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Long-range experimental hydrologic forecasting for the eastern United States

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[1] We explore a strategy for long-range hydrologic forecasting that uses ensemble climate model forecasts as input to a macroscale hydrologic model to produce runoff and streamflow forecasts at spatial and temporal scales appropriate for water management. Monthly ensemble climate model forecasts produced by the National Centers for Environmental Prediction/Climate Prediction Center global spectral model (GSM) are bias corrected, downscaled to 1/8° horizontal resolution, and disaggregated to a daily time step for input to the Variable Infiltration Capacity hydrologic model. Bias correction is effected by evaluating the GSM ensemble forecast variables as percentiles relative to the GSM model climatology and then extracting the percentiles' associated variable values instead from the observed climatology. The monthly meteorological forecasts are then interpolated to the finer hydrologic model scale, at which a daily signal that preserves the forecast anomaly is imposed through resampling of the historic record. With the resulting monthly runoff and streamflow forecasts for the East Coast and Ohio River basin, we evaluate the bias correction and resampling approaches during the southeastern United States drought from May to August 2000 and also for the El Niño conditions of December 1997 to February 1998. For the summer 2000 study period, persistence in anomalous initial hydrologic states predominates in determining the hydrologic forecasts. In contrast, the El Niño-condition hydrologic forecasts derive direction both from the climate model forecast signal and the antecedent land surface state. From a qualitative standpoint the hydrologic forecasting strategy appears successful in translating climate forecast signals to hydrologic variables of interest for water management. *INDEX TERMS:* 1860 Hydrology: Runoff and streamflow; 1863 Hydrology: Snow and ice (1827); 1836 Hydrology: Hydrologic budget (1655); 1833 Hydrology: Hydroclimatology; *KEYWORDS:* climate downscaling, hydrologic forecast, seasonal forecast, streamflow forecast, eastern United States

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1. Introduction

[2] Great strides have been made over the last decade in understanding climate teleconnections, as manifested by ocean-atmosphere phenomena resulting in large part from thermal inertia of the oceans [see, e.g., *Livezey et al.*, 1997; *Shukla*, 1998; *Koster et al.*, 1999], such as El Niño-Southern Oscillation (ENSO), the Pacific Decadal Oscillation (PDO), and the North Atlantic Oscillation. Exploitation of the understanding of these phenomena has resulted in demonstrable improvements in long-lead (months to years) climate forecasting. These forecasts are based on coupled ocean-atmosphere general circulation models (OAGCMs) [*Barnston et al.*, 1999; *Livezey*, 1990; *Kumar et al.*, 1996; *Livezey et al.*, 1996] or statistical methods such as canonical correlation analysis [e.g., *Barnston and He*, 1996]. A recent trend has been to use ensemble forecasting approaches in which a global land-atmosphere-ocean model (initialized with atmospheric, land surface, and ocean conditions at forecast time) is run into the future for forecast horizons of months to years, using prescribed sea surface temperatures (SSTs) derived using one of a variety of forecast methods. Although the atmosphere is essentially chaotic, the prescribed SSTs effectively constrain the evolution of model forecasts. By perturbing the initial atmospheric conditions and repeating the simulation a number of times, an ensemble of forecasts is constructed which represents the range of

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global atmospheric conditions that may occur over the forecast period.

[3] Much of the research in this area has focused on atmospheric simulation outputs having the large subcontinental region (e.g., the southwestern United States) as the minimum scale, in part because of the long-recognized difficulty of atmospheric models in reproducing observed climate at smaller scales (e.g., $<10^7$ km^2) [*IPCC*, 1996, section 6]. As a result, connecting climate forecasts to the scales and features of the hydrosphere in which human society is often most interested (regional and smaller, for land surface variables) has been problematic. In addition to the scale problem, the land surface variables of greatest interest to society, such as surface precipitation and runoff, are generally predicted less reliably than features of large-scale circulation [see, e.g., *Risbey and Stone*, 1996]. In parallel with global scale predictions, however, a number of downscaling methods have evolved, including dynamical approaches that use finer resolution (mesoscale) atmospheric models [e.g., *Cocke and LaRow*, 2000; *Giorgi and Mearns*, 1991], statistical approaches [*Wilby and Wigley*, 1997; *Wilby et al.*, 1998], and climate-analog approaches [*IPCC*, 1996; *Leung et al.*, 1999; *Georgakakos et al.*, 1998]. Recent comparisons of dynamical and statistical methods are given by *Murphy* [1999] and *Kidson and Thompson* [1998].

[4] At much smaller scales, hydrologists have long been concerned with understanding and reproducing the dynamics of the land surface water and energy balance. Hydrologic study has mostly focused on the local scale of catchments or basins (on the order of 10^2–10^3 km^2) at which water management is effected. Much applied hydrologic prediction work, for instance, efforts to abstract the physics of runoff generation and groundwater behavior, has been intended to benefit water resources end uses, such as irrigation, water supply, hydropower generation, fisheries management, and navigation. An intersection of the interests of hydrologists and climate modelers has occurred over the last decade as the difference in spatial scales has narrowed. While general circulation models now often operate at spatial resolutions of 1–3°, macroscale hydrologic models (e.g., those of *Liang et al.* [1994], *Leavesley and Stannard* [1995], and *Beven and Kirkby* [1979]) have increased in scale and geographical coverage so that modeling of continental scale river basins (e.g., the Columbia, the Mississippi) is now possible. Furthermore, the land surface parameterizations in coupled land-atmosphere-ocean models increasingly resemble or borrow from macroscale hydrology model representations, and vice versa [*Koster et al.*, 2000; *Ducharne et al.*, 2000]. In consequence an operational linkage of hydrologic and climate forecasting models is now being pursued at a number of research centers.

[5] Although the motivation for development of macroscale hydrologic models has been in part to improve representation of the land surface in coupled land-atmosphere-ocean models, they can also be implemented using one-way forcing from OAGCMs, such as ensemble climate forecasts. While conceptually simpler than operation in a fully coupled mode, the one-way linkage is still hampered by the need to address regional biases in OAGCM climate simulation outputs. These biases are substantial enough to preclude direct use in hydrologic modeling of OAGCM output fields such as surface precipitation and temperature [*Leung et al.*, 1999; *Chen et al.*, 1996; *Roads et al.*, 1999].

[6] Hydrologists have tended to surmount this difficulty using simple strategies such as OAGCM-conditioned compositing, in which OAGCM output is used to guide the construction or weighting of an ensemble of historically observed meteorological time series, which subsequently is used as input to a hydrologic model [e.g., *Georgakakos et al.*, 1998; *Leung et al.*, 1999]. In theory, at least, the probabilistic assessment of differences between streamflow ensembles resulting from these hydrologic simulation and streamflow ensembles based on observed climatology (inputs without conditioning) may then support recommendations for operational decisions by water resources system managers. A variation on this approach is to derive the conditioning signal from a typecast of the present year related to SST-classified climate modes. *Hamlet and Lettenmaier* [1998, 1999], for instance, demonstrated a simplified method of long-range forecasting (up to a 1-year lead) for the Columbia River basin. The method utilized resampling of previous observed hydrometeorological data for years with apparently analogous climatic characteristics, determined by ENSO- and PDO-based compositing. The shortcoming of this method is that it requires partitioning of the historic record into climate categories, which can result in statistical problems when the number of years in a given class is small. Furthermore, there is an implicit assumption that the classification method is stable over time.

[7] One-way climate model-hydrology model linkages were explored by *Kim et al.* [2000], who applied a mesoscale regional climate model over northern California for downscaling one member of an OAGCM-based 3-month forecast ensemble during the 1997–1998 El Niño event. Using the spatially distributed TOPMODEL [*Beven and Kirkby*, 1979] for hydrologic simulation, they found that the largest hydrologic forecast errors resulted from general circulation model (GCM) errors in precipitation prediction. For a smaller catchment in Colorado, *Wilby et al.* [2000] compared statistical and dynamical downscaling methods, using a regional climate model, for translating National Centers for Environmental Prediction (NCEP)/National Center for Atmospheric Research (NCAR) reanalysis [*Kalnay et al.*, 1996] output into local precipitation and temperature forcing time series for a hydrologic model. Their results underscored the need for bias correcting climate model outputs and confirmed the view that while statistical and dynamical approaches yield similar downscaling skill, statistical techniques are less computationally demanding.

[8] This paper describes an exploratory hydrologic forecast system that uses monthly ensemble climate forecasts of monthly total precipitation (P_{tot}) and monthly average temperature (T_{avg}) for 6-month lead times produced by the NCEP global spectral model (GSM), an OAGCM. We test a relatively simple approach for linking global ensemble forecasts from coupled ocean-land atmosphere models with macroscale hydrologic models, with the intent of improving hydrologic prediction capabilities for soil moisture, runoff, and streamflow.

