Improved Drought Management of Falls Lake Reservoir: Role of Multimodel Streamflow Forecasts in Setting up Restrictions

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Abstract: Droughts, resulting from natural variability in supply and from increased demand due to urbanization, have severe economic implications on local and regional water supply systems. In the context of short-term (monthly to seasonal) water management, predicting these supply variations well in advance are essential in advocating appropriate conservation measures before the onset of drought. In this study, we utilized 3-month ahead probabilistic multimodel streamflow forecasts developed using climatic information—sea surface temperature conditions in the tropical Pacific, tropical Atlantic, and over the North Carolina coast—to invoke restrictions for Falls Lake Reservoir in the Neuse River Basin, N.C. Multimodel streamflow forecasts developed from two single models, a parametric regression approach and semiparametric resampling approach, are forced with a reservoir management model that takes ensembles to estimate the reliability of meeting the water quality and water supply releases and the end of the season target storage. The analyses show that the entire seasonal releases for water supply and water quality uses could be met purely based on the initial storages (100% reliability of supply), thereby limiting the use of forecasts. The study suggests that, by constraining the end of the season target storage conditions being met with high probability, the climate information based streamflow forecasts could be utilized for invoking restrictions during below-normal inflow years. Further, multimodel forecasts perform better in detecting the below-normal inflow conditions in comparison to single model forecasts by reducing false alarms and missed targets which could improve public confidence in utilizing climate forecasts for developing proactive water management strategies.

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Introduction

The multiyear drought during 1998–2002 caused severe hardship and economic losses across most of North Carolina (Weaver 2005). Several local and statewide water supply systems experienced record shortages and many communities operated under mandatory water restrictions from 2001 to 2003 (Weaver 2005). A similar situation existed during the 2005 and 2007 droughts throughout the state (http://www.ncdrought.org/). Economic losses in North Carolina for the year 2002 were estimated to be $398 million for agriculture and $15–$20 million for municipalities (Weaver 2005). Unless closely monitored using various sector-specific indicators, the impacts of droughts are progressive, persistent, and pervasive over a large area. Thus, updating drought management plans not only requires monitoring but also needs to include prognostic information about the streamflow potential in the upcoming seasons to develop proactive management measures such as restrictions and hedging. This study combines 3-month ahead climate information based multimodel streamflow forecasts with a reservoir management model that can take ensembles of reservoir inflows to invoke prescribed levels of restriction for water supply.

Droughts experienced by regional water supply systems often result from reduced streamflow/precipitation potential, which could occur due to varying exogenous climatic conditions such as tropical sea surface temperature (SST) (Ropelewski and Halpert 1987; Piechota and Dracup 1996; Barlow et al. 2001). As water supply systems experience shortages in supply owing to (inflows) natural variability, resulting deficits are further exacerbated by increased demand resulting from urbanization and population growth in the region (Lyon et al. 2005; Vorosmarty et al. 2000). For instance, in the Triangle Area in North Carolina, the demand has grown by about 20–62% from 1995 to 2000 (Weaver 2005) resulting in three severe droughts (summers of 2002, 2005, and 2007) in the past 5 years. Given that most of the water supply systems are multipurpose, operating these systems to meet the increased demand under reduced streamflow availability could be very challenging. The main intent of this study is to apply climate information based streamflow forecasts from three models—parametric regression, semiparametric resampling, and multimodel (obtained by combining the former two models)—for setting up restrictions on water supply releases from the Falls Lake Res-

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ervoir in North Carolina. By performing retrospective reservoir analyses, the study basically compares the forecasted end of the season target storage probabilities with the climatological probabilities to set up restrictions on water supply releases.

The manuscript is organized as follows: a brief overview of the importance of climate forecasts in reservoir management is discussed first. Following that, the reservoir simulation model developed by Arumugam et al. (2003) is detailed, which uses seasonal streamflow forecasts in the form of ensembles, to quantify the reliability of meeting desired releases and the end of the season target storage. Next, the climate information based seasonal streamflow forecasts developed by Devineni et al. (2008) are briefly presented and are utilized to perform retrospective reservoir analyses to set up restrictions during drought conditions. The following section discusses the potential utility of multimodel forecasts and the proposed reservoir simulation framework for other systems. Finally, the findings of the study are summarized along with conclusions.

Background

The National Weather Service River Forecasting System (NWSRFS) issues 3-month lead probabilistic forecasts of streamflow for many river basins in the contiguous United States from 12 river forecasting centers. The Ensemble Streamflow Prediction system from NWSRFS uses conceptual hydrologic models to issue streamflow forecasts based on the current soil moisture, river, and reservoir conditions by assuming that past meteorological events will recur in the future with historical probabilities (Schaake and Larsen 1998). Recent investigations focusing on the teleconnection between conditions in SSTs and regional/continental hydroclimatology show that interannual and interdecadal variability in exogenous climatic indices modulate the continental scale rainfall patterns (Ropelewski and Halpert 1987) and streamflow patterns at both global and hemispheric scales (e.g., Dettinger and Diaz 2000) as well as at regional scales (e.g., Piechota and Dracup 1996; Guetter and Georgakakos 1996).

