

**Evaluation of
operational seasonal
streamflow forecasts**

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**Role of climate forecasts and initial
land-surface conditions in developing
operational streamflow and soil moisture
forecasts in a rainfall-runoff regime:
skill assessment**

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Received: 21 March 2012 – Accepted: 11 April 2012 – Published: 19 April 2012

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Published by Copernicus Publications on behalf of the European Geosciences Union.

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5 Skillful seasonal streamflow forecasts obtained from climate and land surface conditions could significantly improve water and energy management. Since climate forecasts are updated on monthly basis, we evaluate the potential in developing operational monthly streamflow forecasts on a continuous basis throughout the year. Further, basins in the rainfall-runoff regime critically depend on the forecasted precipitation in the upcoming months as opposed to snowmelt regimes where initial hydrological conditions (IHC) play a critical role. The goal of this study is to quantify the role of monthly updated precipitation forecasts and IHC in forecasting 6-month lead monthly streamflow for a rainfall-runoff mechanism dominated basin – Apalachicola River at Chattahoochee, FL. The Variable Infiltration Capacity (VIC) land surface model is implemented with two forcings: (a) monthly updated precipitation forecasts from ECHAM4.5 Atmospheric General Circulation Model (AGCM) forced with sea surface temperature forecasts and (b) daily climatological ensemble. The difference in skill between the above two quantifies the improvements that could be attainable using the AGCM forecasts. Monthly retrospective streamflow forecasts are developed from 1981 to 2010 and streamflow forecasts estimated from the VIC model are also compared with those predicted by using the principal component regression (PCR) model. Mean square error (MSE) in predicting monthly streamflow using the above VIC model are compared with the MSE of streamflow climatology under ENSO conditions as well as under normal years. Results indicate that VIC forecasts, at 1–2 month lead time, obtained using ECHAM4.5 are significantly better than VIC forecasts obtained using climatological ensemble over all the seasons except forecasts issued in fall and the PCR models perform better during the fall months. Over longer lead times (3–6 months), VIC forecasts derived using ECHAM4.5 forcings alone performed better compared to the MSE of streamflow climatology during winter and spring seasons. During ENSO years, streamflow forecasts exhibit better skill even up to six month lead time. Comparison of the

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seasonal soil moisture forecasts developed using ECHAM4.5 forcings with seasonal streamflow also show significant skill at 1–3 month lead time over the all four seasons.

1 Introduction

5 Skillful seasonal forecasts of streamflow and soil moisture are essential for water management as well as to support agricultural operations. Previous studies have shown that application of seasonal streamflow forecasts obtained from climate and land surface conditions could significantly improve water and energy management (Yao and Georgakskos, 2001; Voisin et al., 2006; Sankarasubramanian et al., 2010; Hamlet et al., 2002). Seasonal streamflow forecasts derive their skill from slowly evolving climatic conditions, particularly the Sea Surface Temperature (SST) as well as initial hydrologic conditions (IHC) such as soil moisture and snow cover (Mahanama and Koster, 10 2003; Maurer et al., 2004; Wood and Lettenmaier, 2008).

Considerable progress has been made over the last decade in understanding the role of IHC and climate forecasts in improving the skill of streamflow forecasts. Maurer and Lettenmaier (2003) assessed streamflow predictability in the Mississippi River 15 basin by developing multiple regression models using observed streamflow, El Niño Southern Oscillation (ENSO) indices, and IHC (including soil moisture and snow) and reported that the role of soil moisture dominated forecasting skill for lead times up to 1.5 months. Shukla and Lettenmaier (2011) quantified the role of IHC as well as observed and climatological forcings (CF) in predicting the runoff and soil moisture over 20 the continental US and found that climate forcings dominates soil moisture skills over the Northeastern and Southeastern US.

Streamflow forecasting skill significantly varies across rainfall-runoff and snowmelt-driven regimes. Maurer et al. (2004) reported that snow in its dry state played a crucial 25 role in streamflow predictability up to 4.5 months lead time in the Western US. Koster et al. (2010) concluded that in the snow dominated regions, snow water equivalent (SWE) generally contributed to overall streamflow predictability with the role of

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early-season soil moisture in improving streamflow prediction being relatively small. Initialization of snow also had a greater impact on the overall skill during the spring melt season in the Northwest US while the contribution of soil moisture is particularly high in the Southeast (up to 5 or 6 months) during fall and winter (Mahanama et al., 2012). Mahanama et al. (2012) primarily employed climatology as forcings with updated initial conditions using different LSMs to develop seasonal streamflow forecasts. In the present study, the main focus is to utilize monthly updated precipitation forecasts from GCMs forced with forecasted SSTs to develop monthly streamflow forecasts and also to evaluate their skill against climatological forcings.

Most of studies that developed streamflow forecasts based on land surface models have used observed or climatological meteorological forcings (e.g., Hamlet et al., 2002; Maurer and Lettenmaier, 2004; Mahanama et al., 2012), while only fewer studies have employed retrospective climate forecasts (Luo and Wood, 2008; Luo et al., 2007, Yuan et al., 2011). Wood et al. (2002) found that IHC played a more critical role than climate forecasts (CF) in predicting streamflow during the summer of 2000, whereas both IHC and CF were important in predicting winter streamflow during 1997–1998 El Niño conditions over the Southeastern US. Luo et al. (2007) used bias-corrected climate forecast from multiple models for predicting streamflow in the Ohio River basin and found that climate forecast contributed more than IHC uncertainties at long-lead times of more than one month in predicting the summer flows. Li et al. (2009) pointed out that initial conditions have dominant effect on forecasting skill over a short-term lead time (up to 1 month) while climate forcings control forecasting skill at longer lead times based on two initializations at the beginning of January and July. However, all the above studies that utilized retrospective climate forecasts for assessing the streamflow forecasting skill have primarily focused on evaluating the skill in two critical seasons – summer and winter.

The primary intent of this study is to quantify the role of monthly updated precipitation forecasts and initial hydrologic conditions in forecasting 6-month lead monthly streamflow for a river basin dominated by rainfall-runoff mechanism. Given that monthly

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climate forecasts are issued and updated on a regular basis (Barnston et al., 2003; Goddard et al., 2003), it is imperative to evaluate the potential in developing monthly streamflow forecasts on a continuous basis throughout the year, so that the developed forecasts could be employed for real-time forecasting. Further, basins in the rainfall-runoff regime critically depend on the forecasted precipitation in the upcoming months as opposed to snowmelt regimes where IHC play a critical role (Mahanama et al., 2012). For this purpose, we utilize the retrospective monthly precipitation forecasts available for a long period (1957–till date) from ECHAM4.5 General Circulation Model (GCM) (Li and Goddard, 2005). The six-month ahead precipitation forecasts were updated every month based on the updated SST forecasts developed using constructed analogue method (van den Dool, 1994). Using this long time series of monthly updated six-month ahead precipitation forecasts, we perform a set of experiments to address the following research questions related to developing real-time streamflow and soil moisture forecasts in a rainfall-runoff regime:

1. How does the skill in predicting observed monthly streamflow vary over different seasons and lead time?
2. How does the skill in predicting monthly streamflow and soil moisture forecasts vary during El-Niño Southern Oscillation (ENSO) conditions to normal conditions?
3. What contributes to the variability in the skill in developing streamflow and soil moisture forecasts?

