correction while CSI of soil moisture forecast was improved from 0.6 to 0.67 for 45 day accumulation period.

Using forcing from the IITM-ensemble and the VIC model, anomalies in precipitation, temperature, root-zone soil moisture, and total runoff were successfully predicted, which can be used in decision making in water resources and agriculture. The bias corrected forecast from the IITM ensemble, which outperforms GEFSv2 and CFSv2, can be used to develop a hydrologic prediction platform for India. Information on forecast of anomalies in 7-45 day advance with the existing drought monitoring system in India (Shah and Mishra, 2015) can be valuable for decision-making in water-resources and agriculture. The hydrologic prediction based on the IITM-ensemble and the VIC model can provide a basis to predict both meteorological and hydrological anomalies and the information can be provided to farmers and water managers. The forecast of root-zone soil moisture along with precipitation and temperature anomalies can be used for irrigation planning. Moreover, runoff forecast at 7-45 day accumulation period can be valuable for water managers in India.

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References

Abhilash, S., Sahai, A. K., Borah, N., Chattopadhyay, R., Joseph, S., Sharmila, S., De, S. and Goswami, B. N.: Does bias correction in the forecasted SST improve the extended range prediction skill of active-break spells of Indian summer monsoon rainfall?: Bias correction in SST and extended range prediction, Atmospheric Sci. Lett., 15(2), 114–119, doi:10.1002/asl2.477, 2013.

Abhilash, S., Sahai, A. K., Borah, N., Chattopadhyay, R., Joseph, S., Sharmila, S., De, S. and Goswami, B. N.: Does bias correction in the forecasted SST improve the extended range prediction skill of active-break spells of Indian summer monsoon rainfall?: Bias correction in SST and extended range prediction, Atmospheric Sci. Lett., 15(2), 114–119, doi:10.1002/asl2.477, 2014a.

Abhilash, S., Sahai, A. K., Borah, N., Chattopadhyay, R., Joseph, S., Sharmila, S., De, S., Goswami, B. N. and Kumar, A.: Prediction and monitoring of monsoon intraseasonal oscillations over Indian monsoon region in an ensemble prediction system using CFSv2, Clim. Dyn., 42(9–10), 2801–2815, doi:10.1007/s00382-013-2045-9, 2014b.

Abhilash, S., Sahai, A. K., Borah, N., Joseph, S., Chattopadhyay, R., Sharmila, S., Rajeevan, M., Mapes, B. E. and Kumar, A.: Improved Spread–Error Relationship and Probabilistic Prediction from the CFS-Based Grand Ensemble Prediction System, J. Appl. Meteorol. Climatol., 54(7), 1569–1578, doi:10.1175/JAMC-D-14-0200.1, 2015.

AghaKouchak, A. and Mehran, A.: Extended contingency table: Performance metrics for satellite observations and climate model simulations: TECHNICAL NOTE, Water Resour. Res., 49(10), 7144–7149, doi:10.1002/wrcr.20498, 2013.

Borah, N., Sahai, A. K., Abhilash, S., Chattopadhyay, R., Joseph, S., Sharmila, S. and Kumar, A.: An assessment of real-time extended range forecast of 2013 Indian summer monsoon: AN ASSESSMENT OF REAL-TIME ER FORECAST OF 2013 INDIAN SUMMER MONSOON, Int. J. Climatol., 35(10), 2860–2876, doi:10.1002/joc.4178, 2015.

Dai, A., Trenberth, K. E. and Qian, T.: A global dataset of Palmer Drought Severity Index for 1870-2002: Relationship with soil moisture and effects of surface warming, J. Hydrometeorol., 5(6), 1117–1130, 2004.

Duffy, P. B., Govindasamy, B., Iorio, J. P., Milovich, J., Sperber, K. R., Taylor, K. E., Wehner, M. F. and Thompson, S. L.: High-resolution simulations of global climate, part 1: present climate, Clim. Dyn., 21(5–6), 371–390, doi:10.1007/s00382-003-0339-z, 2003.

Gao, H., Tang, Q., Shi, X., Zhu, C., Bohn, T. J., Su, F., Sheffield, J., Pan, M., Lettenmaier, D. P., Wood, E. F. and others: Water budget record from Variable Infiltration Capacity (VIC) model, Algorithm Theor. Basis Doc. Terr. Water Cycle Data Rec. [online] Available from: https://www.researchgate.net/profile/Xiaogang_Shi/publication/268367169_6_Water_Budget_Record_from_Variable_Infiltration_Capacity_VIC_Model/links/55715dee08aee701d61cc286.pdf (Accessed 2 August 2016), 2010.

Goswami, B. N. and Ajayamohan, R. S.: Goswami_AjayaMohan_ISO_IAV.pdf, Journal of Climatte, 14, 1180–1198, 2000.

Hamill, T. M., Bates, G. T., Whitaker, J. S., Murray, D. R., Fiorino, M., Galarneau Jr, T. J., Zhu, Y. and Lapenta, W.: NOAA's second-generation global medium-range ensemble reforecast dataset, Bull. Am. Meteorol. Soc., 94(10), 1553–1565, 2013.