Seasonal streamflow forecasts based on exogenous climatic indices can be obtained using both dynamic and statistical modeling approaches. The dynamic modeling involves coupling a hydrological model with a regional climate model that preserves the boundary conditions specified by the general circulation model (GCM) outputs by considering the topography of the region (e.g., Leung et al. 1999). However, uncertainty propagation from the coupling of these models (Kyriakidis et al. 2001), representation of physical processes, and low predictive skills of GCM outputs at longer lead time (12–18 months) severely limits the utility of these forecasts for water management. The alternate approach—developing statistical models—focuses on the estimation of conditional distribution of streamflow based on current conditions of snow pack, streamflow volume, and SST anomalies to issue seasonal and long-lead streamflow forecasts. Various statistical techniques have been employed for this purpose ranging from simple parametric regression models (e.g., Hamlet and Lettenmaier 1999), to complex methods such as linear discriminant analysis (Piechota et al. 2001), spatial pattern analysis (Sicard et al. 2002), and semiparametric resampling strategies (Souza and Lall 2003).

Efforts to develop seasonal streamflow forecasts using tropical/extra-tropical climatic conditions and catchment state have resulted in improved management of water supply systems (Hamlet and Lettenmaier 1999; Yao and Georgakakos 2001; Hamlet et al. 2002). Using retrospective streamflow forecasts for the Columbia River (Hamlet and Lettenmaier 1999; Hamlet et al. 2002), studies have shown that long-lead streamflow forecasts can be effectively utilized in operating reservoirs to obtain increased annual average hydropower. Similarly, coupled hydraulic–hydrologic prediction models with robust forecast-control methodologies could also result in increased resiliency of reservoir systems to climate variability and change (Georgakakos et al. 1998). As seasonal streamflow potential changes depending on climatic and land surface conditions, policy instruments and operational rule curves could also be developed to support adaptive water management (Arumugam et al. 2003).

Though the utility of climate forecasts in improving water management has been shown in the literature, it is widely acknowledged that numerous challenges/gaps exist in the real-time application of climate forecasts by water managers (Pagano et al. 2001; Hartmann et al. 2002; Steinmann 2006). The primary challenges are: (1) low confidence on the skill of the forecast; (2) communication of probabilistic forecasts; and (3) nonavailability of decision framework and policy instruments for application. Further, even if the skill of the climate forecasts is significant in a given region, public perception of forecasts particularly goes down due to false alarms (forecast suggests drought, but no drought occurs) and missed targets (forecast suggests normal, but drought occurs) (Steinmann 2006). For a detailed discussion on the use of climate forecasts in the context of drought management, see Steinman (2006). It has been widely shown in the literature that multimodel climate/streamflow forecasts ensure better correspondence between the forecasted probabilities and their observed relative frequencies (Barnston et al. 2003; Doblas-Reyes et al. 2000; Devineni et al. 2008) resulting in reduced false alarms and model uncertainty. The main goal of this study is to understand whether application of multimodel streamflow forecasts results in invoking better management decisions (in comparison to individual model forecasts) such as restrictions for improving water allocation during droughts.

Falls Lake System Details and Management Model Development

Falls Lake is a man-made reservoir in the upper Neuse River, N.C. (Fig. 1) operated by the U.S. Army Corps of Engineers (USACE) since December 1983 to serve five purposes: (1) flood control; (2) water supply; (3) water quality; (4) recreation; and (5) fish and wildlife. The lake is long and narrow in shape and extends 48km up the Neuse River. Three rivers—the Eno, Flat, and Little Rivers—provide the majority of inflows. As a water supply reservoir, Falls Lake provides Raleigh, by contract, with up to 378 million liters of water a day. Due to the population growth in the city of Raleigh and in the suburbs served by Falls Lake over the last decade, storage conditions in Falls Lake have been increasingly stressed recently resulting in three severe droughts (2002, 2005, and 2007) over the last 5 years. Current drought management and monitoring activities are coordinated by the North Carolina Drought Management Advisory Council (NCDMAC) in coordination with various state and federal agencies in North Carolina.