[9] The region chosen for the study was the eastern United States, defined as the area east of the Mississippi

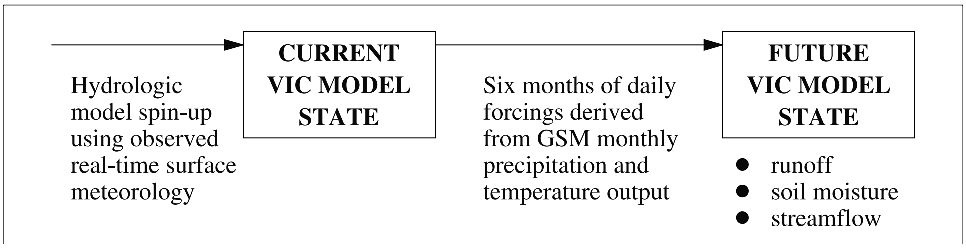

Figure 1. Experimental long-lead hydrologic forecasting approach.

River drainage plus the Ohio River basin but excluding the Laurentian Great Lakes basin, for a forecast period from May to October 2000. This period was selected because a severe drought was anticipated for the southeastern United States as a result of much below normal soil moisture and streamflow during late winter and early spring 2000 (reflected as early as December 1999 in federal agency outlooks such as the National Drought Mitigation Center's weekly Drought Monitor and the Climate Prediction Center's U.S. Drought Monitor). During this period, SST anomalies in the tropical Pacific were returning to near normal from a prior ENSO cold phase (La Niña) episode. Lingering effects of the cold phase, which in the southeastern United States have been correlated with dryness, had the potential to compound the existing soil moisture deficits. We also evaluated the method for a study period (beginning in November 1997) during which SST anomalies reflected a strong El Niño event.

2. Approach

[10] Our forecast approach uses GSM's surface forecast fields (P_{tot} and T_{avg}) to create daily forcing ensembles for the Variable Infiltration Capacity (VIC) macroscale physical hydrology model. Hydrologic model forecasts are produced by first initializing VIC model states with a spin-up period based on observed meteorology prior to the start of forecast and then driving the model with ensemble forecast meteorology through the end of the forecast period. This basic framework is illustrated in Figure 1.

2.1. Global Spectral Model Ensemble Generation

[11] Each month, NCEP's Climate Modeling Branch generates a 20-member ensemble of 6-month lead climate forecasts, simulated with GSM. The forecasts are accompanied by a 210-member ensemble of climate hindcasts (also 6 months long, matching the calendar months of the forecasts) representing the period 1979–1999 (21 years). The 20 forecast ensemble members are produced by using 20 different atmospheric initializations with predicted SSTs in the tropical Pacific Ocean as of the date of the forecasts. The hindcast ensemble generation process is similar, except that the ensemble members are produced by using 10 different atmospheric initializations with observed SSTs for each of the 21 years in the 1979–1999 hindcast. The different atmospheric initializations are in each case drawn from a sequence of atmospheric analysis fields at the beginning of the forecast initialization month (the month prior to the 6-month forecast period), spaced 12 hours apart. This process is repeated every month, and P_{tot} and T_{avg}, among other variables, are archived. In the forecast runs, predicted SSTs over the tropical Pacific domain are specified on the basis of the NCEP OAGCM [*Ji et al.*, 1998]. At the time of our research, GSM forecasts were run at T42 horizontal resolution (2.8125° latitude/longitude).

[12] GSM is actually run at time steps on the order of an hour or less, and therefore in principal the temporal disaggregation is not necessary. Use of monthly ensembles, however, greatly reduces the data distribution and handling overhead. Because our downscaling approach (section 2.3.2) imposes plausible daily temporal structure onto the monthly GSM forecast products as part of the same process that spatially disaggregates the GSM products to 1/8° spatial resolution, the use of the monthly GSM output is not only adequate for purposes of our hydrologic forecast objectives but also streamlines the process considerably.

2.2. VIC Macroscale Hydrology Model

[13] The VIC model [*Liang et al.*, 1994, 1996, 1999] is a semidistributed, grid-based hydrological model that parameterizes the dominant hydrometeorological processes taking place at the land surface-atmosphere interface. A mosaic representation of land surface cover and parameterizations for infiltration and the spatial variability of precipitation account for subgrid scale heterogeneities in key hydrological processes. The model uses three soil layers and one vegetation layer, with energy and moisture fluxes exchanged between the layers. The model has been applied to such large continental rivers as the Columbia [*Nijssen et al.*, 1997], the Arkansas-Red [*Abdulla et al.*, 1996], and the Mississippi [*Maurer et al.*, 1999; *Cherkauer and Lettenmaier*, 1999], and, as part of the Land Data Assimilation System (LDAS) project [*Mitchell et al.*, 2000], to the continental United States [*Wood et al.*, 1998]. A more complete description of model processes is given by *Liang et al.* [1994, 1996]. Runoff generated within a grid cell is routed to the stream gauge locations using methods described by *Lohmann et al.* [1998a, 1998b]. The VIC model uses vegetation and soil parameters produced for use by LDAS and described by *Maurer et al.* [2001].

2.2.1. Forcings

[14] VIC model forcings are used both in driving the hydrologic model during a 1-year spin-up period, and, via resampling, in assembling the daily forecast sequences. Because the meteorological variables most widely available in long-term data archives are daily precipitation and daily temperature minimum and maximum, we estimate most of the other forcing variables required by the VIC model (e.g., downward solar and longwave radiation,

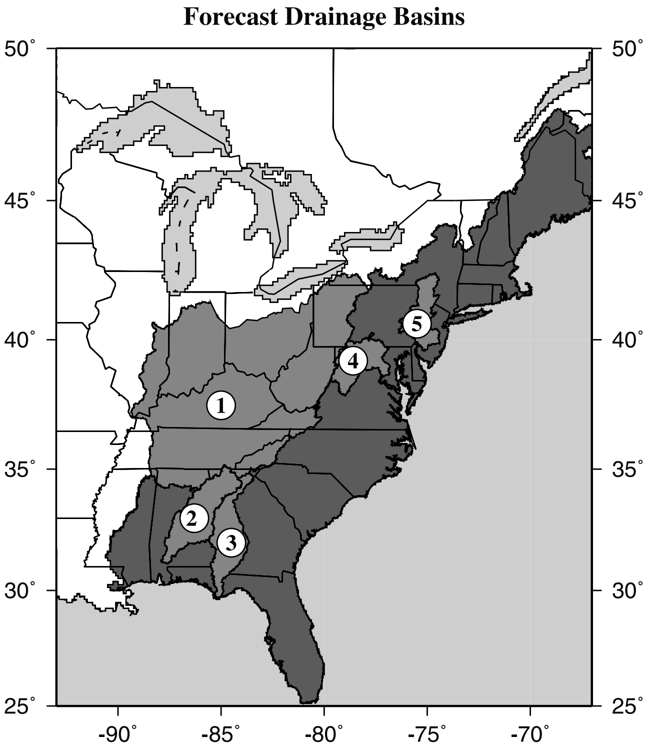

Figure 2. Hydrologic forecasting model domain, including the Ohio River basin (light gray) and the east coast drainages (dark gray). Runoff in numbered basins was routed to produce streamflow: (1) Ohio; (2) Alabama-Coosa-Tallapoosa (ACT); (3) Apalachicola-Chattahoochee-Flint (ACF); (4) Potomac; and (5) Delaware River.

humidity) from this minimum set of variables using methods described by *Maurer et al.* [1999]. Wind speed data are taken from the NCEP/NCAR reanalysis [*Kalnay et al.*, 1996], which are available to within a month of real time. The observational data are typically taken from National Climatic Data Center (NCDC) Cooperative Observer (Co-op) Stations, which are available on the Web within 2–4 months of real time. For real-time data (bridging the gap between the end of the available Co-op data and the forecast date), we used data available from the LDAS project. The LDAS precipitation data are so-called Stage IV observations, a combination of radar and station data produced by NCEP. Temperature data are from the Eta Data Assimilation System (EDAS) and are essentially an analysis product from the NCEP Eta weather forecast model run over the continental United States. LDAS also produces a real-time wind data set (another EDAS product). All LDAS data are produced on a geographic 1/8° grid, for the area from latitude 25°N–53°N, longitude 67°W–125°W. Typical monthly biases in this product revealed by our preliminary verification were a spatially averaged (over the study domain) bias of −5% in monthly precipitation totals, −1.5°C in average maximum temperature, and +1.5°C in average minimum temperature. LDAS wind speeds appear to be significantly higher than those produced by the NCEP/NCAR reanalysis, although recent EDAS modifications appear to have reduced the discrepancy somewhat. Currently, we use the LDAS product without adjustment.

2.2.2. Eastern U.S. Application

[15] The VIC model was implemented at 1/8° latitude/longitude resolution (~150 km^2 cell area) over the domain shown in Figure 2. The domain includes the Ohio River basin, which drains the easternmost portion of the Mississippi River basin, and an east coast region which includes 24 coastal drainage basins, 17 of which flow east-southeast to the Atlantic Ocean and 7 of which drain southward to the Gulf of Mexico. Within the model domain, runoff in smaller subbasins was routed to produce streamflow estimates at U.S. Geological Survey (USGS) river-gauging station locations.

[16] The Ohio River basin and east coast models simulate areas of ~600,000 and 1.1 million km^2, respectively. Subbasins calibrated for streamflow forecasting included the Ohio River, the Delaware River, the Potomac River, the Apalachicola-Chattahoochee-Flint (ACF) River system and the Alabama-Coosa-Tallapoosa (ACT) River system. Principal streamflow routing nodes were the Apalachicola River at Sumatra, Fla. (USGS station 12359170), the Alabama River at Claiborne Lock and Dam near Monroeville, Ala. (USGS station 02428400), the Potomac River near Washington, D.C., Little Falls (USGS station 01646500), the Delaware River at Trenton, N.J. (USGS station 01463500), and the Ohio River at Metropolis, Ill. (USGS station 03611500).

