

Role of Retrospective Forecasts of GCMs Forced with Persisted SST Anomalies in Operational Streamflow Forecasts Development

A. SANKARASUBRAMANIAN

Department of Civil, Construction, and Environmental Engineering, North Carolina State University at Raleigh, Raleigh, North Carolina

UPMANU LALL

Department of Earth and Environmental Engineering, Columbia University, New York, New York

SUSAN ESPINUEVA

Philippine Atmospheric, Geophysical, and Astronomical Services Administration, Quezon City, Philippines

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ABSTRACT

Seasonal streamflow forecasts contingent on climate information are essential for water resources planning and management as well as for setting up contingency measures during extreme years. In this study, operational streamflow forecasts are developed for a reservoir system in the Philippines using ECHAM4.5 precipitation forecasts (EPF) obtained using persisted sea surface temperature (SST) scenarios. Diagnostic analyses on SST conditions show that the tropical SSTs influence the streamflow during extreme years, whereas the local SSTs (0° – 25° N, 115° – 130° E) account for streamflow variability during normal years. Given that the EPF, local, and tropical SST conditions are spatially correlated, principal components regression (PCR) is employed to downscale the GCM-predicted precipitation fields and SST anomalies to monthly streamflow forecasts and to update them every month within the season using the updated EPF and SST conditions. These updated forecasts improve the prediction of monthly streamflows within the season in comparison to the skill of the monthly streamflow forecasts issued at the beginning of the season. It is also shown that the streamflow forecasting model developed using EPF under persisted SST conditions performs well upon employing EPF obtained under predicted SSTs as predictor. This has potential implications in the development of operational streamflow forecasts and statistical downscaling, which requires adequate years of retrospective GCM forecasts for recalibration. Finally, the study also shows that predicting the seasonal streamflow using the monthly precipitation forecasts reproduces the observed seasonal total better than the conventional approach of using seasonal precipitation forecasts to predict the seasonal streamflow.

1. Introduction

Seasonal to interannual climatic variations resulting from changing sea surface temperature (SST) conditions alter the precipitation and streamflow potential at regional to continental scales, impacting the economy and livelihood of the communities that depend on it. Predicting these climatic variations in advance provides useful information to planners and operational agencies

toward developing contingency measures and strategies to cope with the adverse effects of extreme events. Both national and international agencies monitor these climatic conditions, particularly SSTs in the tropical Pacific Ocean, to issue seasonal to interannual climate forecasts. Application of these climate forecasts for water management typically requires transforming precipitation and temperature forecasts to outcomes of hydrological (e.g., streamflow forecasts) and water supply (e.g., reliability of supplying specified water demand during the season) attributes.

The simplest approach to develop seasonal to interannual streamflow forecasts is by relating the observed streamflow to a set of climatic precursors (Souza Filho and Lall 2003; Sankarasubramanian and Lall 2003;

Corresponding author address: A. Sankarasubramanian, Department of Civil, Construction, and Environmental Engineering, North Carolina State University at Raleigh, Raleigh, NC 27695-7908.

E-mail: sankar_arumugam@ncsu.edu

Grantz et al. 2005; Hamlet and Lettenmaier 1999; Piechota et al. 2001; Maurer and Lettenmaier 2004). Despite its simplicity, the difficulty lies in identifying the relevant climatic precursors and substantiating their influence on the streamflow/precipitation potential of the basin through detailed diagnostic analyses for each forecasting time step. Given that many research institutions and agencies are issuing climate forecasts on a monthly basis using general circulation models (GCMs), an alternate approach would be to utilize GCM-predicted fields to develop operational streamflow forecasts. However, GCM-predicted fields are typically available at larger spatial scales ($2.5^\circ \times 2.5^\circ$), which need to be downscaled to obtain streamflow forecasts. Dynamical downscaling, a physical approach of nesting models with different spatial resolutions, uses the GCM-predicted fields as primary input into a regional climate model (RCM) whose finer spatial scale ($60 \text{ km} \times 60 \text{ km}$) forecasts of precipitation and temperature are forced to run a hydrologic model to develop streamflow forecasts (Leung et al. 1999; Roads et al. 2003; Yu et al. 2002; Nobre et al. 2001). One could also employ statistical downscaling, a recalibration technique known as model output statistics (MOS), which maps GCM-predicted fields to the observed streamflow (Landman and Goddard 2002; Tippett et al. 2005) through a statistical model. By utilizing GCM-predicted fields for downscaling, this approach inherently incorporates the nonlinear relationship between SSTs and local hydroclimatology.

The main goal of this study is to develop operational streamflow forecasts that can be employed for short-term (3–6 months) water management by utilizing the monthly updated climate forecasts from ECHAM4.5 GCM forced with SST forecasts. Most of the studies that employed GCM fields for developing streamflow forecasts utilized historical simulations of GCMs forced with observed SSTs. Downscaling GCM fields obtained with observed SSTs as boundary conditions results in overestimation of the actual forecasting skill (Goddard and Mason 2002). In contrast, our study employs monthly precipitation forecasts from ECHAM4.5 forced with persisted SSTs as predictors to develop a principal components regression (PCR) model. Specifically, this study focuses on (i) developing operational streamflow forecasts using monthly precipitation forecasts from ECHAM4.5 forced with persisted SSTs; (ii) updating them every month to improve the within-season predictability; and (iii) eliminating the need for disaggregation schemes by developing separate PCR models for each month over the forecasting period of interest.

An overview of different streamflow forecasting

methodologies is presented in section 2 along with the interconnections between the hydroclimatic variability and Asian monsoon over Southeast Asia. In section 3, baseline information regarding Angat Basin is provided with detailed diagnostic analyses supporting predictor identification and streamflow forecasts development. In section 4, we develop both seasonal and updated monthly streamflow forecasts for Angat Reservoir using the MOS technique. The developed PCR model is then evaluated in obtaining operational streamflow forecasts. We conclude with a summary and discussion in section 5.

2. Background

Climatic variability at interannual and interdecadal time scales resulting from ocean–atmosphere interactions modulates the moisture delivery pathways and has significant projections on continental-scale rainfall patterns (Trenberth and Guillemot 1996; Cayan et al. 1999) and on streamflow patterns at global (Dettinger and Diaz 2000) and regional scales (e.g., Guetter and Georgakakos 1996; Piechota and Dracup 1996). Efforts in understanding the linkages between exogenous climatic conditions such as tropical SST anomalies and hydroclimatology over the United States have offered the scope for predicting the streamflow potential at seasonal to interannual time scales (Hamlet and Lettenmaier 1999; Georgakakos 2003; Wood et al. 2002, 2005). Interannual modes such as the El Niño–Southern Oscillation (ENSO) resulting from anomalous SST conditions in the tropical Pacific Ocean influence the interannual variability over many regions of the globe (Rasmusson and Carpenter 1982; Ropelewski and Halpert 1987). Studies have shown that ENSO conditions also influence the SST conditions in the tropical Atlantic Ocean and Indian Ocean, thereby affecting the global climate.

Studies focusing on the associations between ENSO and the Asian monsoon have mostly focused on the summer monsoon (June–September; Kane 1999; Kripalani and Kulkarni 1997; Lau and Wu 2001; Singhratna et al. 2005). The eastward shift of the Walker circulation in the tropical Pacific during warm episodes of ENSO typically results in reduced rainfall during the Indian summer monsoon (Kumar et al. 1999) and the South China monsoon (Wang et al. 2001). However, a change in the ENSO–monsoon relationship has been noted in recent times, which has been attributed to the shift in SST maxima location in the tropical Pacific [i.e., over the date line or farther east of date line; Singhratna et al. (2005)] or to the time of occurrence of SST maxima over the calendar year of an ENSO event [i.e., May–August or January–May; Kane (1999)]. In com-

parison to the Asian summer monsoon, very few studies have investigated the linkages between ENSO and the Asian winter monsoon (November–February) showing that the warm pool (El Niño) over the tropical Pacific Ocean results in a weakened Asian winter monsoon (Li et al. 2001; Yang et al. 2002). Predictability of Asian monsoons using GCMs shows that the skill is better during winter monsoon (Jiang et al. 2004) in comparison to the summer monsoon (Webster et al. 1998; Gadgil and Sajani 1998; Cherchi and Navarra 2003). To recapitulate, studies show significant associations between ENSO and the Asian monsoon, but predictability using GCMs still remains a challenge.