Data and Operational Constraints

For operational purposes, reservoir storages of Falls Lake are divided into various pools: (1) flood control pool (controlled stor-

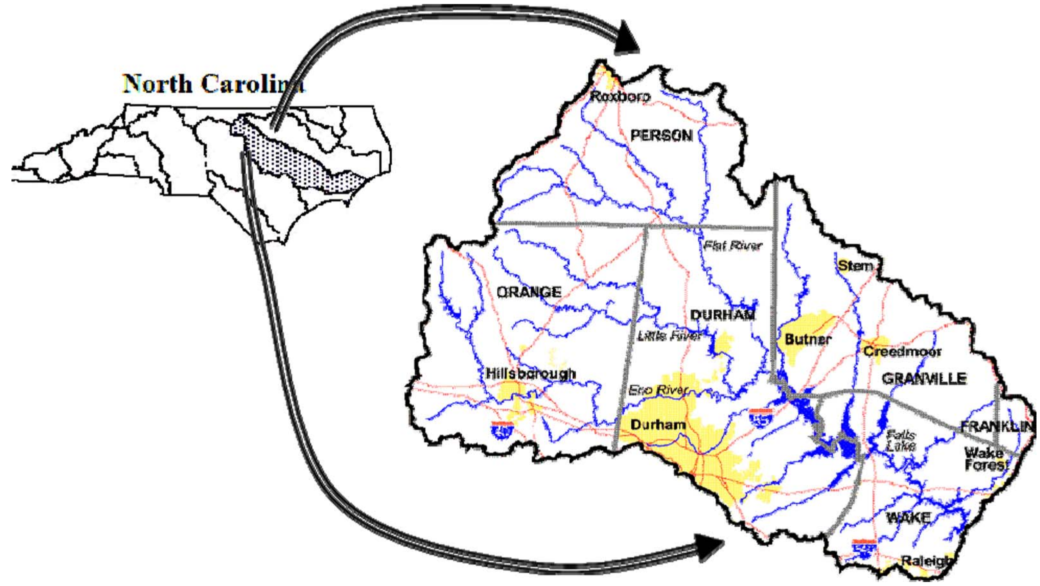

Fig. 1. Location of Neuse River Basin and Falls Lake Reservoir in the upper Neuse River Basin

age, 76.7–87.7 m and uncontrolled storage, 87.7–88.2 m); (2) Conservation pool (72.1–76.7 m) with two separate storage accounts for water quality and water supply; and (3) sediment dead storage (61.0–72.1 m). All elevations (in meters) are based on the North America Vertical Datum of 1927 (NAVD27). Both water supply and water quality releases are met based on the storages in conservation pool by devoting 39% of the conservation pool storage volume to water supply and the remaining 61% to water quality purposes.

The USACE uses 76.7 m [162.1 million cubic meters (MCM)] as the operational rule curve or the target pool level, which is obtained based on the average monthly flows recorded at Falls Lake (http://epec.saw.usace.army.mil\Falls_WC_Plan.pdf). Thus, the USACE tries to ensure the reservoir level at operational rule curve at the beginning (July 1) and end (September 30) of the summer season. During wet summer years (e.g., 1996 and 1999), the above-normal inflows force the reservoir level above 76.7 m posing operational constraints on flood control and recreation. Under such situations, the USACE releases additional water to maintain the operational rule curve to reduce the downstream flood risk. Normal outflows for protecting downstream water quality in the Neuse River are 7.2 cubic meters per second (cms). However, reservoir outflows during below-normal storage conditions could be reduced to 2.8 cms (April to October) and 1.7 cms (November to March) after consultation with all stakeholders. Additional information such as monthly releases, stage–storage, and stage–water spread area relationships was obtained from USACE to develop the Falls Lake simulation model, which is described in detail in the following section.

Falls Lake Reservoir Model Formulation

Given seasonal (T-month lead) ensemble inflow forecasts q_j^k and initial reservoir storage, S_0^*, at the beginning of the allocation period (for these analyses, July 1) with $j=1,2,\ldots,N$ denoting the forecast years (N=total number of years of retrospective forecasts), and $k=1,2,\ldots,K$ index representing a particular member out of K ensembles the Falls Lake simulation model determines the seasonal releases R_1 and R_2 representing water supply and water quality allocations, respectively, with specified reliabilities of $(1\text{-}p_{f1})$ and $(1\text{-}p_{f2})$, where p_f implies failure probability. In addition, the water allocation model incorporates an end of the season target storage, S_T^* (T denoting the forecast lead time in months) that is associated with a failure probability p_s. For instance, in the case of Falls Lake, S_T^* corresponds to the storage of the reservoir at 72.1 m operational rule curve. The simulation model could also estimate the probabilistic constraints [in Eqs. (7) and (8)], reliability of supply for each use [$(1\text{-}p_{f1})$ and $(1\text{-}p_{f1})$], and p_s given the specified demand R_1^* and R_2^*, for each use along with S_T^* and S_0^*. Using the basic continuity equation, the seasonal storage equations for each ensemble member k are updated for the forecasting year j

$$S_{T,j}^k = S_{0,j}^* + q_j^k - E_j^k - (R_{1,j} + R_{2,j}) \tag{1}$$

where seasonal storage equations are constrained so that the storage is between the minimum and maximum possible storage, $S_{\min}$ and $S_{\max}$, respectively

$$S_T^k = \min(S_T^k, S_{\max}), \quad S_T = \max(S_T^k, S_{\min}) \tag{2}$$

In the event, the end of season storage falling below the minimum possible storage, $S_{\min}$, we encounter deficits, SD_j^k, which needs to be distributed among the users as restrictions

$$\mathrm{SD}_j^k = (S_{\min} - S_{T,j}^k) | S_{T,j}^k < S_{\min} \tag{3}$$

$$\mathrm{SD}_j^k = \sum_{i=1}^{2} w_{i,j}^k, \quad w_{i,j} = \alpha_i R_{i,j} \tag{4}$$