[17] The model-forcing data spanned the period 1950-current, where the current date evolved during the experiment. Model calibration was accomplished by varying parameters related to infiltration and subsurface drainage, with the aim of reproducing monthly streamflow volumes while preserving the general features of the daily response (e.g., daily average flow peaks and recessions). Sample calibration results are shown in Figure 3.

2.3. Hydrologic Forecasting Approach

[18] To translate long-range climate predictions to the realm of hydrology, regional biases and the temporal and spatial scale mismatch between models must be resolved. This section describes our bias-correction and downscaling approach and its demonstration as a proof of concept exercise.

2.3.1. Unbiasing of Climate Model Ensembles

[19] The premise of the bias correction step is that despite biases in GSM-simulated climate, the GSM forecasts may have a useful signal if interpreted relative to the GSM climatology rather than the observed climatology. The GSM climatology is defined by the monthly distributions (for months 1–6 in the forecast period, separately) of simulated GSM P_{tot} and T_{avg} taken from the GSM hindcast simulations (i.e., the 210 simulated values for each of the 6 forecast period months, for each variable). The monthly observed climatology spans the same time period as the GSM output (1979–1999) and was created from Co-op station daily observations averaged to a monthly timestep and to the GSM grid resolution; hence the observed monthly distributions for P_{tot} and T_{avg} are defined by only 21 values per variable. Bias correction is achieved by replacing GSM forecast values for T_{avg} and P_{tot} with values having the same percentiles (nonexceedence probabilities) with respect to the observed climatology that the original

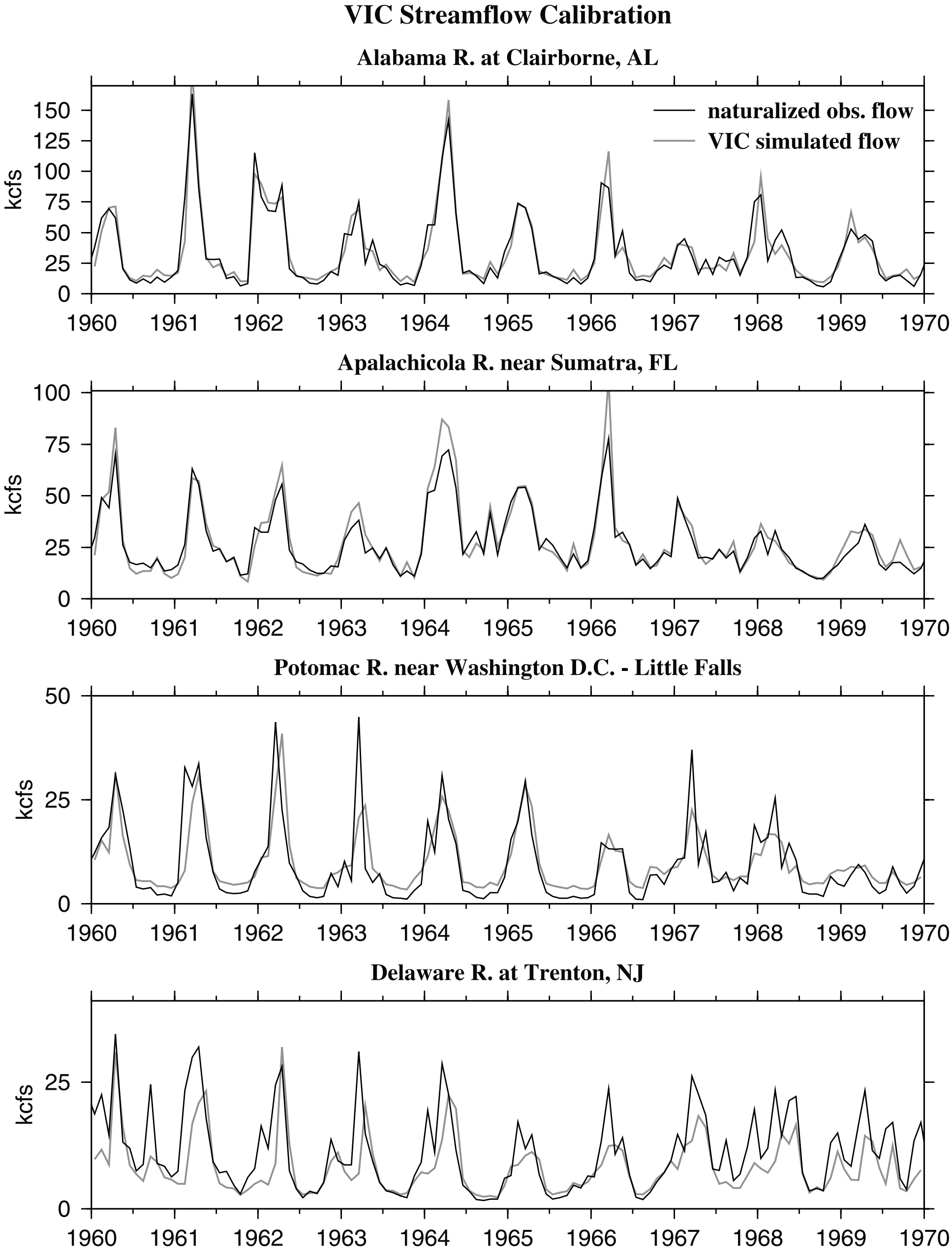

Figure 3. Calibration results for four streamflow forecasting basin gauging locations.

GSM values had with respect to the GSM climatology, for a given month. The forecasts are subsequently expressed as anomalies (temperature shift and precipitation percentage) with respect to the observed monthly means for the 21-year climatology period. Bias correction is performed at the GSM scale, and each GSM cell (23 cells spanned the study region) is treated individually, defining its own set of monthly distributions.

[20] For example, bias correcting a monthly T_{avg} forecast for January–June requires the following steps: (1) The January GSM T_{avg} is assigned a nonexceedence probability (or percentile) within the 210-value GSM climatology distribution for January T_{avg}. (2) A January T_{avg} having the same nonexceedence probability in the observed climatology is then calculated. (3) Steps 1 and 2 are repeated for T_{avg} in months February–June, and the entire process is repeated for each of the ensemble forecast members. (4) Finally, the bias-corrected forecasts are expressed as additive (for T_{avg}) and multiplicative (for P_{tot}) anomalies.

[21] In the precipitation and temperature bias correction scheme, when either the GSM output or the associated percentile falls above or below the range of empirical Weibull percentiles (equal to $1/(N + 1)$ and $N/N + 1$, where N is the number of members from which the probability distribution is estimated), theoretical probability distributions are fit to the data to extend the empirical distributions. This becomes necessary because the historical climatology is defined by the 21 years of historical observations, whereas the model ensembles consist of a larger 210-member data set. For low precipitation, an Extreme Value Type III (Weibull) function

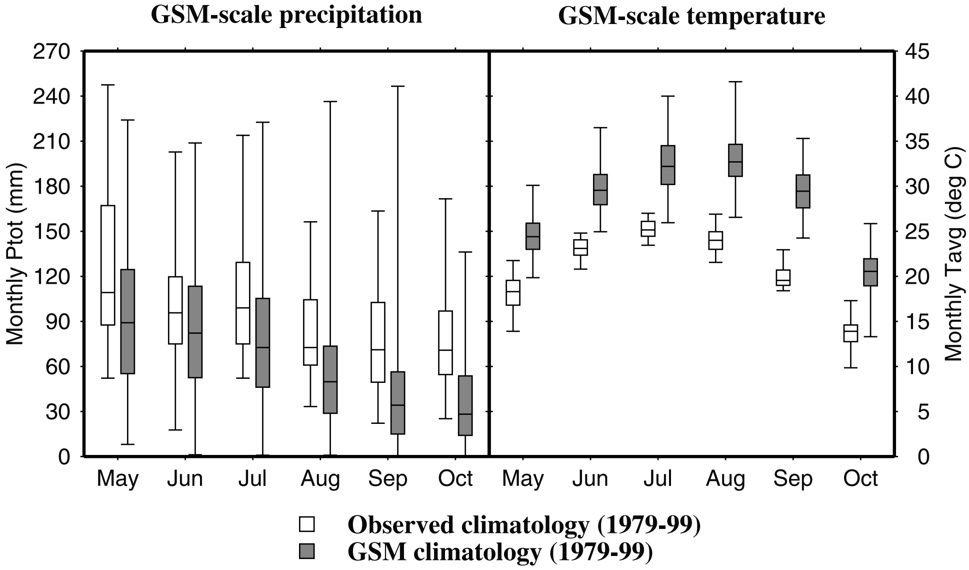

Figure 4. April 2000 global spectral model (GSM) climatology for monthly total precipitation and average temperature, compared with observations averaged over the corresponding geographic area. The data are for the GSM computational cell centered on latitude 37.97°N, longitude 87.19°W, in the Ohio River basin.

was used, with a minimum lower bound of zero; whereas for extreme high precipitation an Extreme Value Type I (Gumbel) distribution was employed. For temperature, a normal distribution was used for both minimum and maximum.

