Ensemble streamflow prediction considering the influence of reservoirs in Narmada River basin, India

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Abstract

Developing an ensemble hydrological prediction system is essential for reservoir operations and flood early warning. However, efforts to build hydrological ensemble prediction systems considering the influence of reservoirs have been lacking in India. We examine the potential of the Extended Range Forecast System (ERFS, 16 ensemble members) and Global Ensemble Forecast System (GEFS, 21 ensemble members) forecast for streamflow prediction in India using the Narmada River basin as a testbed. We use the Variable Infiltration Capacity (VIC) with reservoir operations (VIC-Res) scheme to simulate the daily river flow at four locations in the Narmada basin. Streamflow prediction skills of the ERFS forecast were examined for the period 2003-2018 at 1-32 day lead. We compared the streamflow forecast skills of raw meteorological forecasts from ERFS and GEFS at a 1-10 day lead for the summer monsoon (June-September) 2019-2020. The ERFS forecast underestimates extreme precipitation against the observations compared to the GEFS forecast during the summer monsoon of 2019-2020. However, both the forecast products show better skills for minimum and maximum temperatures than precipitation. Ensemble streamflow forecast from the GEFS performs better than the ERFS during 2019-2020. The performance of GEFS based ensemble streamflow forecast declines after five days lead. Overall, the GEFS ensemble streamflow forecast can provide reliable skills at a 1-5 day lead, which can be utilized in streamflow prediction. Our findings provide directions for developing a flood early warning system based on ensemble streamflow prediction considering the influence of reservoirs in India.

1. Introduction

Floods are one of India's most destructive and frequently occurring natural disasters. Floods accounted for about 47% of natural disasters in India during the last 100 years (Tripathi, 2016). Riverine floods occur during the summer monsoon season affecting approximately five million people annually (Luo et al., 2015). Singh and Kumar (2013) reported an increase in the frequency of floods in India. About 20% of the total flood-prone area gets affected every year (Ray et al., 2019). Floods in 2018 caused an economic loss of more than twelve billion dollars

(USD) and resulted in the loss of 1808 lives (Joshi, 2020). In addition, climate warming is projected to increase the frequency and intensity of riverine floods (Field et al., 2011; Luo et al., 2015; Nanditha and Mishra, 2022; Ali et al., 2019).

Preparedness for disasters like floods can help in mitigating economic loss and reducing flood mortality (Jain et al., 2018). While losses due to floods are projected to rise under the warming climate, human mortality can be reduced with flood early warning systems and effective communication (Dipti, 2017, Nanditha and Mishra, 2021). Therefore, developing a robust flood prediction system is necessary for early warning and preparedness. Streamflow prediction is an essential component of flood forecasting, which helps in planning and decision-making (Georgakakos et al., 2012; Alfieri et al., 2013). Most of the streamflow prediction systems in India are based on the deterministic approach (Harsha, 2020a; Todini, 2017, Nanditha and Mishra, 2021), which do not account for perturbations in initial conditions to quantify the uncertainty (Bowler et al., 2008). Uncertainty quantification in streamflow prediction can reduce the risk of false alarms based on deterministic forecast (Todini, 2017). In addition, ensemble streamflow prediction is essential for the probabilistic flood forecast. The probabilistic approach performs better than the deterministic approach by quantifying uncertainties associated with flood prediction and early warning system (Krzysztofowicz, 2001). Previous studies used ensemble streamflow prediction in flood forecasting (Cloke and Pappenberger, 2009; Wu et al., 2020) using ensemble meteorological forecast and hydrological models (Zhang et al., 2020). Ensemble weather forecast provides multiple members at the same location and time that can be used for probabilistic hydrological prediction. However, several challenges are associated with the operational ensemble streamflow forecast, including computational limitations, explanation of ensemble forecasts to non-experts, and up-gradation in the policy to use the forecast for decision making (Demeritt et al., 2010; Arnal et al., 2020). Despite these challenges, ensemble flood forecasts consider the uncertainty that can be used for preparedness and planning compared to the deterministic forecast approach. (Pappenberger et al., 2012; Cloke and Pappenberger, 2009).

Indian river basins are considerably affected by human interventions including presence of reservoirs, water withdrawal for irrigation, and inter/intra basin water transfer (Nanditha and Mishra, 2021; Madhusoodhanan et al., 2016; Gosain et al., 2006). India has more than 5000 large dams while about 450 are currently under construction (NRLD, 2017). Reservoirs and irrigation can considerably modulate terrestrial water and energy budgets in India (Shah et al., 2019). For instance, Shah et al. (2019) showed that evapotranspiration and latent heat flux are increased under the presence of irrigation and reservoirs in Indian river basins compared to their natural conditions. Dong et al. (2022) reported that reservoirs can significantly (~ 25%) contribute to the variation of terrestrial water storage in China. In addition, the presence of reservoirs can considerably affect streamflow variability in the downstream regions (Zajac et al., 2017; Yun et al., 2020; Chai et al., 2019). Reservoirs in India are multipurpose as these store water for the dry season, generate hydropower, and attenuate floods in the downstream regions (Tiwari and Mishra, 2022). Reservoirs store water during the summer monsoon season and release water during the dry season for irrigation. Similarly, based on the reservoir rule curve, a buffer storage is kept during the wet season to accommodate high inflow so that flood risk can be minimized in the downstream region. Therefore, there are several challenges associated with the streamflow forecast in the river basins that are affected by reservoirs. Most often hydrological model-based flood/streamflow forecast does not consider the influence of reservoirs that could lead to under or overestimation of flow depending on the season (Nanditha and Mishra, 2021; Dang et al., 2019). Incorporating reservoir influence in hydrological models is essential as reservoirs significantly affect the magnitude and timing of streamflow (Zajac et al., 2017; Yassin et al., 2019; Dang et al., 2019). Several efforts have been made to incorporate the influence of reservoirs in the hydrological models (Boulange Julien and Hanasaki Naota, 2013; Dang et al., 2019; Hanasaki et al., 2018). However, most of the previous studies on flood forecasts and early warnings in India did not consider the influence of reservoirs (Goswami et al., 2018; Sikder and Hossain, 2019).

The Central Water Commission (CWC) manages flood forecast systems in India. The flood forecast network monitors 325 stations across India. CWC observes real-time water level and discharge along the major rivers of India during the designated flood period. The flood forecast is performed using statistical correlation methods from gauge to gauge. Moreover, Quantitative Precipitation Forecast (QPF) from the India Meteorological Department (IMD) is used to forecast floods at a 3-day lead time (Teja and Umamahesh, 2020). The current model-based flood forecast approach used by CWC is deterministic, which lacks incorporating uncertainties in the forecast and early warning system. An ensemble forecast system can help in flood early warning and decision-making (Harsha, 2020b; Nanditha and Mishra, 2021). Various ensemble forecast products are available from the India Meteorological Department (IMD) and the Indian Institute of Tropical Meteorology (IITM). However, the utility of these forecast products for streamflow prediction and flood early warning at the river basin scale has not been examined. In addition, despite the advantages of ensemble hydrological prediction, India's current hydrological forecast systems are mainly deterministic. Given the increasing flood damage in India, the overarching aim of this work is to explore the utility of ensemble forecast products for streamflow prediction in India. We considered the Narmada River basin as a testbed to examine the potential of ensemble hydrological prediction. We used the Variable Infiltration Capacity (VIC) with reservoir operations (VIC-Res) scheme, which incorporates the effect of reservoirs (Dang et al., 2019). Extended Range Forecast System (ERFS) and Global Ensemble Forecast System (GEFS) ensemble forecasts developed by IITM are used to examine the hydrological prediction skills at the selected gauge stations in the Narmada basin.

2. Data and methods

2.1 Study region and datasets

Narmada is the fifth biggest and the largest west-flowing river in India. The Narmada river basin falls in two states, Gujarat and Madhya Pradesh. Many tributaries contribute to the river through its way to the Arabian Sea, with the

Tawa river being its longest tributary. The catchment area of the river basin at the outlet is approximately 98,796 km^2. The upper portion of the basin falls in Madhya Pradesh. The mean annual rainfall in the Narmada basin is 1064 mm. Most of the total annual precipitation occurs during the summer monsoon season (June-September). We used observed daily streamflow at four stations: Sandia, Handia, Mandleshwar, and Garudeshwar (Fig. 1). There are several ongoing hydropower and irrigation projects in the Narmada basin. Our hydrological modelling framework has considered four dams: Bargi, Tawa, Indira Sagar, and Sardar Sarovar (Table 1). Bargi and Tawa reservoirs were primarily constructed for irrigation purposes (Table 1). At the same time, Indira Sagar (0.975 Billion Cubic Meters (BCM)) and Sardar Sarovar (5.8 BCM) are the two largest reservoirs that are used for multi-purpose.

Table 1. Parameters of reservoirs that were considered in hydrological simulations

Sr No	Name of dam	Year of completion	Height above lower foundation (m)	Length of dam (m)	Gross storage capacity (BCM)	Effective storage capacity (BCM)
1	Bargi	1988	69.8	5357	3.92	3.18
2	Tawa	1978	57.92	1944.92	2.312	1.94
3	Indira Sagar	2006	91.4	654	12.22	9.75
4	Sardar Sarovar	2017	163	1210	9.5	5.8