The restrictions, w_i, for each user could be specified exogenously as a fraction, α_i, of the target release, R_i. The restriction fraction, α_i, could also be allowed to vary depending on the restriction level. Evaporation, E_j^k, is computed as a function of average storage during the season using the water spread area and storage information of the reservoir

$$E_j^k = \psi_j \delta_1 ((S_0^* + S_T^k)/2)^{\delta_2} \tag{5}$$

where ψ_j=seasonal evaporation rate and δ_1 and δ_2=coefficients describing the area–storage relationship. Spline interpolation was employed for obtaining the water spread area corresponding to the average season storage computed for each ensemble. It is important to note that the evaporation is evaluated implicitly for each streamflow member in the ensemble. The estimated average lake evaporation rate (ψ_j)=0.303 m/season (after adjusting with the pan coefficient of 0.7) for the summer, which is obtained from the monthly pan evaporation recorded at Chapel Hill, N.C.

The objective is to determine R_i, such that the releases for ith use is bound by the minimum and maximum demand for the season

$$R_{i,\min} \leq R_i \leq R_{i,\max} \tag{6}$$

Similarly, the study also enforces the probability of having the end of the season storage, S_T, less than the target storage, S_{T*}, to be small represented by its failure probability (Prob), p_s, using

$$\mathrm{Prob}(S_T \leq S_T^*) \leq p_s \tag{7}$$

To ensure the obtained release, R_i, being met with high reliability, (1-p_{fi}), the model includes

$$\mathrm{Prob}(w_i \leq w_i^*) \leq p_{fi} \tag{8}$$

where w_i^*, specified by the user, denotes the maximum restriction that could be enforced for each user as part of the restrictions. This constraint basically accounts for the uncertainty in releases. Thus, the obtained seasonal release may be between the desired bounds $R_{i,\min}$ and $R_{i,\max}$, but the specified release R_i has a small probability, p_{fi}, of facing restrictions being less than w_i^*. The restriction w_i is calculated for each ensemble member k using the restriction fraction, α_i, based on Eq. (4). For all the analyses, $w_i^*=0$ is assumed.

Looking across all the traces in the ensemble, the model computes the following probabilities to evaluate Eqs. (7) and (8):

1. $\mathrm{Prob}(w_i \leq w_i^*)$ is estimated from the number of traces in which ($w_i \leq w_i^*$) out of total number of traces, N. This includes the calculation of the failure to meet the two specified demands, water supply and water quality.
2. $\mathrm{Prob}(S_T < S_T^*)$ is obtained from the number of traces in which ($S_T < S_T^*$) out of total number of traces, N.

N=500 ensembles are considered that represent the average seasonal streamflow during the summer [July, August, and September, (JAS)]. In this study, instead of obtaining R_1 and R_2 for the specified constraints, the water supply release (in Fig. 2), $R_{1,j}^*$, and water quality release, $R_{2,j}^*$, (with the average flow being equal to 7.2 cms or 2.8 cms) are specified to estimate the probabilistic constraints in Eqs. (7) and (8). The above-mentioned probabilities are then computed across the ensembles to evaluate the above-listed constraints. Though the model is presented in a simulation framework, it could be extended into an optimization-simulation model by including compensations under restrictions along with a detailed contract structure (Arumugam et al. 2003).

Reservoir Model Verification

Prior to performing the retrospective reservoir analyses using the streamflow forecasts, model verification was performed from 1991 to 2005 by comparing the reservoir model's ability to simulate the observed end of September storages. The model simulations were performed by forcing the model with the observed flows during JAS and initial storages in July to determine the end of the September storages by allocating the reported releases for water quality and water supply. Basically, this verification provides a check on the mass balance of the reservoir model as well as in its ability to model the conservation storage pool into two

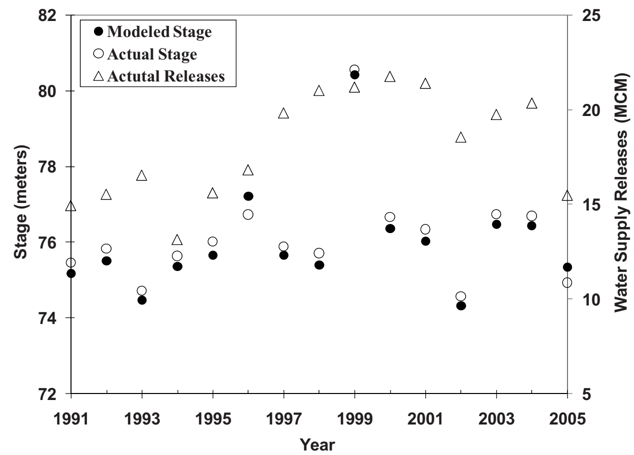

Fig. 2. Comparison of modeled stages with the observed stages in September for the period 1991–2005. The reported water supply releases during JAS from Falls Lake are also shown. Modeled stages are obtained upon simulating the model with observed flows, releases, and by forcing the model with the initial storage recorded each year on July 1.

