



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 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), the Global Ensemble Forecast System (GEFSv2) and four products from the Indian Institute of Tropical Meteorology (IITM), here we show that the IITM ensemble mean (mean of all four products from the IITM) can be used operationally to provide a hydrologic forecast in India at a 7–45-day 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 the all-India median mean absolute error – MAE), while all-India median bias corrected temperature forecast was improved by 2.1 °C for a 45-day accumulation period. Moreover, the Variable Infiltration Capacity (VIC) model 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 and 10 states, and that caused an estimated loss of 650 000 crore Indian rupee (Rs 6.50.000 crore, 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, 2016; Shah and Mishra, 2015), 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 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 an appropriate lead time, planning of the agricultural and water resource sectors is 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 rain-

fall. Furthermore, water resources, reservoir operations, and irrigation planning are affected in the absence of a skilful forecast at a sufficient lead time. Prediction of anomalies in meteorological and hydrological conditions well in advance can assist timely decision making to minimize impact on the agricultural and water resource sectors. R. D. Shah and Mishra (2016) showed the potential of the Global Ensemble Forecast System (GEFS; Hamill et al., 2013) for hydrologic prediction in India with a lead time of up to 7 days. They reported that, up to 7 days in 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 and Wood (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 evaluating the potential of these products to provide forecasts at a 7–45-day accumulation period that can be used for agricultural and water resource planning in India. Here we provide an assessment of skill in hydrologic forecast that can be utilized for drought forecast at a 7–45-day 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 the India Meteorological Department (IMD). We used the 0.25° daily gridded precipitation product from the 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 the spatial variability of the monsoon season rainfall and features related to orographic rainfall in the Western Ghats and foothills of the Himalayas. We used 0.5° daily observed maximum and minimum temperatures from the IMD, which were developed based on 395 stations across India (Srivastava et al., 2009). The gridded air temperature dataset is available for 1951–2013 and has been used in many previous studies (Mishra et al., 2014; Shah and Mishra, 2015, 2014; R. D. Shah and Mishra, 2016; 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 fore-

cast 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 9 months' lead time and at 1° 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 US (CONUS) up to a 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 reforecasts are available at 1° resolution for lead times of up to 16 days and at 0.5° for an 8-day lead from 1985 to the present. R. D. Shah and Mishra (2016) evaluated the skill of GEFSv2 reforecast for drought prediction in India for an accumulation period of 7 days and found that the GEFS reforecast showed a correlation of more than 0.5 with drought estimates from the observed data.

We obtained four forecast products from the IITM. The forecast products of the IITM are generated from the same CFSv2 model that has been described above. Abhilash et al. (2014b) developed an ensemble prediction system using CFSv2 at T126 horizontal resolution (~ 100 km) (hereafter: IITM-CFST126) for prediction of monsoon intraseasonal oscillations (MISOs) 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. Sharmila et al. (2013) reported that CFSv2 simulates the northward propagating MISO reasonably well, but it has a cold bias in sea-surface temperature (SST) and tropospheric temperatures. Thus, Abhilash et al. (2014a) implemented a lead-time-dependent SST bias correction, 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 ~ 35 km; 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 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., 2015a, b; Sahai et al., 2013, 2015b). Subsequently, bias corrected SST forced GFS was also run at T382 resolution (hereafter: IITM-GFST382). Thus the IITM's forecasts are available for four models, named IITM-CFST126, IITM-GFST126, IITM-CFST382, and IITM-GFST382. Model integrations for the years from 2001 to 2015 are carried out from 16 May and continued up to 28 September at every 5-day interval (16, 21, 26 May, . . . , 23, 28 September) for the next 45-day period. Forecast ensemble members from the IITM are available at 1° resolution. The 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 whether IITM forecast products provide better prediction skill than CFSv2 and GEFSv2. Moreover, the product that provides 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 the ensemble mean (of all available ensemble members) of individual forecast products for evaluation. We selected forecasts at every 15th day, which was evaluated for the 7-, 15-, 30-, and 45-day accumulation periods 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 16 May till the end of September as currently the IITM provides forecast during the monsoon season. However, the IITM will extend forecast to the non-monsoon season in the near future. We aggregated all the observed and forecast variables (precipitation, maximum and minimum air temperatures) to the daily scale (if they were available at a 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 the 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 1 June and the lead time 15 days, accumulated precipitation and mean temperature for 15 days from 1 June for each of the products were estimated for the period 2001–2009. As the period for evaluation was 2001–2009, the 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 the coefficient of correlation, mean absolute error (MAE), and critical success index (CSI) to evaluate the performance of the forecast products. A non-parametric Spearman rank correlation coefficient (Wilks, 2006) was used to evaluate the performance of forecast products in capturing the temporal relationship with observations (OBS). For this the forecast product and the corresponding OBS are assigned ranks and then the correlation was estimated using the following Eq. (1):

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

where r_s is the Spearman rank correlation coefficient; d_i is the difference in rank between paired forecast and OBS; and n is the 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 the 5% significance level.