[22] The need for bias correction is demonstrated by an example that compares GSM's precipitation and temperature climatology for one typical cell (centered on latitude 37.97°N, longitude 87.19°W, in the Ohio River basin) with observed values (Figure 4). As alluded to in the introduction, biases of the magnitude shown (e.g., up to 15°C for T_{avg} in August) are occasionally found in climate model simulations of surface variables, particularly if one examines the output for individual cells rather than for a region or continent. The lack of agreement with observations stems in part from poor climate model resolution of subgrid scale land surface related heterogeneities, such as orography or soil wetness. Such biases preclude the use of the climate model output as a direct input to the hydrology model.

2.3.2. Downscaling of Long-Range Ensemble Forecasts

[23] Following bias correction, the monthly GSM scale forecast anomalies are translated to the spatial and temporal scale of VIC model inputs. The T_{avg} and P_{tot} anomalies are spatially interpolated to the 1/8° VIC cell centers and applied to the monthly observed 1979–1999 1/8° cell means (derived from Co-op station observations as described in section 2.2.1), to create monthly forecast sequences at the VIC model scale, in the following manner:

$$T_{\mathrm{VICfcst}}(m,e) = T_{\mathrm{VICmean}}(m) + T_{\mathrm{ANOMfcst}}(m,e)$$

$$P_{\mathrm{VICfcst}}(m,e) = P_{\mathrm{VICmean}}(m) \times P_{\mathrm{ANOMfcst}}(m,e).$$

Here $T_{\mathrm{VICfcst}}(m, e)$ is the forecast monthly T_{avg} for a given VIC cell in month m (m = 1–6) of a forecast ensemble member e (e = 1–20). $T_{\mathrm{VICmean}}(m)$ is the observed 1979–1999 mean T_{avg} for month m, and $T_{\mathrm{ANOMfcst}}(m, e)$ is the additive T_{avg} forecast anomaly for month m and ensemble member e. Likewise, $P_{\mathrm{VICfcst}}(m, e)$ is the forecast monthly P_{tot} for a given VIC cell in month m of a forecast ensemble member e, $P_{\mathrm{VICmean}}(m)$ is the observed 1979–1999 mean P_{tot} for month m, and $P_{\mathrm{ANOMfcst}}(m, e)$ is the multiplicative P_{tot} forecast anomaly for month m and ensemble member e. The addition of temperature anomalies will hereafter be referred to as shifting, and the multiplication by precipitation anomalies will be referred to as scaling.

[24] The final step in preparing the forecasts for input to the VIC model is to replace the monthly mean sequences by daily sequences. For each month (e.g., January) in each forecast ensemble, one year from the climatology period is randomly selected (e.g., 1988). For each VIC cell, the observed daily values of precipitation for the selected year and month (e.g., 1988, January) are scaled so that the monthly total precipitation is equal to the forecast P_{tot} for the ensemble member and month. The resulting values of daily precipitation become the daily sequence for that month of the particular forecast ensemble member. Daily T_{min} and T_{max} from the same selected year (e.g., 1988) are shifted equally so that their average, $(T_{min} + T_{max})/2$, reproduces the monthly forecast T_{avg} for the ensemble member and month, and the resulting values of T_{min} and T_{max} become the daily sequence for that month of the particular forecast ensemble member. Daily wind speed is taken without adjustment from the VIC daily values for the selected year and month, forming the fourth daily forcing used by the VIC model. The same year is used to select the daily data for a given month of an ensemble forecast member in every cell of a study area (the Ohio River basin and east coast). Using the same year-month combination for resampling over the large-scale hydrologic units helps to preserve a degree of spatial synchronization in the

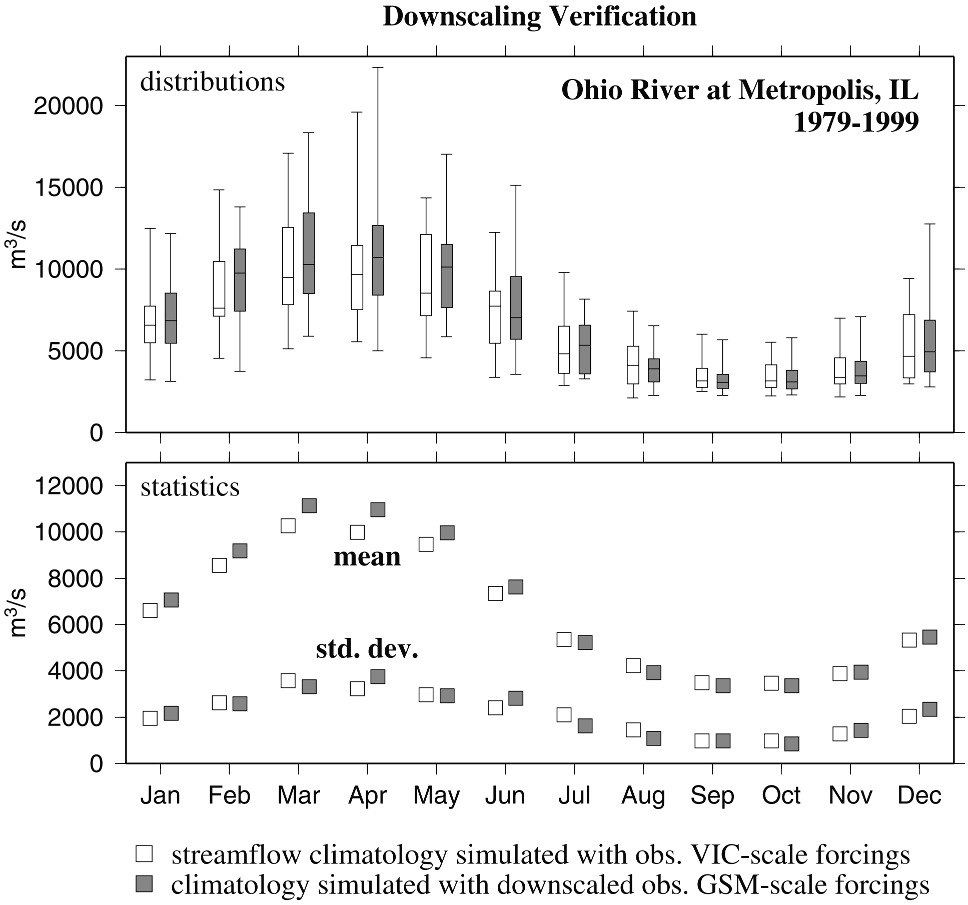

Figure 5. Climatology period (1979–1999) streamflow distribution simulated from daily variable infiltration capacity (VIC) 1/8° observations, compared with a parallel simulation from monthly GSM-scale (2.8125°) spatially averaged observations, after the downscaling and disaggregation procedure.

weather components driving hydrologic response. The random sampling of a climatology year for selection of daily sequences is repeated for each month in each forecast ensemble member.

[25] We performed a test of this method using observed total monthly precipitation and average temperature timeseries for 1979–1999, aggregated to the GSM scale, as raw forcings over the Ohio River drainage area. These large-scale forcings were processed (using the interpolation and temporal disaggregation steps) into daily VIC scale forcings, with which we simulated streamflow. Figure 5 shows that the method is able to reproduce the mean and variance of the basin streamflow climatology without introducing substantial method-related bias.

2.3.3. Producing Hydrologic Forecasts

[26] Near the tenth day of each month the GSM ensemble forecasts become available, and we process the monthly GSM output into format suitable for input to VIC. By the twentieth day of the month, during the period April–September 2000, the hydrology model state was initialized through that current date using a 1-year spin-up simulation, the forcings for which were the gridded observational data described in section 2.2.1. Once the current hydrology model moisture states were obtained, the 20 forecast ensemble members were run to produce an ensemble of six month long hydrologic forecasts, beginning the following month.

[27] In addition to the forecast ensemble, we also generated a hydrologic ensemble hindcast by applying the procedures described in sections 2.3.1–2.3.2 to the ensemble members of the GSM hindcast in place of the forecast. This hydrologic ensemble hindcast yields a hydrologic climatology for 1979–1999 derived by the methods used to derive the hydrologic ensemble forecast. Rather than comparing the forecast ensemble results directly with the empirial probability distribution of observed streamflow or of model-simulated fields (e.g, grid cell runoff or soil moisture) based on observations, we compared the hydrologic ensemble forecasts with the hydrologic ensemble hindcast. In this experiment, we wanted to ensure than any incidental forecast error associated with the approach would also arise in the climatology distributions with which the forecasts were compared. Upon completion of each forecast or hindcast run, monthly total precipitation, evaporation and runoff (surface plus base flow), and monthly average soil moisture and temperature were archived, and the daily streamflow routing was performed for the selected subbasins (shown in Figure 2).