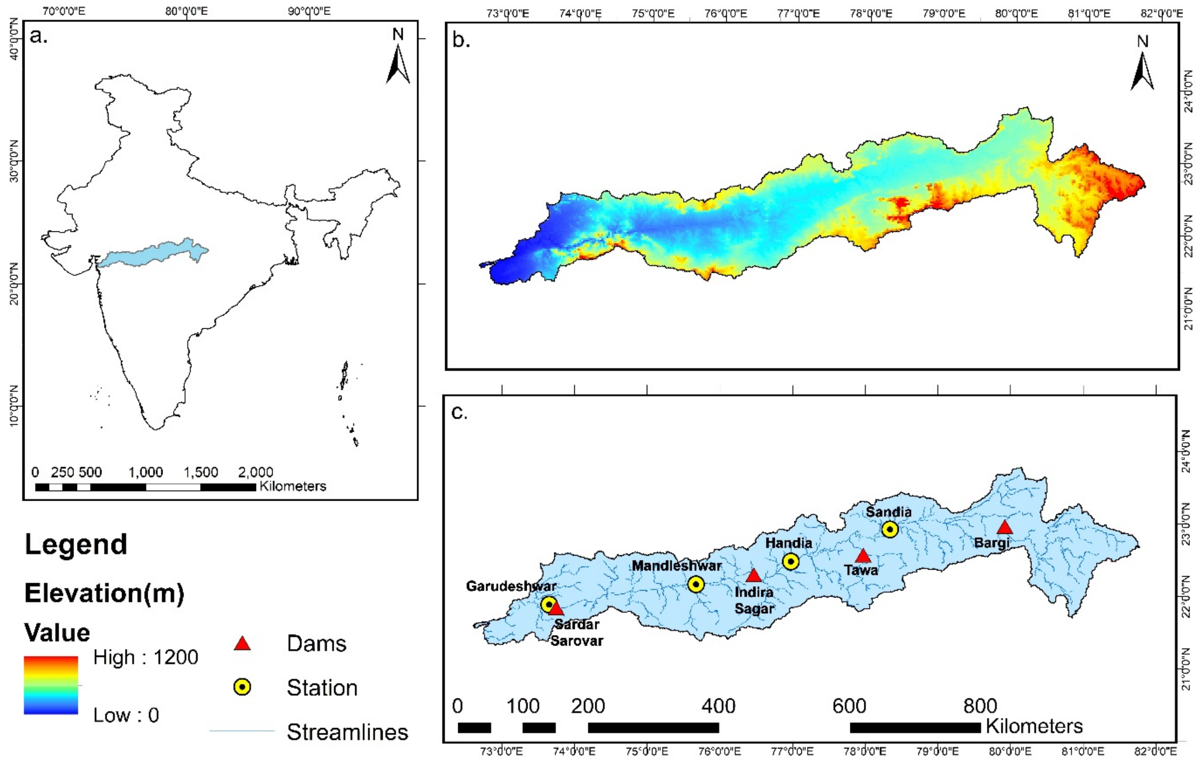

Figure 1. Basic information about (a) location in India, (b) topography, c) streamlines, location of streamflow gauge stations and reservoirs

We used 0.25° (approximate spatial resolution; ~27.5 x 27.5 km) gridded daily precipitation from IMD for the 1951-2020 period (Pai et al., 2014). The daily gridded precipitation product is developed using observations from 6955 rain gauge stations (Pai et al., 2015). Pai et al. (2015) examined daily rainfall trends, long-term climatology, and variability over the central Indian region. The high resolution (0.25°) gridded precipitation captures spatial variability in better manner compared to previous coarse-gridded rainfall products. We obtained daily 1° gridded maximum and minimum temperatures from IMD (Srivastava et al., 2009). Srivastava et al. (2009) developed the gridded temperature dataset using observations from 395 stations. We used bilinear interpolation to convert the 1° gridded temperature to 0.25° resolution to make it consistent with the gridded precipitation. The VIC model also requires daily wind speed as an input. We obtained the wind speed from the National Centers for Environmental Prediction (NCEP)-National Centers for Atmospheric Research (NCAR) (https://psl.noaa.gov/data/gridded/data.ncep.reanalysis.pressure.html). The wind speed at a coarser (1.875° x 1.905°) resolution was interpolated using bilinear interpolation to 0.25° to make it consistent with the other meteorological datasets. The VIC model's vegetation parameters were obtained from the Advanced Very High-Resolution Radiometer (AVHRR) global land cover, which is available at 1-km spatial resolution (Sheffield and Wood, 2007). Soil parameters at 0.25° were developed using the Harmonized World Soil Database (HWSD version 1.2) [Gao et al., 2009]. We used digital elevation model data from Shuttle Radar Topography Mission

(SRTM) at 90 m spatial resolution (Jarvis, 2008). The hydrological model considers sub-grid variability of topography and vegetation (Gao et al. 2010). Therefore, the high-resolution vegetation and elevation datasets were used to extract values for different tiles within a grid.

We obtained observed daily streamflow, reservoir water level, and reservoir live storage data from the India - Water Resources Information System (IWRIS; http://www.indiawris.gov.in), which is a joint venture of the Central Water Commission, the Ministry of Jal Shakti, and the Indian Space Research Organization (ISRO). Streamflow and reservoir levels are monitored at various locations in the Narmada basin by CWC. We selected the gauge stations (Sandia, Handia, Mandleshwar, and Garudeshwar) that have observed flow data for at least 15 years. The reservoir storage and water level data were obtained for different periods depending on the data availability.

We obtained the Extended Range Forecast System (ERFS) meteorological forecast for the 2003-2020 period. In addition, the Global Ensemble Forecast System (GEFS) meteorological forecast was obtained for the summer monsoon season (July-September) of 2019-2020 from the IITM. Both the ERFS and GEFS forecast products are developed at IITM and are currently being used for the operational weather forecast by the IMD. In June 2018, the high-resolution GEFS forecast was developed and then transferred to the IMD for operational forecasting (Mukhopadhyay et al., 2018). The GEFS dataset has a horizontal resolution of T1534 (~12.5 km) and consists of 21 ensemble members (one control and twenty perturbed). The dynamic core of the model is based on semi-Lagrangian framework, which reduces considerable computational requirements. The initial conditions (ICs) for meteorological forecasts are obtained from Global Data Assimilation System (GDAS). The GEFS is being run operationally for the ten-day lead forecast using daily Initial Conditions (ICs) during the summer monsoon period. The GEFS forecast successfully predicted the 2018 Kerala extreme rainfall at 2-3 days lead and showed reasonable forecast skills at 5-7 days lead (Mukhopadhyay et al., 2018).

The ERFS multi-model system consists of four (CFSv2T382, CFSv2T126, GFSbcT382 and GFSbcT126) suites, each having four ensemble members (one control and three perturbed). Therefore, sixteen ensemble members are available for the ERFS forecast. The model is being run operationally for 32 days lead based on the initial conditions of every Wednesday. Atmospheric and oceanic initial conditions from the National Center for Medium-Range Weather Forecasting (NCMWRF) and Indian National Centre for Ocean Information Services (INCOSIS) assimilation system are used by the models in ERFS. We used the sixteen ensemble meteorological forecasts to simulate the daily streamflow at 1-32 days leads at selected stations in the Narmada river basin. Shah et al. (2017) reported that ERFS performed better than the Global Ensemble Forecast System v2 (GEFSv2) and Climate Forecast System v2 (CFSv2) in precipitation forecast during the summer monsoon season over India.

2.2 The VIC-Res hydrological model

We used the VIC-Res hydrological model (Dang et al., 2019), a novel variant of the VIC model (Liang et al., 1994), to simulate streamflow. A combination of the VIC model and the routing model developed by Dang et al. (2019) was used to simulate streamflow at the selected locations in the basin. Dang et al. (2019) incorporated the effect of reservoirs by considering the reservoir storage dynamics and operating rules within the streamflow routing model in the VIC-Res model. The rainfall-runoff model generates water and energy fluxes within each grid using climate forcing, soil parameters, land use/land cover, and the digital elevation model. The model uses vegetation cover for each tile and three soil layers for each grid cell. The upper two soil layers control runoff, infiltration, and evaporation, while the bottom layer governs baseflow. The routing model uses water fluxes (runoff and baseflow) from each grid to simulate streamflow at selected gauge stations using the linearized Saint-Venant equations. The routing model uses flow direction, fractional area within a grid, and station location as input to generate streamflow. In addition, the VIC-Res model requires reservoir parameters and location as inputs. The reservoir parameters include full reservoir level (FRL), dead water level, storage capacity, dead storage, rated head, and the year when reservoir became operational. The VIC-Res considers a grid as a reservoir and the incoming streamflow to that reservoir is considered as the inflow. In addition to the reservoir parameters, observed seasonal cycle is also required as input to the routing scheme. The model implements mass balance equation at each time step to calculate storage and outflow/release from the reservoir. The VIC-Res model simulates daily reservoir inflow, outflow, live storage, and water level. Dang et al. (2019) reported that even the model without a reservoir exhibits almost the same level of accuracy. However, as the parametrization is inappropriate when the model is calibrated using the observed flow that is affected by reservoirs, hydrological processes simulated by the model can be erroneous.

We used observed daily precipitation, maximum and minimum temperatures from IMD, and wind speed from NCEP-NCAR reanalysis as meteorological forcing. We used reservoir storage observations to input the seasonal cycle for each reservoir into the model. An autocalibration module developed by Dang et al. (2020) was used to calibrate soil parameters of the VIC-Res model for the Narmada River basin. The autocalibration module uses the ε-NSGAII multi-objective evolutionary algorithm (Reed et al., 2013) to adjust the values of sensitive soil parameters. The autocalibration module can be used to calibrate model parameters at the outlet of different sub-basins within a river basin. First, we used autocalibration to calibrate parameters of upstream basins, then the parameters for the downstream basins were calibrated for the grids that are not part of the upstream basins. We used five soil parameters (B_{inf}, D_s, D_{smax}, W_s, and depth of three soil layers) to calibrate daily streamflow at the selected gauge stations in the basin as described in Mishra et al. (2010). B_{inf} is the variable infiltration curve parameter. D_{smax} is the maximum velocity of baseflow. D_s is a fraction of D_{smax} where non-linear baseflow begins. W_s is a fraction of maximum soil moisture non-linear baseflow occurs (Liang et al., 1994). Further details of the calibration parameters can be obtained from Mishra et al. (2010). The autocalibration module optimizes the model's performance in simulating streamflow at selected stations considering reservoir dynamics. We set our objective to maximize Nash-Sutcliffe Efficiency (NSE) [Dawson et al., 2007; Nash and Sutcliffe, 1970]. The model performance was evaluated for daily streamflow, the water level of reservoirs, and the live storage of reservoirs using NSE and coefficient of determination (R^2). Daily streamflow was calibrated and evaluated at Sandia, Handia, Mandleshwar, and Garudeshwar. We selected different periods for the calibration and evaluation of the VIC-Res model based on the availability of observed streamflow. For instance, we selected the years 1986-2000, 1986-2000, 1998-2005, 1998-2005 as the calibration period, while the years 2001-2018, 2001-2018, 2015-2018, 2015-2018 as the evaluation period for stations Sandia, Handia, Mandleshwar, and Garudeshwar, respectively. The VIC-Res model performance was also evaluated against water level and live storage for Bargi, Tawa, Indira Sagar, and Sardar Sarovar reservoirs.