The 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 the mean of all the years was taken to estimate MAE. The 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). The CSI is ratio of hit events and the 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 the 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 the 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 the 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 the vegetation library that was developed at the 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, 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 the unavailability of either observations or the model version that has the representation of human interventions. The VIC model set-up used in this study is well calibrated and evaluated against observed streamflow and satellite-based evapotranspiration and soil moisture in H. L. Shah and Mishra (2016) and R. D. Shah and Mishra (2016). The VIC model has been widely used for hydrologic prediction at watershed and regional scales (Mo and Lettenmaier, 2014; R. D. Shah and Mishra, 2016; Shukla and Lettenmaier, 2011; Yuan and Wood, 2012b).

2.5 Bias correction of precipitation and temperature forecast

Improvements in hydrologic prediction can be achieved by post-processing the forecast of meteorological variables (precipitation, maximum and minimum temperatures). We corrected precipitation forecast using the linear scaling approach as described in R. D. Shah and Mishra (2016) and Shah and Mishra (2015). For each forecast date, we corrected precipitation for the selected (7-, 15-, 30- and 45-day) accumulation period. We first corrected accumulated precipitation due to extreme events (above the 90th percentile) for each forecast date in the training period and a scaling factor was obtained for each forecast date based on the ratio of precipitation for the 45-day 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 the 45-day accumulation period, for each forecast date from the forecast products and OBS for the entire training period. Scaling factors were estimated for the training period (9 years), which were evaluated in the testing period (1 year). More detailed information on this method can be obtained from R. D. Shah and Mishra (2016).

To correct the daily mean (of maximum and minimum) temperature from the forecast, we performed quantile–quantile (Q–Q) mapping (Wood et al., 2002). Initially, we prepared yearly time series of a 45-day accumulation period average temperature forecast for all the forecast dates along with the corresponding observed time series. For each forecast date and for each grid cell, we estimated quantiles of mean temperature for the 45-day accumulation period for each year using the climatology of the entire period. To estimate quantiles, cumulative distribution functions (CDFs) were fitted. The Weibull plotting position was used to map the cumulative distribution function when percentiles fall between $1/(N+1)$ and $N/(N+1)$, where N is the number of climatological years during the training period. In cases 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 R. D. Shah and Mishra (2016). 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 the corresponding value based on OBS. We estimated the bias corrected mean temperature using Q–Q mapping. Bias (difference between the corrected and uncorrected 45-day average mean temperature) was then added equally to daily raw T_{\max} and T_{\min} to get the corrected values of daily maximum and minimum temperatures. We did not bias correct T_{\max} and T_{\min} individually, as that will affect the diurnal temperature range ($T_{\max}-T_{\min}$). We adopted the multi-fold validation approach of leaving 1 year out for testing both precipitation and mean temperature (R. D. Shah and Mishra, 2016).

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 the forecast skill of soil moisture and runoff simulated using meteorological variables from the IITM ensemble. Using the raw and bias corrected forecasts (precipitation, maximum and minimum temperatures), the Variable Infiltration Capacity (VIC) model was run to obtain a soil moisture and total runoff (surface runoff + baseflow) forecast. We evaluated improvements in the 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 (Fig. S14). For simulating runoff and soil moisture, forcings from all three prod-

ucts were used to run the VIC model at 0.25° 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 the 7–45-day accumulation period. We considered the 45-day accumulation period to evaluate the hydrologic prediction skill, as for shorter lead times forecast skill is generally higher owing to persistence of initial hydrologic conditions.

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 periods. 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 a significantly high (more than 0.75) Spearman rank correlation (Fig. 1a–n) in the majority of India for the accumulation period of 7 days, indicating a higher skill for a shorter lead time. We noticed that correlation declines as the accumulation period was increased from 7 to 15 days, especially in the central region (Fig. 1). Moreover, we find that GEFSv2 and the IITM ensemble (correlation more than 0.6 for the majority of India) perform better than CFSv2 for the 15-day accumulation period. Correlations between observation 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 the 7- and 15-day accumulation periods (Fig. 1 and Table S1 in the Supplement). 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 periods of 7 and 15 days (Fig. S1 in the Supplement). 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 western India during the monsoon season,