2.3.4. Retrospective ENSO Event Forecast Simulation

[28] As an additional test of the method, we performed a retrospective comparison of the 10-member hindcast ensemble associated with the November 1997 SSTs (just prior to the strong 1997–1998 El Niño), which was extracted from

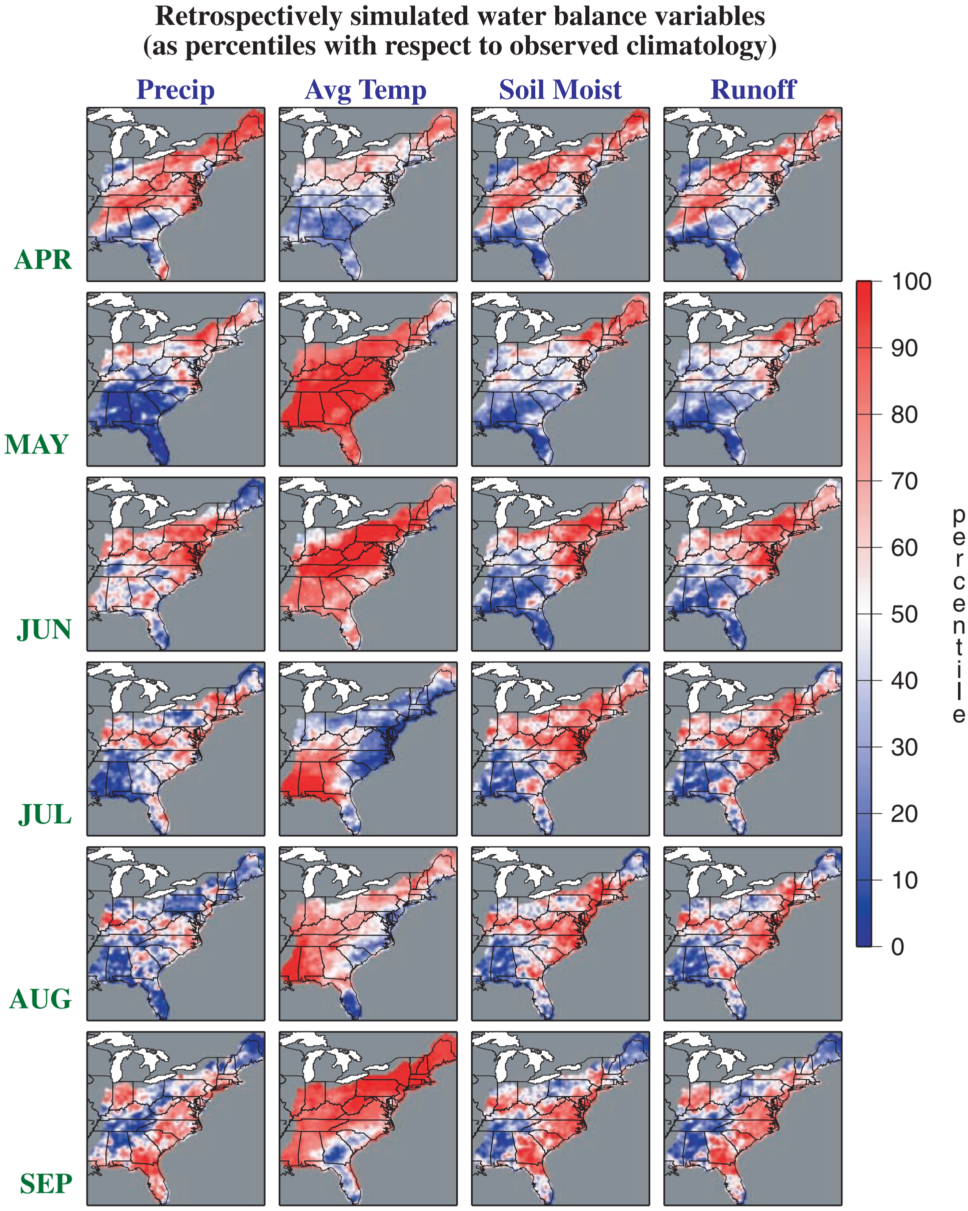

Figure 6. Observed climatology for April through September 2000, defined as the monthly gridded observations of total precipitation and average temperature, and associated simulated analyses of average soil moisture and total runoff. These are shown as percentiles of the variables' observed and simulated (21 year) climatological distributions, respectively.

the 210-member climatology ensemble for November. The purpose of this analysis was to evaluate forecast performance made from a month exhibiting strong SST anomalies in the tropical Pacific Ocean, that is, conditions favorable for skillful climate forecasting. The NINO3 index, which measures the deviation from normal of the sea surface temperature in the eastern Pacific, and which is high during an El Niño event, reached its highest value in decades in winter 1997. We treated the 10-member ensemble for 1997 as a surrogate for an actual forecast made at that time, even though the SSTs used in the hindcast from which it was drawn were prescribed according to observations, rather than projected. In that particular month, however, forecast skill for tropical Pacific SSTs was relatively high; thus the prescribed SSTs and forecast SSTs would not have differed as greatly as in other periods. The hydrologic forecast ensemble based on the 10-member El Niño ensemble members was compared with ensembles yielded from use of the entire 210-member November hindcast.

3. Results

[29] We evaluated the results of the experiment using two types of output: (1) spatially distributed variables such as surface forcings, hydrologic model runoff, and soil moisture and (2) streamflow at selected locations. These outputs were generated for the six monthly forecast dates beginning in April 2000. We report here a representative sample of the

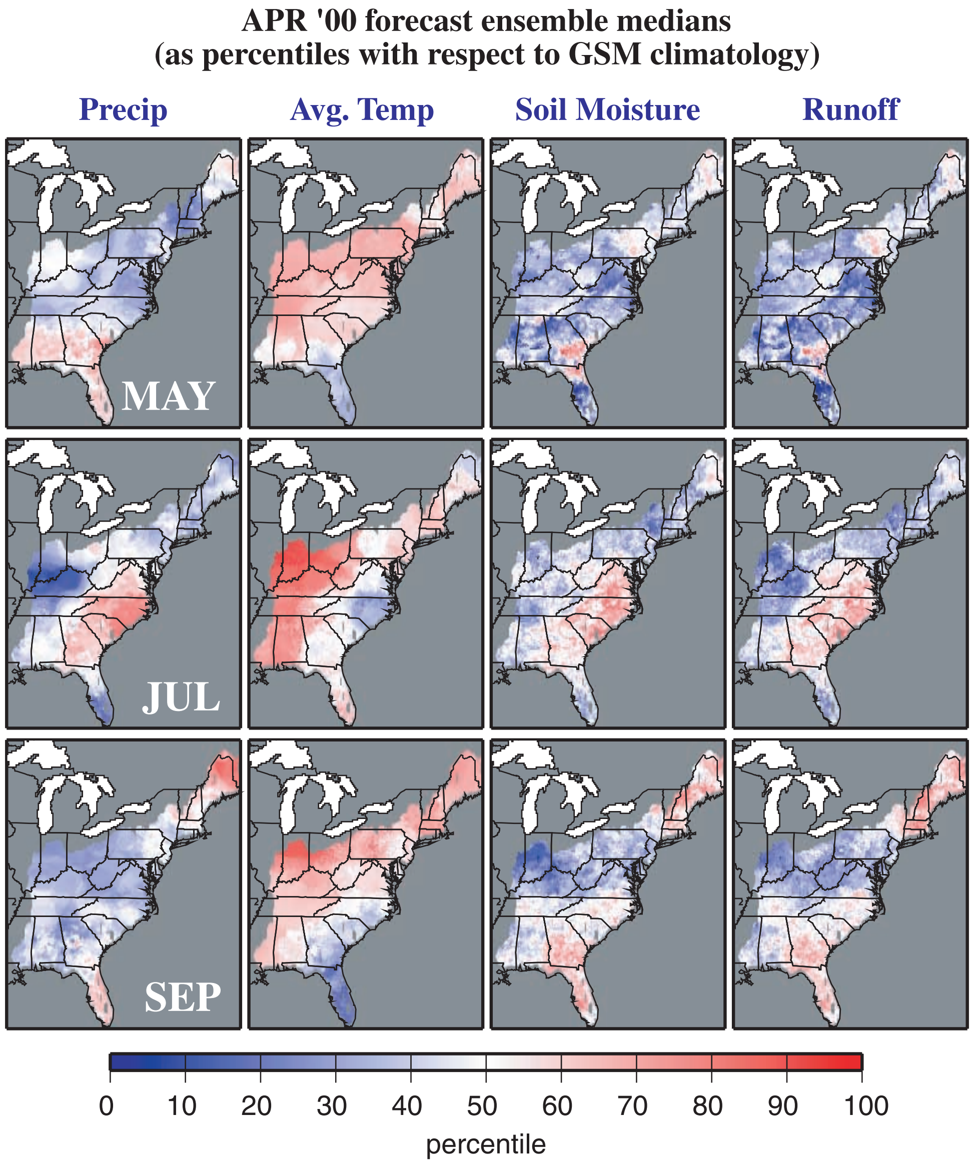

Figure 7a. April 2000 GSM forecast ensemble medians for May, July, and September monthly total precipitation and average temperature and GSM forecast-based (VIC simulated) ensemble medians of average soil moisture and total runoff, shown as percentiles of the 21-year GSM hindcast climatology distribution for each respective variable.

forecast results for three starting dates, 20 April, 20 June, and 20 August, and observed conditions for May, July, and September. For spatial forecast results the forecast ensemble medians are plotted as a percentile of GSM climatology ensembles derived from GSM hindcasts. These percentiles are verified against the observation-based, retrospective forecast fields, shown as percentiles of the observation-based, retrospective climatology. For streamflow forecast results, GSM forecast and hindcast (climatology) distributions (discussed in section 2.3.3) are shown, in addition to observations that have become available since the forecasts were made.