As discussed earlier, one could pursue either dynamical downscaling or statistical downscaling to develop climate-information-based streamflow forecasts. Development of point forecasts such as reservoir inflows are much easier to obtain with statistical downscaling since observed streamflows can be directly mapped to GCM precipitation forecasts. Statistical downscaling of GCM precipitation to local precipitation/streamflow has been pursued through various methodologies: a parametric regression model (Tippett et al. 2005; Clark and Hay 2004), generalized linear regression model (Buishand et al. 2004), nonparametric approach (Gangopadhyay et al. 2005), and complex nonhomogeneous hidden Markov model (Robertson et al. 2004). Statistical downscaling has also been employed to obtain various hydroclimatic attributes such as precipitation (Landman and Goddard 2002), daily rainfall occurrence (Robertson et al. 2004), streamflow (Landman and Goddard 2002), and soil moisture variability (Georgakakos and Smith 2001). Most of the studies that employ downscaling methods to obtain forecasts of various hydroclimatic attributes have typically used GCM forecasts forced with observed SSTs. Such an approach would naturally overestimate the forecasting skill of downscaled streamflows, since it assumes that boundary conditions (i.e., SSTs) for forcing GCMs are completely known over the forecasting period of interest (Goddard and Mason 2002). Instead, we employ retrospective precipitation forecasts from ECHAM4.5 GCM forced with persisted SSTs for developing monthly updated operational streamflow forecasts for the Angat Basin.

3. GCM forecasts, baseline information, and diagnostic analyses

Developing seasonal to interannual climate forecasts basically involves two steps: (i) prediction of SSTs for the forecasting period and (ii) forcing the GCMs using the predicted SSTs to forecast precipitation and other atmospheric variables of interest (Barnston et al. 2003).

At the International Research Institute for Climate and Society (IRI), climate forecasts are currently developed by forcing the multiple GCMs with three different SST prediction schemes for the tropical Pacific: 1) the National Centers for Environmental Prediction (NCEP) coupled model, 2) the Lamont-Doherty Earth Observatory (LDEO) coupled ocean–atmosphere model, and 3) the NCEP/Climate Prediction Center’s constructed analog statistical model (Goddard et al. 2003). SST forecasts for the Indian Ocean and the Atlantic Ocean are obtained from statistical models. Thus, predicted SSTs for the tropical oceans from these three models and the persisted SSTs (discussed under ECHAM4.5 forecasts) provide the boundary conditions for forcing the GCMs over the forecasting period. (For more information on seasonal climate forecasting carried out at IRI, see the tutorial online at <http://iri.columbia.edu/climate/forecast/tutorial2/>.)

a. ECHAM4.5 retrospective and real-time climate forecasts

Beginning October 1997, IRI has been producing global climate forecasts, which were initially issued on a quarterly basis for two seasons. From August 2001, IRI has been producing global climate forecasts on a monthly basis for four overlapping seasons (3 months) from mid-2001. For additional details, refer to Goddard et al. (2003). For this study, we select the climate forecasts from ECHAM4.5 GCM due to the availability of a long period (from 1968) of retrospective forecasts (Roeckner et al. 1996) (<http://iridl.ldeo.columbia.edu/SOURCES/.IRI/.FD/.ECHAM4p5/.Forecast/.asst/.ensemble/.MONTHLY/>).

Since application of statistical downscaling requires climate forecasts issued for yesteryears, we employ retrospective monthly climate forecasts from ECHAM4.5 GCM forced with globally persisted SSTs, which are available for a 5-month lead time from 1968 onward. One of the simplest procedures to forecast the SSTs is through persisting SSTs over the forecasting period of interest. For instance, if December 2005 SST at a particular grid point is 1.5°C above its climatology, then an anomalous 1.5°C is persisted for 5 months above the respective month’s climatology at that grid point to develop the boundary conditions for forcing the GCMs. In other words, we expect the anomalous conditions in SSTs to persist over the forecast lead time. Studies have shown that using persisted SSTs for forcing GCMs is a very realistic way of assessing the skill of the forecasts and it is a reasonable estimate for predicting the SSTs in the Pacific (Goddard and Mason 2002). Apart from this, we also use the historical simulations of ECHAM4.5 precipitation for diagnostic analyses,

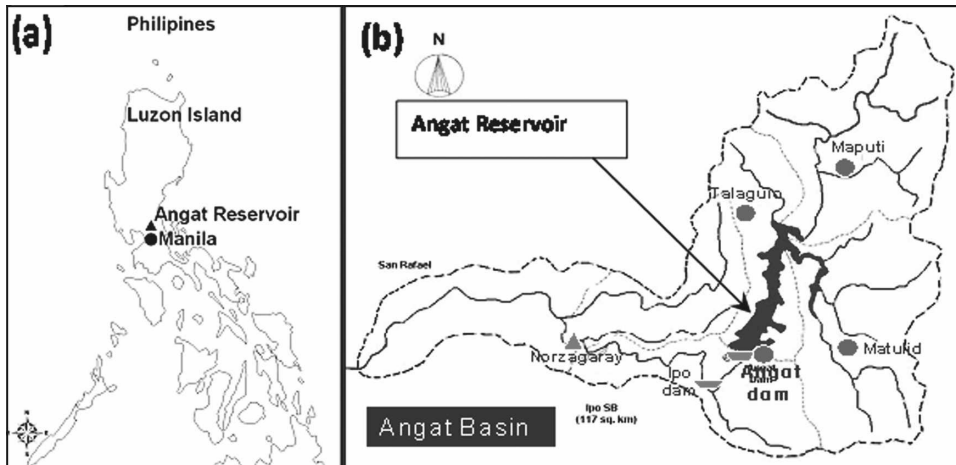


FIG. 1. (a), (b) Location of Angat Basin and Angat Reservoir in Luzon Island, Philippines. The four circled locations indicate the location of four precipitation stations upstream of the Angat Reservoir.

which are primarily obtained by forcing the GCMs with observed SSTs (perfect forcings).

b. Baseline information—Angat watershed

To demonstrate the role of GCM climate forecasts forced with persisted SSTs in the development of operational streamflow forecasts, we consider predicting monthly inflow forecasts during the Asian winter monsoon season (October–February) for a watershed located in Luzon Island, Philippines (Fig. 1). Angat upper watershed with a total catchment area of 568 km² receives an average annual rainfall of 292 cm. Angat Reservoir, located in the upper basin, accounts for 97% of the water supply needs of Metro Manila apart from supplying water for irrigation in the Bulacan Province and generating hydropower having an installed capacity of 248 MW. Given the small size of the basin, development of operational streamflow forecasts utilizing GCM forecasts requires either statistical or dynamical downscaling. The average annual inflow into the reservoir is 150 million cubic meters with the seasonality reflecting strong bimodality (Fig. 2a). Figure 2a shows two dominant seasons with the inflows during June–September and during October–February accounting for 30% and 55% of the annual flow respectively. This is based on the observed inflows into the Angat Reservoir for the period October 1968 to February 2002 (hereafter, 1968ONDJF flow denotes the observed flow from October 1968 to February 1969). The inflows during June–September (JJAS) are primarily from the southwest monsoon (Asian summer monsoon) and October–February (ONDJF) flows are from the northeast monsoon (Asian winter monsoon).

c. Diagnostic analyses—SST, ECHAM4.5 precipitation forecasts, and streamflow

A commonly used index to denote ENSO is Niño-3.4, which indicates the average sea surface temperature anomaly in the eastern equatorial Pacific (5°N–5°S and 170°–120°W). A 3-month lag correlation between Niño-3.4 (July–September) and the observed average streamflow during the northeast monsoon (October–February) is -0.55 , which is statistically significant. However, a 3-month lag correlation between Niño-3.4 (March–May) and the observed flows during the southwest monsoon (June–September) do not seem to be associated with ENSO. The primary reason is that the ENSO cycle is either in the incipient stage or in the ending stage (<http://iri.columbia.edu/climate/ENSO/background/pastevent.html>) during March–May. Figure 2b summarizes the temporal correlation structure exhibited by the inflows. The concurrent monthly correlation between precipitation (average precipitation of the four stations shown in Fig. 1) and streamflow is statistically significant during the two rainy seasons and during low flow seasons. Lag 1 monthly correlation in streamflows (Fig. 2b) is high and statistically significant only during March and April, indicating the strong presence of rainfall–runoff regime. Figure 2b also shows that the lag 1 monthly correlation between rainfall and streamflow is statistically insignificant in most of the months, indicating the limited role of land surface storage. From Fig. 2b, we understand that for modeling ONDJF streamflows, it is important to predict the precipitation falling in the respective months during ONDJF. Further, the relationship between rainfall and runoff during concurrent months is strongly linear during ONDJF (figure