We first generated daily meteorological forcing of both ERFS and GEFS forecasts. The ERFS forecast is available for the extended range (1-32 day lead), while the GEFS forecast is available at 1-10 day lead. We developed observed initial conditions for each forecast date by forcing the long-term (20 years) observed meteorological forcing from IMD into the calibrated VIC-Res model. Therefore, the model spin-up is considered in the observed initial state. We simulated a daily streamflow forecast at all the four selected gauge stations using the meteorological forcing and initial conditions. The VIC-Res simulations were run for all the ensemble members for ERFS and GEFS forecasts. The ensemble streamflow forecasts were simulated for 1-32 days lead and ten days lead for ERFS and GEFS datasets. The ERFS forecast simulations were run for 1-32 days lead with the initial conditions of every Wednesday generated from VIC-Res model using the observed forcings. Similarly, GEFS streamflow forecast simulations were performed for 1-10 days lead with initial conditions one day before the forecast.

2.3 Forecast skill evaluation

We evaluated the skills of the streamflow forecast generated using the ERFS and GEFS meteorological forecast by comparing the simulated streamflow forecast to the observed daily streamflow at each of the four locations. The model simulated streamflow forecast was evaluated against the VIC-Res model simulated daily streamflow using the observed forcing due to the unavailability of the observed streamflow for the years 2019-2020. The ERFS meteorological forcing was used to run the VIC-Res model for 1-32 days from each forecast date using the initial condition generated using the observed forcing from IMD. Similarly, we ran the GEFS ensemble members for a 1-10 days lead for each forecast date. We used bias and Normalized Root Mean Square Error (NRMSE) to evaluate the performance of individual ensemble forecast members, which can be estimated as follows:

$$Bias = \sum_{i=1}^{n} (Q_{,i} - Q_{obs,i}) \tag{1}$$

$$NRMSE = \frac{RMSE}{\overline{O}} \tag{2}$$

where, $\overline{O} = mean\ of observations.$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(Q_{,i} - Q_{obs,i}\right)^2}{n}} \quad (3)$$

where $Q_{obs,i}$ and $Q_{sim,i}$ are observed and simulated streamflow, respectively. Bias provides a measure of correspondence between the mean of observations and the mean of the VIC-Res model simulations, while NRMSE represents the relative magnitude of the squared error. We also evaluated the skills of ERFS forecast using Continuous Ranked Probability Score (CRPS) [Hersbach, 2000], which measures the closeness between the distributions of forecast and observations. The CPRS can be estimated as follows:

$$CRPS(F,x) = \int_{-\infty}^{\infty}\left(F(y) - H(y-x)\right)^2 dy \quad (4)$$

where F(x) is the cumulative distribution function (CDF) associated with probabilistic forecast and H(x) is the Heaviside function (H(x) = 1 for $x \geq 0$ and zero otherwise). The unit of CRPS is the same the of observations. Gneiting and Raftery (2007) suggested CPRS as a direct measure to compare deterministic and probabilistic forecasts.

3 Results

3.1 Skill evaluation of ERFS and GEFS meteorological forecasts

First, we evaluated ERFS precipitation and temperature forecast skills for 1-, 7-, 15-, and 31-day leads. We used bias, NRMSE, and correlation coefficient (r) to estimate the forecast skills. The forecast skill was evaluated for the period 2003-2018. We estimated the forecast skill for each ensemble member and then calculated the median of the forecast skill of all the sixteen members for each grid in the Narmada river basin. Precipitation forecast from ERFS shows a negative bias indicating an underestimation compared to observed rainfall. The dry bias in precipitation forecast increases with the lead time (Fig. 2). For the 1-day lead, precipitation forecast from ERFS showed a moderate positive correlation (median ~0.49), which declines with the lead time. Similarly, NRMSE in precipitation forecast is large (>2.0) over the river basin. We also estimated bias in the precipitation forecast exceeding the 90^{th} percentile (Fig. 3). The extreme rainfall in the raw ERFS forecast dataset exhibited a weaker correlation with the observed extreme precipitation. Moreover, a considerable dry bias in the extreme precipitation forecast was found. We also evaluated forecast skills for maximum and minimum temperature against the observed temperatures from IMD for the 2003-2018 period (Fig. S1 and S2). The daily temperature forecast showed a relatively higher positive correlation with the observed temperatures from IMD. Moreover, lower NRMSE was noted for the temperature forecast than the observed maximum and minimum temperatures. However, a positive bias of ~1.5 °C (median of all grids in the basin) was found in minimum temperature forecast at all the lead times.

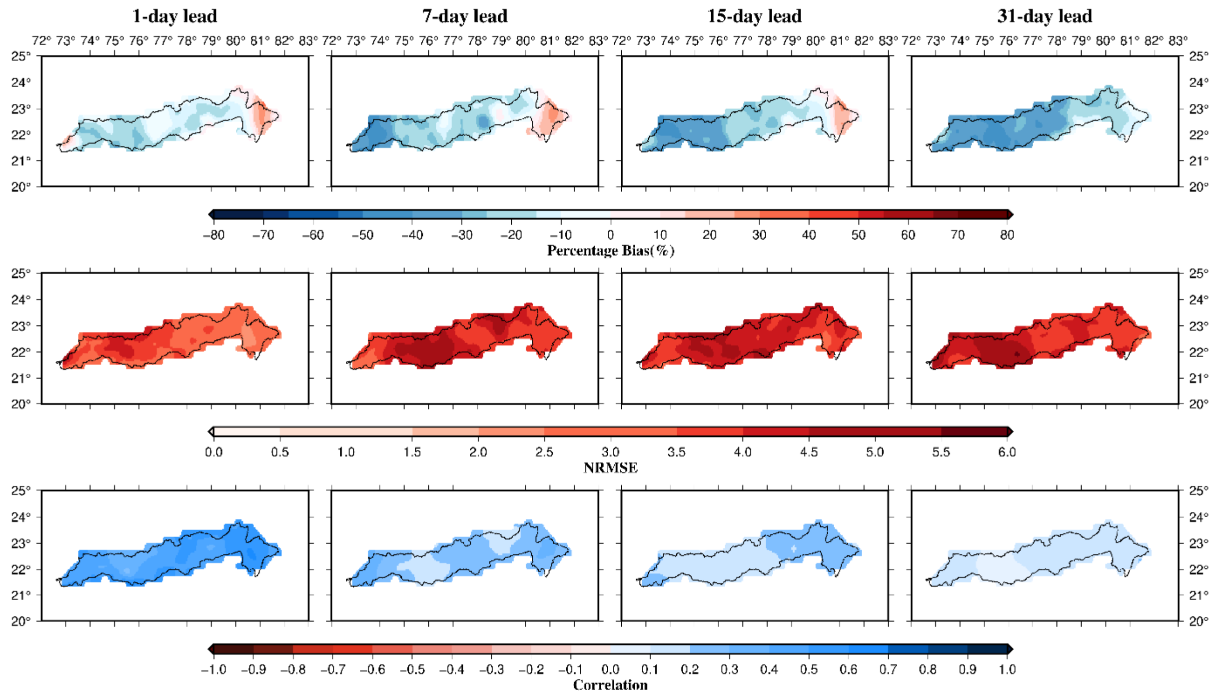

Figure 2. Evaluation of ERFS precipitation forecast against observations for the 2003-2018 period. Forecast skills were evaluated using bias, NRMSE, and correlation for each ensemble member and the median skill is presented.

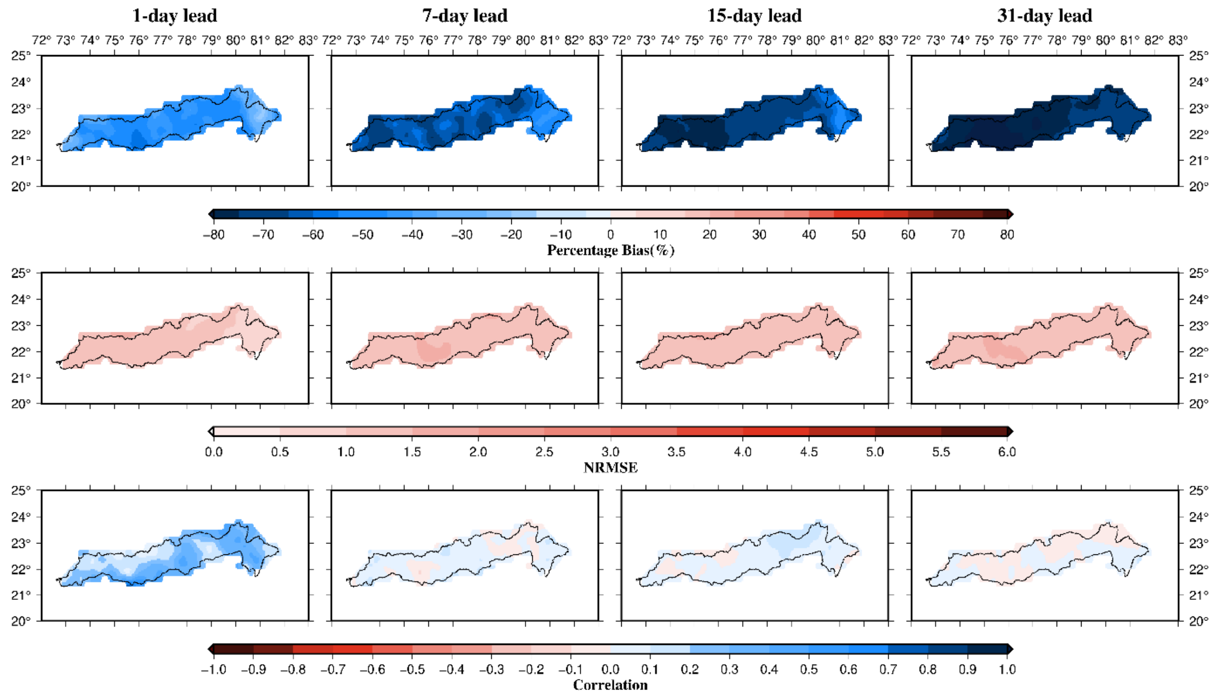

Figure 3, Evaluation of extreme precipitation (>90th percentile) forecast skill from ERFS for the 2003-2018 period. Forecast skills were evaluated using bias, NRMSE, and correlation for each ensemble member and the median skill is presented.