3.1. Spatial Analyses

[30] Figure 6 shows observation-based gridded precipitation and temperature fields and corresponding simulated soil moisture and runoff. Data and model deficiencies notwithstanding, these are treated as surrogate observations for the summer 2000 period. The broad features of the results for simulated soil moisture and runoff are consistent with the signals in precipitation and temperature, modulated by the simulated antecedent soil moisture conditions (characterized by general deficits in the southeast throughout the study period). Soil moisture and runoff percentiles were quite similar, which reflects the VIC model tendency for precipitation inputs to elevate runoff and base flow in concert with soil moisture, especially considered from a monthly standpoint. Against these we contrast Figures 7a and 7b, which show GSM-based forecasts of the same fields.

[31] In the observational analyses, extremely low May precipitation coupled with high temperatures deepened drought conditions throughout the Ohio River valley and

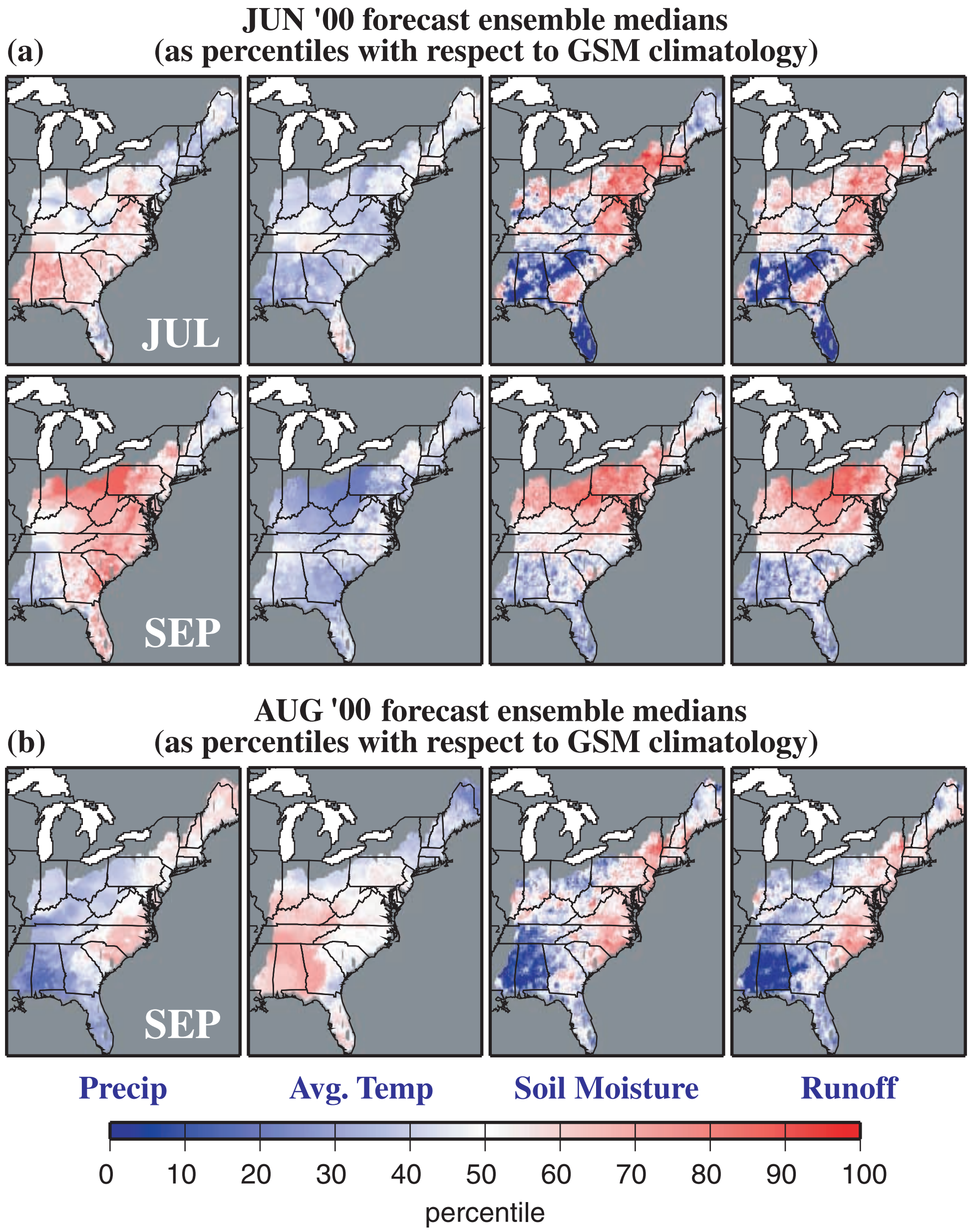

Figure 7b. (a) June and (b) August 2000 GSM forecast ensemble medians for July and September monthly total precipitation and average temperature and GSM forecast-based (VIC simulated) ensemble medians of average soil moisture and total runoff, shown as percentiles of the 21-year GSM hindcast climatology distribution for each respective variable.

southeast, while the northeastern United States experienced slightly higher than average precipitation (with respect to the 1979–1999 climatology) (Figure 6). By July, temperatures along the east coast and the northern Ohio River valley were cooler, and precipitation had risen to above normal in many locations, while the relative dryness and heat persisted from the Gulf Coast to the southern Ohio River valley. September brought high temperatures everywhere except Florida and Georgia, and the region of low precipitation shifted north, while the drought eased along the Gulf Coast. In response to these forcings, anomalously low soil moisture and runoff, which had been general over the entire domain south of New England, recovered gradually along the east coast and the northern Ohio River valley. The center of the drought-stricken region, which initially included Florida, shifted west toward Alabama and Louisiana.

[32] The April ensemble forecasts (spanning the period May–October) showed above-normal precipitation in the southeastern United States in May and on the east coast (excepting Florida) in July, but then it showed slightly below-normal precipitation everywhere except Florida in September (Figure 7a). The median forecast was for temperatures slightly above normal everywhere except Florida in May, then for temperatures more strongly above normal west of the Atlantic states in July and September. Normal to cool conditions were forecast in the Atlantic states during the study period. Consequently, initially dry soil moisture and below-normal runoff were predicted to recover (at least in

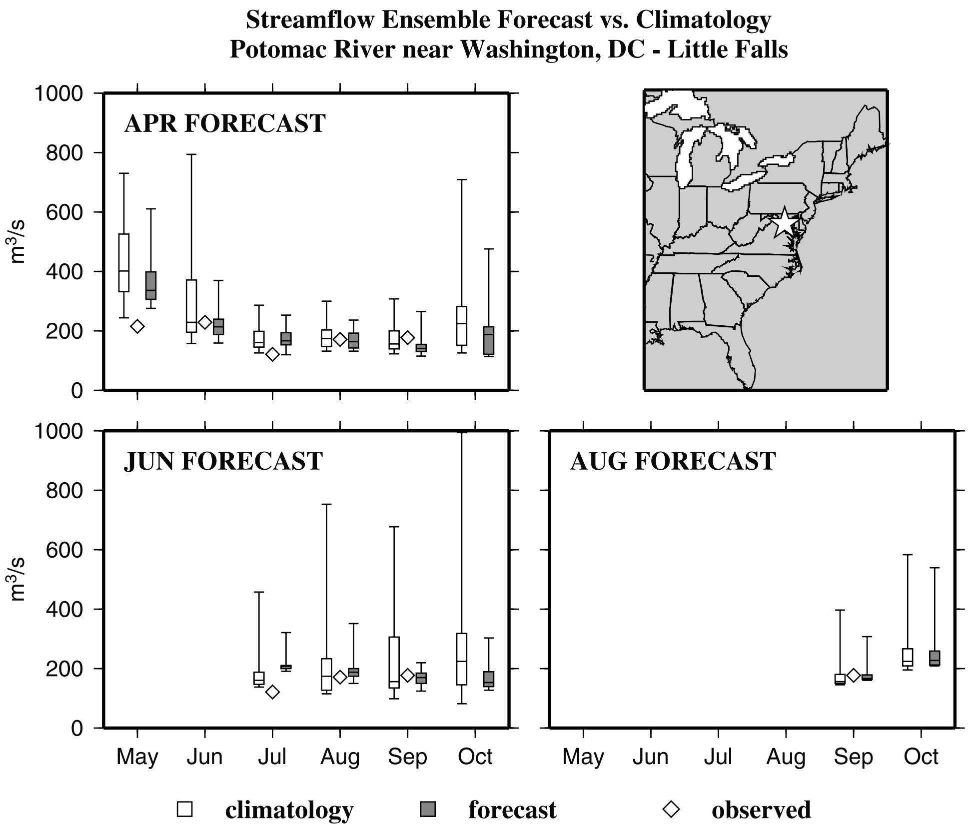

Figure 8. April, June, and August 2000 monthly average streamflow forecast and hindcast (climatology) ensembles compared with observed values, for the Potomac River near Washington, D.C., Little Falls (location shown in the upper right).

the median forecast) in Florida and the mid-Atlantic states by July but to linger in parts of Alabama and Louisiana. In southern New England and the Ohio River valley, however, the median forecast called for a continuation of dryness and heat and hence low soil moisture and runoff.