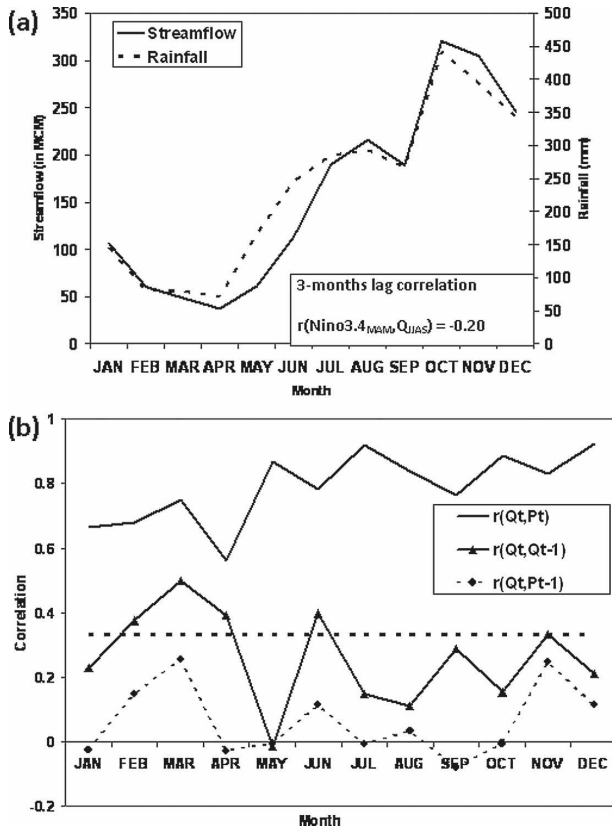


FIG. 2. Hydroclimatology of the Angat Basin: (a) seasonality of Angat Basin and (b) monthly correlation structure. In (a) the percentage contribution of annual flows from the southwest monsoon (JJAS) and the northeast monsoon (ONDJF) is also given. Panel (a) also gives the 3-month lag correlations between Niño-3.4 and the average flows during the two seasons. Panel (b) shows the concurrent correlation between streamflow and precipitation [$r(Q_t, P_t)$], lag 1 monthly correlation between the streamflow [$r(Q_t, Q_{t-1})$], and lag 1 monthly cross correlation between streamflow and precipitation [$r(Q_t, P_{t-1})$], along with the significant correlation (dotted horizontal line) for the dataset.

not shown), which could also be inferred from the strong correlation shown in $r(Q_t, P_t)$.

Figures 3a and 3b show the correlation between the ECHAM4.5 predicted precipitation and the observed streamflow at Angat Reservoir for the ONDJF season for two schemes: ECHAM4.5 forced by observed SSTs and ECHAM 4.5 forced by persisted SSTs. As expected, precipitation from ECHAM 4.5 forced with observed SSTs (Fig. 3a) has higher correlation with the streamflow than the precipitation forecasts obtained by using persisted SSTs (Fig. 3b). Thus, employing GCM precipitation obtained using observed SSTs would result in overestimation of the skill of the streamflow forecasting model. Furthermore, predicting precipitation using observed SSTs assumes that we have perfect information about the boundary conditions (SSTs) over

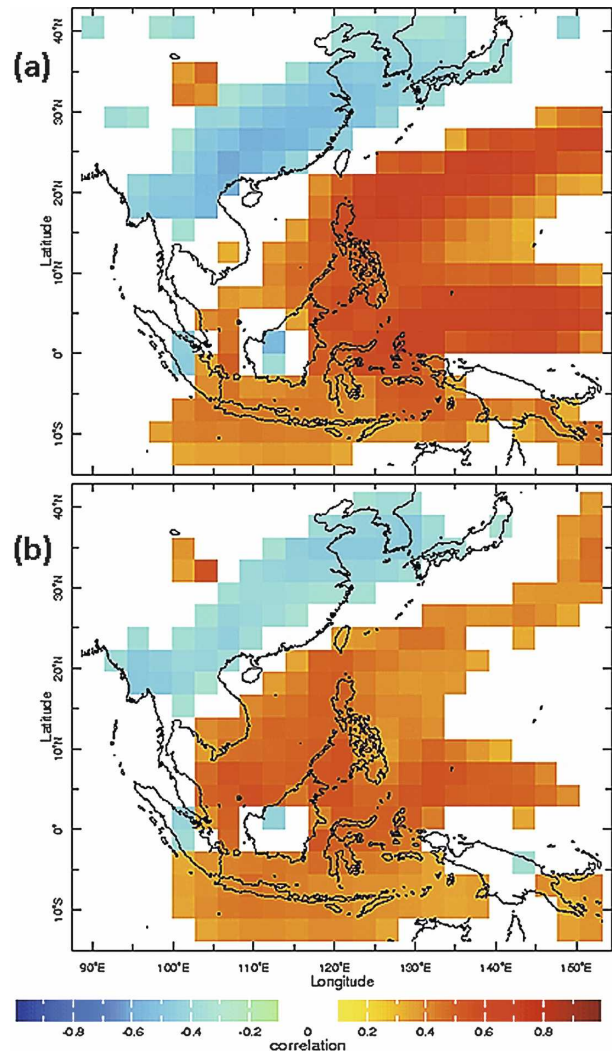


FIG. 3. Relationship between EPF and streamflow into the Angat Basin. Panels show the correlation (>0.33 and <-0.33) between the ECHAM4.5 predicted precipitation (ensemble mean) and the observed ONDJF streamflow during 1968–2001. (a) Simulated (history) precipitation from ECHAM4.5 forced with observed SSTs; (b) 5-month-ahead precipitation forecasts from ECHAM4.5 forced with persisted SSTs. The averaged correlations between GCM-predicted precipitation and ONDJF streamflow over the domain (0° – 25° N, 115° – 130° E) are 0.57 for (a) and 0.47 for (b).

the forecasting period, which is not the case, and therefore needs to be replaced with forecasted SSTs in developing real-time climate forecasts. This is consistent with the findings of previous studies (Goddard and Mason 2002), which show that persisted SSTs are a reasonable forecasting scheme over the tropical Pacific to obtain climate forecasts.

With regard to developing operational streamflow forecasts for the Angat Basin, the ability of ECHAM4.5 precipitation forecasts (EPF) obtained using persisted

SSTs to predict streamflow during the Asian summer monsoon (June–September) is very limited, whereas the predictability of flows during the northeast monsoon (October–February) using EPF is statistically significant. Figure 4a shows the interconnections between Niño-3.4, EPF, and observed streamflow at Angat Reservoir. Figure 4a shows clearly that above-normal SST conditions (years: 1972, 1982, 1991, 1994, 1997) in the tropical Pacific result in reduced inflow conditions whereas La Niña conditions (years: 1973, 1975, 1988, 1995, 1998) in the tropical Pacific induce above-normal inflow conditions. It is important to note that when ENSO conditions are neutral (years: 1980, 1983, 1985, 1989), the observed streamflow and GCM precipitation are in opposite directions. Figure 4a also shows that warm-pool (cold-pool) El Niño (La Niña) conditions in the equatorial Pacific results in below- (above) normal inflow conditions. The observed streamflows and EPF obtained under persisted SSTs are out of phase, particularly during a few years of normal SST conditions over the tropical Pacific.