and MAE was higher during the months of July–September (Fig. S1o and p). MAE, however, decreases as the forecast accumulation period was increased from 7 to 15 days, which is due to a longer accumulation period for precipitation. We noticed that the all-India median MAE (median of all the grids) in the forecast products varies with the date of forecast; however, both CFSv2 and the IITM ensemble mean showed comparable MAE at the all-India scale for the 7-day accumulation period (Fig. S1o and Table S1). However, for the 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 the 7- and 15-day accumulation periods 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, the Madden–Julian oscillation (MJO), and the Inter Tropical Convergence Zone (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 intraseasonal and interannual variability in precipitation (Webster et al., 1998). Improvements in the 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-day accumulation periods, we evaluated skill in maximum (T_{\max}) and minimum (T_{\min}) temperatures from all the forecast products against observed air temperatures from the IMD (Fig. S2). T_{\max} averaged for the 7-day accumulation period from all the forecast products showed a good correlation with OBS over most of India (Fig. S2a–g). Similar to precipitation from the IITM ensemble, T_{\max} showed the highest correlation with OBS (0.78; Table S1). However, correlation for the 15-day accumulation period was lower than that of the 7-day accumulation period (Fig S2h–n and p; Table S1). The IITM ensemble showed correlation above 0.8 over most of the regions in India and generally skill in the T_{\max} forecast is 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 the Himalayas (Mishra, 2015).

At the 7-day accumulation period, the forecast products showed a higher MAE in the northwestern arid region, Himalayan range, and Western Ghats (Fig. S3). The IITM products and the 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