This study systematically addresses the above questions by utilizing monthly updated climate forecasts from ECHAM4.5 GCM forced with constructed analogue SST forecasts.

The manuscript is structured as follows: Sect. 2 details study area and retrospective climate forecasts used in the study. Section 3 provides experimental details on developing real-time streamflow forecasts with the results and analyses summarized in the following section. Finally, Sect. 5 presents the summary and findings from the study.

2 Study area and data

2.1 Study area

Apalachicola River originates in the Appalachian Mountains and it joins the Chattahoochee and Flint Rivers at Chattahoochee, Florida, draining about 44 032 km² through Georgia, and some parts of Alabama and Florida (Fig. 1a). It is one of the major river basins in the Southeast United States, where precipitation is pretty uniform resulting in significant runoff throughout the year. Thus, developing streamflow forecasts on a continuous basis throughout the year is critical in the region from an operational perspective as well as for management during critical seasons. For this study, we consider the entire Apalachicola River at Chattahoochee basin for developing monthly updated streamflow forecasts over the period 1981–2010. The average annual precipitation in the basin is about 1280 mm with no seasonality in precipitation and the mean monthly runoff peaks in March with the lowest monthly flows occurring during the fall (Fig. 1b).

2.2 Observed meteorological and streamflow data

The daily meteorological forcing data for precipitation, maximum and minimum air temperatures, and wind speed from 1951 to 2010 were obtained from Maurer et al. (2002) at 1/8° spatial scale (~14 km by 12 km). The monthly observed streamflow data from 1957 to 2010 was obtained from the US Geological Survey (USGS) at Apalachicola River at Chattahoochee (site # 02358000). This site is minimally affected by anthropogenic interventions such as reservoir operations as it is included in the Hydro-Climatic Data Network (HCDN) database (Slack et al., 1993). Since the monthly streamflow data from the USGS observed streamflow is same as HCDN data during the overlapping period (1928 to 1988), we have extended the observed daily streamflow till 2010 based on the daily observed records from USGS.

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2.3 ECHAM4.5 precipitation forecasts

Retrospective monthly updated climate forecasts were obtained from the International Research Institute of Climate and Society (IRI) data library (Li and Goddard, 2005) for the ECHAM4.5 General Circulation Model (GCM). ECHAM4.5 GCM was forced with constructed analogue Sea Surface Temperatures (SSTs) forecasts to develop retrospective climate forecasts up to 6 months lead time beginning since January 1957. Seven ECHAM4.5 grids were selected that exhibited significant rank correlations with spatially averaged (monthly) observed precipitation over the study area. For these seven grids, we averaged monthly time series of the 24 ensembles from ECHAM4.5 precipitation forecasts up to 6-month lead from 1957 to 2010. These forecasts were downscaled using canonical correlation model to drive the land surface model at 1/8° spatial resolution. Details regarding the spatial downscaling and temporal disaggregation are provided in the next section.

3 Retrospective streamflow forecasts development

3.1 Variable Infiltration Capacity (VIC) model

The VIC model (Liang et al., 1994, 1996; Cherkauer et al., 2003) is a semi-distributed macro-scale land surface model that estimates water and energy balance. Streamflow is computed at the basin outlet using a stand-alone routing model (Lohman et al., 1998a, b). The details of the VIC model are described in Liang et al. (1994, 1996). The soil and vegetation input parameters are described in Sinha et al. (2010). The daily meteorological forcings are described in Maurer et al. (2002).

3.1.1 VIC model calibration and evaluation

The VIC model was first calibrated for the Apalachicola River at Chattahoochee (site # 02358000) at monthly time step from 1951 to 1980 (Table 1) using observed streamflow

HESSD

9, 5225–5260, 2012

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obtained from USGS. The calibration was performed to match overall hydrograph shape and volume of observed monthly streamflow. Finally, the model was validated from 1981 to 2010 (Fig. 1b) and the overall Nash–Sutcliffe efficiency (NSE) during this period was 0.81. The monthly NSE was also high for most of the months except during the low flow months of September to November, where it was relatively low (Table 1).

3.1.2 Spatial downscaling

For each month, precipitation forecasts from 7 ECHAM4.5 grids ($\sim 2.8^\circ$ by 2.8°) over the Apalachicola River basin at Chattahoochee were used to obtain monthly precipitation time series at $1/8^\circ$ spatial resolution. Given the forecasts from these grid points as well as the observed precipitation over $1/8^\circ$ resolution are correlated, we employed Canonical Correlation Analysis (CCA) such that the low-dimensional components of predictors and predictands were used to develop regression models for spatial downscaling (Tippet et al., 2003; Oh and Sankarasubramanian, 2011). CCA maximizes inter-relationships between two data sets in contrast to Principal Component Analysis (PCA) where variability is maximized within a single data set (Wilks, 1995). For each month, the following steps were followed to spatially downscale precipitation forecasts:

1. Monthly anomalies (Z) for each of the 251 $1/8^\circ$ grids covering the entire study area were estimated by subtracting basin's monthly spatial average precipitation during 1957 to 1980 (pre-forecast period) from each grid's monthly precipitation.
2. First six principal components (e.g., $Y^T = Y_1, Y_2, \dots, Y_6$, dimension = $n \times 6$, where $n = 54$ yr and "T" denotes transpose) which explained more than 95% variability in precipitation anomalies of the 251 grids, were retained from 1957 to 2010 to reduce the dimensionality and were used as the predictands.
3. Similar to step 2, six principal components were retained from the anomalies of ECHAM4.5 monthly precipitation forecasts that served as predictors (e.g., $X^T = X_1, X_2, \dots, X_6$, dimension = 54×6).

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4. A CCA model was developed using split sampling approach, where monthly data from 1957 to 1980 was used for training while monthly precipitation from 1981 to 2010 was predicted using the CCA model. The CCA identified a linear combination of 6 predictors, $X^* = \mathbf{a}^T X$, which maximized linear combination of 6 predic-
tands $Y^* = \mathbf{b}^T Y$. The vectors \mathbf{a} and \mathbf{b} were chosen such that

$$\frac{(\mathbf{a}^T \Sigma_{XY} \mathbf{b})}{\sqrt{\{(\mathbf{a}^T \Sigma_{XX} \mathbf{a})(\mathbf{b}^T \Sigma_{YY} \mathbf{b})\}}}$$

was maximized where Σ denotes the variance-covariance matrix between the two variables (see details in Wilks, 1995).

5. The estimated anomalies were transferred back to the original anomaly space (Z) by

$$Z^T = E * U^T$$

where E is eigenvectors of the anomalies of 251 grids (dimension 251×6) and U^T is the transpose of the CCA predicted anomalies (dimension 6×54) (see details in Tippet et al., 2003).

6. Finally, the observed monthly spatial mean was added back to the anomalies to obtain the monthly values from 1981 to 2010 for each of the $251 \frac{1}{8}^\circ$ grid. For less than 2% of the cases among all the 251 grids, the spatially downscaled monthly precipitation was less than or equal to zero. In those months, a historical minimum monthly precipitation (during 1957–1980) of 5 mm was assigned.