To identify climatic predictors that influence the Angat inflows during near-normal situations, we plot the correlation between the observed streamflows and SSTs over the Philippines Sea (Fig. 4b) during normal inflow conditions. SSTs shown here are obtained from the analysis of Kaplan et al. (1998), which uses optimal estimation in the space of 80 empirical orthogonal functions (EOFs) in order to interpolate ship observations of the Met Office database. Inflow in a particular year is considered to be normal if the flow falls between 33rd and 66th percentiles of the observed streamflow climatology. The significant correlation between streamflow and SST indicates the importance of local SST conditions in modulating the Angat flows during neutral ENSO conditions. Thus, in this study, we use EPF, Niño-3.4, and local SSTs in the Philippine Sea as predictors to develop climate-information-based streamflow forecasts for the period ONDJF for the Angat Basin.

4. Climate-information-based streamflow forecasts development

The intent of this study is to develop operational streamflow forecasts using climate information at seasonal time scales. For this purpose, we employ precipitation forecasts from ECHAM4.5 forced with predicted SSTs, Niño-3.4, and local SSTs as predictors to develop streamflow forecasts. The streamflow forecasts developed for the ONDJF season for the Angat watershed based on these predictors are analyzed under four different categories: (i) leave-one-out cross-validated monthly streamflow forecasts issued in October, (ii) up-

dated monthly streamflow forecasts during the season, (iii) operational streamflow forecasts using EPF obtained from predicted SSTs, and (iv) seasonal streamflow forecasts and disaggregation. Performance of the streamflow forecasts using EPF alone is compared with the performance of the streamflow forecasts using EPF along with local and tropical SSTs to show the importance of local and tropical SSTs in improving the forecasts.

a. Statistical downscaling of ECHAM4.5 precipitation forecasts

The approach we employ for developing streamflow forecasts is principal components regression, which is one of the commonly employed methodologies for statistical downscaling (Landman and Goddard 2002; Hidalgo et al. 2000). Given that the precipitation fields obtained from GCMs and SSTs are spatially correlated, application of principal components analysis (PCA) rotates the original GCM fields into orthogonal components with the first mode representing the maximum variance of the original GCM fields. PCA, also known as EOF analysis, on the predictors (GCM and SST fields) could also be performed by singular value decomposition on the spatial correlation matrix or covariance matrix of the predictors. Since PCA is scale dependent, loadings (eigenvectors or EOF patterns) obtained from the covariance matrix and the correlation matrix are different. Importance of each EOF pattern is quantified by the fraction of the variance the principal component represents with reference to the original predictor variance. In the case of PCA performed using correlation matrix approach, the sum of all eigenvalues is equal to the total number of elements in the data. For instance, if the predictor contains five grid points of precipitation fields and two grid points of SST, then the sum of all eigenvalues obtained from the correlation matrix of predictors will be equal to seven. Figure 5 provides an outline of the statistical downscaling scheme employed using PCR. PCA based on correlation matrix is usually employed when predictors denote various ocean and atmospheric conditions expressed in different units (e.g., precipitation and SST). Mathematics of PCA and the issues in selecting desired principal components can be found in Dillon and Goldstein (1984) and Wilks (1995).

1) DIMENSION REDUCTION AND PREDICTOR SELECTION

For developing operational streamflow forecasts for the Angat Basin, we consider two candidate predictors for statistical downscaling: (i) ECHAM4.5 precipitation forecasts obtained using persisted SSTs over the Phil-

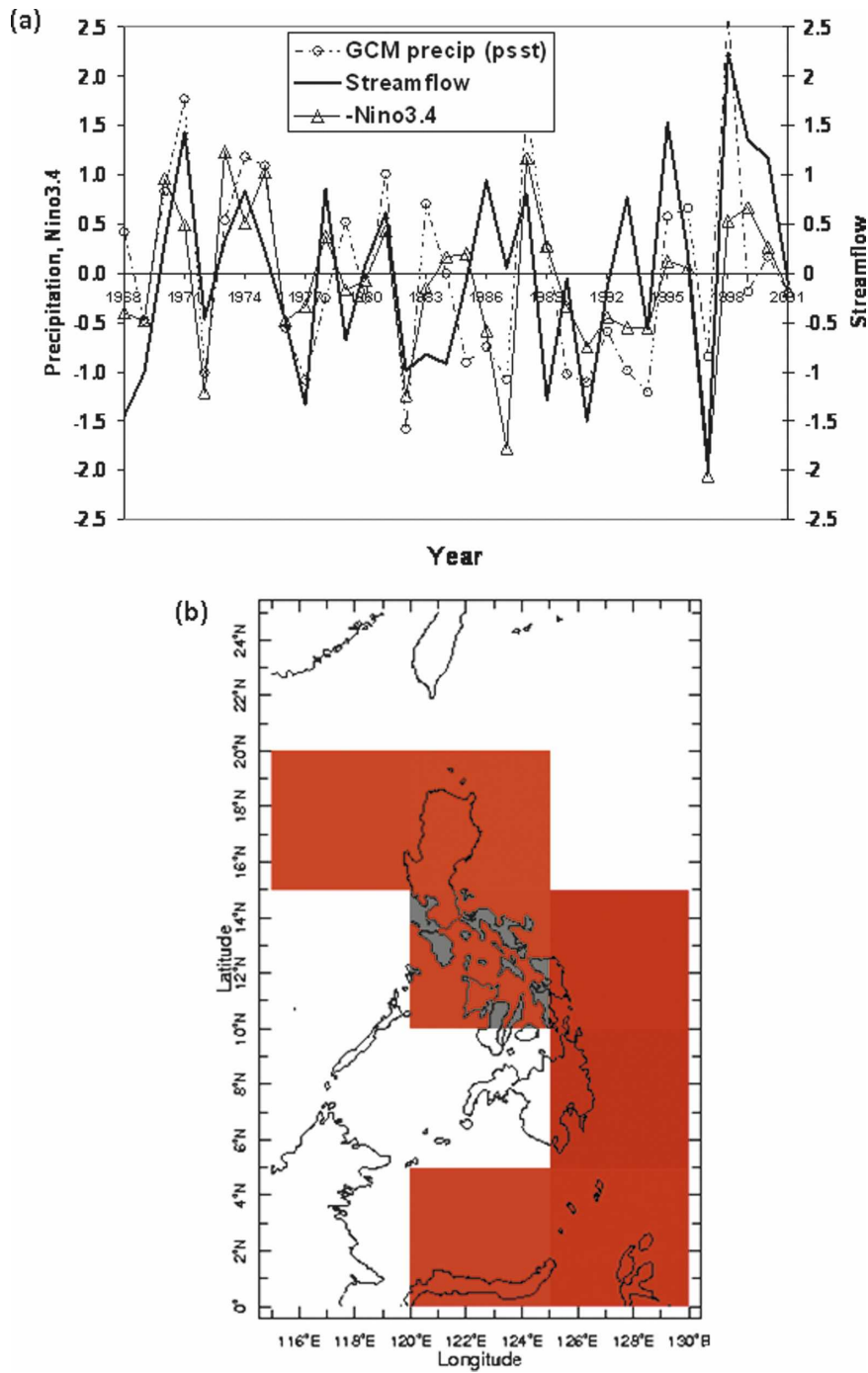


FIG. 4. Importance of local and tropical SSTs in influencing the ONDJF streamflow into the Angat Reservoir and EPF over the domain (0°–25°N, 115°–130°E). (a) The connections between ENSO (indicated with reversed sign of Niño-3.4), EPF, and ONDJF streamflow. (b) The correlation between SST over Philippines and Angat streamflow during normal inflow conditions. Only correlations that are greater than 0.62 (95% significance level for 10 normal inflow years) are shown.