Next, we compared the ERFS and GEFS ensemble forecast skills for the summer monsoon (June-September) of the 2019-2020 period. We limit the comparison to the two years as the GEFS ensemble forecast is available only for 2019-2020. We evaluated forecast skills for 1-, 5-, and 10-day leads (Fig. 4). Our results show that the ERFS precipitation forecast has a dry bias across the river basin and all the leads (Fig 4). The GEFS precipitation forecast showed a positive (wet) bias in the majority of the Narmada river basin. The forecast products (ERFS and GEFS) underestimate extreme rainfall in the Narmada basin (Fig 5). The dry bias in extreme rainfall increases with lead time in the ERFS and GEFS forecasts (Fig. 5). The forecast products showed a poor correlation with the observed extreme precipitation in the Narmada river basin (Fig. 5). However, both the forecast products demonstrated relatively better skills for maximum and minimum temperatures than precipitation (Fig. S3 and S4).

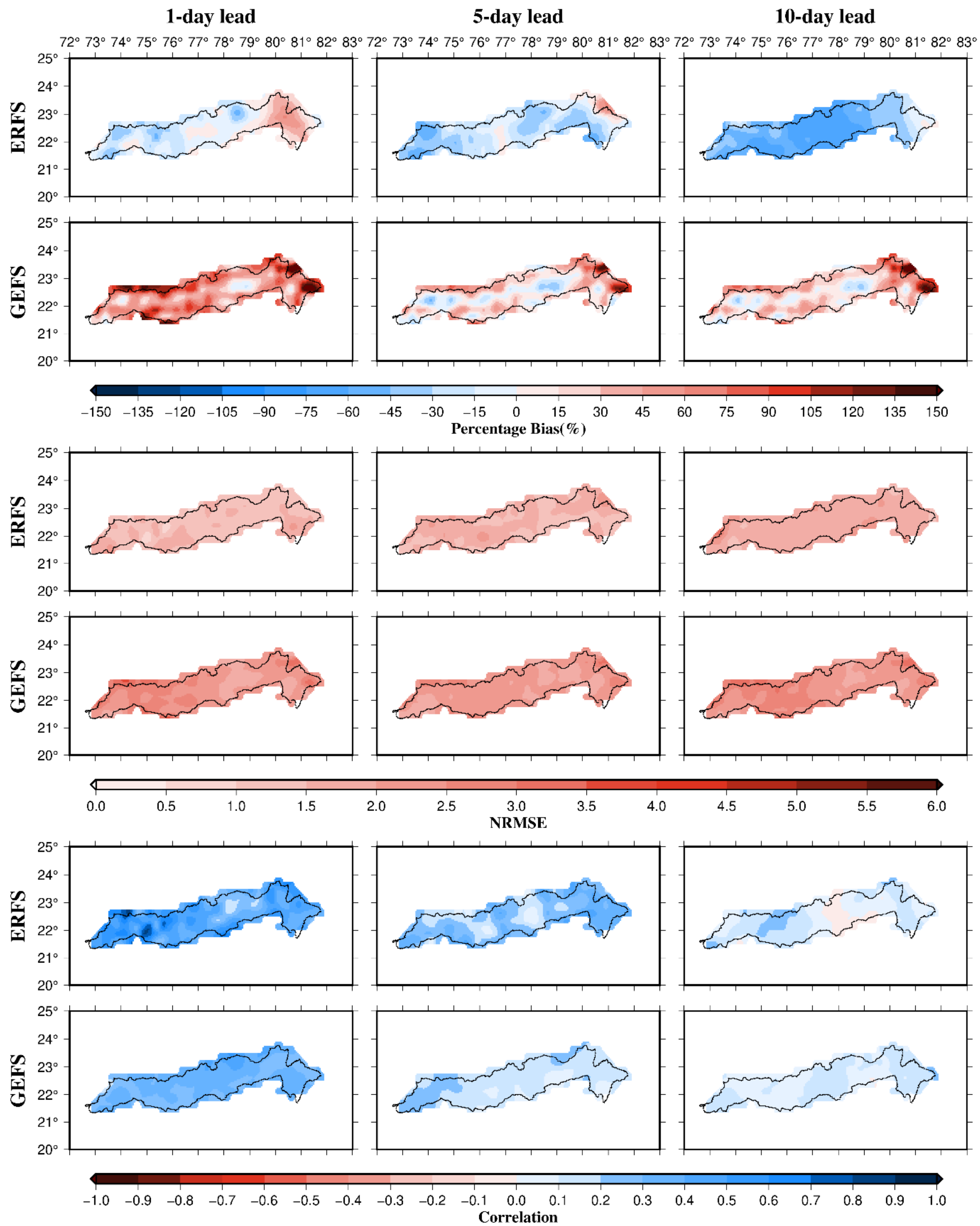

Figure 4. Comparison of the precipitation forecast skills from ERFS and GEFS for the summer monsoon period during 2019-2020. Forecast skills were evaluated using bias, NRMSE, and correlation for each ensemble member of ERFS and GEFS and the median skill is presented.

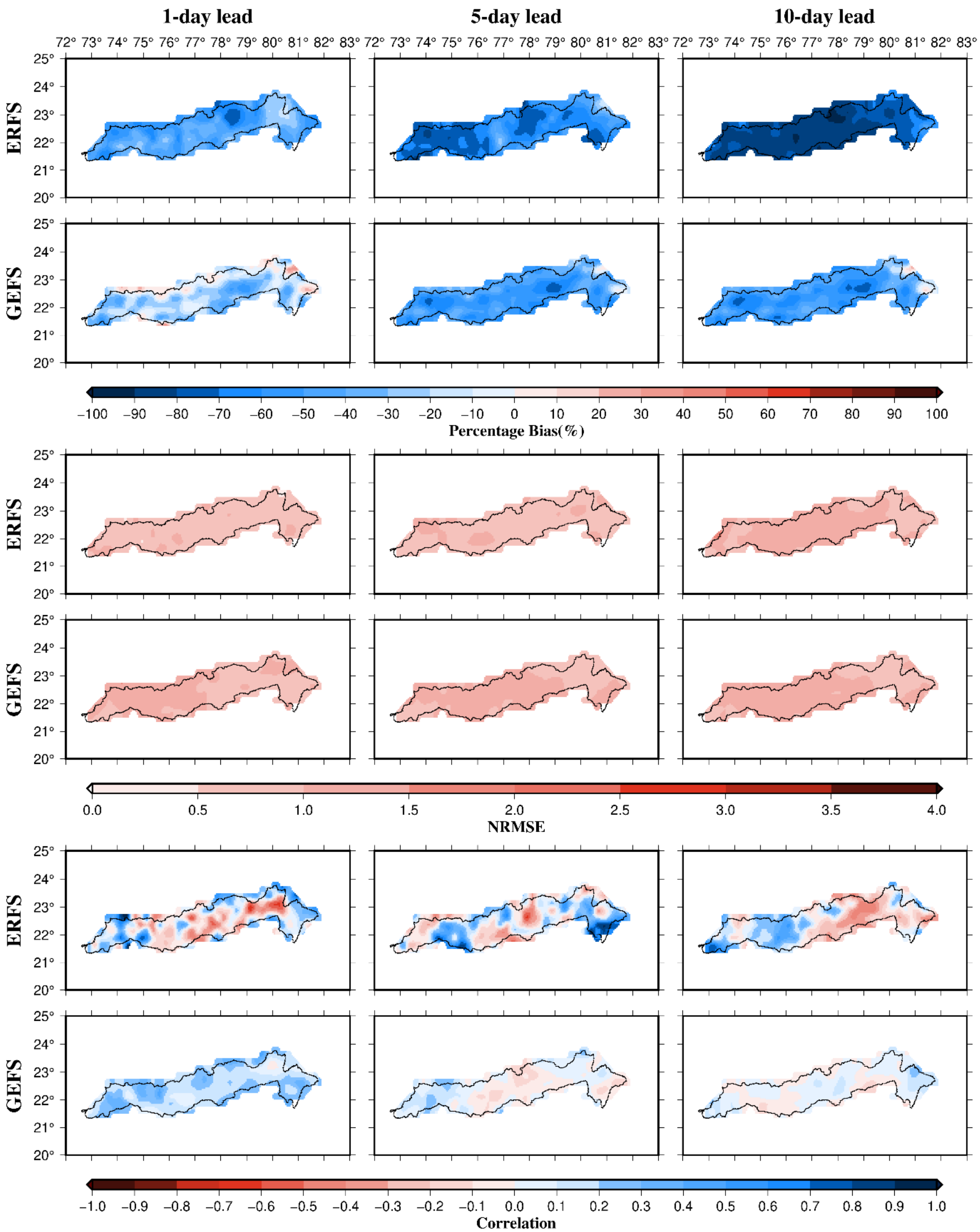

Figure 5. Comparison of the extreme precipitation (exceeding 75th percentile) forecast skills from ERFS and GEFS for the summer monsoon period during 2019-2020. Forecast skills were evaluated using bias, NRMSE, and correlation for each ensemble member of ERFS and GEFS and the median skill is presented.

3.2 Calibration and evaluation of the VIC-Res model

We performed calibration of reservoir level and storage and calibration of daily streamflow. Daily storage and water level calibrated the VIC-Res model for four major reservoirs (Bargi, Tawa, Indira Sagar and Sardar Sarovar) in the Narmada basin. The upstream catchment area of all the gauge locations and calibration parameters are shown in supplementary Figure S5. We evaluated the VIC-Res model's performance using the coefficient of determination (R^2) and Nash Sutcliffe Efficiency (NSE) (Fig. 6). The VIC-Res model simulates daily streamflow at the selected stations in the basin. R^2 and NSE values were above 0.65 at Sandia, Handia, and Mandleshwar stations for the calibration period. While at Garudeshwar, the VIC-Res model performed comparatively weaker ($R^2 = 0.55$ & NSE = 0.53) for the calibration period.