[33] The June forecasts (Figure 7b, top, shows July and September) anticipated, in the median, above-normal precipitation in the southeastern United States in July and on the East Coast and Ohio River valley (except in New England) in September and cooler temperatures everywhere in both months. Even so, the forecasts indicated that the dry soil moisture and below normal runoff would fail to recover fully in the southern and Gulf states, while in southern New England and the Ohio River valley, they would to transition to above-normal levels.

[34] The median August forecasts (Figure 7b, bottom, for September) called for dry and hot conditions in Florida, the Gulf states, and the Ohio River valley, with above-normal precipitation and cooler to normal temperatures from the mid-Atlantic states to New England. These circumstances would serve to aggravate the low August soil moisture centered on Alabama.

3.2. Streamflow Evaluation

[35] Predicted streamflows reflected the condition of soil moisture and runoff, although the deviation from normal was generally small relative to the variability exhibited by both the climatological and forecast ensemble distributions. Figures 8 and 9 show the location of the streamflow sites (upper right) and the forecast to climatology ensemble comparisons for the same three forecast start dates detailed in Figure 7.

[36] Figure 8, for the Potomac River near Washington, D.C., Little Falls, shows forecast streamflow distributions for the April forecast which are similar to the hindcast climatology distributions but a bit lower in May and September, when it can be seen from Figure 7a that the entire watershed is drier than normal. The observed streamflows in May were lower than either distribution suggested, but the forecast correctly indicates the direction of the anomaly. In June and August the forecasts and climatology distributions have similar medians except for July streamflow in the June forecast, when the forecast is erroneously higher, reflecting the above-normal precipitation forecast. The forecasts in June and August agree fairly well with observations, which were not far from normal for the June to September period.

[37] In Figure 9, showing the April forecast for the Alabama River at Claiborne Lock and Dam, the forecast ensemble distributions are slightly lower than the climatology ensembles in the first 2 months of the forecast period but thereafter are similar. The forecasts give a slight indication that streamflows will be low early in summer but give no indication of the severity of the streamflow anomaly that is observed. This result is consistent with the above-normal simulated antecedent soil moisture for April (Figure 6) in half of the watershed and the forecast of above-normal precipitation in July (Figure 7a). Subsequent

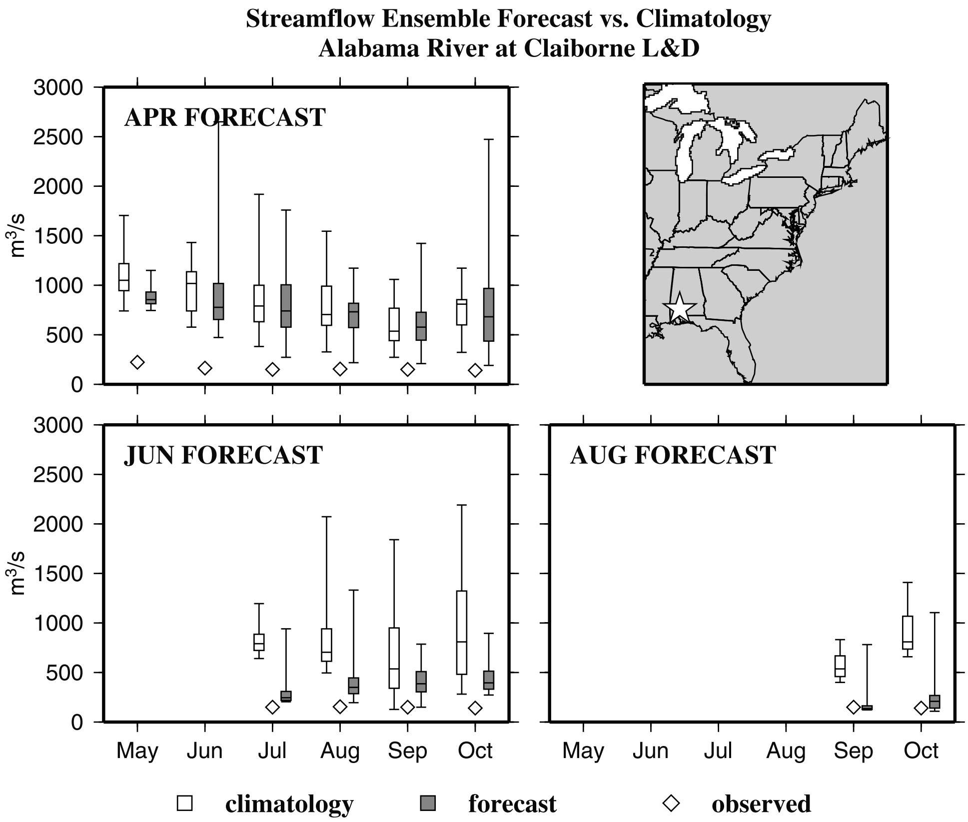

Figure 9. April, June, and August 2000 monthly average streamflow forecast and hindcast (climatology) ensembles compared with observed values, for the Alabama River at Claiborne Lock and Dam, Ala. (location shown in the upper right).

forecasts in June and August, however, are significantly lower than the climatology ensemble distributions, responding to the dry initial conditions for those forecasts (Figure 6) and near- or below-normal precipitation thereafter (Figure 7b). The June and August forecasts distinctly anticipated the severe declines in summer streamflow that were observed.

3.3. El Niño Period Forecast Results

[38] Consistent with the expectation of an anomalously wet winter season in the southeast associated with the El Niño climate phase [*Changnon*, 1999; *Barnston et al.*, 1999], the gridded observed precipitation and temperature and associated hindcast hydrologic simulations of soil moisture and runoff for November 1997 (not shown here) showed wetter than normal (again, with respect to the 1979–1999 climatological period) precipitation in the southeastern United States and the Atlantic drainages, with drier than average conditions in the Ohio River basin, a pattern echoed in the relative soil moistures and runoff. At the same time, temperatures throughout the study domain were relatively and uniformly cool. In December, the southeastern states were again very wet while the rest of the domain received about normal precipitation, and the entire region was still relatively cool, but less so than in the previous month. In January through March, the entire domain received above-average precipitation, but by April drier weather appeared to move north from Florida, eventually extending to the entire southeast. During this time, with the exception of a cool March in the southeast, temperatures were mostly above normal throughout the domain. The net result for soil moisture and runoff for fall and winter 1997–1998 was wetter than average in the southeastern United States and along the east coast, with the largest soil moisture anomaly in the southeastern United States in December 1997 to March 1998 and in the northeastern United States in March and April 1998.

[39] The spatial (perfect SST) forecasts made in November 1997 appear to correctly indicate the direction of soil moisture and runoff anomalies; that is, the median forecast was for wetter than normal conditions. Exceptions were the northeastern United States and the Ohio River basin, where the median forecasts were wetter than average as early as December 1997 and drier than average in April and May 1998, whereas the retrospective analysis showed the opposite condition. Also, the forecast percentiles tended toward the median relative to the hindcast percentiles, perhaps as a result of the finer resolution afforded the probability scale by the use of 210 ensemble members for the climatology compared with the 21 ensemble members used to provide statistical context for the forecasts. A comparison of months 1–3 (December 1997 to February 1998) of the hindcast and the forecast is shown in Figure 10.

[40] A sample of streamflow results for the El Niño period forecast is given in Figure 11 for the Potomac River near Washington, D.C., Little Falls. The Potomac River watershed's slightly below-normal precipitation in December and near-normal soil moisture (Figure 10) led to a forecast ensemble with a similar median to the climatology