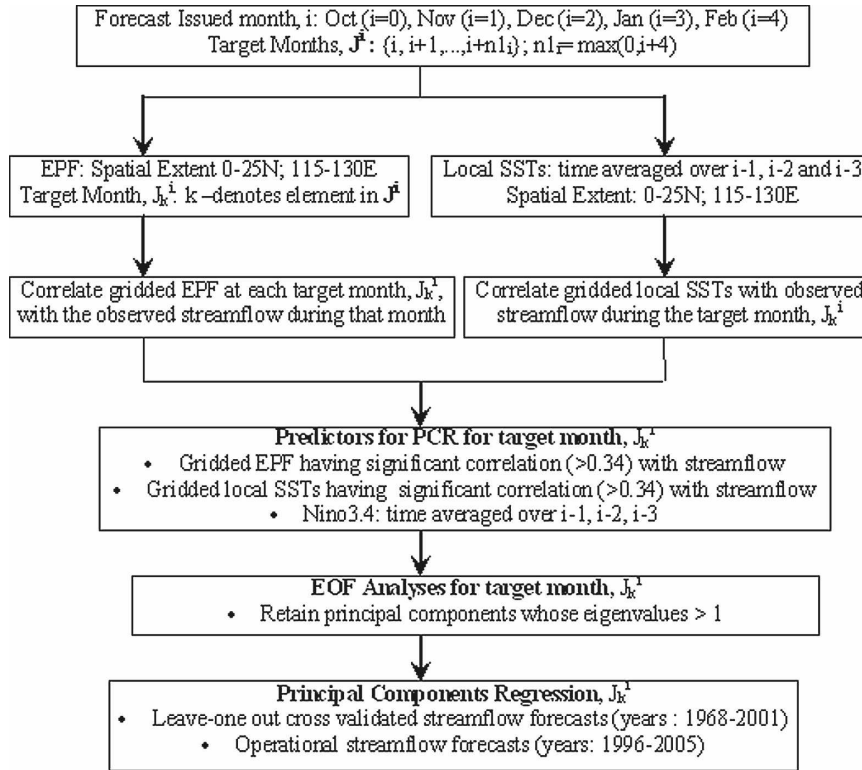


FIG. 5. Flowchart of the streamflow forecasts development using PCR employed in the study.

ippines (0° – 25° N and 115° – 130° E) (hereafter EPF), (ii) a combined predictor set of EPF, SSTs over the same domain (0° – 25° N and 115° – 130° E), and Niño-3.4 (hereafter, $ESN = EPF + SST + Ni\tilde{no}-3.4$). Table 1 provides the spatially averaged correlation between the 3-month average SSTs over the Philippines available at the forecasting month and inflows into the Angat Reservoir during ONDJF. One main reason for having similar correlation under two predictors, local SSTs and EPF, is mainly due to the role of persisted SSTs. Since EPF for the target months are obtained by adding current SST anomalies with the target month’s climatological

values, we do not see any significant difference in correlation. It has been shown in the literature (Goddard and Mason 2002) that persisted SSTs provide a good scenario for forecasting the SSTs in the Pacific. In other words, an anomalous SST condition that is seen on the forecast-issued month is a good candidate for obtaining anomalous SST conditions during the target month.

To develop predictor vectors for these two candidate predictors, EPF and ESN, we consider only the grid points of EPF and SSTs whose absolute values of correlations are greater than 0.33 (95% significance level) with the Angat flows during ONDJF. PCA based on

TABLE 1. Correlation between 3-month average SST over Philippines with the Angat flows during ONDJF. Values in parentheses indicate the correlations between ECHAM4.5 precipitation forecasts issued in the respective months with the target monthly flows at Angat. Correlations whose absolute values are greater than 0.33 (95% significance level) are only considered for computing the average correlation over the domain (0° – 25° N, 115° – 130° E). For the target month of November (forecast issued: November), a threshold of 0.25 was used, since not even one grid point had correlation greater than the threshold of 0.33.

Forecast issued month	SST	Target month				
		Oct	Nov	Dec	Jan	Feb
Oct	Jul–Sep	0.48 (0.43)	0.28 (0.42)	0.40 (0.38)	0.38 (0.38)	0.34 (0.34)
Nov	Aug–Oct		0.27 (0.27)	0.40 (0.44)	0.38 (0.38)	0.38 (0.34)
Dec	Sep–Nov			0.42 (0.46)	0.42 (0.41)	0.38 (0.40)
Jan	Oct–Dec				0.44 (0.44)	0.41 (0.41)
Feb	Nov–Jan					0.45 (0.41)

TABLE 2. Correlation between the selected dominant components for PCR and observed streamflow in the target month. Values in the parentheses indicate the % of variance explained by each component in the corresponding predictor set given in Table 2.

Forecast issued month	Target month				
	Oct	Nov	Dec	Jan	Feb
Oct	-0.48 (65)	-0.40 (59)	-0.43 (68)	-0.41 (65)	-0.10 (66)
	-0.21 (5)	0.24 (16)	-0.38 (3)	-0.35 (4)	-0.11 (12)
	-0.23 (2)	0.30 (5)		-0.39 (3)	-0.58 (5)
Nov		-0.22 (56)	-0.57 (50)	-0.45 (53)	-0.23 (68)
		0.36 (22)		0.48 (3)	0.28 (7)
		-0.35 (4)			-0.24 (3)
Dec			-0.54 (58)	-0.54 (58)	-0.41 (56)
			-0.28 (3)		-0.44 (7)
				0.33 (3)	
Jan				-0.44 (44)	0.44 (54)
				0.32 (29)	0.42 (20)
				-0.29 (4)	
Feb					-0.56 (55)
					-0.21 (25)

correlation matrix was performed for these two candidate predictors (EPF and ESN) and the principal components that have eigenvalues greater than one were retained for developing PCR. This basically implies that any principal component retained for further analyses (e.g., developing regression) should account for more variance than any single element in the standardized test score space (Dillon and Goldstein 1984).

Since selecting principal components using the eigenvalue criterion (>1) considers only the explained variance among the predictors, we select a subset of selected principal components that have significant correlation with the observed streamflows for developing the PCR. An alternate approach performs detailed stepwise regression analyses (Draper and Smith 1998) to select the principal components that maximize the relationship between the observed streamflow and the retained principal components using eigenvalue criterion. Since we had only very few principal components (Table 2) with eigenvalues greater than one, we selected a subset of them purely based on their correlation with the predictand. Given that we have a different predictor set for each target month under a particular forecast-issued month, the number of principal components retained for developing PCR and their correlation with observed streamflows also differ (in Table 2). Thus the final set of principal components retained for regression analyses not only explains the spatial variability in original predictors, but also explains the temporal variability in the predictand (streamflows).

2) MODEL OUTPUT STATISTICS

Principal components regression, otherwise known as MOS (Wilks 1995) when employed with gridded predictors, primarily recalibrates large-scale GCM fields or the principal components of the GCM fields to the observed smaller spatial-scale hydroclimatic variable of interest using regression analyses. The predictand could be either streamflow or observed rainfall over a region. PCR not only relates large-scale climatic information to the smaller spatial-scale variable of interest, but also eliminates systematic errors and biases in GCM fields by regressing with the predictand fields. Thus, application of PCR requires retrospective forecasts of GCM fields and the predictand for developing the statistical relationship.

b. Retrospective monthly streamflow forecasts for the ONDJF season

In this section, we develop retrospective monthly streamflow forecasts during the ONDJF season for the Angat Reservoir based on the climatic information available in October. The 5-month-ahead streamflow forecasts are developed for the period 1968–2001 by leave-one-out cross validation using EPF and ESN as two candidate predictors. Leave-one-out cross validation is a rigorous model-validation procedure that is usually carried out by leaving out the predictand and predictors from the observed dataset ($Q_t, \mathbf{X}_t, t = 1, 2, \dots, n$) for the validating year and the parameters of