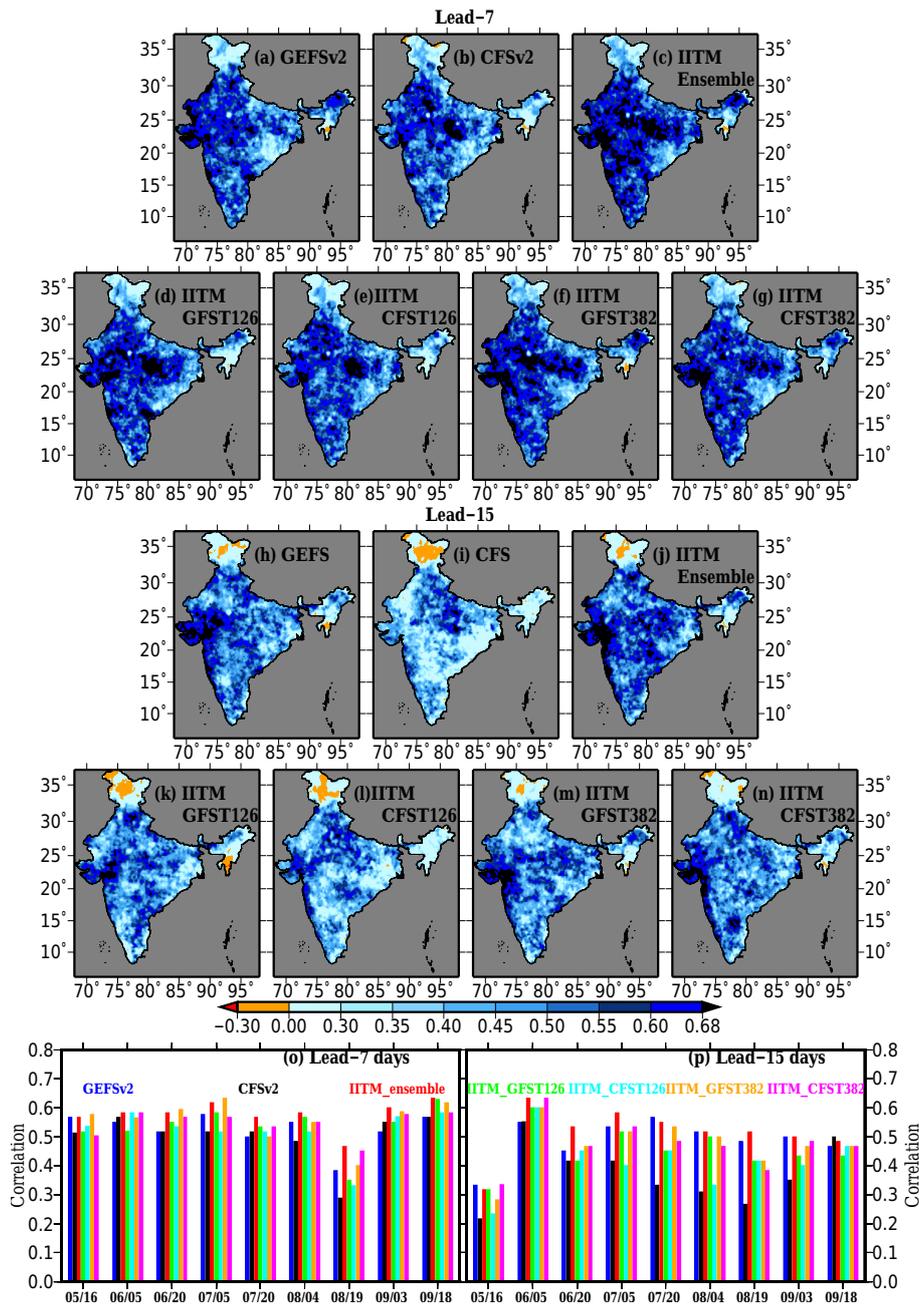


Figure 1. Correlation between precipitation forecasts and observed precipitation (OBS). (a) Correlation between precipitation forecast from the GEFSv2 accumulated up to a 7-day accumulation period and the corresponding OBS. (b) Same as (a) but for the CFSv2. (c) Same as (a) but for the IITM ensemble. (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 an accumulation period of 15 days. (o) All-India median correlation between different precipitation forecasts at a 7-day accumulation period and the corresponding OBS for the forecasts initiated on different dates. (p) Same as (o) but for an accumulation period of 15 days (period: 2001–2009).

and o; 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 a lower all-India median MAE (1.2 °C) as compared to GEFSv2 (2.0 °C) and CFSv2 (1.7 °C) for the 15-day accumulation period (Fig. S3h–n and p). Similar to the 7-day

accumulation period, the all-India median MAE in T_{\max} was the lowest in the IITM ensemble for the 15-day accumulation period. CFSv2 models showed better skill in T_{\max} than GEFSv2, which is consistent with the findings of R. D. Shah and Mishra (2016).

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

3.1.2 Lead time 30 and 45 days

Since GEFSv2 reforecast is available only up to a lead time of 16 days, our comparison for the accumulation periods 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 the 30-day accumulation period in the IITM ensemble. However, at the 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, reasonable skill can be obtained in the precipitation forecast from the IITM products. Precipitation forecast at the accumulation periods of 30 and 45 days showed spatial patterns similar to that of MAE, as were observed for the accumulation periods 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 the accumulation periods of 30 and 45 days (Fig. S7m and n). This improvement in correlation and MAE can be attributed to the 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 T_{\max} from the IITM ensemble showed significant and higher correlation with OBS at the 30-day accu-

mulation period, with a major contribution from the IITM-GFST382 product (Fig. S8). We notice that the IITM ensemble showed correlations of more than 0.6 for the majority of India between OBS and predicted T_{\max} at the 30-day accumulation period. At the 45-day accumulation period, correlation decreases (in comparison to the 30-day accumulation period); however, predictions of T_{\max} from the IITM ensemble mean showed better skill than CFSv2 with OBS. Spatial patterns of MAE in T_{\max} prediction for the accumulation periods of 30 and 45 days were consistent with spatial patterns for the accumulation periods of 7 and 15 days, indicating larger errors in predicted T_{\max} in the northern and western parts of the country (Fig. S9). Predictions of T_{\min} showed lower correlation as compared to T_{\max} (similar to shorter lead times), especially in the northwestern region, where correlations were negative (Fig. S10). Predictions of T_{\min} from the IITM-GFST126 and GFST382 showed better correlation in the southern peninsula. Spatial patterns of MAE in T_{\min} predictions at the accumulation periods of 30 and 45 days were consistent with spatial patterns for the 7- and 15-day accumulation periods (Fig. S11). Predictions from the IITM-CFST382 product showed lower errors as compared to all the other products (Table S1). Predictions of T_{\min} from the IITM ensemble mean showed lower error (30-day accumulation period: 0.9; and 45-day accumulation period: 1.1 °C) as compared to CFSv2 (1.2 and 1.2 °C for the 30- and 45-day 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 the IITM, the performance of the IITM ensemble was compared against CFSv2 for 7–45-day accumulation periods (Fig. 2). Since the forecast skill declines with the lead time, we discuss forecast skill at a 45-day accumulation period in detail, and results for the other leads are presented in Fig. S12. At the 45-day accumulation period, correlation in the precipitation forecast from CFSv2 is more than 0.2 only in a few regions (mainly centered in northern and western India) (Fig. 2a). The IITM ensemble showed a correlation (~ 0.3) higher than CFSv2 (Fig. 2b) in most of the regions, especially during the July–August months (Fig. 2c). For the T_{\max} and T_{\min} forecasts, the IITM ensemble showed higher correlations than CFSv2 in the 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 the 7-day accumulation period, precipitation forecast from CFSv2 and the IITM ensemble showed a correlation of more than 0.6 in most regions in India; therefore, for shorter accumulation periods, the difference in the forecast skill of CFSv2 and the IITM ensemble is moderate (Fig. S12a). For 15- and 30-day accumulation periods, the difference in correlations shown by CFSv2 and the IITM ensemble was higher than for the 45-day accumu-