Joseph, S., Sahai, A. K., Abhilash, S., Chattopadhyay, R., Borah, N., Mapes, B. E., Rajeevan, M. and Kumar, A.: Development and Evaluation of an Objective Criterion for the Real-Time Prediction of Indian Summer Monsoon Onset in a Coupled Model Framework, J. Clim., 28(15), 6234–6248, doi:10.1175/JCLI-D-14-00842.1, 2015a.

Joseph, S., Sahai, A. K., Sharmila, S., Abhilash, S., Borah, N., Chattopadhyay, R., Pillai, P. A., Rajeevan, M. and Kumar, A.: North Indian heavy rainfall event during June 2013: diagnostics and extended range prediction, Clim. Dyn., 44(7–8), 2049–2065, doi:10.1007/s00382-014-2291-5, 2015b.

Kirtman, B. P., Min, D., Infanti, J. M., Kinter III, J. L., Paolino, D. A., Zhang, Q., Van Den Dool, H., Saha, S., Mendez, M. P., Becker, E. and others: The North American multimodel ensemble: phase-1 seasonal-to-interannual prediction; phase-2 toward developing intraseasonal prediction, Bull. Am. Meteorol. Soc., 95(4), 585–601, 2014.

Kumar, K. K., Rajagopalan, B. and Cane, M. A.: On the Weakening Relationship Between the Indian Monsoon and ENSO, Science, 284(5423), 2156–2159, doi:10.1126/science.284.5423.2156, 1999.

Kumar, K. K., Rajagopalan, B., Hoerling, M., Bates, G. and Cane, M.: Unraveling the Mystery of Indian Monsoon Failure During El Niño, Science, 314(5796), 115–119, doi:10.1126/science.1131152, 2006.

Liang, X., Lettenmaier, D. P., Wood, E. F. and Burges, S.: A simple hydrologically based model of land surface water and energy fluxes for general circulation models, J. Geophys. Res., 99(D7), 14415–14428, doi:10.1029/94JD00483, 1994.

Liang, X., Wood, E. F. and Lettenmaier, D. P.: Soil Moisture SimulationSurface soil moisture parameterization of the VIC-2L model: Evaluation and modification, Glob. Planet. Change, 13(1), 195–206, doi:10.1016/0921-8181(95)00046-1, 1996.

Livneh, B. and Hoerling, M. P.: The Physics of Drought in the U.S. Central Great Plains, J. Clim., doi:10.1175/JCLI-D-15-0697.1, 2016.

Maurer, E. P., Wood, A. W., Adam, J. C., Lettenmaier, D. P. and Nijssen, B.: A long-term hydrologically based dataset of land surface fluxes and states for the conterminous United States*, J. Clim., 15(22), 3237–3251, 2002.

McEvoy, D. J., Huntington, J. L., Mejia, J. F. and Hobbins, M. T.: Improved seasonal drought forecasts using reference evapotranspiration anomalies, Geophys. Res. Lett., 43(1), 377–385, doi:10.1002/2015GL067009, 2016.

Mishra, V.: Climatic uncertainty in Himalayan water towers: Climatic uncertainty, J. Geophys. Res. Atmospheres, 120(7), 2689–2705, doi:10.1002/2014JD022650, 2015.

Mishra, V., Smoliak, B. V., Lettenmaier, D. P. and Wallace, J. M.: A prominent pattern of year-to-year variability in Indian Summer Monsoon Rainfall, Proc. Natl. Acad. Sci., 109(19), 7213–7217, doi:10.1073/pnas.1119150109, 2012.

Mishra, V., Shah, R. and Thrasher, B.: Soil Moisture Droughts under the Retrospective and Projected Climate in India, J. Hydrometeorol., 15, 2267–2292, doi:10.1175/JHM-D-13-0177.1, 2014.

Mo, K. C. and Lettenmaier, D. P.: Hydrologic Prediction over the Conterminous United States Using the National Multi-Model Ensemble, J. Hydrometeorol., 15(4), 1457–1472, doi:10.1175/JHM-D-13-0197.1, 2014.

Pai, D. S., Sridhar, L., Badwaik, M. R. and Rajeevan, M.: Analysis of the daily rainfall events over India using a new long period (1901–2010) high resolution (0.25° × 0.25°) gridded rainfall data set, Clim. Dyn., 45(3), 755–776, doi:10.1007/s00382-014-2307-1, 2015.

Palmer, T. N., Doblas-Reyes, F. J., Hagedorn, R., Alessandri, A., Gualdi, S., Andersen, U., Feddersen, H., Cantelaube, P., Terres, J.-M., Davey, M., Graham, R., Délécluse, P., Lazar, A., Déqué, M., Guérémy, J.-F., Díez, E., Orfila, B., Hoshen, M., Morse, A. P., Keenlyside, N., Latif, M., Maisonnave, E., Rogel, P., Marletto, V. and Thomson, M. C.: DEVELOPMENT OF A EUROPEAN MULTIMODEL ENSEMBLE SYSTEM FOR SEASONAL-TO-INTERANNUAL PREDICTION (DEMETER), Bull. Am. Meteorol. Soc., 85(6), 853–872, doi:10.1175/BAMS-85-6-853, 2004.