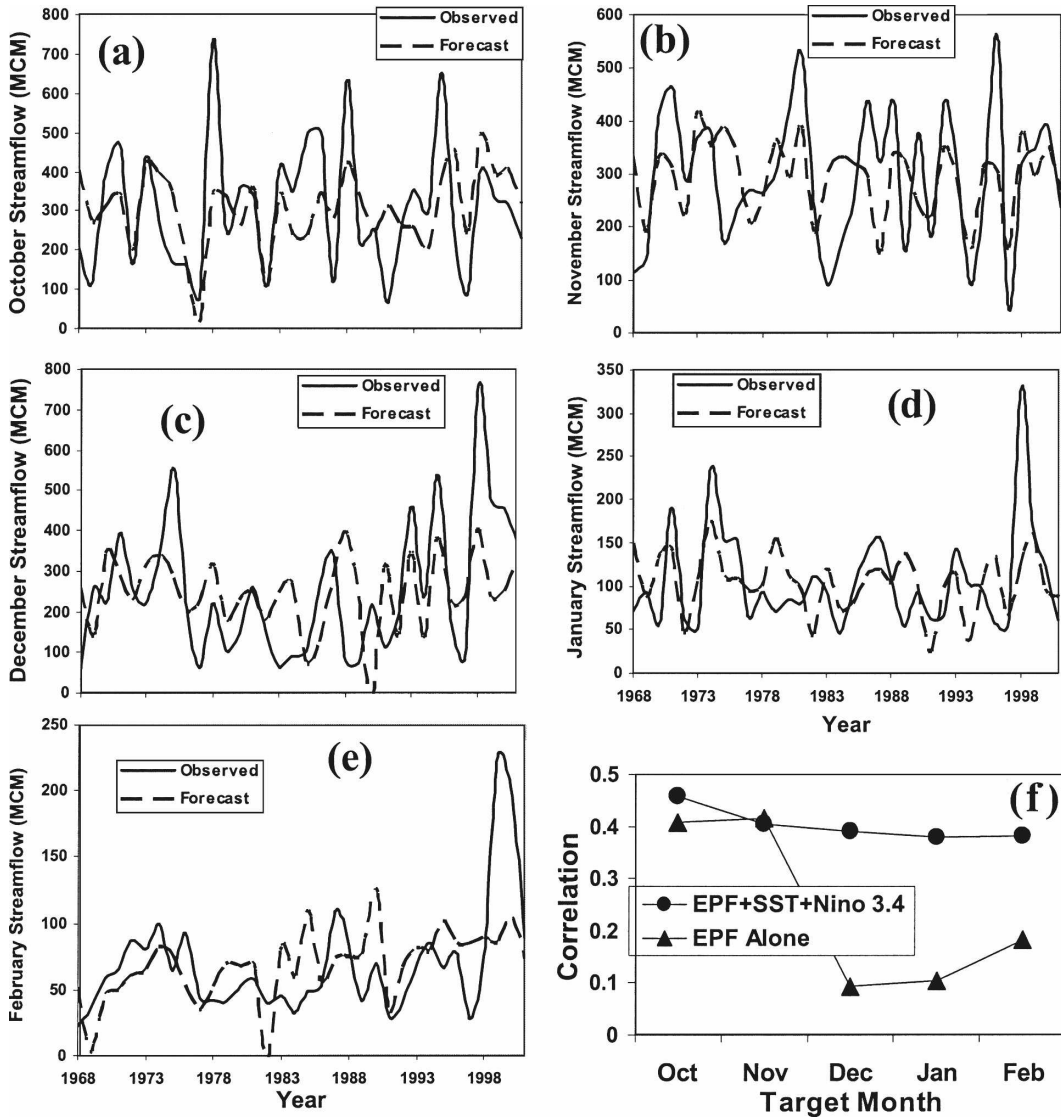


FIG. 6. Leave-one-out retrospective streamflow forecasts for the ONDJF season based on climate information in October. (a)–(e) The respective monthly streamflow forecasts developed using the combined predictor, ESN, having EPF forecasts for the respective month along with JAS average SST over (0°–25°N, 115°–130°E) and JAS Niño-3.4. Solid (dashed) line indicates the observed (forecasted average) streamflow for the period 1968–2001. (f) The correlation between the observed flows and the predicted streamflow for each target month using predictor ESN along with the skill for the alternate predictor set, which considers EPF alone.

the PCR model are estimated using the remaining ($n - 1$) observations, where n is the total length of observed records in a given site. Using the PCR developed with ($n - 1$) observations, the ability of the model to predict the left-out observation is performed using the state of the predictor at the validating year. Thus, if we have “ n ” years of data, then a total of n different regression relationships were developed by leaving out predictors and predictands for the validating year. Using the principal components in Table 2 for the forecast-issued

month of October, we employ PCR and develop leave-one-out monthly streamflows for the ONDJF season.

Figure 6 shows the cross-validated streamflow forecasts for the ONDJF season using the climate information available up to October for the predictor ESN. Figure 6f provides the correlation between the observed flow and the PCR-predicted flow under each target month for predictors ESN and EPF considered in the study. The 95% significance level correlation for rejecting the null hypothesis that observed streamflows

TABLE 3. Normalized root-mean-square error for the leave-one-out cross-validated forecasts using the predictor ESN. Normalized RMSE is the ratio of root-mean-square error to the average monthly streamflow of the target month.

Forecast issued month	Target month				
	Oct	Nov	Dec	Jan	Feb
Oct	0.482	0.404	0.621	0.526	0.582
Nov		0.406	0.592	0.492	0.629
Dec			0.574	0.493	0.548
Jan				0.480	0.530
Feb					0.528

and predicted flows are not correlated is 0.33 (for 34 yr of data). From Fig. 6f, we can clearly see that the predictive ability of PCR using ESN is far better than the predictor using EPF alone. However, the ability of EPF in predicting the streamflow for the target months October and November is significant and comparable to the skill obtained using ESN as predictor. Figure 6f also shows that the predictive ability of the predictor, ESN, decreases with increased lead time. Figures 6c–e corroborate this with poor prediction of high-flow years during the target months of December–February. Based on Table 1, we clearly understand that monthly updated precipitation forecasts from ECHAM4.5 and updated SST conditions indicate better correlation with respect to the rest of the target months in the ONDJF season. The following section explores the importance of the role of monthly updated climate forecasts and SST conditions in improving monthly streamflow forecasts during the ONDJF season.

c. Updated monthly streamflow forecasts and skill improvement

Given that development of climate forecasts using GCMs over a particular lead time requires primarily SST forecasts over that time period, forcing GCMs with updated persisted SST anomalies would lead to improved GCM precipitation forecasts for the target months within the season. Using the predictors given in Table 2 for each forecast-issued month from November to February, we develop updated streamflow forecasts for each target month based on the selected PCs (Table 3) that meet the eigenvalue criterion. Thus, a total of 15 leave-one-out cross-validated forecasts are developed, 5 (ONDJF) for October, 4 (NDJF) for November, 3 (DJF) for December, 2 (JF) for January, and 1 (F) for February, for each forecast-issued month using either EPF or ESN as a predictor. Results for the forecast-issued month of October are discussed in section 4b.

Figure 7 provides the correlation between the observed flow and the updated streamflow forecasts is-

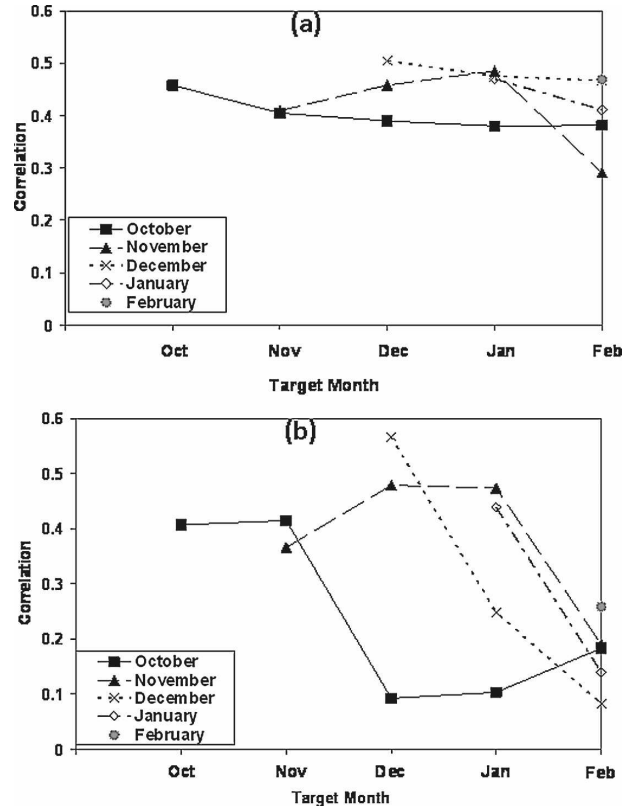


FIG. 7. Performance of monthly streamflow forecasts issued at the beginning of each month using predictors ESN and EPF, which are updated every month during the season. The skill between the observed flow and cross-validated forecasts is provided using two predictors: (a) ESN and (b) EPF.