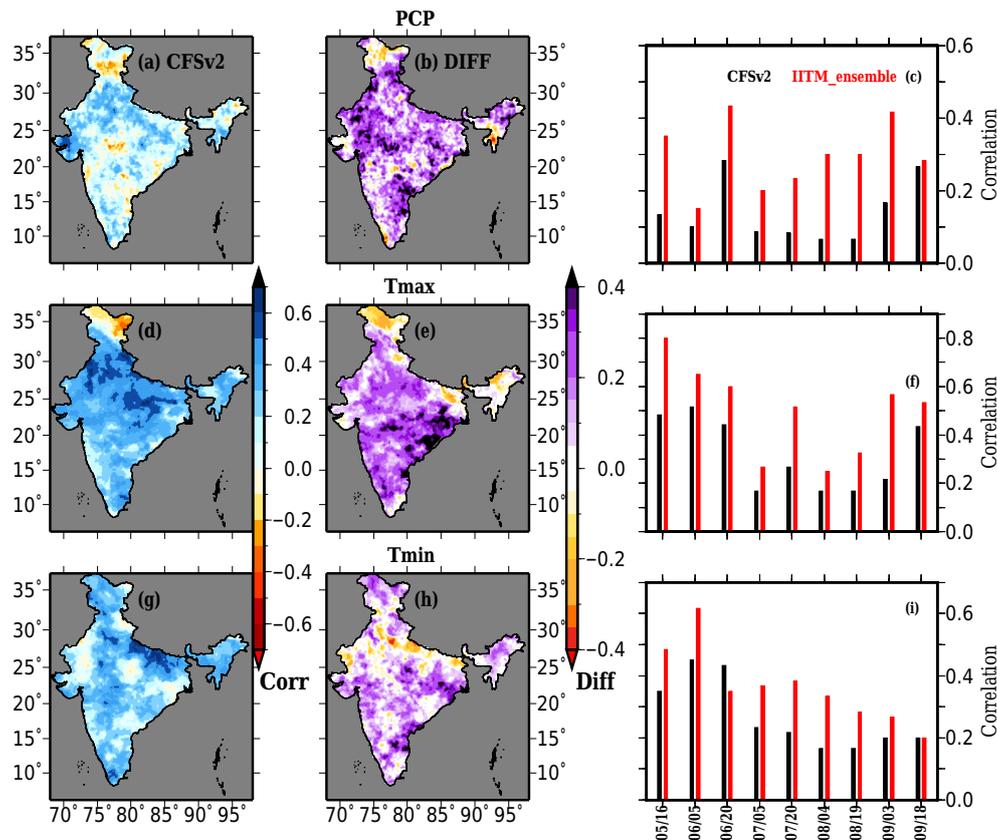


Figure 2. Improvements in correlations in the IITM ensemble forecast in comparison to CFSv2 for the 45-day accumulation period. (a) Correlation between precipitation forecast from the CFSv2 and OBS. (b) Change in the correlation coefficient of the precipitation forecast from the IITM ensemble and OBS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

lation period (Figs. S13 and S14). These results show that the IITM ensemble forecast of precipitation, T_{\max} , and T_{\min} 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 the 30- and 45-day accumulation periods, the IITM ensemble showed relatively better forecast skill than that of CFSv2.

3.2 Performance of the bias corrected IITM ensemble

Our results show that the bias correction resulted in a 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 the north-eastern region (Fig. 3a and b). We find substantial improvements in the MAE of maximum and minimum temperatures after the bias correction (Fig. 3d and 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°C . We find that the bias cor-

rection substantially improved temperature forecast from the IITM ensemble. This improvement in temperature forecast can be valuable for hydrologic applications. For instance, air temperature influences the 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 the Western Ghats and positive bias in the Himalayan range and the southern peninsula. During the testing period (1 year), improvement in bias is consistent with the training period (9 years; Fig. S15c and d). Improvements in the correlation of all-India average precipitation predictions from the IITM ensemble before and after bias correction can be noticed (Fig. S16). At a 45-day accumulation period a substantial improvement was noticed as compared 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