Park Williams, A., Allen, C. D., Macalady, A. K., Griffin, D., Woodhouse, C. A., Meko, D. M., Swetnam, T. W., Rauscher, S. A., Seager, R., Grissino-Mayer, H. D., Dean, J. S., Cook, E. R., Gangodagamage, C., Cai, M. and McDowell, N. G.: Temperature as a potent driver of regional forest drought stress and tree mortality, Nat. Clim. Change, 3(3), 292–297, doi:10.1038/nclimate1693, 2012.

Pattantyus-Abraham, M., Kiraly, A. and Janosi, I.: Nonuniversal atmospheric persistence: differrence scaling of daily minimum and maximum temperatures, Phys. Rev. E, 69(021110), 1–7, 2004.

Pitman, A. J. and Perkins, S. E.: Global and Regional Comparison of Daily 2-m and 1000-hPa Maximum and Minimum Temperatures in Three Global Reanalyses, J. Clim., 22(17), 4667–4681, doi:10.1175/2009JCLI2799.1, 2009.

Rahman, S. H., Sengupta, D. and Ravichandran, M.: Variability of Indian summer monsoon rainfall in daily data from gauge and satellite, J. Geophys. Res., 114(D17), doi:10.1029/2008JD011694, 2009.

Rajeevan, M., Bhate, J., Kale, J. D. and Lal, B.: Development of a high resolution daily gridded rainfall data for the Indian region, Met Monogr. Climatol., 22, 2005, 2005.

Rajeevan, M., Bhate, J., Kale, J. D. and Lal, B.: High resolution daily gridded rainfall data for the Indian region: Analysis of break and active monsoon spells, Curr. Sci., 91(3), 296–306, 2006.

Rajeevan, M., Gadgil, S. and Bhate, J.: Active and break spells of the Indian summer monsoon, J. Earth Syst. Sci., 119(3), 229–247, 2010.

Robson, A. J.: Evidence for trends in UK flooding, Philos. Trans. R. Soc. Math. Phys. Eng. Sci., 360(1796), 1327–1343, doi:10.1098/rsta.2002.1003, 2002.

Roebber, P. J., Schultz, D. M., Colle, B. A. and Stensrud, D. J.: Toward improved prediction: High-resolution and ensemble modeling systems in operations, Weather Forecast., 19(5), 936–949, 2004.

Roxy, M. K., Ritika, K., Terray, P., Murtugudde, R., Ashok, K. and Goswami, B. N.: Drying of Indian subcontinent by rapid Indian Ocean warming and a weakening land-sea thermal gradient, Nat. Commun., 6, 7423, doi:10.1038/ncomms8423, 2015.

Saha, S., Moorthi, S., Wu, X., Wang, J., Nadiga, S., Tripp, P., Behringer, D., Hou, Y.-T., Chuang, H., Iredell, M., Ek, M., Meng, J., Yang, R., Mendez, M. P., van den Dool, H., Zhang, Q., Wang, W., Chen, M. and Becker, E.: The NCEP Climate Forecast System Version 2, J. Clim., 27(6), 2185–2208, doi:10.1175/JCLI-D-12-00823.1, 2014.

Sahai, A. K., Sharmila, S., Abhilash, S., Chattopadhyay, R., Borah, N., Krishna, R. P. M., Joseph, S., Roxy, M., De, S., Pattnaik, S. and others: Simulation and extended range prediction of monsoon intraseasonal oscillations in NCEP CFS/GFS version 2 framework, Curr. Sci., 104(10), 1394–1408, 2013.

Sahai, A. K., Abhilash, S., Chattopadhyay, R., Borah, N., Joseph, S., Sharmila, S. and Rajeevan, M.: High-resolution operational monsoon forecasts: an objective assessment, Clim. Dyn., 44(11–12), 3129–3140, doi:10.1007/s00382-014-2210-9, 2015a.

Sahai, A. K., Chattopadhyay, R., Joseph, S., Mandal, R., Dey, A., Abhilash, S., Krishna, R. P. M. and Borah, N.: Real-time performance of a multi-model ensemble-based extended range forecast system in predicting the 2014 monsoon season based on NCEP-CFSv2, Curr. Sci., 109(10), 1802–1813, 2015b.

Shah, H. L. and Mishra, V.: Hydrologic Changes in Indian Sub-Continental River Basins (1901-2012), J. Hydrometeorol., doi:10.1175/JHM-D-15-0231.1, 2016a.

Shah, R. and Mishra, V.: Evaluation of the Reanalysis Products for the Monsoon Season Droughts in India, J. Hydrometeorol., 15(4), 1575–1591, doi:10.1175/JHM-D-13-0103.1, 2014.