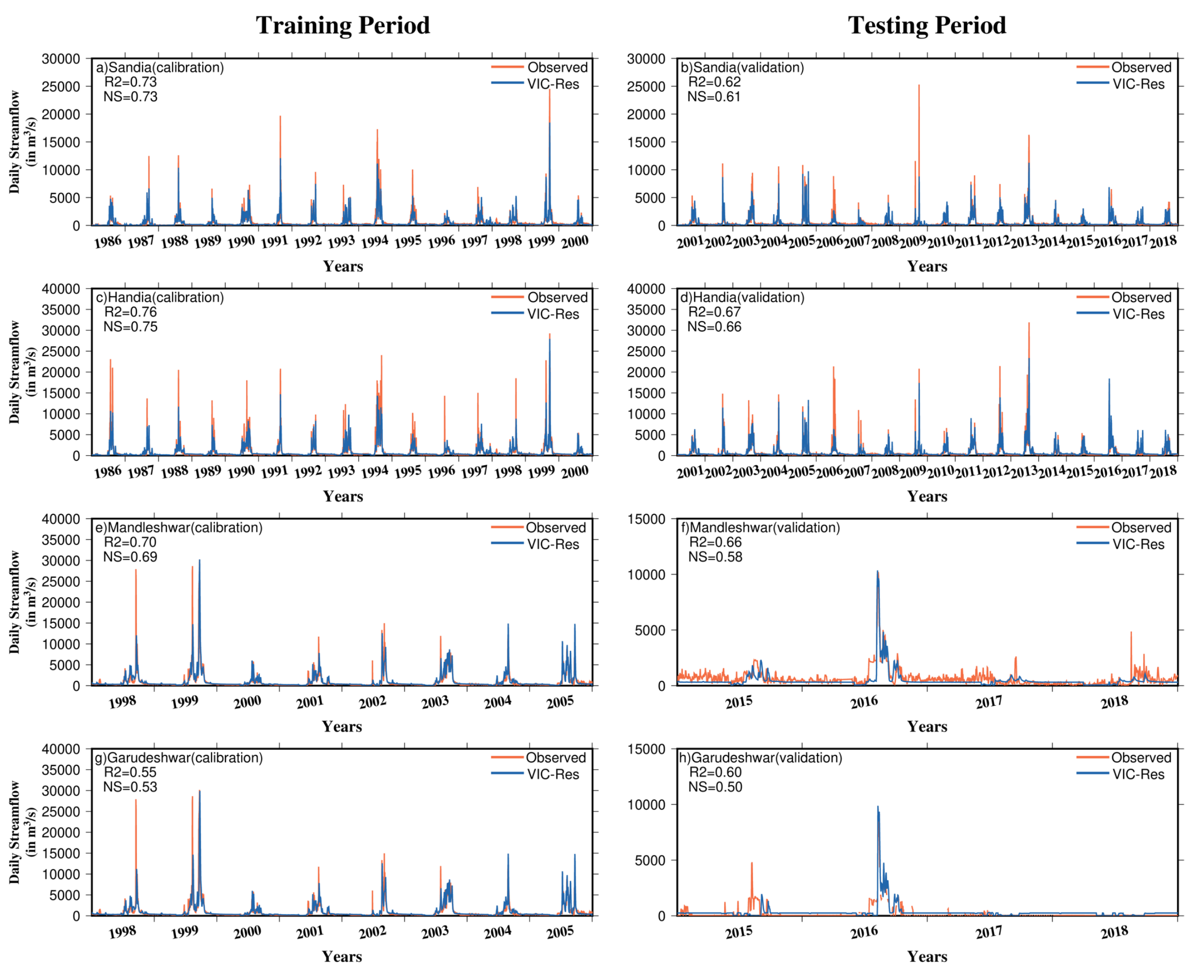

Figure 6. Calibration and evaluation of the VIC-Res model against observed daily streamflow at gauge stations at Sandia, Handia, Mandleshwar and Garudeshwar. The performance of the VIC-Res model in simulating daily streamflow was evaluated using the R^2 and NSE.

We considered the influence of major reservoirs on the simulated daily streamflow. Therefore, the VIC-Res model's performance in simulating daily reservoir storage and the water level was evaluated against the streamflow observations. We selected 2000-2016, 2000-2016, 2007-2016, and 2008-2013 as evaluation periods for Bargi, Tawa, Indira Sagar, and Sardar Sarovar reservoirs, respectively, based on the availability of observations. We estimated R^2 and NSE to evaluate the model's performance (Fig. 7). The model performed well in simulating all the reservoirs' water levels and storage (R^2>0.78 and NSE>0.62). We also compared the seasonal cycle of the observed and simulated reservoir storage for all the four major reservoirs (Fig. 8). The model simulated monthly seasonal cycle of reservoir storage compares well with the observed storage for all the dams with R^2 of more than 0.77. We find that the model underestimates storage for Bargi reservoir, which can be due to relatively smaller upstream catchment area that may not capture the spatial variability of rainfall. Overall, we find that the VIC-Res model can evaluate the ensemble streamflow forecast in the Narmada river basin.

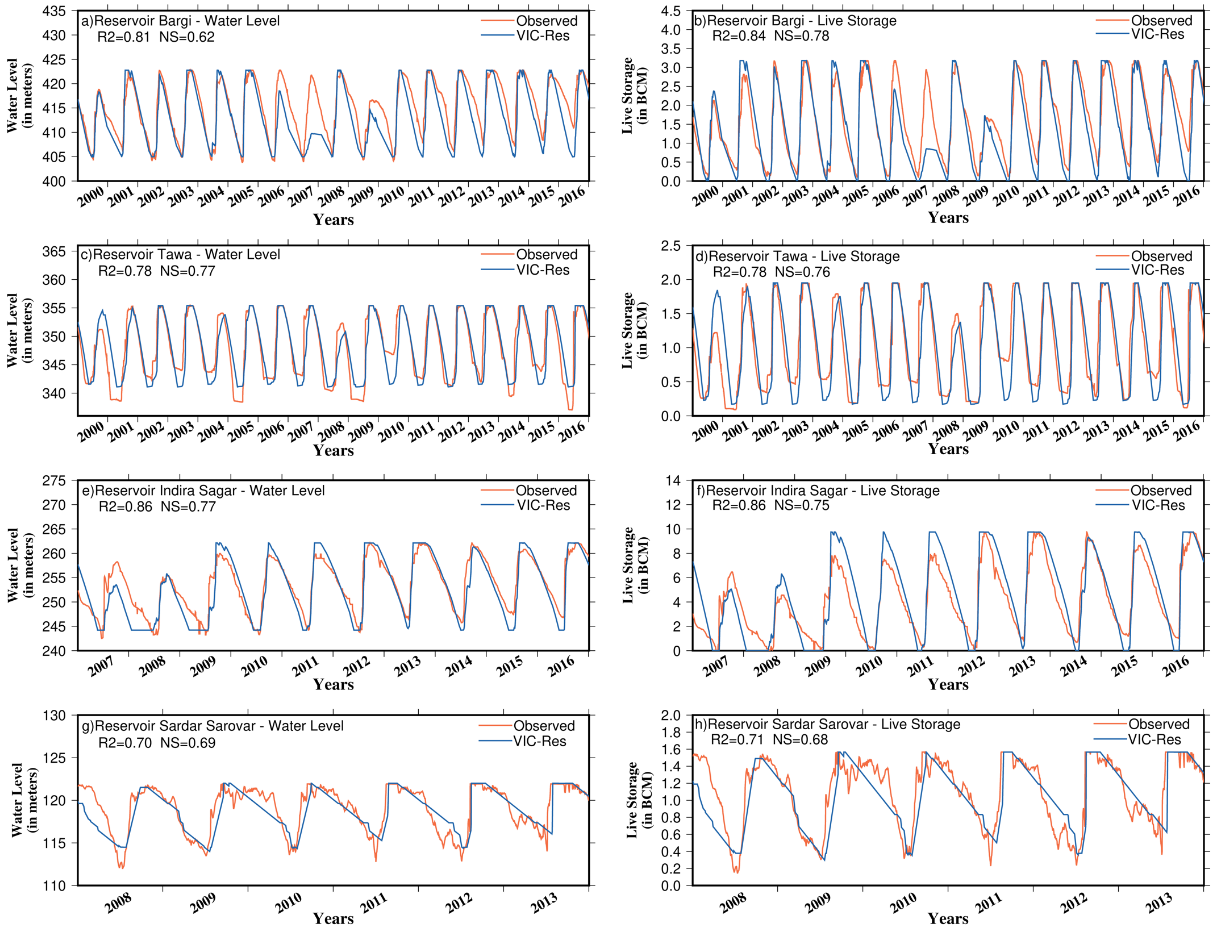

Figure 7. Evaluation of the VIC-Res model in simulating daily water level and daily live storage at four major reservoirs Bargi, Tawa, Indira Sagar and Sardar Sarovar.

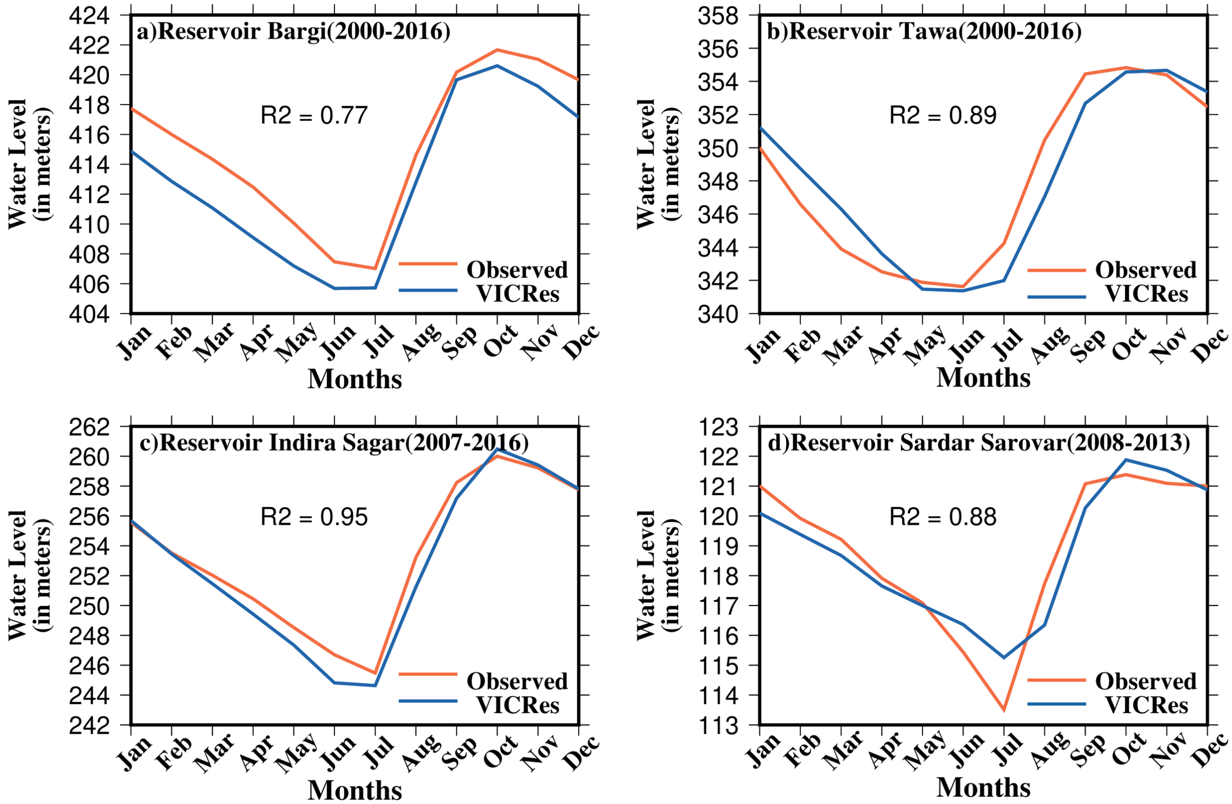

Figure 8. Comparison of observed and the VIC-Res model simulated reservoir water levels for four reservoirs in Narmada River basin.