separate accounts (i.e., water supply and water quality storages). Fig. 2 shows the observed and model predicted stages at the end September—the end of the season stage. The observed and modeled storages obtained from the reservoir model were converted into stages using the available stage–storage relationship for Falls Lake. Fig. 2 clearly shows that the developed model is quite reasonable in predicting the observed September storages upon simulation with observed flows and reported releases. This gives the confidence in employing the simulation model presented here for further analyses that utilize the seasonal streamflow forecasts from three models for invoking restrictions.

Seasonal Streamflow Forecasts for Falls Lake

This section briefly describes the development of streamflow forecasts for Falls Lake during the summer season. For additional details on the streamflow forecasting model, predictor identification, and the skill of cross-validated forecasts, see the forecasting paper (Devineni et al. 2008) and the technical report (Sankarasubramanian et al. 2006) (available online: http://www.stat.ncsu.edu/library/papers/mimeo2595.pdf). Seasonal streamflow forecasts were developed for the summer season based on April, May, and June (AMJ) climatic information, denoted by anomalous SST conditions in the tropical Pacific, tropical North Atlantic, and over the North Carolina coast.

Predictor identification using Spearman rank correlation was performed on the International Research Institute for Climate and Society (IRI) data library between the global SSTs (http://iridl.ldeo.columbia.edu/SOURCES/.KAPLAN/.EXTENDED/.v2/.ssta/) and the seasonal streamflows. Grid points of SSTs (black rectangles) in Fig. 3(a) that have significant correlation with the predictand were considered as predictors in developing the forecasts. The correlations shown in Fig. 3(a) are for 78 years of flows. Thus, if the absolute value of correlation is greater than 0.22, then one expects the correlation between the predictor and predictand to be statistically significant (at 95% confidence level). As the SST grid points were spatially correlated, principal component analysis was performed and the first two principal compo-

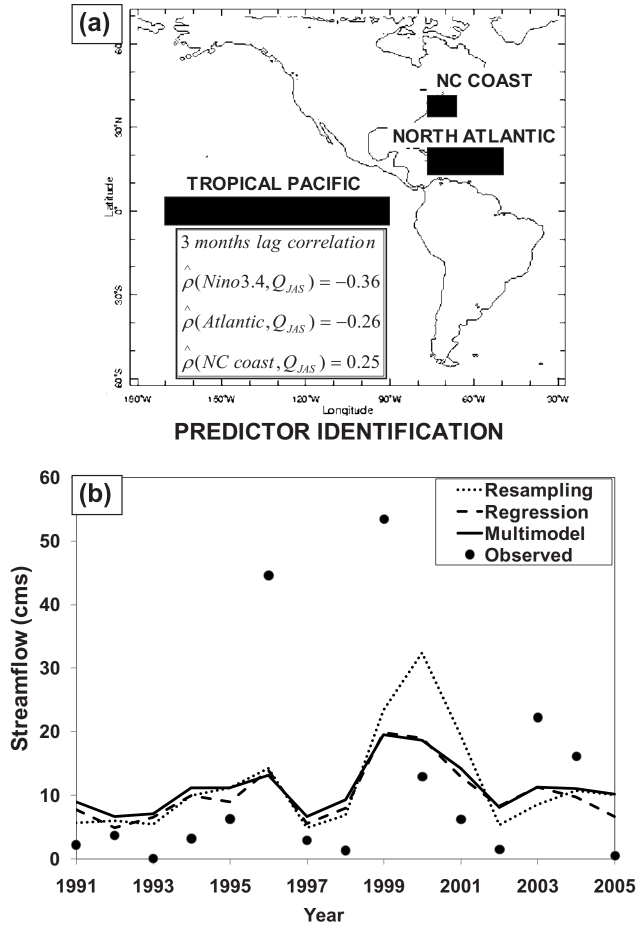

Fig. 3. Leave one out cross-validated seasonal (JAS) streamflow forecasts for the Falls Lake from three forecasting models [(b) regression, resampling, and multimodel] along with the employed predictors (a). Principal components of the three SST regions [shown as rectangles in (a)] were performed and the dominant two components were employed for developing the streamflow forecasts represented in the form of ensembles.

nents (explained 73% of total variance exhibited in SSTs) were retained for model development. Spring season (April–June) streamflow and the previous month's streamflow (June alone) were also considered as surrogate predictors to incorporate land surface conditions such as soil moisture. But, the correlations between the previous month/seasonal flows and the summer flows are statistically not significant.