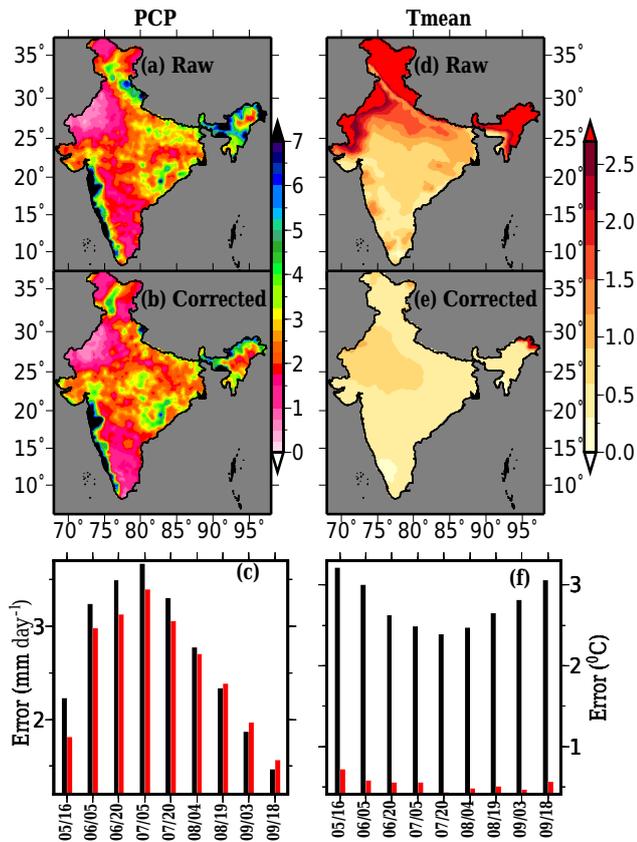


Figure 3. Median absolute error (MAE) in forecast at the 45-day accumulation period from the IITM ensemble before and after bias correction. (a, b) Median (of all forecast dates) MAE (mm day^{-1}) in precipitation forecast before and after bias correction. (c) Comparison of the all-India median MAE for each forecast date. (d–f) Same as (a–c) but for daily mean temperature in $^{\circ}\text{C}$.

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 a 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, satellite soil moisture and evapotranspiration (H. L. Shah and Mishra, 2016; R. D. Shah and Mishra, 2016). In this study, we used the 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 the IMD (Fig. S17). For all the forecast dates, predicted root-zone soil moisture (top 60 cm soil moisture; Fig. S14) showed a higher correlation than total runoff (Fig. S17), which is due to a higher persistence in soil moisture as compared to runoff (R. D. Shah and Mishra, 2016). The bias corrected IITM ensemble showed higher correlations than the uncorrected IITM ensemble and CFSv2. The CSI of predicting the dry anomaly in precipitation using the IITM ensemble was higher in the northwestern region but lower in the Himalayan range and southern peninsula as compared to CFSv2, which is consistent with the results based on correlation and MAE (Fig. 4). The bias corrected IITM ensemble showed an improved CSI in comparison to the raw forecast from the IITM ensemble and CFSv2 for the majority of the regions in India. However, the CSI of predicting warm temperature anomalies was lower than that of the CSI of predicting dry precipitation anomalies (Fig. 4), especially in the Himalayan range. This can be due to higher uncertainty among observations in this region (Mishra, 2015). The CSI in runoff and soil moisture is higher as compared to precipitation and temperature due to persistence in initial hydrologic conditions (Fig. 4). For the 7-, 15- and 30-day accumulation periods the CSI is higher than that of the 45-day accumulation period (Fig. S18). We observed that as the accumulation period was increased from 7 to 45 days, the CSI of runoff declines in the arid and semi-arid regions of the northwest. Overall, we found that the bias correction of the forecast improves the 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 analysed the forecast for one of the recent drought years in India. Anomalies of total runoff and root-zone soil moisture predicted on 15 July 2009 for the 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 a sufficient lead time can be helpful in decision making related to water resources and agriculture. We found that the IITM ensemble-bc successfully captured the 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 the 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 a 45-day accumulation period of forecast. Early warning based