Errors due to spatial downscaling of monthly precipitation forecasts

Errors in spatial downscaling of 6-month lead ECHAM4.5 monthly precipitation forecasts to 251 grids at $1/8^\circ$ spatial scale were evaluated using relative Root Mean Square

Error (R-RMSE). The R-RMSE, relative to its monthly climatology, was estimated on the monthly basis using Eq. (1):

$$\text{R-RMSE}_t = \frac{\sqrt{\sum_{t=1}^n (P_t - \hat{P}_t)^2}}{\overline{P}_t} \quad (1)$$

where t is time in months, n is number of months, P_t is observed monthly precipitation, \hat{P}_t is statistically downscaled precipitation (from CCA) and \overline{P}_t is the average observed monthly precipitation (climatology). Figure 2 suggests that the median relative RMSE at 1-month lead time is higher during fall months specifically during September through November. This implies that during these months, the variability captured in spatially downscaled monthly precipitation forecasts is relatively lower in comparison to observed variability over the 251 $1/8^\circ$ grid cells. The relative errors are lower during spring and summer months (Fig. 2).

3.1.3 Temporal disaggregation

Daily time series of precipitation was derived from spatially downscaled monthly ECHAM4.5 forecasts using the temporal disaggregation technique described in Prairie et al. (2007). The temporal disaggregation involved classifying forecasted monthly time series into daily time series by identifying similar monthly conditions in the historical record based on K-Nearest-Neighbor (K-NN) approach. A brief description is provided here for clarity. For further details of the K-NN approach, see Prairie et al. (2007). Typically, K-NN approach resamples monthly data from daily historic data, generating values that were observed. In this study, K-NN approach was implemented (Prairie et al., 2007) where K-nearest neighbors were obtained by computing the distance between predicted time series (from CCA) and the historic series during 1951–1980. The observed daily values from the “K” neighbors were resampled based on Lall and Sharma kernel (Lall and Sharma, 1996). The number of neighbors for each month was chosen based on leave-five out cross-validation during the training period 1951–1980.

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3.1.4 Land surface model implementation

Figure 2 illustrates the experimental set up for streamflow forecasts development using the VIC model. The implementation of the VIC model was performed in the following ways: (i) the VIC model was driven using observed meteorological forcings data from 1975 to 2010 in order to estimate initial soil moisture conditions prior to each month of forecasting period (1981–2010); (e.g., to forecast streamflow in January 1981, initial soil moisture conditions at the end of December 1980 were updated to force the VIC model); and (ii) the statistically downscaled and temporally disaggregated monthly precipitation forecasts (at daily scale) from January 1981–December 2010 with lead time of 1 to 6 months were used to drive the VIC model with updated initial land surface conditions estimated from (i). Since the primary objective of this study is to analyze the role of initial soil moisture and precipitation forecasts, other input variables such as maximum and minimum air temperatures and wind speed were used from the observed $1/8^\circ$ meteorological forcings during the forecasting period. To compare the skill in developing streamflow forecasts using retrospective precipitation forecasts, we also utilized climatological forcings by forcing the VIC model with the daily climatological (daily precipitation during 1957 to 1980) forcings with updated initial land surface conditions using the Ensemble Streamflow Prediction (ESP) approach (Day, 1985; Franz et al., 2003). For both these schemes, ECHAM4.5 forecasts and climatology, predicted streamflow was routed at the basin outlet for each set of VIC model simulations. The routed streamflow at the basin outlet were bias corrected on monthly basis based on the VIC model calibration summary (Table 1). Thus, for each year, streamflow ensemble developed using climatological ensemble was averaged to evaluate the performance measures (discussed in Sect. 4). Thus, the final product from the VIC model was bias-corrected six-month ahead monthly streamflow forecasts from January 1981 to December 2010 obtained using precipitation forecasts (VIC_{fcst}) and for climatology (VIC_{clim}).

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3.2 Principal component model – implementation

Streamflow forecasts were also developed using statistical models for comparing the skill of VIC model in predicting the monthly streamflow. Under statistical modeling approach, Principal Component Regression (PCR) was developed between the forecasting month's streamflow (predictand) and monthly forecasts from the selected ECHAM4.5 grids along with previous month's streamflow (predictors). PCR, otherwise known as Model Output Statistics (MOS), recalibrates the GCM forecasts over a larger area or correlated predictors into orthogonal components for estimating streamflow (Landman and Goddard, 2002; Sankarasubramanian et al., 2008). The monthly time series from 1957 to 1980 were used as training period with predictions being made from 1981 to 2010. For predicting streamflow at 1-month lead time, observed streamflow from previous month was used with ECHAM4.5 precipitation forecasts to predict current month's streamflow. For subsequent lead times (2–6 months), PCR predicted streamflow for the previous month (\hat{Q}_{t-1}) and precipitation forecasts (fcst) for the corresponding month were used as predictors. Thus, for each month, six PCR models were developed under each lead time scheme using the climate predictability tool available from IRI (<http://portal.iri.columbia.edu/portal/server.pt?open=512&objID=697&PageID=7264&mode=2>). Skill obtained from the PCR model is compared with the skill obtained for each month using VIC_{fcst} and VIC_{clim} over the period 1981–2010.

3.2.1 Forecast skill scores

The performance of VIC model and the PCR model in predicting monthly/seasonal streamflow was evaluated using Spearman rank correlation and Mean Square Skill Score (MSSS) (Wilks, 1995). The spearman rank correlation was tested for its statistical significance by checking whether the estimated correlation is greater than $1.96/\sqrt{n-3}$, where n denote the number of observation and forecasts pairs. MSSS was also estimated for each month/season using:

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$$\text{MSSS} = 1 - [(\text{Mean Square Error}_{\text{forecast}})/(\text{Mean Square Error}_{\text{climatology}})] \quad (2)$$

where Mean Square Error (MSE)_{forecast} is the average squared difference between the forecast and observations pairs, and MSE_{climatology} is the averaged squared difference between the observations and the climatological streamflow. The climatological estimates of streamflow are obtained by averaging the observed streamflow over 1957–1980. If MSSS is greater than zero, it indicates forecasts have better skill than climatology. Two forecasts from VIC (VIC_{fcst} and VIC_{clim}) model are compared with PCR model at monthly and seasonal time scales using spearman rank correlation and MSSS. Improvements in MSSS of VIC_{fcst} over VIC_{clim} quantify the fractional reduction in mean squared error (MSE) in predicting the observed flows by utilizing the ECHAM4.5 precipitation forecasts. Similarly, positive MSSS of VIC_{clim} quantifies the fractional reduction in MSE that could be obtained using initial hydrologic conditions over the observed streamflow climatology.

4 Results and analysis

In this section, we present the skill of monthly streamflow forecasts developed using VIC model during 1981–2010 as well as over the ENSO years. We also compare this skill with the forecasts developed using climatological forcings as well as with the forecasts developed using PCR. Following that, we present rank correlations between VIC model forecasted total soil moisture and observed streamflow at multiple locations along with the spatial variability in the forecasted soil moisture during La Niña years.