Two nonlinear models, parametric regression (with the predictand being cube-root of the flows) and semiparametric resampling models (Souza and Lall 2003), were considered in developing multimodel forecasts. With regard to individual model selection, one can even consider the land surface model in developing streamflow forecasts. As the skewness of the recorded summer flows is 1.9, cube-root transformation was applied for developing the parametric regression model. With regard to individual model selection, one can even consider the land surface model in developing streamflow forecasts. Studies have considered objective criterion along with stepwise regression to select the best combination of nonlinear models in developing multimodel forecasts (Regonda et al. 2006). In this study, the resulting seasonal streamflow forecasts from parametric regression and semiparametric resampling models were combined using a multimodel combination algorithm to develop improved seasonal streamflow forecasts (Devineni et al. 2008, Sankarasubramanian et al. 2006).

This study employed seasonal streamflow forecasts from three models—regression, resampling, and multimodel—for improving the drought management of Falls Lake. The adaptive forecasts for the period 1976–2005 were developed by training the model using the observed flows and predictors available from 1928 to 1975. The correlations between the observed flows and the ensemble mean of the seasonal streamflow forecasts are 0.44, 0.49, and 0.51 for resampling, regression, and multimodel, respectively, which are statistically significant for the 30 years of validation. Fig. 3(b) shows the adaptive forecasts from the three models for the period 1991–2005. The forecasts [in Fig. 3(b)] are shown as conditional mean, which is obtained from the 500 ensembles of the conditional distribution of streamflows developed for each year. Representing the conditional distribution with large ensembles will only lead to better estimates of probability constraints [Eqs. (7) and (8)] without improving the skill of the probabilistic forecasts. For instance, with regard to the parametric regression model, the actual information content in the forecasts is purely determined by its conditional mean and conditional variance. The null forecast, the climatological ensembles, whose ensembles was also considered were developed by simple bootstrapping of JAS flows. This approach is reasonable, as there is no year-to-year correlation between summer flows at Falls Lake. These streamflow forecasts and the initial storages observed on July 1 were provided as inputs to the reservoir management model to estimate the reliability of meeting the water supply releases (in Fig. 2) and minimum water quality releases as well as to estimate the probability of end of September storage being below the target storage (corresponding to target stage 72.1 m) [$\text{Prob}(S_T < S_T^*)$].

Results and Analyses

The following analyses show the utility of streamflow forecasts in predicting the below-normal storage conditions that could result by releasing the required water supply and water quality releases. This is different from identifying the streamflow forecasts as below normal, as future reservoir storages need to account for the initial conditions in July as well as lake evaporation, which in turn depend on unknown future storages. Thus, the analyses presented here utilized the streamflow forecasts from three models [Fig. 3(b)] to obtain: (1) the reliability of supplying the seasonal demand for water quality and water supply uses and (2) probability of having end of September storage less than the target storage [$\text{Prob}(S_T < S_T^*)$]. Based on the obtained target releases from each model, the performance of streamflow forecasts from each model is validated in predicting future storage conditions by combining reservoir releases with the observed flows. The study also identified possibilities for imposing restrictions based on the end of the season target storage probabilities estimated by each forecasting model. Predicting below-normal storage conditions well in advance would help in imposing restrictions before the summer season, which could improve the resilience of the system during prolonged droughts.

Reliability of Meeting the Target Releases

The proposed simulation model [Eqs. (1)–(8)] could be employed in one of the following two ways for a given use: (1) obtain the

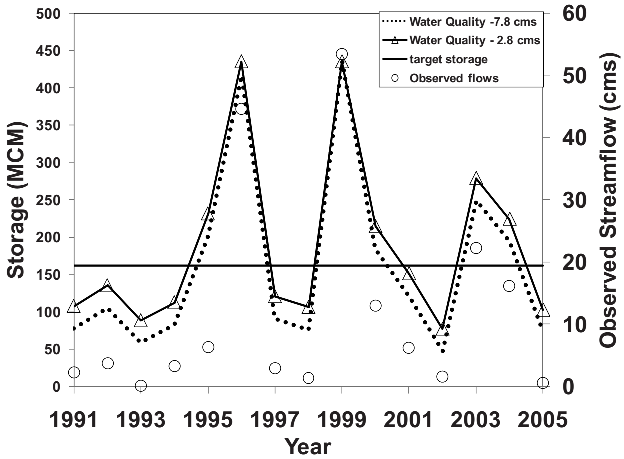

Fig. 4. Modeled storages for two water quality release scenarios: normal (7.8 cms) and drought (2.8 cms) conditions along with the observed streamflows and the target storage (solid horizontal line). The storages shown are obtained by combining the observed streamflows with the chosen water quality release and the corresponding year's summer water supply release in Fig. 2.

release for the specified reliability; or (2) obtain the reliability for the specified target release. The first approach is more useful when the seasonal demand is more than the initial storage and the forecasted inflows, whereas the latter is more useful when the initial storage and the forecasted inflows are more than the net seasonal demand. On the other hand, if the initial storage itself could meet the net seasonal demand including lake evaporation, then the reliability of meeting target releases is 100%. Under those situations, there is limited/no use of forecasts, as the available storage itself ensures the total seasonal demand. The required seasonal release for water quality use is 53.73 MCM (7.8 cms) . Under severe droughts, this could be reduced to 22.51 MCM (2.8 cms) with the approval of NCDMAC.