Shah, R. D. and Mishra, V.: Development of an Experimental Near-Real-Time Drought Monitor for India*, J. Hydrometeorol., 16(1), 327–345, doi:10.1175/JHM-D-14-0041.1, 2015.

Shah, R. D. and Mishra, V.: Utility of Global Ensemble Forecast System (GEFS) Reforecast for Medium-Range Drought Prediction in India, J. Hydrometeorol., 17(8), 1781–1800, doi:http://dx.doi.org/10.1175/JHM-D-15-0050.1, 2016b.

Sharmila, S., Pillai, P. A., Joseph, S., Roxy, M., Krishna, R. P. M., Chattopadhyay, R., Abhilash, S., Sahai, A. K. and Goswami, B. N.: Role of ocean–atmosphere interaction on northward propagation of Indian summer monsoon intra-seasonal oscillations (MISO), Clim. Dyn., 41(5–6), 1651–1669, doi:10.1007/s00382-013-1854-1, 2013.

Shepard, D. S.: Computer Mapping: The SYMAP Interpolation Algorithm, in Spatial Statistics and Models, edited by G. L. Gaile and C. J. Willmott, pp. 133–145, Springer Netherlands, Dordrecht. [online] Available from: http://dx.doi.org/10.1007/978-94-017-3048-8_7, 1984.

Shukla, S. and Lettenmaier, D. P.: Seasonal hydrologic prediction in the United States: understanding the role of initial hydrologic conditions and seasonal climate forecast skill, Hydrol. Earth Syst. Sci. Discuss., 8(4), 6565–6592, doi:10.5194/hessd-8-6565-2011, 2011.

Shukla, S., Safeeq, M., AghaKouchak, A., Guan, K. and Funk, C.: Temperature impacts on the water year 2014 drought in California: TEMPERATURE IMPACTS ON THE 2014 DROUGHT, Geophys. Res. Lett., 42(11), 4384–4393, doi:10.1002/2015GL063666, 2015.

Srivastava, A. K., Rajeevan, M. and Kshirsagar, S. R.: Development of a high resolution daily gridded temperature data set (1969-2005) for the Indian region, Atmospheric Sci. Lett., n/a-n/a, doi:10.1002/asl.232, 2009.

Stockdale, T. N.: Coupled ocean-atmosphere forecasts in the presence of climate drift, Mon. Weather Rev., 125(5), 809–818, 1997.

Tian, D., Wood, E. F. and Yuan, X.: CFSv2-based sub-seasonal precipitation and temperature forecast skill over the contiguous United States, Hydrol. Earth Syst. Sci. Discuss., 1–24, doi:10.5194/hess-2016-376, 2016.

Webster, P. J., Magana, V.O., Palmer, T. N., Shukla, J., Tomas, R. A., Yanai, M. and Yasunari, T.: webster_etal_1998_intraseasonal.pdf, J. Geophys. Res., 103(C7), 14451–14510, doi:10.1029/97JC02719/, 1998.

Wilks, D. S.: Statistical Methods in the Atmospheric Science, Academic Press, New York., 2006.

Wood, A. W.: Long-range experimental hydrologic forecasting for the eastern United States, J. Geophys. Res., 107(D20), doi:10.1029/2001JD000659, 2002.

Woolnough, S. J., Vitart, F. and Balmaseda, M. A.: The role of the ocean in the Madden–Julian Oscillation: Implications for MJO prediction, Q. J. R. Meteorol. Soc., 133(622), 117–128, doi:10.1002/qj.4, 2007.

Yuan, X. and Wood, E. F.: Downscaling precipitation or bias-correcting streamflow? Some implications for coupled general circulation model (CGCM)-based ensemble seasonal hydrologic forecast: DOWNSCALING PRECIPITATION OR BIAS-CORRECTING STREAMFLOW, Water Resour. Res., 48(12), n/a-n/a, doi:10.1029/2012WR012256, 2012a.

Yuan, X. and Wood, E. F.: On the clustering of climate models in ensemble seasonal forecasting: CLUSTERING OF SEASONAL FORECAST MODELS, Geophys. Res. Lett., 39(18), n/a-n/a, doi:10.1029/2012GL052735, 2012b.

Yuan, X., Wood, E. F., Luo, L. and Pan, M.: A first look at Climate Forecast System version 2 (CFSv2) for hydrological seasonal prediction: A FIRST LOOK AT CFSv2, Geophys. Res. Lett., 38(13), n/a-n/a, doi:10.1029/2011GL047792, 2011.