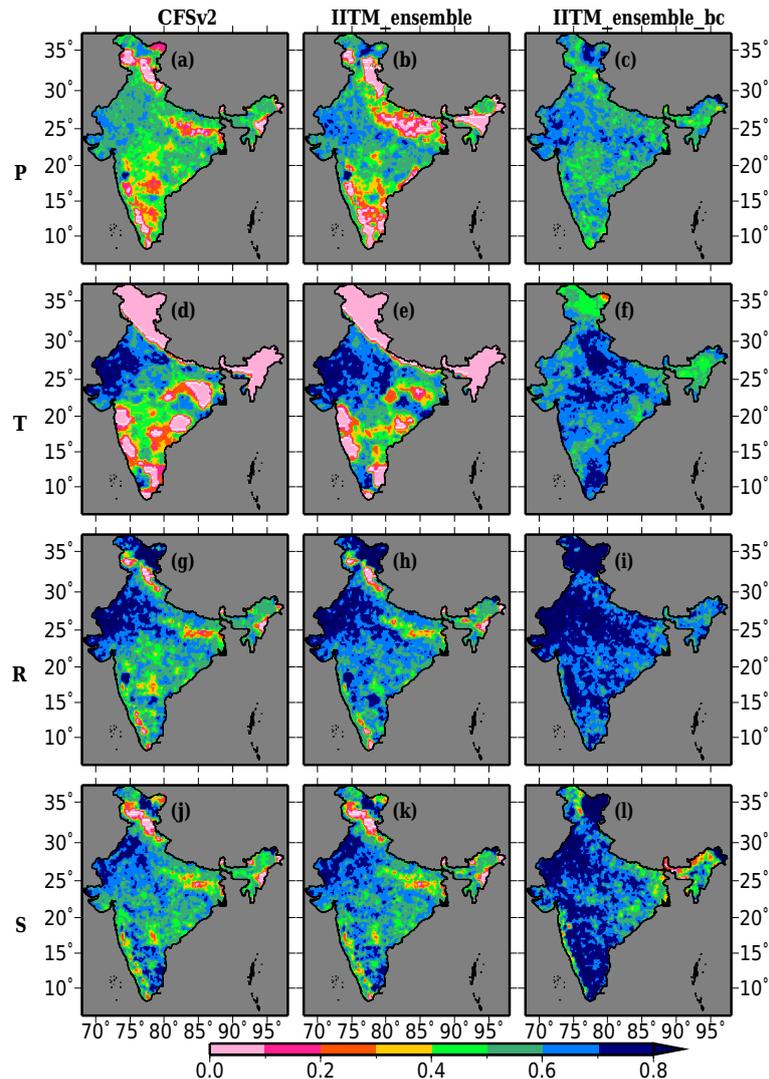


Figure 4. Critical success index (CSI, averaged for forecast dates) of predicting precipitation (a–c), temperature (d–f), runoff (g–i), and soil moisture (j–l) anomalies with respect to the observed anomalies for CFSv2, the IITM ensemble, and the bias corrected IITM ensemble (IITM ensemble_bc).

on predictions can be helpful in decision making in the water resource and agricultural sectors so as to minimize risk.

4 Summary and conclusions

Hydrologic forecast at the 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 periods of

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 conditions used at the IITM. For instance, Roxy et al. (2015) reported that CFSv2 has a cold bias of 2–3 °C in SSTs which may lead to a dry bias in the monsoon season in India. Abhilash et al. (2014a) showed that forcings from the GFS and CFS models with bias corrected SSTs lead to improvement in predictability over the Indian region, and that is due to improvement in the 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 the findings of Palmer et al. (2004) and Kirtman et al. (2014), where they reported that the multimodel ensemble outperforms the individual model. One of the limitations of the evaluation of the