4.1 Performance of six-month ahead monthly streamflow forecasts

Skill scores, rank correlation and MSSS, for six-month ahead monthly streamflow forecasts from the VIC model with ECHAM4.5 and climatology forcings are shown in Figs. 4 and 5 along with the skill from the PCR model. Panels a–f in both figures indicate the

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lead time and the x-axis indicate the month for which the skill is assessed. For instance, the skill under Fig. 4f for the month of October indicates the ability of the forecasting scheme to predict October flows based on the initial conditions prior to May and using the six-month ahead monthly precipitation forecasts issued in May for the month of October. At 1-month lead time (Fig. 4a), all the forecasting schemes exhibit statistically significant skill in predicting the observed streamflow over the entire year. The only exception is in September during which VIC model forced with ECHAM4.5 forecasts did not produce statistically significant forecasts. Comparing the performance of the three forecasting schemes, we infer that VIC model based forecasting schemes perform better than PCR forecasts in almost all the months with the exception being February and October. The performance of VIC_{fcst} (ECHAM4.5) and VIC_{clim} is almost similar in all months except during fall months. One possible reason for the poor performance of VIC_{fcst} is due to the model's inability to predict the low flow season (Fig. 1b), during which the model exhibited significant bias (Table 1). Further, the relative RMSE of the downscaled precipitation forecasts is also significantly higher during the fall months (Fig. 3).

Based on MSSS (Fig. 5a), VIC_{fcst} developed using ECHAM4.5 performs better than VIC_{clim} in almost all the months except during September–December. Though both VIC model based forecasts have similar correlation at 1-month lead time (Fig. 4a), ECHAM4.5 forcings result in reduced mean squared error (MSE) in prediction as compared to the MSE of VIC forecasts obtained with climatological forcings. The skill of VIC_{clim} also quantifies the reduced MSE arising from updating initial hydrologic conditions in the VIC model. Given that MSSS is computed in relation to the MSE of streamflow climatology, MSSS basically quantifies the percentage reduction in MSE of climatology resulting from the forecasting scheme. Thus, except during the months of November and December, streamflow forecasts developed from the VIC model with climatological forcings provide better streamflow predictions than using observed climatology of streamflow. In comparison to the VIC-model based forecasting schemes, the performance of PCR model is generally inferior in most of months with the exception

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being February and October. This implies that PCR model captures only variability, but the errors in predicting the observed streamflow are relatively higher than the errors of the VIC model.

For lead times 2 to 4 months (Figs. 4b–d and 5b–d), PCR model performed poorly indicating almost no skill in predicting streamflow beyond 1 month. The computed correlation for PCR model is statistically significant only in fewer months. However, VIC_{fcst} and VIC_{clim} capture the variability in the streamflow with significant correlations in predicting the observed streamflow in all the months except during October and November. Evaluating the performance of these two schemes based on MSSS also show that VIC_{fcst} performed slightly better than VIC_{clim} in the winter and spring seasons. During the rest of the months, none of the forecasting schemes showed significant reduction in MSE compared to the MSE of climatology. Beyond 4 months, only VIC_{fcst} showed significant skill in capturing the interannual variability in streamflow during the spring season (Fig. 4e–f), but the MSSS is still below zero at lead times of 5 and 6 months. The primary reason for improved performance during spring months is due to smaller interannual variability in precipitation during those months. We discuss this issue in detail under discussion (Sect. 5). The significant correlation under 5–6 months for VIC_{fcst} during spring season primarily indicates the importance of using precipitation forecasts as forcings as opposed to using climatology as a forcing.

To recapitulate, six-month ahead streamflow forecasts issued using VIC_{fcst} and VIC_{clim} have higher skills than that of the PCR model in almost all the months. Similarly, VIC_{fcst} perform better than VIC_{clim} in almost all the seasons except during the fall. The primary reason for the poor performance during the fall months is due to the poor skill in downscaled precipitation forecasts as well as due to the VIC model's inability to simulate low flows. The low MSSS of VIC_{clim} (lesser than zero) beyond one month (see Fig. 5), indicates that initial soil moisture conditions are useful only up to a month in reducing the MSE in predicting the observed flows that could be obtainable using streamflow climatology. The improved performance of VIC_{fcst} over VIC_{clim}

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indicates the importance of precipitation forecasts in developing skillful monthly streamflow forecasts.

4.2 Source of skill for ECHAM4.5 forecasts – ENSO conditions

Given that streamflow forecasts developed using ECHAM4.5 forecasts performed better in almost all the seasons except the fall, we investigate the source of skill for ECHAM4.5 precipitation forecasts in relation to ENSO conditions. Since ENSO is one of the dominant climatic modes that influence the winter hydroclimatology of the Southeast US (Ropelewski and Halpert, 1987; Devineni and Sankarasubramanian, 2010), we evaluate the skill of streamflow forecasts conditioned on ENSO modes. For this purpose, we consider the Nino3.4 index which was obtained from the National Weather Service Climate Prediction Center (http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml). Nino3.4 denotes the average SST anomalies over 5° N to 5° S and 120° to 170° W in the tropical Pacific with positive (negative) anomalous conditions denoting El Niño (La Niña). El Niño (La Niña) conditions were identified for each forecasting month if the past 3-month average Nino3.4 was above the threshold of $>0.5^{\circ}\text{C}$ ($<-0.5^{\circ}\text{C}$). For each month, the skill of VIC_{fcst} was compared with the skills of VIC_{clim} and PCR predicted flows during ENSO and non-ENSO years.

Figure 6 shows the rank correlation for the three forecasting schemes over six different lead times based on ENSO conditions. At 1-month lead time, VIC_{fcst} and VIC_{clim} forecasts are statistically significant in predicting the observed flows in almost all months. The only exception is VIC_{fcst} being not significant in September. Comparing the correlations in Fig. 6 with Fig. 4, we understand that the skill is almost similar for all the months except during October-December (OND) at 1-month lead time. Under OND, the ability to predict the observed flows is slightly higher under ENSO conditions for 1–2 months lead forecasts. This is because ENSO conditions typically peaks around OND. On the other hand, the performance of the PCR model is statistically significant

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for 1-month lead time for the period July–March. For the rest of the lead times, PCR model's skill is statistically significant only on February/March.

For 3–6 months lead times, VIC model based forecasts show statistically significant skill only for the forecasts issued during spring (i.e., predicting the summer flows). For forecasts issued in the rest of the months, VIC model based forecasts did not show statistically significant skill. However, the performance of VIC model in issuing 3–4 month lead forecast is good for all the months over the entire validation period (Fig. 4). We also observe that the performance of VIC_{fcst} is slightly better for forecasts issued in the spring compared to the skill of VIC_{clim} .

To further understand the role of ENSO in improving the prediction of monthly streamflow forecasts, we plot (Fig. 7) the MSSS for VIC forecasts under ENSO (VIC_{fcst_enso} , VIC_{clim_enso}) and normal tropical Pacific conditions (VIC_{fcst_norm} , VIC_{clim_norm}) over various lead times. Under ENSO conditions, the skill of VIC model forced with ECHAM4.5 precipitation forecasts (VIC_{fcst_enso}) is better than the skill of VIC_{clim_enso} for the forecast issued during February to May as well as during July–August under one-month lead time. However, VIC_{clim_enso} performs better during the fall months. This indicates that the one-month forecasts obtained using ECHAM4.5 precipitation forecasts primarily derive its skill from ENSO during winter months. During normal ENSO times, ECHAM4.5 precipitation forecasts based streamflow predictions (VIC_{fcst_norm}) issued during the winter season perform better than VIC_{clim_norm} , whereas climatology based streamflow forecasts issued during the summer season perform better than VIC_{fcst_norm} . This is again consistent with the earlier findings of Devineni and Sankarasubramanian (2010) indicating the skill of precipitation forecasts being significant during ENSO occurrences.