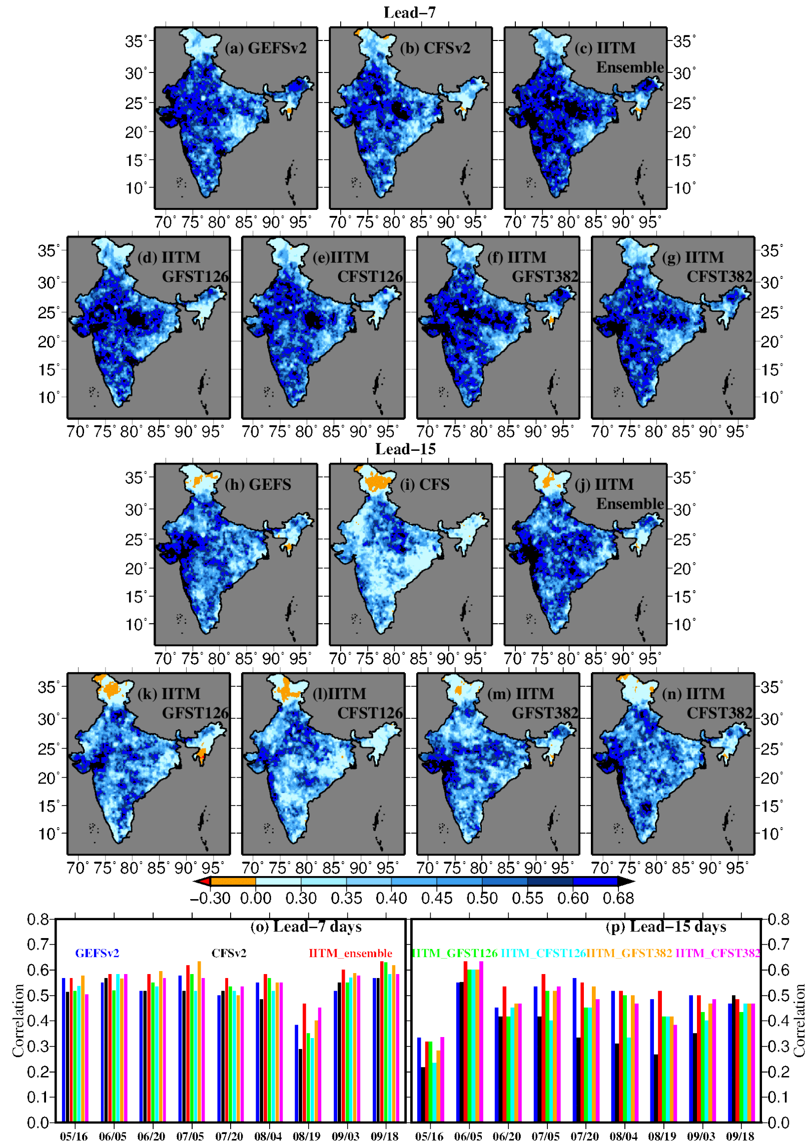

Figure 1: Correlation between precipitation forecasts and observed precipitation (OBS). (a) Correlation between precipitation forecast from the GEFSv2 accumulated up to 7-days accumulation period and corresponding OBS, (b) same as (a) but for the CFSv2 (c) same as (a) but for the IITM Ensemble, (d) same as (a) but for the IITM GFST126 (e) same as (a) but for the IITM GFST382, (f) same as (a) but for the IITM CFST382 (h-n) same as (a-f) but for accumulation period of15 days. (o) All-India median correlation between different precipitation forecasts at 7-day accumulation period and corresponding OBS for the forecasts initiated on different dates (p) same as (o) but for accumulation period of15 days (period: 2001-2009).