Without constraining the end of the season target storage [Eq. (7)], the initial storage itself was able to supply the required water quality release of 7.8 cms and the required water supply releases for all 15 years considered for analyses. Fig. 4 shows the modeled storages and stages for the two scenarios of water quality releases. The modeled storages and stages were obtained by combining the observed streamflows during JAS with the specified water quality and water supply releases. As seen in Fig. 4, the modeled end of September storages were greater than 30.93 MCM (72.1 m) —the storage at the bottom of conservation pool. Thus, the initial storage itself was able to supply the entire water quality and water supply releases each year.

All the streamflow forecasting models guaranteed the target release with 100% reliability, thereby limiting the use of forecasts when the end of the season target storage is not constrained. In other words, it is important that the total water demand (water supply and water quality releases along with evaporation losses) over the forecast lead time needs to be constrained by the available storage. Under those conditions, the forecasts are useful in assigning the reliability for various uses. If the initial storages do not constrain the net demand, then there is limited/no use of forecasts in quantifying the future storage scenarios. Thus, results shown in Fig. 4 correspond to 100% reliability of supplying the target releases with all the streamflow forecasting models suggesting the same release scenarios which leaves the forecasts redundant. On the other hand, by enforcing the end of the season target

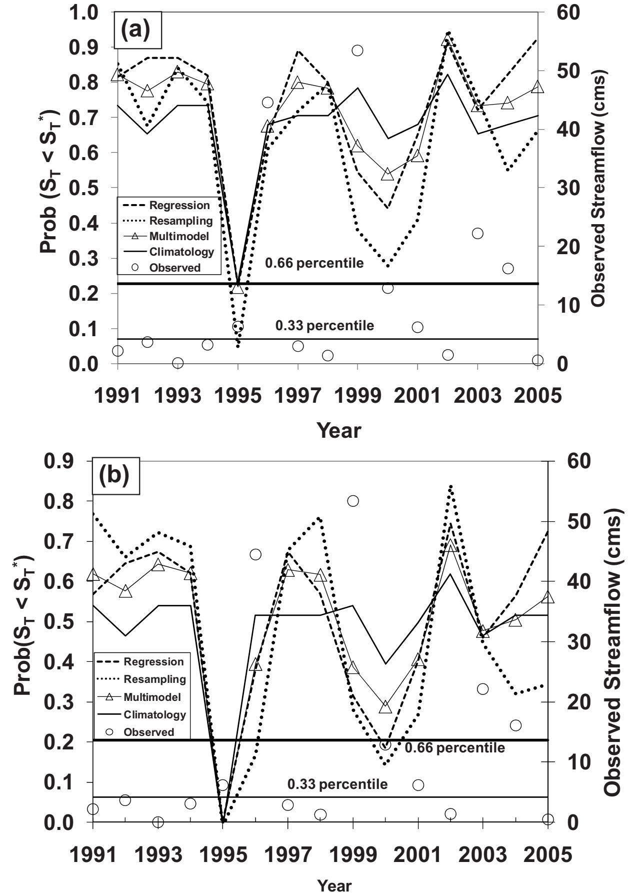

Fig. 5. Role of streamflow forecasts in predicting the end of the season target storage that corresponds to the stage of 72.1 m, mean sea level. (a) Normal water quality release of 7.8 cms. (b) Restricted water quality release of 2.8 cms. Note that the multimodel forecasts clearly suggest increased risk of not meeting the target storage in comparison to the risks suggested by the climatology during below-normal years.

storage constraint with $p_s=0.5$, water quality and water supply releases are reduced considerably for a specified reliability of 90%. This shows that the end of the season target storage is the binding constraint, which could be effectively used to invoke restrictions even though the initial storage may ensure 100% reliability of supplying the total seasonal demand. The following analyses shows in detail on how restrictions could be employed based on the estimates of Prob$(S_T<S_T^*)$ obtained from the reservoir simulation model.

End of the Season Target Storage Probabilities

Given the streamflow forecast ensembles and the initial storage conditions in July, one can estimate the Prob$(S_T<S_T^*)$ [Eq. (7)] that would result upon releasing any of the two water quality release scenarios and the corresponding required water supply releases shown in Fig. 2. Fig. 5 shows the estimates of Prob$(S_T<S_T^*)$ where $S_T^*=162.1$ MCM for releasing the water supply demand (in Fig. 2) and for two water quality release scenarios. Thus, the probability estimates shown were obtained from each streamflow forecasting model and from climatological ensembles, which were constructed by simply bootstrapping JAS stream-