For longer lead times (2–6 months), under ENSO conditions, VIC_{fcst_enso} and VIC_{clim_norm} indicated positive MSSS for the forecasts issued during January–March and July, respectively. The two other candidates, VIC_{clim_enso} and VIC_{fcst_norm} did not show positive MSSS in most of the months. Thus, our analyses of splitting the MSSS shown in Fig. 7 clearly indicate that ECHAM4.5 precipitation forecasts based

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streamflow forecasts issued during the winter season perform well under all lead-times during ENSO conditions, whereas the performance of forecasts is good during fall months only up to 1–2 month lead time under ENSO conditions. Under neutral ENSO conditions, both VIC_{fcst_norm} and VIC_{clim_norm} exhibit good skill for forecasts issued with a shorter lead time (1–2 months), whereas both ECHAM4.5 and climatology forcings did not exhibit any significant skill for streamflow predictions issued with a longer lead time. Based on this understanding, we extend our analyses for developing 6-month ahead soil moisture forecasts.

4.3 Skill of monthly soil moisture forecasts

The VIC model simulated spatially averaged soil moisture in the top 90 cm soil layer over the two sub-basins are compared with the USGS observed streamflow: (a) Flint River at Newton, GA; and (b) Apalachicola River at Chattahoochee, FL (Fig. 1a). The rank correlations over different seasons indicate a strong relationship between spatially average soil moisture and observed seasonal streamflow over the two sites. As expected, the correlations are relatively lower at higher lead time (Table 2). The skill in predicting soil moisture is highest at 1-month lead time. Among all the seasons, spring season (April–June) exhibits the highest correlations followed by summer season (July–September) for the two Rivers. The Apalachicola River shows statistically significant correlations over all the four seasons during lead times up to 6 months. On the other hand, the Flint River shows significant correlations up to lead time of 3 months after which the correlations behave differently over different seasons. For instance, the correlations are lower for the Flint River during winter (January–March) at lead time greater than 3 months. Therefore, the results of VIC model forecasted soil moisture aggregated over all the seasons are reasonably well up to 3 months lead time.

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4.4 Average soil moisture forecasts and anomalies

The VIC model 1-month lead monthly streamflow forecasts show good skills during spring and summer months which are crucial for agricultural operations. Figure 8 indicates spatial variation of total soil moisture content in the top 90 cm of soil surface as simulated by the VIC model. The spatial plot of soil moisture climatology (Fig. 8g–l) indicates that soil moisture is lowest in the central regions of the study area. Total soil moisture availability decreases as we move from April to September due to increased evapotranspiration. Soil moisture forecast anomalies were estimated by subtracting total soil moisture during La Niña years by soil moisture climatology during 1981 to 2010. Thus, positive values indicate deficit during La Niña years from climatology. Typically, the La Niña climatic oscillations lead to cool and dry conditions over the study area. During the La Niña conditions, southern regions in the study basin are relatively drier during July to September while northern and north-western regions are relatively wetter. The most pronounced effect of La Niña conditions occurs in June and August, which are relatively drier than other months in the growing season.

5 Discussion and concluding remarks

This study focuses on quantifying the utility of monthly updated precipitation forecasts and the role of initial soil moisture conditions in developing monthly streamflow forecasts. We focused on a rainfall-runoff dominant basin – Apalachicola River at Chattahoochee, FL – located in the Southeastern US. We calibrated the VIC land surface model to monthly observed streamflow for the study area and then forced the model with: (a) statistically downscaled and temporally disaggregated 6-months lead ECHAM4.5 precipitation forecasts, and (b) ensemble of daily climatology estimated over 1957–1980. Under both cases (a) and (b), the initial soil moisture conditions were updated prior to the forecasting period. Thus, the difference in skill between the two forecasting schemes quantifies the improvements or potential degradation in skill that

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could be attributable to the precipitation forecasts obtained from the GCM. In addition, statistical models were also used to compare the forecasting skill over different lead times up to 6 months. This section provides discussion related to the three questions proposed in the introduction (Sect. 1).

5.1 Skill variations over various seasons and lead time

Results from Figs. 4 and 5 suggest that at one-month lead time monthly streamflow forecasts developed using precipitation forecasts have better skill in predicting observed streamflow during winter, spring and summer seasons, whereas monthly forecasts developed using climatological forcings have better skill during the fall season. These results are in agreement with Luo et al. (2007) and Li et al. (2009) who reported that downscaled climate forecasts outperformed ESP approach for 1–3 months lead time. In particular, land surface modeling streamflow forecasts were relatively poor during late summer (September) and fall months (September–December). The poor performance of precipitation forecasts during the fall season is partly due to high R-RMSE in the precipitation forecasts. However, one-month ahead streamflow forecasts developed using the statistical model performed better than VIC_{clim} during the fall season. This indicates that the poor performance could be due to the limited ability of VIC model in simulating flows (see Table 2 NSE is low) or due to the error arising from spatial downscaling and temporal disaggregation. This requires further investigation. At 2–6 month lead times, streamflow forecasts developed using the precipitation forecasts showed better correspondence (i.e., correlation) in matching the interannual variability of observed flows, but all the three forecasting schemes performed poorer than climatology in terms of accuracy (i.e., MSSS < 0). Thus, the streamflow forecasts developed using GCM precipitation forecasts capture the variability better for longer lead times, but fails to reduce the mean square error. However, the uncertainty over the longer lead times could be reduced by continuously updating the monthly streamflow forecasts as we progress through the season (Sankarasubramanian et al., 2008).

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5.2 Role of ENSO conditions

By analyzing the skill of the three forecasting schemes under ENSO conditions, streamflow forecasts developed using ECHAM4.5 precipitation forecasts show higher skill for the forecasts issued during winter, spring and summer seasons over 1–4 month lead time (Fig. 4), whereas the streamflow forecasts developed using climatology forcings have better skill for the fall season. Thus, under ENSO conditions, we see better ability to predict observed streamflow over a longer lead time. Further, our analyses of splitting the MSSS (Fig. 7) based on ENSO and normal conditions clearly show that ECHAM4.5 precipitation forecasts based streamflow forecasts issued during the winter season perform well up to six-month lead time under ENSO conditions. However, this skill (i.e., positive MSSS) to predict streamflow over a longer lead time decreases substantially under normal ENSO conditions, where streamflow forecasts developed using the GCM precipitation forecasts perform better only up to 1–2 month lead time. On the other hand, streamflow forecasts developed using climatology based forcings perform better in terms of MSSS for the forecasts issued during fall months with 1–2 month lead time under ENSO conditions. Under normal ENSO conditions, in general, the MSSS is negative for longer lead times for both ECHAM4.5 and climatology forcings indicating the limited skill in predicting the observed streamflow. Thus, this analysis provides critical information that during ENSO conditions, we not only have better skill in predicting the observed streamflow using precipitation forecasts from GCMs, but also gain increased lead time in predicting the observed flows.