3.3 Evaluation of ensemble streamflow forecast skills of ERFS

We estimated forecast skills of daily streamflow for 2003-2018 generated from each ensemble member of ERFS for the twelve lead times (1-day to 10-day, 15-day, and 31-day). We selected a 1-10 day lead as GEFS forecast is also available with the same lead. In addition, two other lead times (15 and 31 days) were selected to evaluate the forecast skill of streamflow forecast from all the sixteen members of ERFS (Fig. 9). Both bias and NRMSE showed a relatively lesser spread for the shorter lead (1-3 day) streamflow forecast from all the ensemble members of ERFS (Fig. 9). However, uncertainty in streamflow forecast due to different ensemble members increases with the lead time. NRMSE of streamflow forecast from ERFS also rises with the lead at all the stations. Ensemble streamflow forecast from ERFS showed a positive bias for Sandia, Handia, and Garudeshwar, while a negative bias was found for Mandleshwar station (Fig. 9). We estimated the CRPS, which is higher for 1-day lead compared to 3-day leads and increases with the lead time (Figure S6).

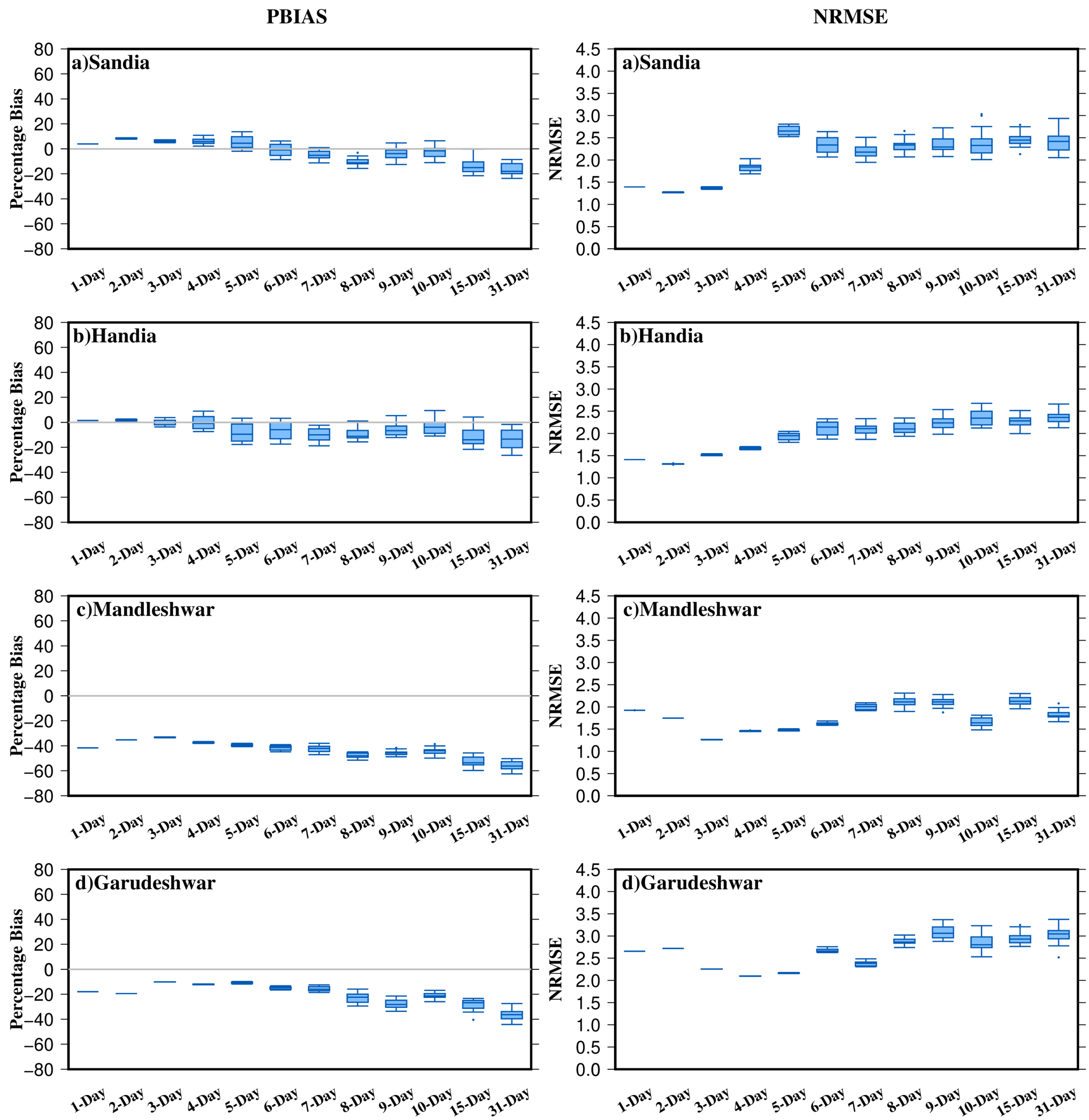

Figure 9. Ensemble streamflow forecast skill based on the ERFS forecast for 2003-2018. The forecast was evaluated using bias (%) and NRMSE. Box and whisker plots show the skill for all 16 ensemble members at lead 1-10 day, 15 day and 31 days at four gauge stations.

We estimated the forecast skill in streamflow exceeding certain thresholds (50,70,80,90, and 95th percentiles) [Fig. 10]. We find less spread in bias among different ensemble members for 1-day lead streamflow forecast from ERFS. However, the spread of bias in streamflow forecast due to different ensemble members increases with the lead time (Fig. 10). Moreover, bias in streamflow forecast remains stable for all the selected percentile thresholds at a 1-day lead at all the four-gauge stations. On the other hand, bias in streamflow forecast increases for higher percentiles at longer lead times. For instance, dry bias in streamflow forecast in all the ensemble members is higher for the 95th percentile than for the 50th percentile. Therefore, our results show that regardless of the spread among the ensemble members from ERFS, almost all the ensemble members underestimate the high flow at all the gauge stations in the Narmada river basin (Fig. 10).

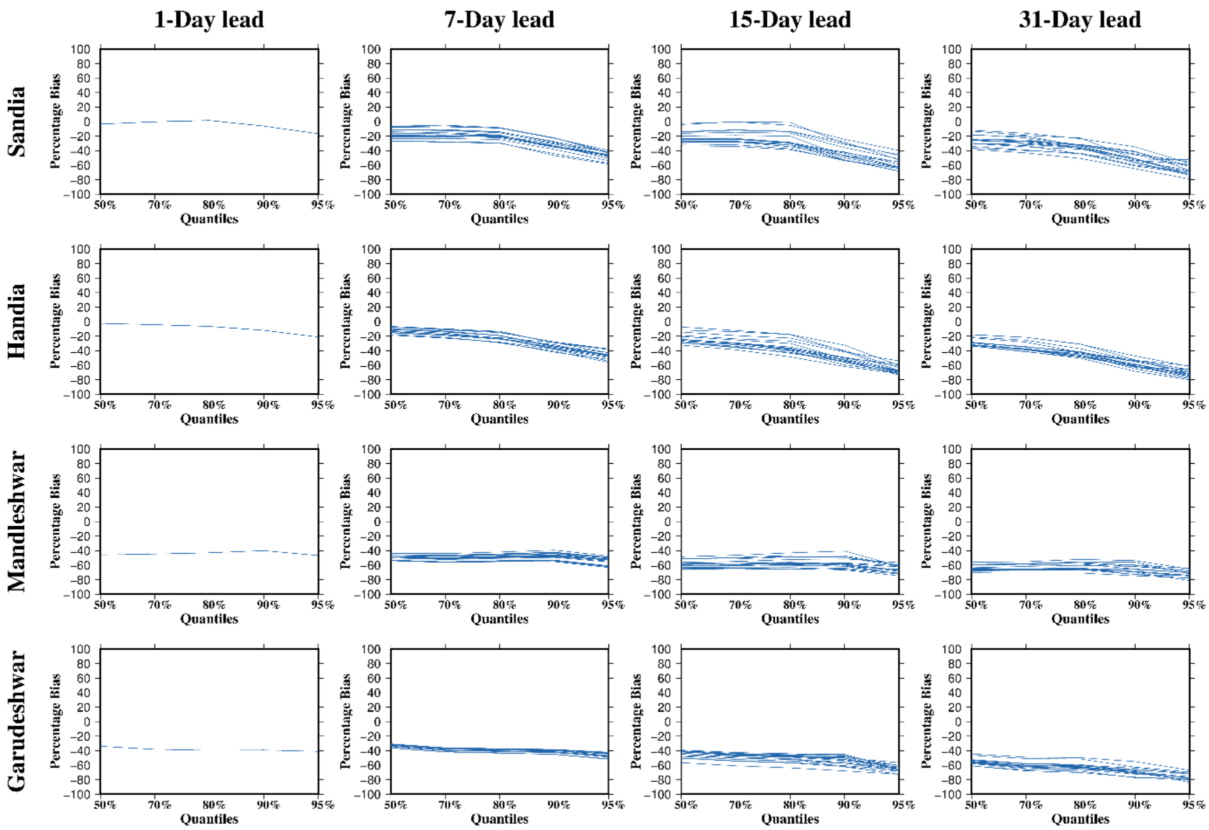

Figure 10. Bias in ensemble streamflow forecast estimated using ERFS for 2003-2018 for streamflow percentiles exceeding 50th, 70th, 80th, 90th, and 95th thresholds. Bias in ensemble streamflow forecast was evaluated at 1, 7, 15, and 31 day lead.