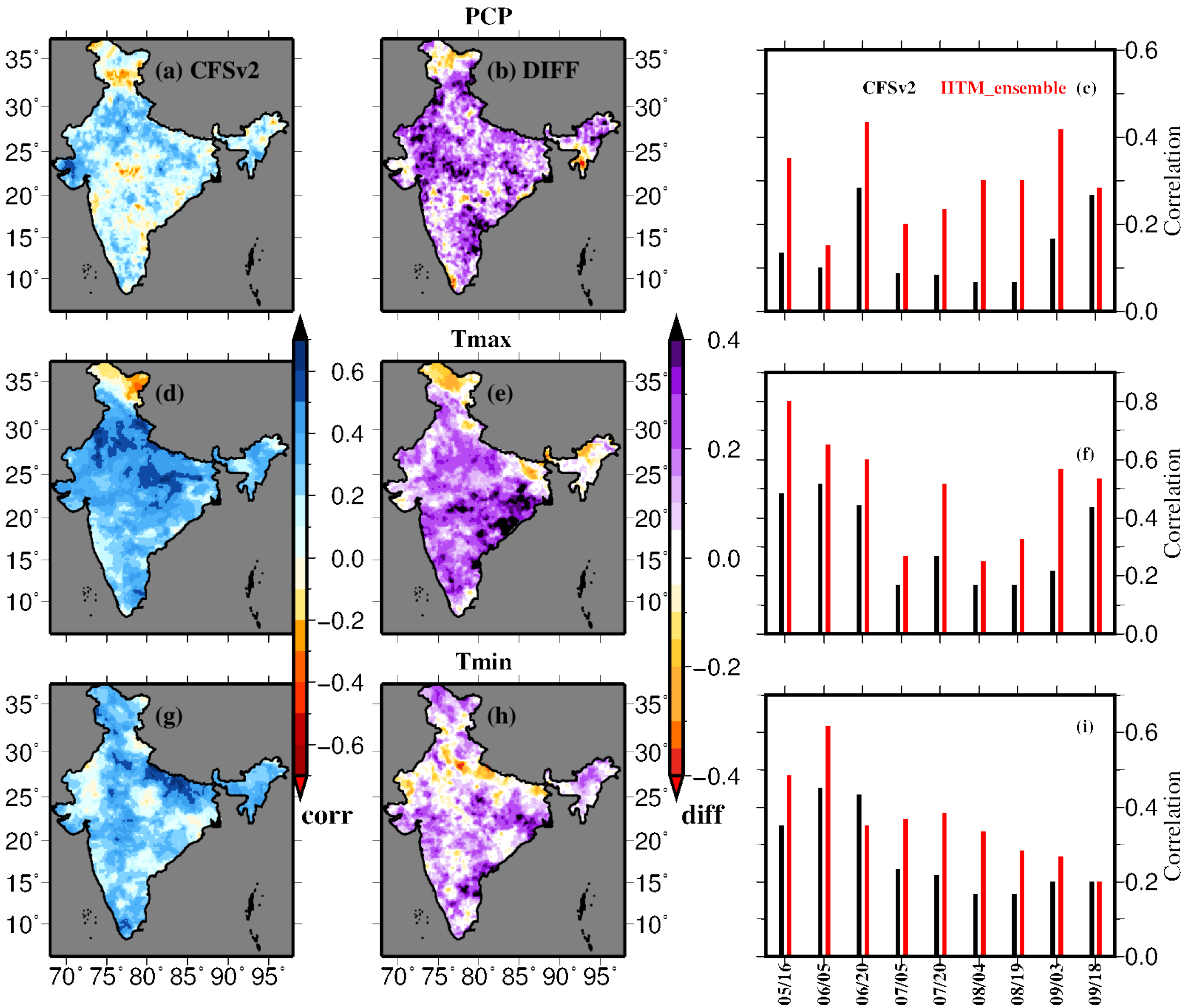

Figure 2: Improvements in correlations in the IITM-ensemble forecast in comparison to the CFSv2 for 45 day accumulation period. (a) correlation between precipitation forecast from the CFSv2and OBS (b) change in correlation coefficient of precipitation forecast from the IITM-ensemble and OBS as compared to (a). Correlations in (a) and (b) are median of correlations for the different forecast dates during the monsoon season. (c) All-India averaged median correlation for forecast initiated on different forecast dates. (d-f) is same as (a-c) but for daily maximum temperature and (g-i) is same as (a-c) but for daily minimum temperature.