5.3 Difference in skill variations in streamflow and soil moisture forecasts

Our previous discussion suggest that the primary source of variability in the skill on predicting streamflow arises from ENSO conditions. Given that we don't have observed soil moisture information, we compared the seasonal soil moisture forecasts to the observed seasonal streamflow. The VIC model soil moisture forecasts compare reasonably well with the observed streamflow at two sites particularly up to 1–3 months

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lead time. VIC model soil moisture climatology suggests that April is the wettest while September is the driest month in the growing season. During La Niña conditions, the drying effect is more pronounced in June and August months. The correlation between the soil moisture forecasts for the winter and spring seasons and the corresponding observed seasonal streamflow increase as the drainage area increases. On the contrary, the correlation between the soil moisture forecasts for the summer and fall seasons and the observed streamflow decrease as the drainage area increases. This is primarily due to the increased role of temperature during the summer and fall seasons leading to enhanced evapotranspiration over a larger area resulting in decreased correlation with streamflow.

Climate forecasts from the ECHAM4.5 GCM along with the updated initial conditions provide useful information which can be utilized in improving the management of water and energy systems. This study quantified the additional skill that could be gained using precipitation forecasts from ECHAM4.5 forecasts over the climatological forcings. This study uses precipitation forecasts from one GCM; however, combining climate information from multiple models has been shown to result in improved streamflow forecasts (Devineni et al., 2008). The climatological forcings were run as ensemble and the mean of the streamflow ensemble was used to quantify the skill. Similarly, effort should be focused on representing the precipitation forecasts as ensemble to develop streamflow forecasts. Given the amount of computation time required to run the VIC model, we resorted to using the mean of the precipitation forecasts at $1/8^\circ$ spatial resolution to run the land surface model. Further, it also needs to be analyzed how spatial downscaling and temporal disaggregation contributes to the limited skill during the fall season since the statistical model seems to outperform both VIC model based forecasting schemes. Since basins in the Southeastern US have no seasonality in precipitation, it is also important to understand the source of error arising from downscaling and disaggregation scheme. We intend to address these issues as part of our continuing research on developing operational streamflow forecasts over the Southeast US.

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Acknowledgements. We are thankful to NOAA for providing funding for this research through grant NA09OAR4310146.

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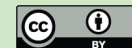
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Table 1. VIC model calibration summary for the period 1951–1980. NSE represents Nash-Sutcliffe Efficiency.

Month	NSE	Rank Correlation	% Bias	RMSE
Jan	0.80	0.93	8.0	5474.8
Feb	0.68	0.94	16.8	7669.4
Mar	0.66	0.95	16.5	9251.6
Apr	0.89	0.95	8.1	5713.6
May	0.86	0.87	−0.2	3996.8
Jun	0.72	0.87	−8.4	3654.3
Jul	0.40	0.75	−1.7	3839.1
Aug	0.62	0.84	−9.0	3287.5
Sep	−1.70	0.43	−12.5	4840.5
Oct	0.57	0.82	−10.8	4207.0
Nov	0.18	0.67	−16.1	4668.9
Dec	0.81	0.87	−1.3	4316.7

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Table 2. Rank correlation between seasonal soil moisture forecasts and seasonal observed streamflow at (a) Flint river at Newton, GA; and (b) Apalachicola River at Chattahoochee, FL. Locations of these sites are shown in Fig. 1a. The values in bold represent correlations that are statistically insignificant (< 0.38).

Sub-basin	Drainage area (km ²)	Lead (months)	JFM	AMJ	JAS	OND
(a) Flint	14 694	1	0.79	0.88	0.87	0.76
		2	0.59	0.89	0.90	0.84
		3	0.45	0.73	0.74	0.69
		4	0.31	0.66	0.55	0.58
		5	0.35	0.71	0.44	0.57
		6	0.30	0.68	0.34	0.58
(b) Apalachicola	44 032	1	0.84	0.85	0.75	0.64
		2	0.71	0.87	0.82	0.70
		3	0.56	0.76	0.73	0.64
		4	0.53	0.71	0.61	0.55
		5	0.52	0.80	0.58	0.58
		6	0.45	0.81	0.46	0.61

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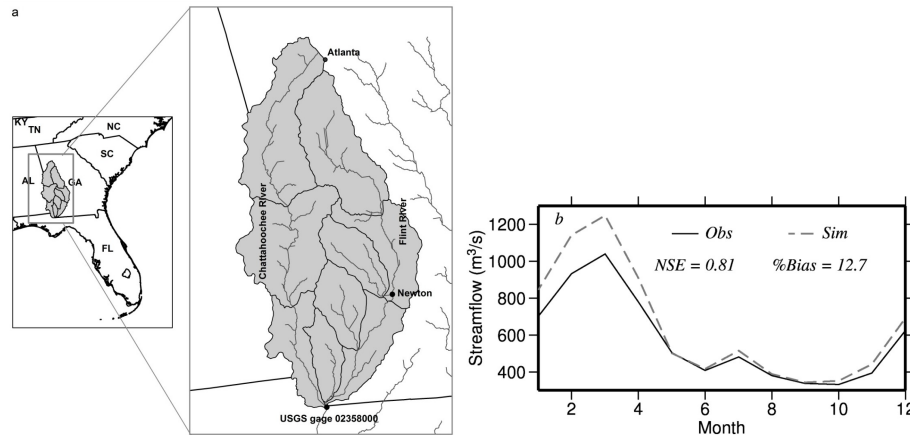
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Fig. 1. Location of the Apalachicola River at Chattahoochee, FL **(a)** and Observed (Obs) and VIC model simulated (Sim) streamflow seasonality **(b)** for the VIC model evaluation period of 1981–2010 at USGS gauging station 02358000. **(b)** also shows the Nash-Sutcliffe efficiency (NSE) and % bias over the entire evaluation period.

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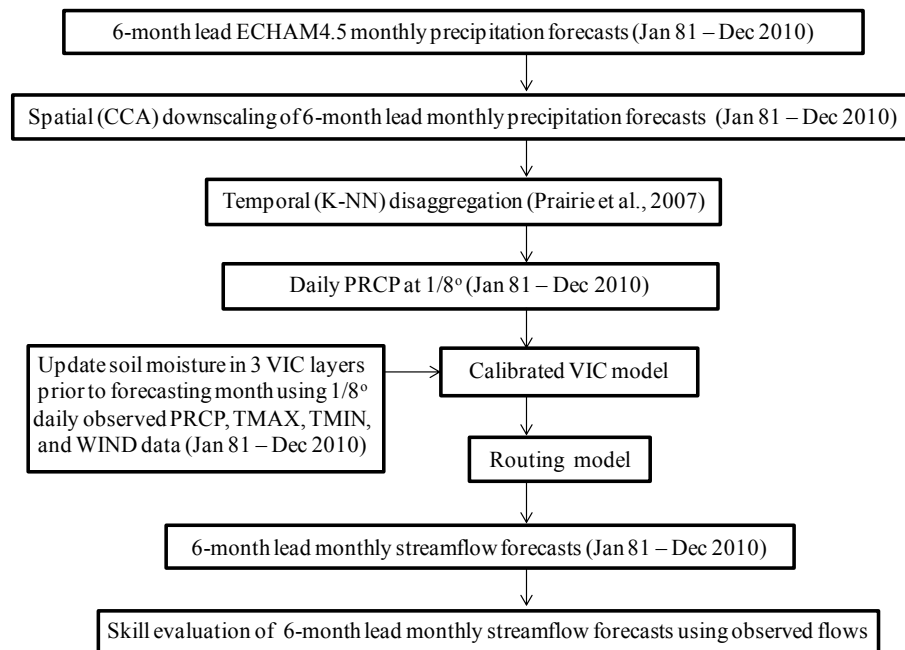


Fig. 2. Experimental design to develop monthly updated 6-month ahead monthly streamflow forecasts. CCA refers to Canonical Correlation Analysis and K-NN represents Kernel-Nearest Neighbor approach. PRCP refers to precipitation, TMAX to maximum air temperature, TMIN to minimum air temperature, and WIND to wind speed.