3.4 Comparison of ensemble streamflow forecast skills ERFS and GEFS

We compared the streamflow forecast skills of 16 ensemble members from ERFS and 21 ensemble members from GEFS. Since GEFS meteorological forecast is available only for 2019-2020, we compared the summer monsoon season of these two years. ERFS forecast is available weekly for 1-32 days, while the GEFS forecast is generated every day. Therefore, we compared the daily streamflow forecast from both the products for the weeks for which the ERFS forecast was available for the summer monsoon of the 2019-2020 period. We compared the streamflow forecast skills for all the ensemble members at 1 to 10 day leads at Sandia, Handia, Mandleshwar, and Garudeshwar

(Fig. 11). We find that the GEFS forecast has a better skill for the short lead time (~1-5 days) with less bias and NRMSE. On the other hand, the ERFS ensemble forecast showed higher bias and NRMSE at shorter leads for most of the selected locations in the Narmada basin. Streamflow forecast skill of GEFS declines rapidly after the 3-4 day lead time for most of the locations in the Narmada basin. The forecast products showed a larger spread among the streamflow forecast ensemble members after five days lead. For short to medium range (~1 to 5 days), the streamflow forecast from GEFS performed better with low NRMSE and bias for streamflow exceeding the 75th percentile of the summer monsoon period (Fig. S7). Moreover, streamflow forecast skill from the ERFS was considerably lower than the GEFS at most of the locations for flow exceeding 75th percentiles (Fig. S7).

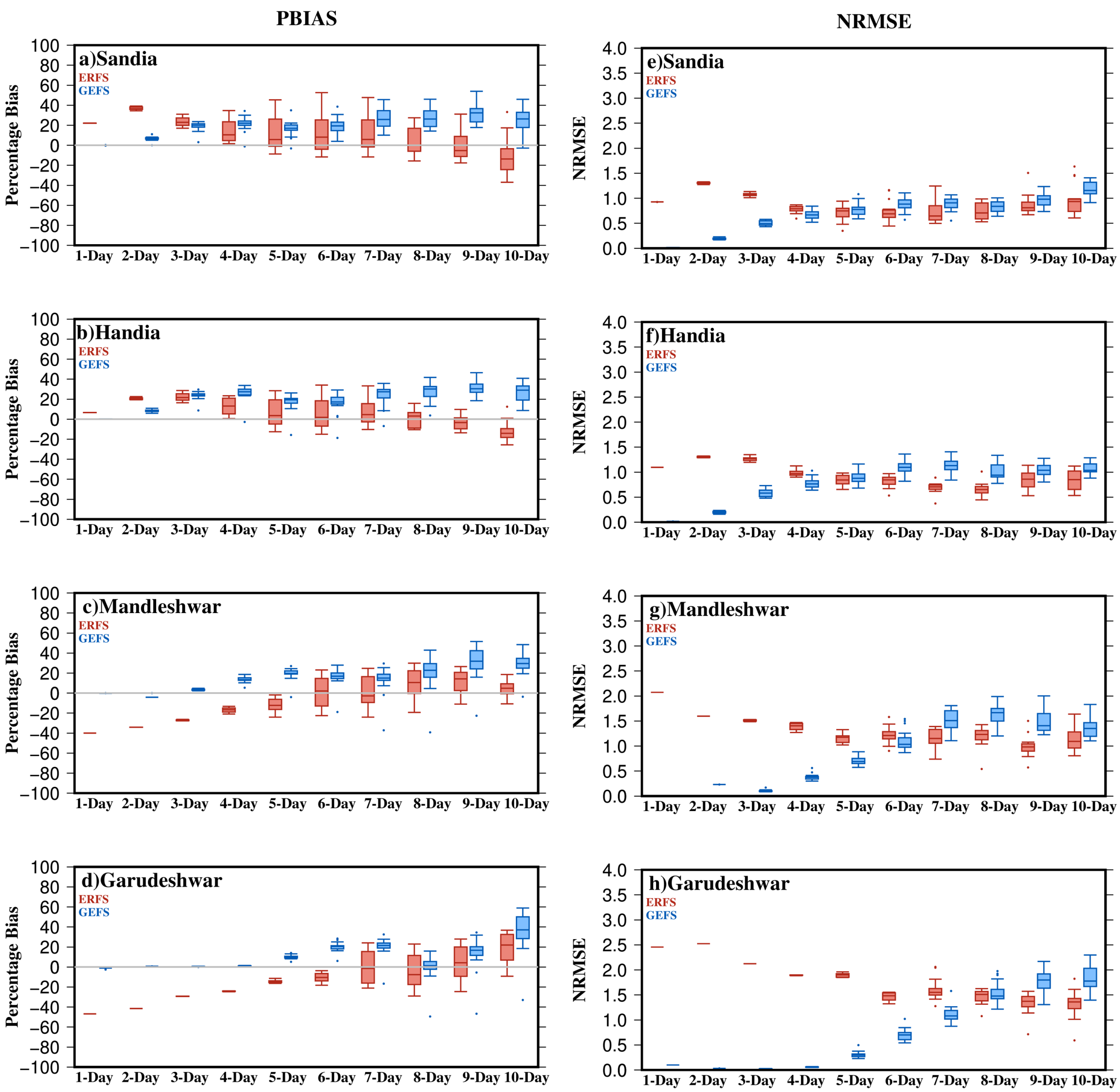

Figure 11. Comparison of ensemble streamflow forecast skills from ERFS and GEFS for 2019-2020. The forecast skill was evaluated considering the VIC-Res simulated streamflow with the observed forcing from IMD due to unavailability of observed flow.

We examined the daily streamflow forecast skill at 3-day, 5-day, and 10-leads from ERFS and GEFS forecasts for the summer monsoon season of 2019 & 2020 against VIC-Res simulated streamflow using the observed meteorological forcing at all the four gauge stations (Fig. 12 and Fig. S8). Since observed daily streamflow was unavailable for skill assessment, the comparison was made against the VIC model simulated flow with the observed meteorological forcing (Fig. 12 and Fig. S8). The GEFS forecast successfully captured streamflow peaks in both 2019 and 2020 at a 3-day lead. In 2019, GEFS forecasts overestimated streamflow peaks at 3-day and 5-day leads during the summer monsoon. On the other hand, the ensemble streamflow forecast developed using the ERFS meteorological forecast showed a higher spread than GEFS (Fig. 12, Fig. S8). The spread in ensemble streamflow forecast increases for both ERFS and GEFS forecast at a 10-day lead. However, the ERFS's streamflow forecast showed a better skill at the 10-day lead. Despite having fewer ensemble members than the GEFS, the ERFS forecast showed a broader spread in streamflow prediction, highlighting a higher uncertainty in prediction. We find that GEFS overestimate streamflow the ERFS underestimates most of the locations and lead times.

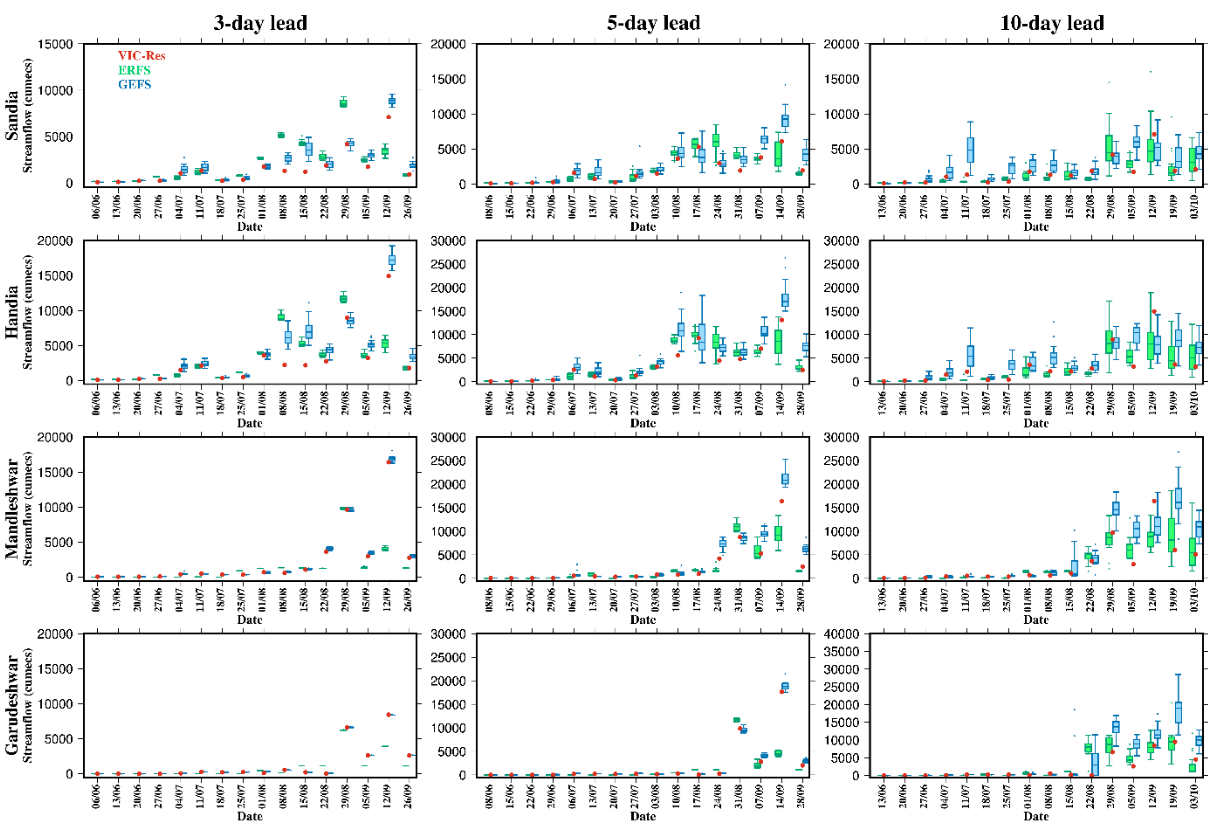

Figure 12. Comparison of ensemble streamflow simulated using the VIC-Res model with ERFS and GEFS forecast products during the summer monsoon of 2019. The forecast skill was evaluated considering the VIC-Res simulated streamflow with the observed forcing from IMD due to unavailability of observed flow.