sued for each of the target months during the ONDJF season. Figure 7 shows that streamflow forecasts developed using monthly updated EPF and ESN predictors improves the streamflow predictability overall in comparison to the forecasts issued in the previous month. Table 3 further confirms this inference using the normalized root-mean-square error (RMSE) for the streamflow forecasts obtained using the predictor ESN. RMSE is the square root of the mean square error, which is computed by averaging the square of the residuals (observed value – predicted value). RMSE is normalized by the respective month's climatology to compare the prediction error across different months. Both Fig. 7 and Table 3 show that updating the forecasts on a regular basis improves monthly streamflow prediction and results in reduced prediction error. It is important to note that we are able to achieve such high predictability without including any land surface processes. This is primarily due to the reason that Angat is a humid basin and the soil is predominantly silty clay. In other words, runoff is mostly controlled by the precipi-

tation, since the soil moisture is near to its capacity due to high precipitation and low infiltration rate.

d. Operational streamflow forecasts: Using EPF from predicted SSTs

The main aim of this section is to assess the performance of the streamflow forecasting model developed with GCM precipitation forecasts under persisted SST conditions, when using GCM precipitation forecasts obtained by forcings of predicted SSTs (Atlantic-blended SSTs—for details, see <http://iri.columbia.edu/>) as a predictor. We presume that this will promote future application of operational ECHAM4.5 and multi-model (multiple GCMs) precipitation forecasts for developing operational monthly streamflow forecasts for the Angat Basin. For this purpose, we develop the streamflow forecasting model using EPF from persisted SSTs available for the period 1968–95 and employ that model for predicting streamflows during 1996–2005 using EPF obtained from predicted SSTs as the predictor. To develop ESN predictor sets for the period 1996–2005, we use the EPF forced with Atlantic-blended global SSTs for the period 1997–2005. Since we do not have the EPF forced with Atlantic-blended SSTs for years 1996 and 1997, we use the EPF forced with the constructed analog model's SST forecasts (Van den Dool 1994), which has been reported to have a similar predictability as that of EPF obtained with persisted SST scheme (Li and Goddard 2005). Since real-time climate forecasts are issued on a monthly basis only from 2001, we do not consider developing updated monthly streamflow forecasts during the ONDJF season using the predicted SSTs.

Figure 8 shows the monthly streamflow forecasts obtained using EPF forced with predicted SSTs for the period 1996–2005. Figure 8f provides the skill in predicting the monthly streamflow for the ONDJF season. From Fig. 8, we clearly understand that the model has excellent skill in predicting the streamflow for the months October and November. For December and January months, the skill of the model in predicting the streamflow is above the significance threshold of 0.62 for 10 yr of data (95% significance level). For February, the skill is insignificant. But, the conditional bias in predicting the extreme years seems to be high, particularly in extreme years for the months December–February. However, the change in potential is detected by the model (indicated by the correlation), but the magnitude of flows is underestimated. Based on the discussions in section 4b and from Table 3, we could expect that the prediction error associated with December–January streamflow will reduce if one uses the updated climate forecasts as predictors for developing up-

dated streamflow forecasts during the season. This shows clearly that there is potential in developing operational monthly streamflow forecasts for the ONDJF season for the Angat Basin. Despite the limited predictability and increased conditional bias for the months December–February, the model seems to be reasonably predicting the changes in streamflow potential from climatology during the validation period 1996–2005.

e. Seasonal streamflow forecasts and disaggregation

This section explores the skill in predicting seasonal streamflow (average streamflow for the ONDJF season) based on the following three approaches: (i) by developing a PCR with predictand as seasonal streamflow and the predictor ESN available at the time of October (shown as ESN average in Fig. 9a), (ii) seasonal streamflow obtained using the individual month's streamflow forecasts in section 4b for the forecast issued time of October (ESN-October), and (iii) seasonal streamflow obtained based on the updated streamflow forecasts developed in section 4c (ESN-updated). For the ESN-average approach, the predictors are chosen from the grid points of 5-month average EPF (forced with persisted SSTs), local SSTs over the Philippines, and Niño-3.4. From this pool, only the grid points that have significant correlation (>0.33) with the seasonal streamflow (ONDJF average streamflow) are considered for PCA. For the ESN-updated, we calculate the average streamflow forecasts for the ONDJF season by considering the updated monthly streamflow forecasts for each month (October–February) issued at the beginning of that month. In other words, the most recently updated monthly streamflow forecast before the occurrence of that month's flows is considered for calculating ESN-updated. For instance, the best update we can hope to get for February flows is the monthly streamflow forecasts issued in the beginning of the month of February before the February flow occurs. ESN-October is just the average of the monthly forecasts shown in Fig. 6.

Figure 9a shows the ability of the three approaches in predicting the seasonal streamflow for the ONDJF season. The correlation between the observed and ESN-average, ESN-October, and ESN-updated are 0.47, 0.62, and 0.64, respectively. The relative RMSE for the forecasts shown in Fig. 9a for ESN-average, ESN-October, and ESN-updated are 0.34, 0.28, and 0.24, respectively. As expected, the updated monthly forecasts have better correlation in predicting the seasonal streamflow compared to the other two approaches (ESN-October and ESN-average). Though the correlation is similar between ESN-October and ESN-up-

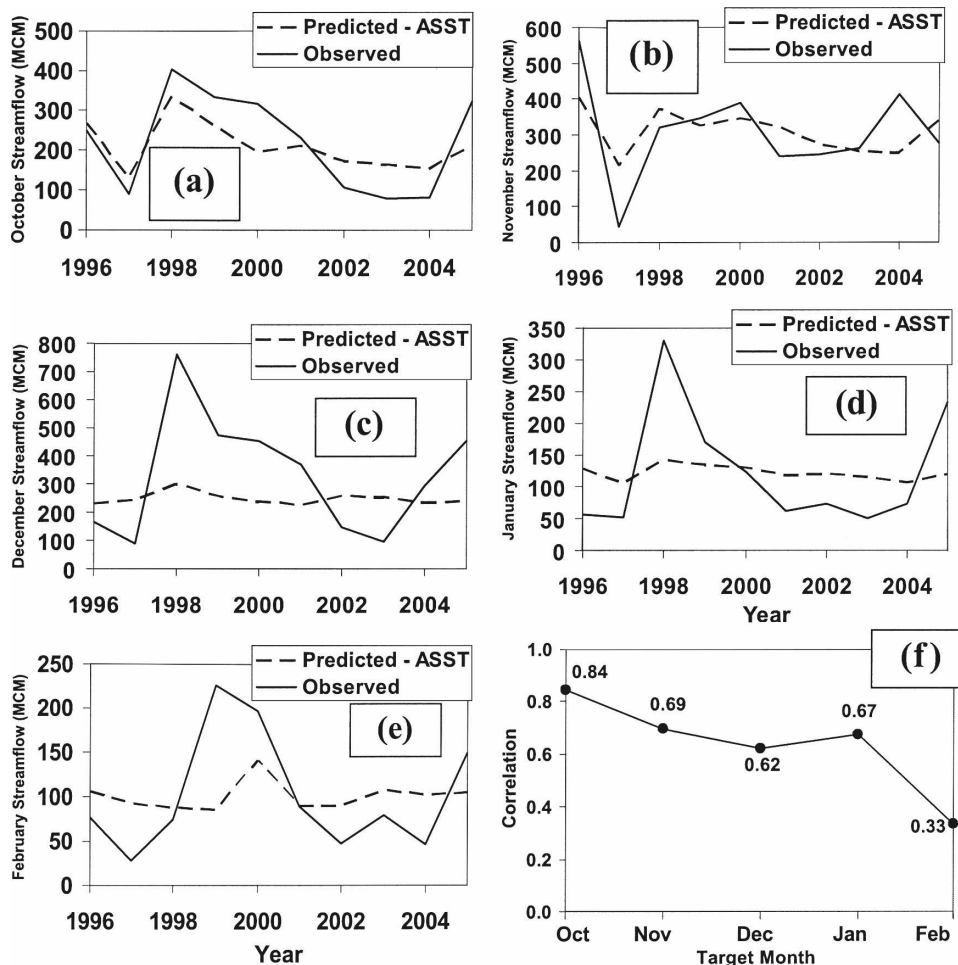


FIG. 8. Operational streamflow forecasts issued in October for the Angat system using EPF obtained by forcing with predicted SSTs (Atlantic blended SSTs). Using the PCR model developed for the period 1968–95 based principal components reported in Table 3 (forecast issued month—October), operational monthly streamflow forecasts were obtained for the period 1996–2005 using the corresponding year's EPF, SST, and Niño-3.4. (a)–(e) The observed and predicted flows for the period 1996–2005 are compared. (f) The correlation between the observed flows and the predicted flows.