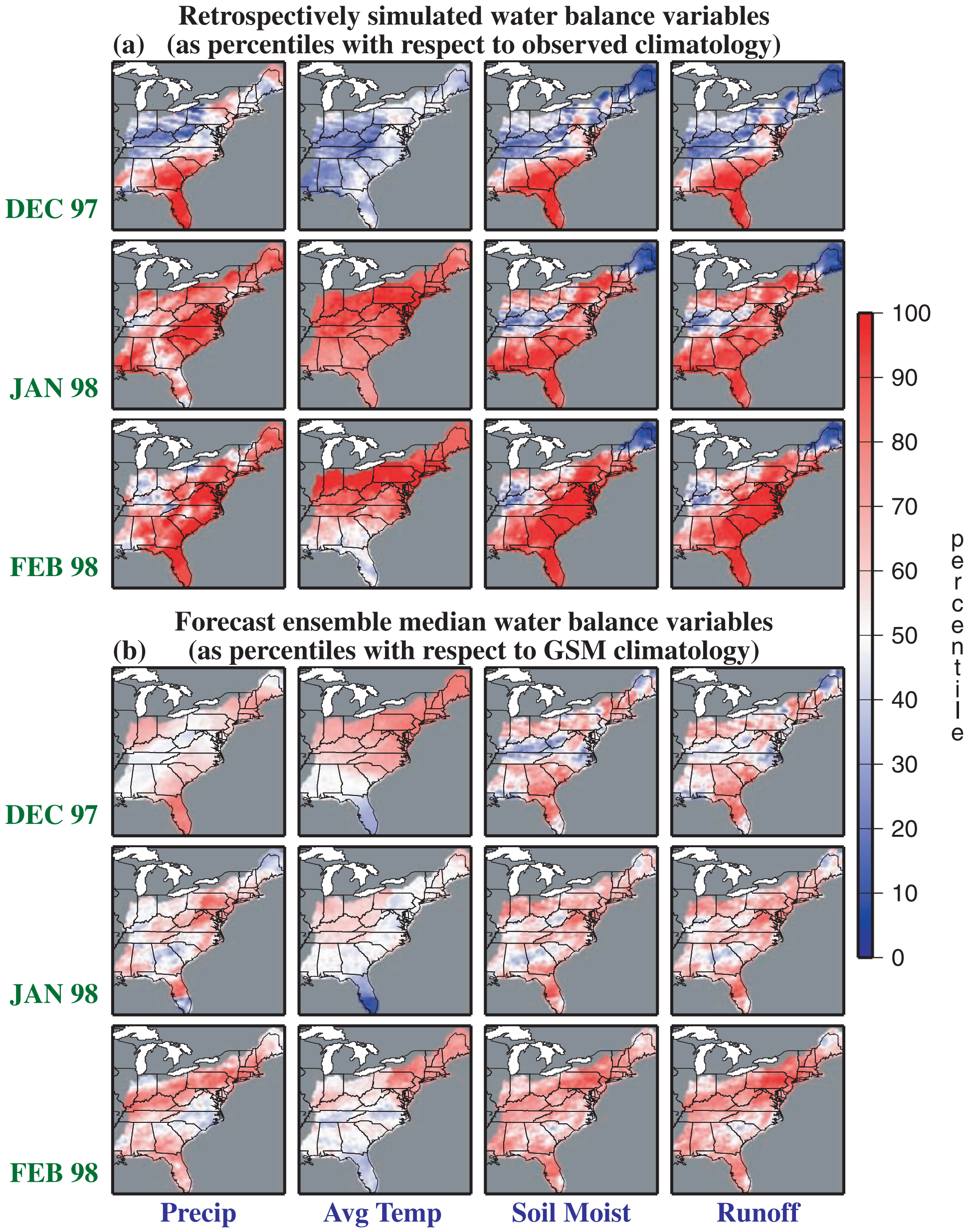

Figure 10. (a) December 1997–February 1998 gridded observed monthly total precipitation and average temperature and associated analyses of average soil moisture and total runoff, shown as percentiles of the observed climatology; (b) November 1997 GSM-derived forecasts for the same period, shown as percentiles of the GSM-based hindcast climatology.

ensemble in December. Both ensembles were slightly higher than the observed streamflow. The forecasts' above-normal precipitation in January and February produced above-normal forecast distributions for streamflow in those months, although the forecasts, as in the Alabama River example shown in Figure 9, failed to anticipate the magnitude of the anomaly actually observed, which continued throughout the forecast period.

4. Discussion

[41] We evaluated the spatial forecasts from a qualitative standpoint only, broadly assessing the consistency of anomaly direction in the climate forecasts and resulting hydrology forecasts without undertaking to determine the skill of the climate model and resulting hydrologic forecasts quantitatively (hence the term "skill" is here used loosely to indicate general consistency of forecasts with observed values). We did not focus on climate model forecast skill because our primary purpose was to develop a framework within which ensemble climate forecasts could be used for hydrological purposes. A secondary objective was to determine whether the climate model forecast signal or hydrologic (soil moisture) persistence would dominate in situations where the climate forecast anomalies were significant. We conclude from this exercise that the downscaling procedure successfully transfers the climate forecast signals to the hydrologic variables. It is especially encour-

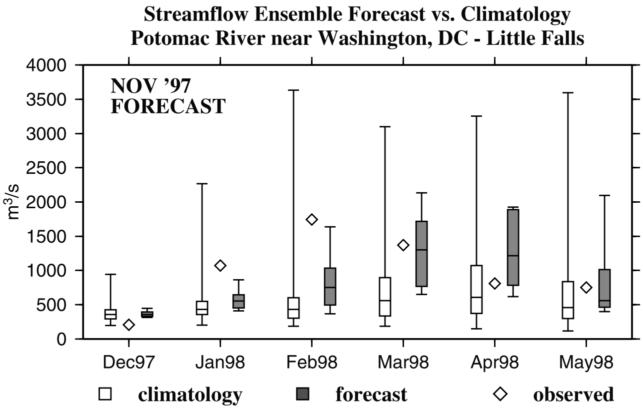

Figure 11. El Niño condition streamflow forecast for the Potomac River near Washington, D.C., Little Falls, using a 10-member GSM hindcast ensemble for November 1997 as a forecast surrogate, compared with the GSM hindcast ensembles for November 1979–1999 (a climatology) and with observed streamflows.

aging that the hydrologic model, which performs a nonlinear transformation of temperature, precipitation, and other inputs to streamflow, was able to retrieve the observed streamflow climatology from the downscaled, GSM-scale observed precipitation and temperature climatology.

[42] One feature of this approach that may require further evaluation is the spatial interpolation of bias-corrected GSM-scale output anomalies, rather than their associated probability values, directly to the VIC 1/8° resolution grid cell centers. Interpolation of anomaly quantiles (in probability space) to the VIC resolution would yield a joint probability anomaly for the thousands of VIC cells in each basin far exceeding the original GSM anomaly quantile, so the latter approach was chosen as a method of bridging the scale gap between GSM output and VIC input. It also appears that the downscaling procedure may increase the variability of the forecasts somewhat by producing high outliers in the precipitation fields (as a result of the rescaling of sampled daily patterns to match monthly anomalies), and refinements will be pursued in future applications to resolve this problem.

[43] For the summer 2000 study period and region the climate model forecasts had a mixed performance, as estimated spatially from the precipitation, temperature, runoff, and soil moisture ensemble medians and from the streamflow comparisons. For example, in the April and June month 1 median forecasts (Figure 7), the southeast is slightly wetter than the climatology median, while our retrospective analysis shows that the region continued to be dry. In each case, however, the persistence of antecedent low soil moisture from the hydrology model maintained low soil moisture and runoff several months into the forecast period, so that the forecast results still agreed reasonably well with the retrospective analysis for lead times of several months. Here the weak and at times incorrect direction of the climate model forecasts was balanced by a degree of skill derived from persistence in the hydrologic states.

[44] For the El Niño-condition forecasts of November 1997 (Figure 10), in contrast to the summer 2000 results, the hydrologic forecast results appeared to be determined by the climate model forecast signal, as well as by persistence in the antecedent hydrologic model state. The initial soil moisture signature, characterized by a decreasing gradient in soil moisture and runoff percentile from south to north (which resulted from the antecedent conditions) was largely erased by the normal to wetter than average precipitation forecasts coupled with normal to cooler than average temperature forecasts (after the December warmth in the northeast). By February (forecast month 3) the wet anomaly over the entire region was consistent with, although weaker than, the anomaly revealed in the hindcast analysis.

[45] One issue that bears mention is the high variance in forecast ensemble and climatology ensemble spatial fields (for a given point) and hence in the streamflow ensembles (Figures 8, 9, and 11). Given a high variance, a large shift in the mean of the forecast distribution is required to produce a statistical difference in the forecast outcome; hence the discrimination of the forecast system (in the sense described by *Wilks* [1995]) is weaker than it would be for a narrower distribution of ensembles. A wide forecast distribution prohibits water managers from making decisions that effectively rule out one end or the other (or, in some cases, both) of the climatological distribution of expected hydrologic conditions for the forecast period. Future work in refining methods to bias-correct and downscale climate forecasts for use in hydrologic prediction must therefore take care to minimize the addition of method-related uncertainty.

[46] Further exploration of the approach should also include a broader range of climate and land surface conditions than were examined here. Where snowpack plays a major role in the seasonal cycle, for example, contributions of the hydrologic and climate components of the forecasts are expected to be significantly different at different times of the year. An effort to determine a priori where and when long-range forecasts are likely to have skill, purely on the basis of land surface and climate considerations, would be useful.

[47] Our experience in this study suggests that future work to apply the climate-hydrology model forecasting approach in real time and to assess the outputs quantitatively should also concentrate on improvements in two areas. First, the accurate estimation of initial hydrologic conditions for the forecasts is critical for capturing the influence of land surface anomalies that persist into the forecast period; hence an improvement in real-time access to meteorological data for hydrologic simulation of initial conditions would increase the accuracy of the forecasts. Second, quantitative evaluation of the climate forecasts would benefit from the existence of retrospective meteorological forecast data sets generated with the identical methods (to the extent possible) used in producing the current forecasts, for a climatology period of several decades. The retrospective perfect SST-based surrogate forecast of the type explored here hints only at an upper bound on forecast performance, rather than an estimate of performance consistent with the forecasts produced in real time.

[48] Nonetheless, from an end user standpoint, the forecasting approach appears to have potential utility for conditioning water resources related outlooks, particularly when there is either a strong anomaly signal in the climate forecasts or highly anomalous antecedent conditions in the hydrologic model state. A quantitative exploration into the suitability of the spatial and streamflow forecasts for particular water resources applications appears to be warranted.

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