We examined the streamflow forecast generated by all the ensemble members of ERFS and GEFS for a few events using the VIC-Res model (Fig. 13). The ensemble streamflow prediction was compared considering the model simulated streamflow with the observed forcing from IMD. In 2019, the ensemble mean streamflow from all the ensemble members of ERFS considerably underestimated the peak flow (Fig. 13). However, a few ensemble members of the ERFS forecast captured the peak flow at the four locations of the Narmada river basin (Fig. 13). At Handia station, 1 out of 16 ensemble members exceeds the observed streamflow. Moreover, GEFS forecasts at short leads (3-5 days) performed well in capturing peaks (Fig. 13). However, GEFS forecasts showed a smaller spread in ensemble streamflow at the short lead time (1-5 days). Overall, we find that ensemble forecasts can be used for probabilistic streamflow prediction.

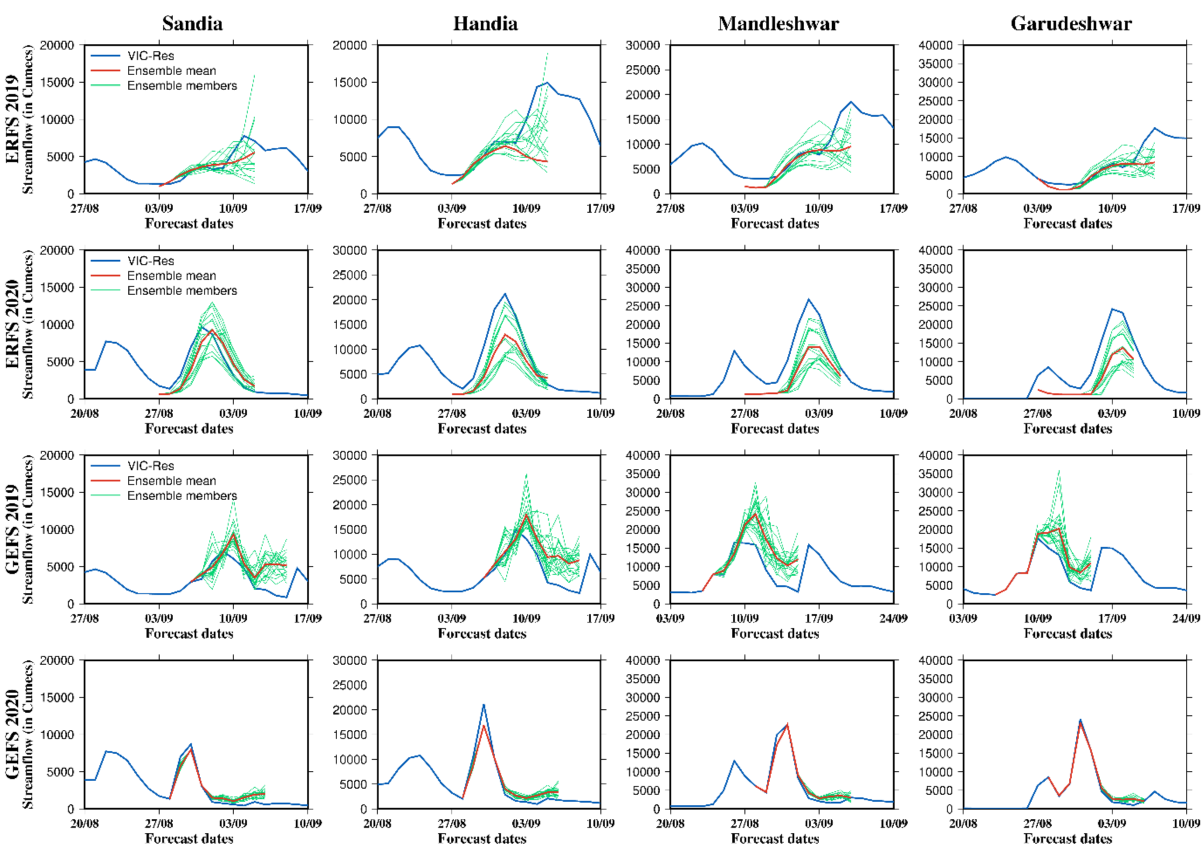

Figure 13. Ensemble streamflow simulations using the ERFS forecast at 5-11 day lead and GEFS forecast at 3-5 day lead against the VIC-Res simulated streamflow with the observed meteorological forcing for 2019 and 2020.

4 Discussion and conclusions

Streamflow forecast plays an essential role in efficient reservoir operations and flood mitigation (Chen et al., 2016; Mediero et al., 2007). A reliable streamflow forecast can reduce uncertainty in reservoir operations and enhance the development of a flood early warning system. Notwithstanding the considerable progress in an operational meteorological forecast from different agencies, efforts to establish an ensemble streamflow forecast system at river basin scales have been limited for India. Moreover, it remains unclear if other meteorological forecast products have different streamflow forecast skills. We used the two meteorological ensemble forecast products from IMD to examine streamflow forecast skills in the Narmada river basin. The presence of reservoirs influence the water budget and streamflow (Shah et al., 2019 Zajac et al., 2017; Yun et al., 2020; Chai et al., 2019). Hydrological model parameters calibrated without considering the role of reservoirs can be erroneous and leading to errors and uncertainty in simulated hydrological processes (Dang et al., 2019). Therefore, we used the ensemble streamflow prediction approach to generate the daily streamflow simulations considering the influence of reservoirs in the Narmada river basin. We compared the performance of ERFS and GEFS ensembles for the summer monsoon period of 2019-20. We also assessed the skills of the ERFS dataset solely for a more extended period from 2003 to 2018.

The ERFS ensemble forecast is available once a week at 1-32 days lead time. On the other hand, GEFS ensemble forecasts are available daily at 1-10 days lead for the summer monsoon period of 2019-2020. Hagedorn et al. (2005) reported that bias-correction of the raw forecast does not necessarily increase the forecast skill. Moreover, statistical correction of the raw forecast is inappropriate, which can lose its effect propagating through the hydrological model (Zalachori et al., 2012; Crochemore et al., 2016; Benninga et al., 2017; Hagedorn et al., 2005). Therefore, we did not bias-correct the raw meteorological ensemble forecasts from ERFS and GEFS. The skills of ERFS and GEFS precipitation and temperature (minimum and maximum) forecasts were estimated for 1-, 5- and 10-day lead. The GEFS raw forecast showed better skills than the ERFS forecast for mean and extreme precipitation. As precipitation plays a vital role in streamflow forecast (Meaurio et al., 2017; Demargne et al., 2014; Pappenberger et al., 2005), our results show that GEFS forecast provides better skills for streamflow prediction in the Narmada River basin. The post-processing of streamflow data can significantly improve performance (Tiwari et al., 2021; Muhammad et al., 2018), which can be used in the future to examine the improvements in streamflow prediction. Moreover, a multi-model approach can be used to reduce the errors and uncertainty in streamflow forecasts that could arise due to the parameterization of hydrological models (Velázquez et al., 2011; Zarzar et al., 2018; Muhammad et al., 2018).

The skills of ERFS and GEFS ensemble forecasts were estimated for 1, 5 and 10-day leads. GEFS raw forecasts illustrated better skills than ERFS forecasts for overall rainfall and extreme precipitation. As studies show that rain plays a vital role in streamflow forecast (Demargne et al., 2014; Meaurio et al., 2017; Pappenberger et al., 2005), we also observed the same results. The ensemble forecast with better skills performed well in predicting daily streamflow. Correcting the bias of the input forecast may shrink the variability range of the result. However, ensemble forecasts aim to capture uncertainties. Studies suggest that the post-processing of streamflow data can significantly improve performance (Muhammad et al., 2018; Tiwari et al., 2021). A multi-model approach, where more than one hydrological model is used, can generalize the uncertainty introduced by the hydrological model. Various studies have reported improved forecast skills using the multi-model approach (Muhammad et al., 2018; Velázquez et al., 2011; Zarzar et al., 2018). Also, our analysis is based on just for the 2019-2020 as the GEFS hindcast is available only for this period. Availability of longer hindcast from the GEFS can help to understand the forecast skills for hydrological extremes (drought and floods). Moreover, we did not examine the forecast skill of reservoir storage, which can provide a better understanding of the impacts of storage during the floods.

Flood forecasting using the available meteorological forecast products can help in mitigating the losses through early warnings. To account for the uncertainty arising from initial state and model parameterization, the individual members of the ensemble weather forecast can provide better information than their ensemble mean (Saleh et al., 2019). The probabilistic approach over the deterministic method provides the range of variability, which can help determine the probability of exceeding a specific threshold of streamflow (Hsiao et al., 2013). The shift from the existing 'flood forecast system' to the 'ensemble-based probabilistic forecast' requires modifications in the current flood forecast practice. The transition is expected to change various aspects of the existing decision-making process. The forecasters need to train the on-duty officers adequately and the authorities on probabilistic forecasts. We evaluated the streamflow forecast skills at 1-32 day lead in the Narmada river basin. The increased lead time in streamflow forecast can assist in developing efficient communication methods of information (Arnal et al., 2020; Ramos et al., 2010). Moreover, ensemble streamflow forecast at longer leads can be effectively used in optimizing reservoir operations (Alemu et al., 2011). Our results show that, while the mean of the ensemble members failed to capture the high flows, a few individual ensemble members performed better in capturing peak flow, which can be used to develop probabilistic early warnings.

Based on our findings, the following conclusions can be made:

1) The raw precipitation forecast from both GEFS and ERFS datasets showed moderate skills (bias, NRMSE and correlation) against observations from IMD at 1-day, 5-day and 10-day lead times. While both (ERFS and GEFS) forecast products underestimated extreme precipitation, dry bias in the ERFS forecast was more prominent than the GEFS forecast. For instance, raw precipitation forecast from ERFS showed negative bias across the Narmada river basin. On the other hand, the raw precipitation forecast from GEFS exhibited both negative and positive bias. Both the forecast products showed better skills for maximum and minimum temperatures than precipitation.
2) We calibrated and evaluated the VIC-Res model to simulate streamflow, considering the influence of reservoirs at four gauge stations in the Narmada River Basin. The model reproduced daily streamflow, reservoir water level, and storage reasonably well against the observations.

3) Comparing the streamflow forecast skills of both the ensemble forecasts showed that GEFS forecasts performed better than the ERFS at all the locations in the basin. However, both the forecast products underestimated the extremes, which can be due to dry bias in extreme precipitation. The spread in streamflow due to different ensemble members increased with the forecast lead time. Overall, an ensemble forecast can be used to develop a probabilistic forecast based flood early warning system.

Data availability: All the datasets used in this study can be obtained from the corresponding author.

Competing interest: Authors declare no competing interest.

Author contributions: VM designed the study. UV conducted simulations and wrote the first draft. UV and VM discussed the results and prepared the final version.

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