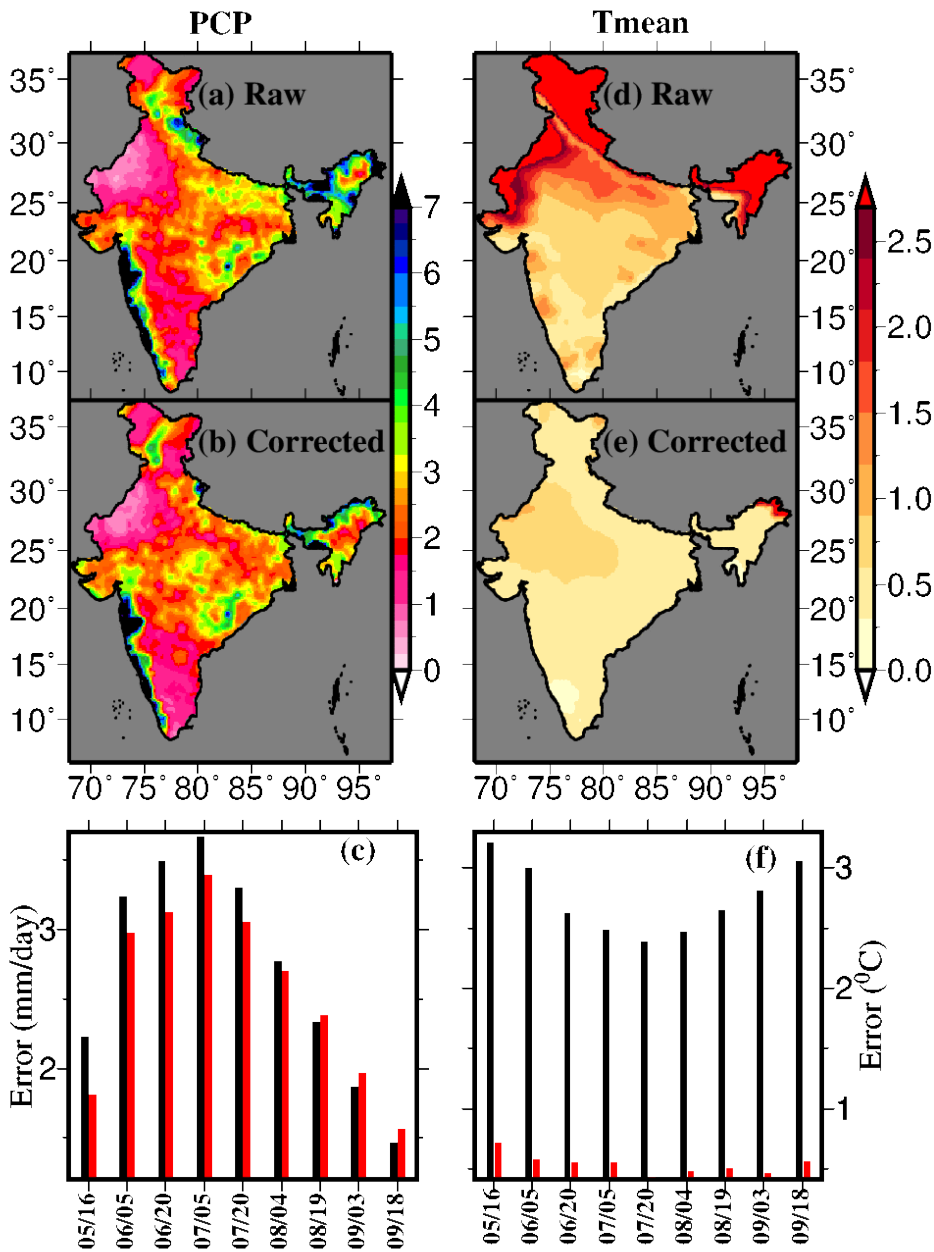

Figure 3: Median absolute error (MAE) in forecast at 45 day accumulation period from the IITM-ensemble before and after bias correction. (a and b) Median (of all forecast dates) MAE (mm/day) in precipitation forecast before and after bias correction. (c) Comparison of all-India median MAE for each forecast dates (d-f) same as (a-c) but for daily mean temperature in °C.

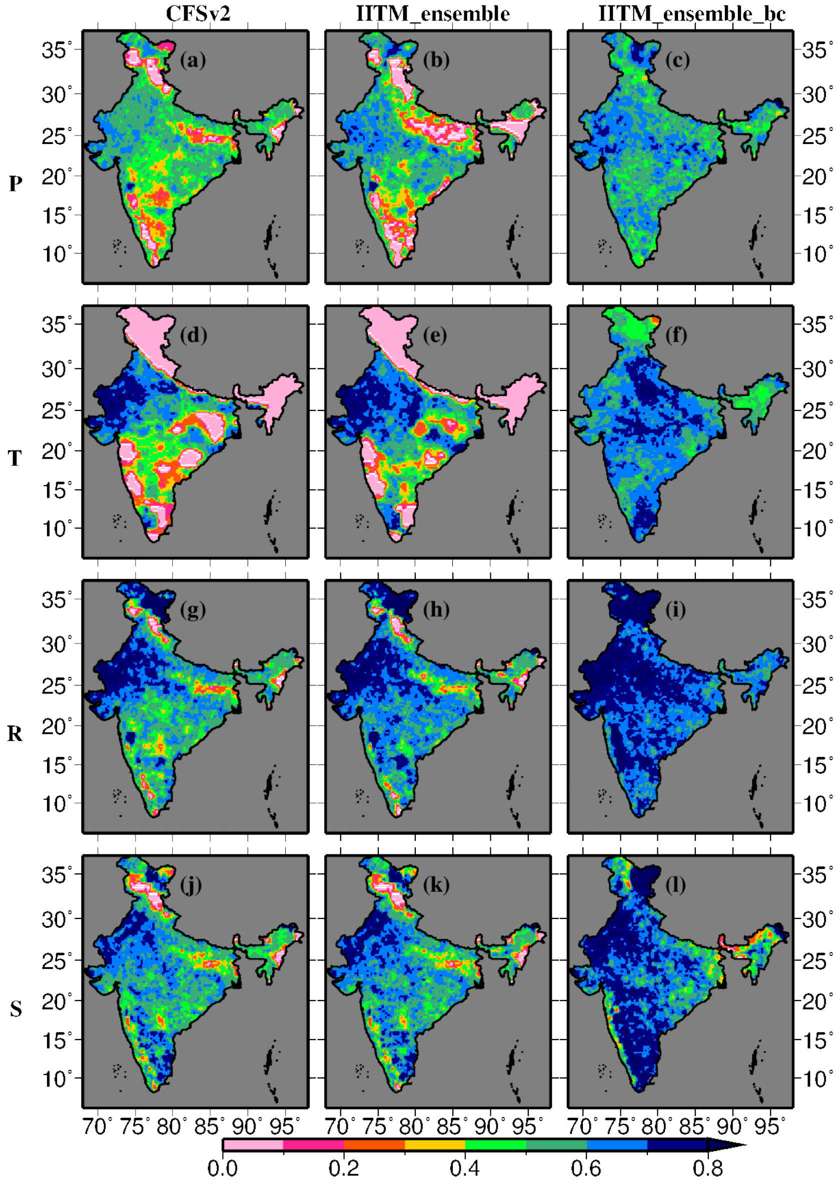

Figure 4: Critical Success Index (CSI, averaged for forecast dates) of predicting precipitation (a-c), temperature (d-f), runoff (g-i), and soil moisture (j-l) anomalies with respect to the observed anomalies for CSFv2, IITM-ensemble, and bias correctedIITM-ensemble(IITM-ensemble_bc).