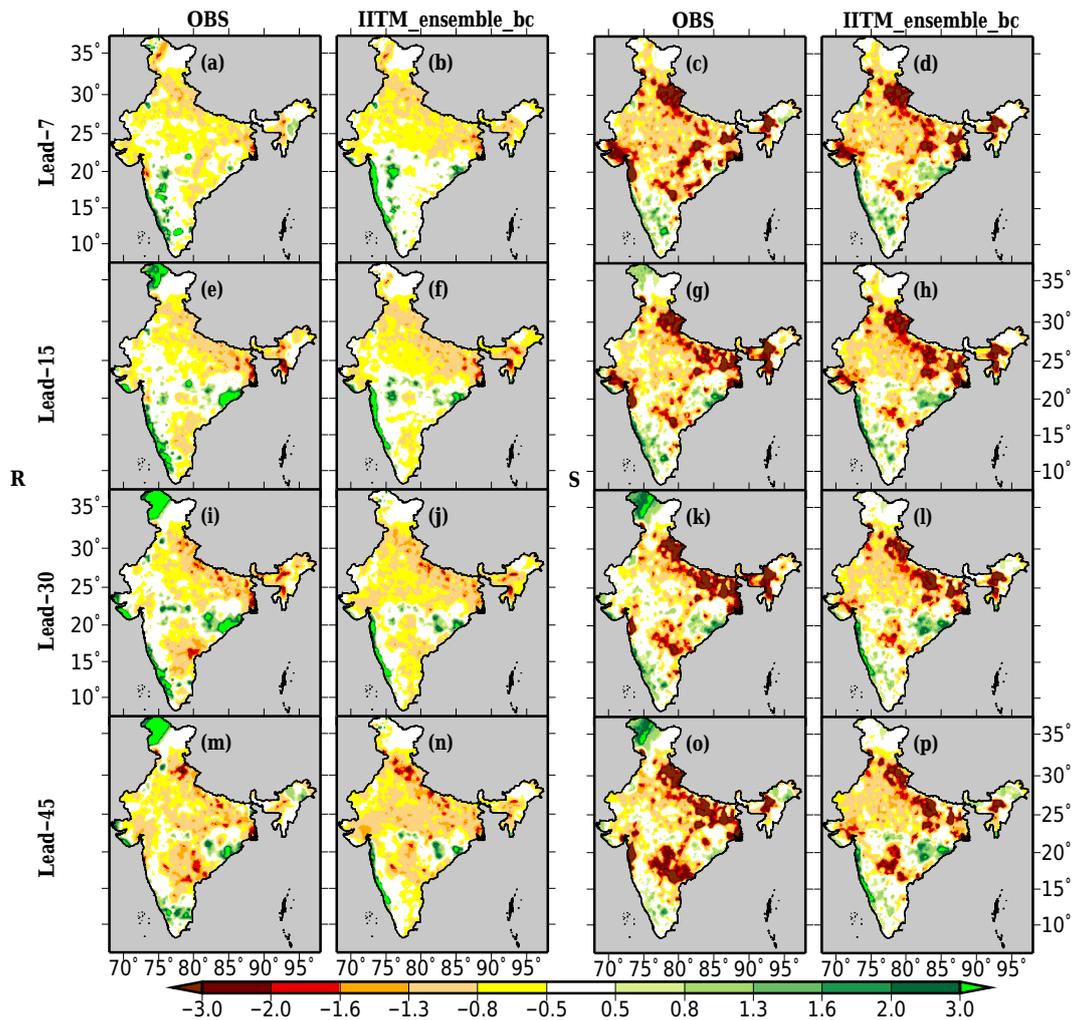


Figure 5. Predicted anomalies of hydrologic variables for the forecast initiated on 15 July 2009 for the accumulation periods of 7, 15, 30, and 45 days. (a) Observed (standardized) anomalies in (VIC-simulated) runoff at a lead time of 7 days. (b) Anomalies in (VIC-simulated) runoff using the bias corrected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

forecast products in this study is the small sample size. The evaluation of all the forecast products was based on 10 common years between all products and nine forecast dates during the monsoon season. Increasing the sample size in future based on the availability of forecasts for a 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 the following.

i. Ensemble members of the IITM forecast are generated by perturbing initial atmospheric conditions to improve simulation of northward propagation.

ii. Improvements in the boundary conditions with bias corrected SST result in improved precipitation prediction.

iii. A higher spatial resolution of the IITM forecast can better resolve orographic rainfall.

We evaluated the performance of the bias corrected forecast from the IITM ensemble for accumulation periods of 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 southern central region. Bias correction of precipitation and air temperatures resulted in an improvement of about 2.1 mm and 2.1 °C, respectively, in the all-India median of mean absolute error. Total runoff and root-zone soil moisture forecasts obtained using the cor-

rected IITM ensemble showed higher skill as compared to CFSv2 and a raw IITM ensemble for an accumulation period of up to 45 days. We found that the all-India median CSI for runoff forecast was improved from 0.63 to 0.71 after bias correction, while the CSI of soil moisture forecast was improved from 0.6 to 0.67 for a 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 days' 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 for predicting 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 the 7–45-day accumulation period can be valuable for water managers in India.

5 Data availability

Gauge-based gridded precipitation and temperature can be obtained from the India Meteorological Department (<http://www.imd.gov.in/WelcomeToIMD/Welcome.php>).

The NOAA's GEFSv2 reforecast data are available from NCEP (<ftp://ftp.cdc.noaa.gov/Projects/Reforecast2/>).

The CFSv2 data are available from NCEP (<https://nomads.ncdc.noaa.gov/data/cfsr-rfl-ts9/>).

IITM's Forecast product can be obtained from the IITM (<http://www.tropmet.res.in/>).

The Supplement related to this article is available online at doi:10.5194/hess-21-707-2017-supplement.

Competing interests. The authors declare that they have no conflict of interest.

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