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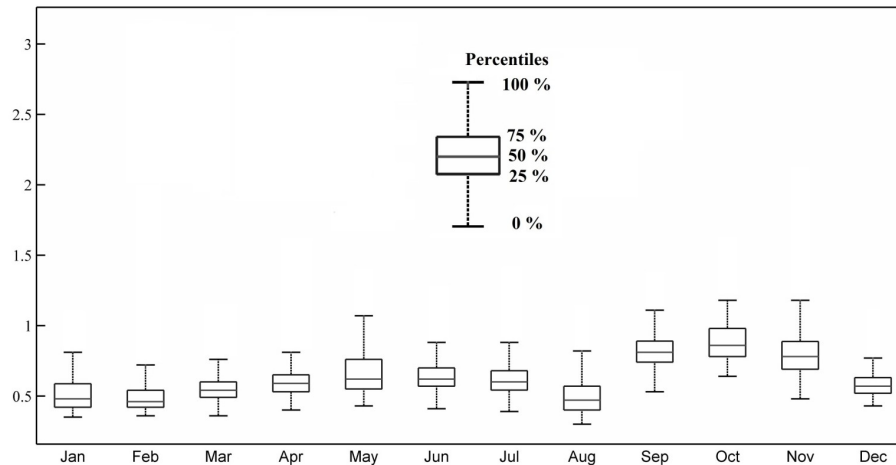
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Fig. 3. Box plots of relative Root Mean Square Error in spatial downscaling of 1-month lead ECHAM4.5 monthly precipitation forecasts for 251 $1/8^\circ$ grid cells.

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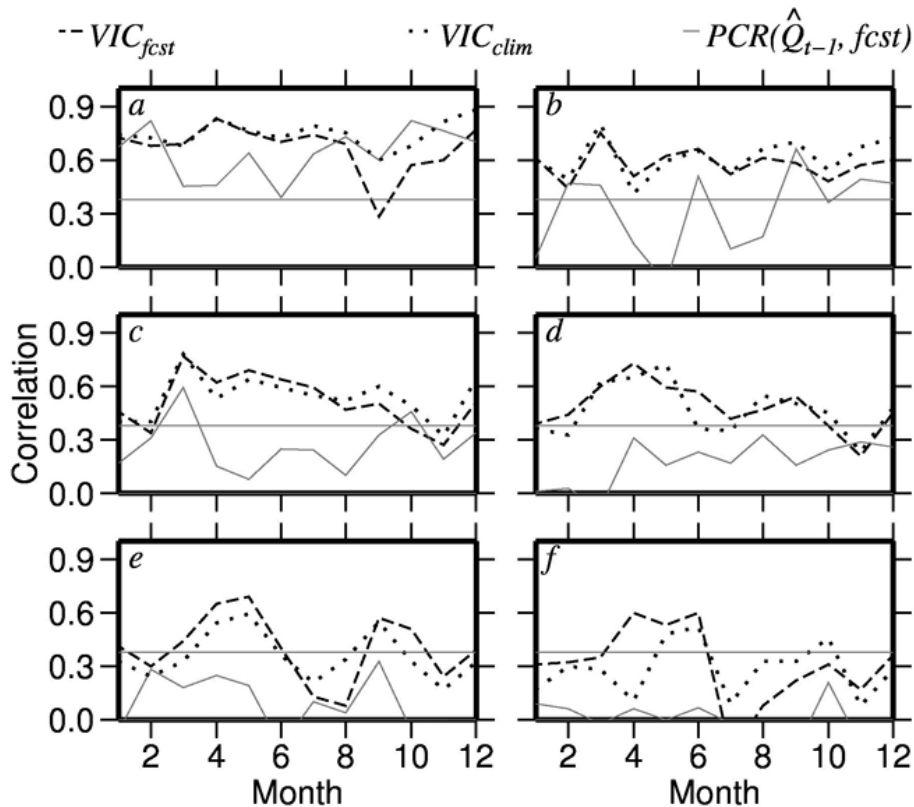


Fig. 4. Spearman rank correlations between estimated streamflow and observed streamflow at lead times 1 (a) to 6 (f) months. The horizontal gray line (at 0.38) indicates statistically significance correlation at 95 % confidence interval. VIC_{fcst} and VIC_{clim} represent VIC model estimations when forced with ECHAM4.5 monthly precipitation forecast and daily climatology, respectively. $PCR(\hat{Q}_{t-1}, fcst)$ represent Principal Component Regression based on PCR with updated initial conditions (updated previous month's streamflow for subsequent lead times).

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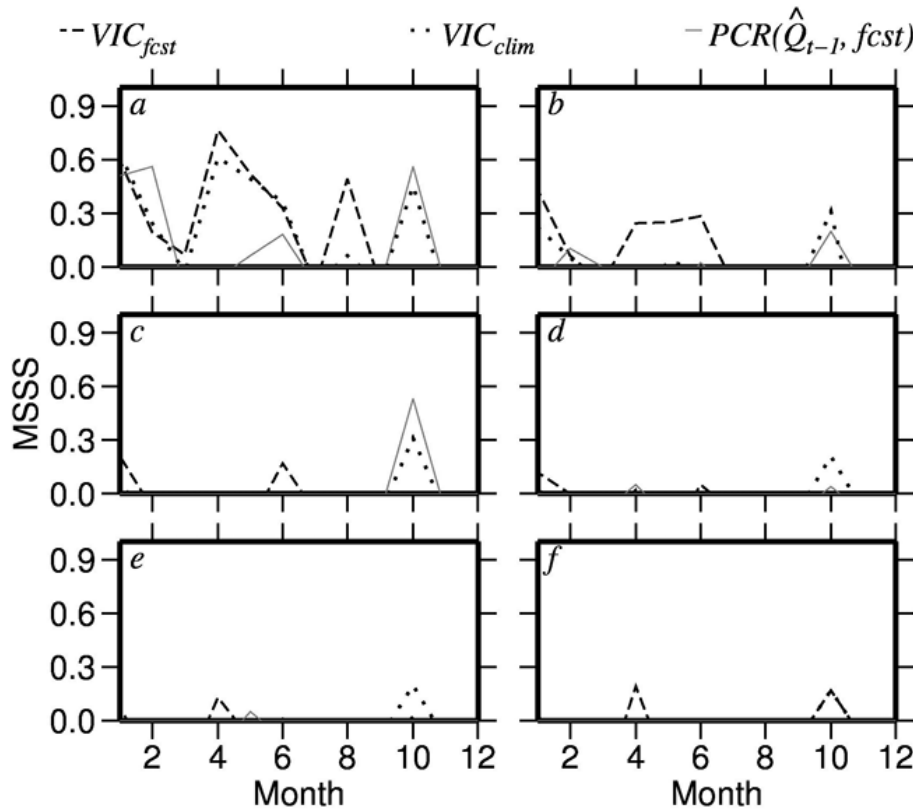


Fig. 5. Mean Square Skill Score comparison of estimated streamflow at lead times 1 (a) to 6 (f) months.