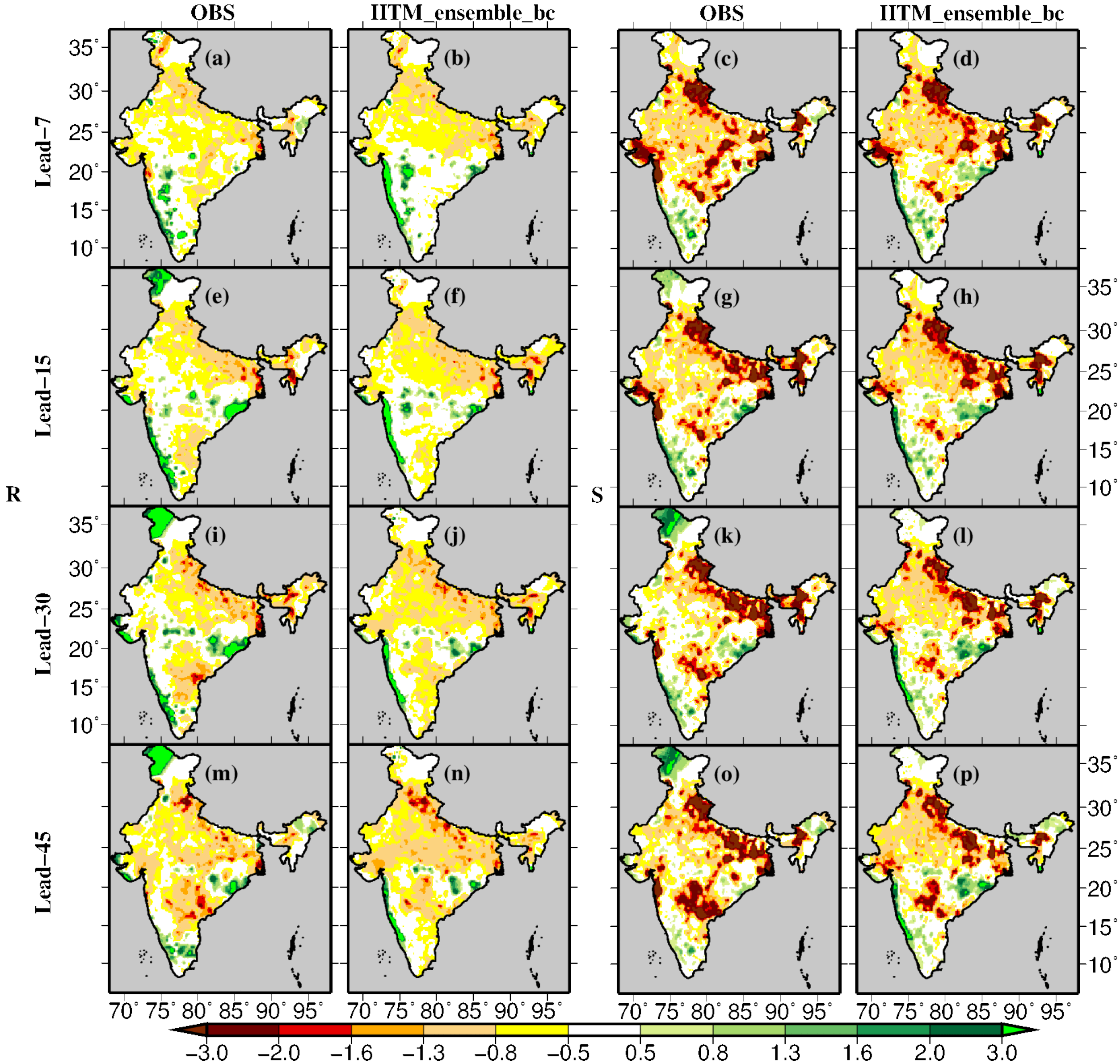

Figure 5: Predicted anomalies of hydrologic variables for forecast initiated on 15th July, 2009 for accumulation periods of 7, 15, 30, and 45 days. (a) Observed (standardized) anomalies in (VIC-simulated) runoff at lead time 7 days (b) anomalies in (VIC-simulated) runoff using bias-corrected IITM-ensemble for accumulation period of7 days. (c and d) same as (a and b) but for root-zone soil moisture (e-h), (i-l), (m-p) same as (a and b) for accumulation period of 15, 30 and 45 days, respectively.