dated, around 4% improvement in predicting the seasonal streamflow is obtained using ESN-updated. But, it is interesting to note the significant difference between ESN-average and the forecasts obtained using the remaining two approaches (ESN-October and ESN-updated). As mentioned earlier, the predictor for ESN-average is obtained in a similar way as that for the other two approaches, but we select only grid points of 5-month average EPF and July–September average SSTs (over the Philippines) that are significantly correlated with the ONDJF season average flows. By averaging both the EPF and the predictand, we primarily reduce the variability exhibited on both predictors and predictands, which results in reduced predictive skill. Since the streamflow forecasts from ESN-average give reduced skill in comparison to ESN-October and ESN-

updated, further application of disaggregation procedures on ESN-average forecasts can result in reduced predictability of monthly streamflows. As we can infer from Fig. 2b, the lag 1 correlation in streamflows is not significant during October–January, thus offering limited scope for disaggregation. Given that monthly precipitation forecasts are updated on a continuous basis, it is prudent to develop monthly forecasts through individual monthly streamflow forecasting models rather than develop a seasonal streamflow forecasting model whose output needs to be disaggregated to obtain monthly streamflow forecasts.

Figure 9b shows the predictability of seasonal streamflow based on the results in section 4d. The correlation between the observed ONDJF average streamflow and the predicted seasonal streamflow using EPF

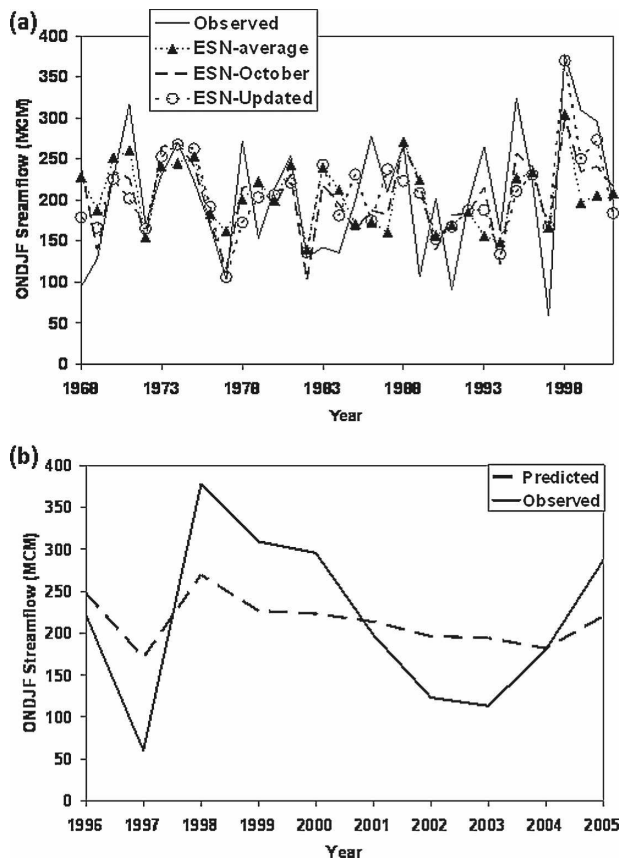


FIG. 9. Retrospective streamflow forecasts and operational forecasts for the ONDJ season for Angat Reservoir. (a) The ONDJ average streamflow by three different approaches described in section 4e. (b) The ONDJ season average streamflow obtained by training the model using the PCR for the period 1968–95. ESN-average forecasts are obtained by developing a PCR between the seasonal averages of ESN with the ONDJ average streamflow. ESN-October and ESN-Updated denote the forecasts obtained by developing PCR for individual months using the ESN predictor available at October and the ESN predictor updated every month, respectively.

(obtained using predicted SSTs) for the period 1996–2005 is 0.85. From Fig. 9b, we can see that the model shows significant conditional bias in extreme years like 1997 and 1998, but the model's ability in predicting changes in seasonal streamflow potential seems to be very good. Thus, the model seems to have good predictability even though the predictors used for training (EPF using persisted SSTs) are different from the predictors used for validation (EPF using predicted SSTs). The developed streamflow forecasting model using EPF, obtained using persisted SSTs, as a predictor could be employed for obtaining operational streamflow forecasts for the Angat Basin. The conditional bias in Fig. 9b could be reduced through continuous updating of streamflow forecasts within the season. Results

presented in this section clearly show that utilizing updated monthly climate forecasts would result in improved skill in obtaining both seasonal and monthly streamflow forecasts.

5. Summary and discussion

Climatic conditions associated with precipitation and streamflow variations during the Asian winter monsoon over the Philippines were reviewed, and the ability of ECHAM4.5 precipitation forecasts in predicting streamflows into Angat, a multipurpose reservoir, during the ONDJF season was summarized. Through detailed diagnostic analyses, we show that monthly streamflows during ONDJF are significantly correlated with 5-month-ahead monthly precipitation forecasts from ECHAM4.5 forced with persisted SSTs, tropical SSTs (Niño-3.4), and local SSTs. Local SSTs around the Philippines play an important role particularly in modulating the streamflow into the Angat Basin during neutral ENSO conditions. Thus, we consider a predictor set encompassing Niño-3.4 and grid points EPF and SSTs over the domain (0° – 25° N, 115° – 130° E) that have significant correlation with the monthly streamflow for developing operational streamflow forecasts.

By employing PCR, we develop monthly streamflow forecasts for the ONDJF season and update it every month during the season using the updated EPF and SST conditions. The ability of PCR model to predict streamflows is tested based on leave-one-out cross validation and by developing operational streamflow forecasts for the period 1996–2005. Both cross-validated streamflow forecasts and operational streamflow forecasts developed for the Angat Basin show that precipitation forecasts from ECHAM4.5 forced with persisted SSTs have significant skill in predicting monthly streamflow forecasts for the ONDJF season. Further, the skill of the monthly streamflow forecasts improves considerably by updating monthly streamflow forecasts within the season by statistical downscaling of the latest updated EPF forecasts and SST conditions.

An important finding from this study is that streamflow forecasting models developed using climate forecasts obtained from persisted SSTs perform well on employing climate forecasts obtained using predicted SSTs as predictors. This has importance in developing operational streamflow forecasts, particularly using the MOS approach, which requires considerable years of retrospective GCM precipitation forecasts that are currently available only under persisted SST forcings and under constructed analog SST forcing. This study also offers insight into the importance of statistical downscaling in developing operational streamflow forecasts.

A two-step approach of developing streamflow forecasts—relating GCM fields first to average precipitation estimated from station data and then forcing the downscaled precipitation with a hydrologic model—could result in increased error because of the bias in estimating spatial precipitation. This error could be reduced substantially by pursuing a direct approach of developing a statistical relationship between GCM fields with streamflows, since streamflow is an expression of basinwide precipitation. Finally, the study also shows that improved seasonal streamflow forecasts can be obtained by utilizing the monthly precipitation forecasts from GCMs instead of using the seasonal average precipitation forecasts from GCMs.

Given that climate forecasting centers have been issuing experimental climate forecasts every month at seasonal to interannual time scales, it is important that such advancements need to be extended to developing operational streamflow forecasts. Developing such experimental, operational streamflow forecasts will not only lead to continuous improvements in forecasting methodologies documented in the climate forecasting literature (Goddard et al. 2003; Barnston et al. 2003) for application needs, but it will also promote a user-driven approach to development of climate forecasts. This study shows that employing retrospective precipitation forecasts of GCMs forced with persisted SSTs (instead of using observed SSTs) provides an opportunity for developing operational streamflow forecasts through statistical downscaling. The developed model has also been shown to predict streamflows well upon employing EPF obtained using predicted SSTs. Our ongoing study on the application of climate forecasts for the management of the Angat Basin in the Philippines will utilize these findings to develop operational streamflow forecasts for the coming years on an experimental basis by considering ECHAM4.5 precipitation forecasts obtained from predicted SSTs as well as by utilizing precipitation forecasts obtained from an optimal combination of multiple GCMs (Rajagopalan et al. 2002; Barnston et al. 2003).

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