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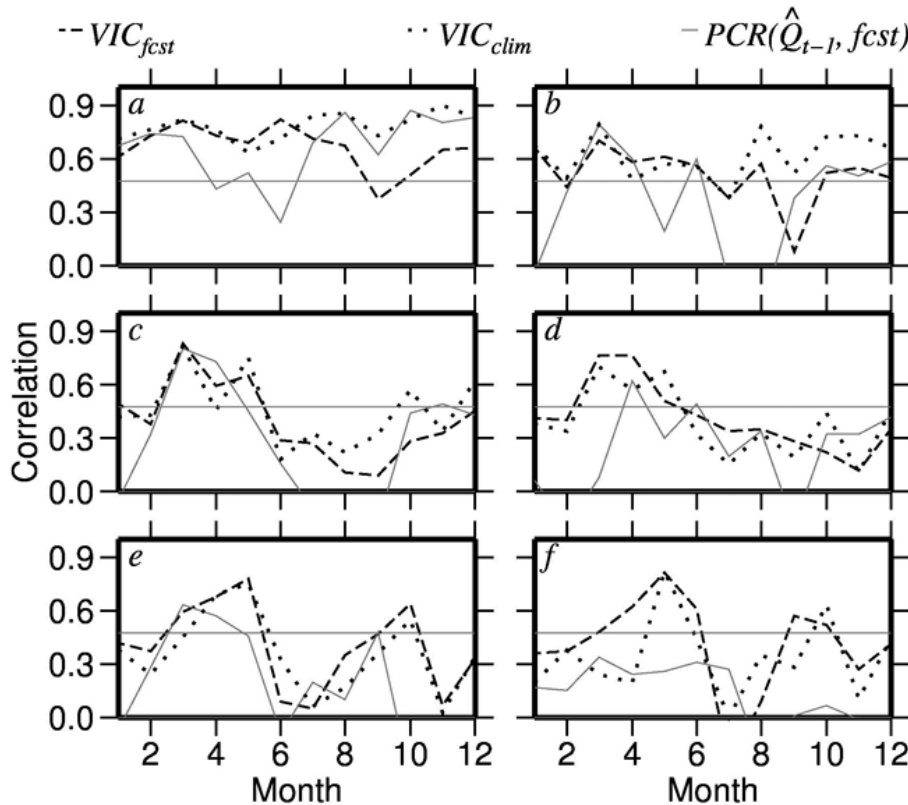


Fig. 6. Similar to Fig. 4, but the skill evaluated only for ENSO conditions.

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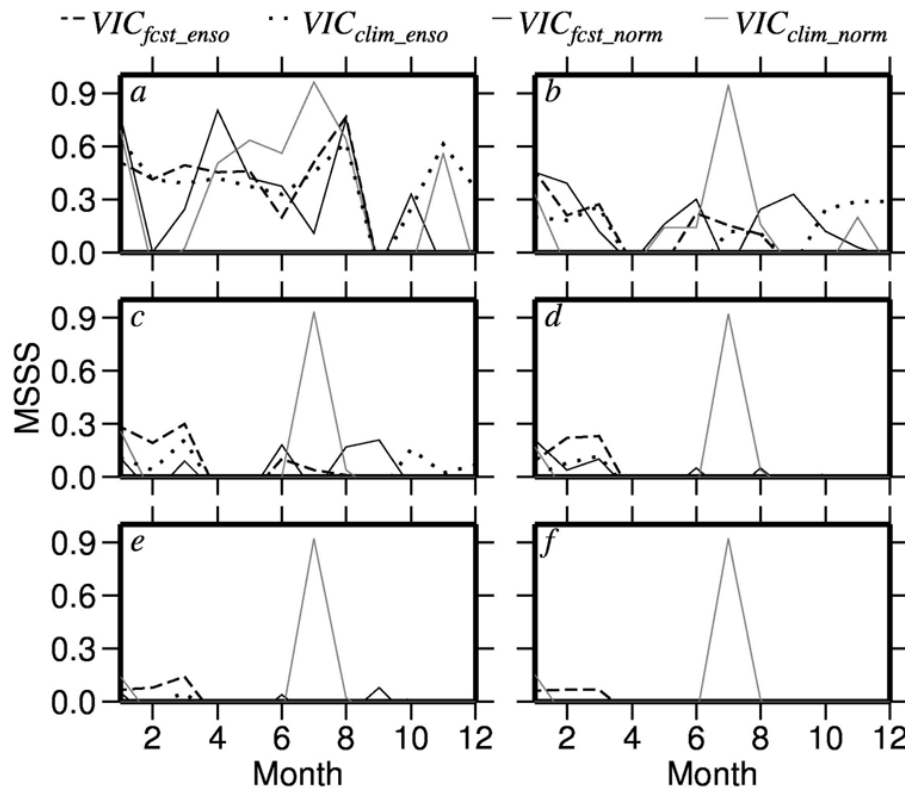


Fig. 7. Same as Fig. 5, but MSSS calculated separately under ENSO conditions (VIC_{fcst_enso} , VIC_{clim_enso}) and normal tropical Pacific (VIC_{fcst_norm} , VIC_{clim_norm}) conditions.

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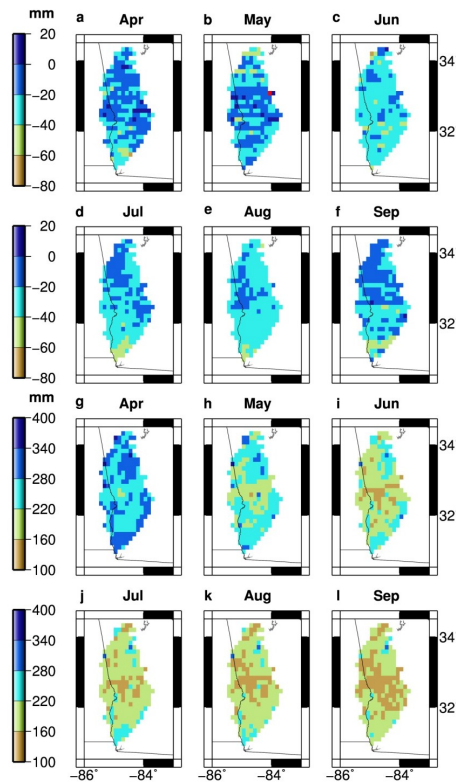


Fig. 8. VIC model estimated average monthly soil moisture: **(a–f)** forecasted anomalies (at 1-month lead) estimated by subtracting total soil moisture during La Niña years by soil moisture climatology during 1981 to 2010, which is shown in panels **(g–l)**.

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