flows. Fig. 5 also shows the observed streamflows in each year suggesting their tercile category ($Q_t < 0.33$ percentile—below normal; $Q_t > 0.66$ percentile—above normal; otherwise—normal). Both Fig. 5(a) (normal water quality releases = 7.8 cms) and Fig. 5(b) (drought conditions water quality releases = 2.8 cms) demonstrate that the estimates of Prob($S_T < S_T^*$) vary depending on the forecasted streamflow potential by each model. In comparison, estimates of Prob($S_T < S_T^*$) from climatological ensembles do not vary much, with the values hovering between 0.6 and 0.7 for the normal water quality releases and from 0.5 to 0.6 for the drought conditions water quality release. The small variations that are seen under climatological ensembles are primarily due to differences in initial storage conditions. Similarly, for the year 1995, the estimates of Prob($S_T < S_T^*$) are very low due to increased initial storage with the reservoir's initial stage at 78.02 m, which is almost 1.3 m above the operational rule curve of 76.7 m. It is important to note that Fig. 5 does not use the observed streamflows to estimate Prob($S_T < S_T^*$), as the forecasts were developed based on the climatic information available during April–May–June.

Figs. 5(a and b) also show clearly that the estimates of Prob($S_T < S_T^*$) from streamflow forecasts are above the estimates of Prob($S_T < S_T^*$) from climatological ensembles during below-normal inflow conditions and vice-versa during above-normal inflow years indicating the variability in predicted summer flows. This is perfectly in line with the expectation that the probability of attaining the target storage will be low (high) during below-normal (above-normal) inflow conditions. Thus, the initial storage may ensure 100% reliable supply during the season, but the estimates of Prob($S_T < S_T^*$) could be utilized to invoke restrictions for improving the end of September storage conditions during below-normal years. For instance in 2002, estimates of Prob($S_T < S_T^*$) are between 0.7 and 0.85 from the three forecasting models with drought condition water quality releases, which suggests the need for invoking restrictions even before the beginning of summer season.

For further analysis on invoking restriction levels, only water quality releases of 2.8 cms, were considered, as that corresponds to minimum acceptable release under drought conditions for meeting the downstream flow requirements. Even with drought condition water quality releases, the streamflow forecasts suggest significant risk of falling below the target storage in comparison to the climatology, which suggest the need for restrictions on water supply releases during below-normal inflow years. Naturally, the amount of restriction on water supply could be determined based on the estimates of Prob($S_T < S_T^*$) suggested by each model, whose performance (in terms of reduced releases) could be validated by simulation with the observed flows. Issues related to identifying appropriate restriction levels and varying restrictions based on the estimates of Prob($S_T < S_T^*$) are discussed in the following sections.

Comparison between Multimodel Forecasts and Individual Model Forecasts

The estimates of Prob($S_T < S_T^*$) in Figs. 5(a and b) differ for each streamflow forecast, as the conditional distribution in the form of ensembles exhibit different skill. The multimodel forecasts were obtained by combining forecasts from regression, semiparametric resampling models along with climatological ensembles by evaluating each forecasting model's skill from the predictor state. The main argument behind multimodel combinations based on predictor state space is that if the prediction from a particular model (including climatological ensembles) is poor during particular conditions, then it chooses the best performing model under those conditions. For additional details, see Sankarasubramanian et al. (2006) and Devineni et al. (2008).

From Figs. 5(a and b), it is clearly seen that the estimates of Prob($S_T < S_T^*$) of multimodel forecasts are much closer to the estimates of Prob($S_T < S_T^*$) from climatology, which indicates reduced risk of falling below the target storage. But, the utility of multimodel forecasts is more apparent in years 2004 and 2005 with the observed streamflows being above normal and below normal, respectively. The estimates of Prob($S_T < S_T^*$) from the regression model for both years suggest a higher risk of not meeting the target storage in comparison to the climatological probabilities. On the other hand, the estimates of Prob($S_T < S_T^*$) from the resampling model suggest a lower risk of not meeting the target storage in comparison to the climatological estimate of Prob($S_T < S_T^*$) during both years. From Fig. 4, it is clear that the modeled storages in 2004 and 2005 are above and below the target storage (162.1 MCM), respectively. Thus, if one invoked restriction measures based on regression forecasts in 2004 (false alarm) and ended up not invoking any restriction based on resampling forecasts in 2005 (missed target), then the individual model forecasts would have consequently advocated incorrect management measures. However, in both Figs. 5(a and b) multimodel forecasts seem to predict the outcome correctly suggesting that the Prob($S_T < S_T^*$) is lower than the climatology in 2004 and the probability of ($S_T < S_T^*$) is higher than the climatological risk in 2005. This suggests that the improved predictability of multimodel streamflow forecasts results in improved analyses of future reservoir storage conditions.

Enforcing Restriction Based on the Estimates of Prob($S_T < S_T^*$)

The restriction analyses presented in this section are primarily focused on below-normal years (1991, 1992, 1993, 1994, 1997, 1998, 2002, and 2005) shown in Fig. 5. From reservoir management perspective, as the observed flows are not realized in July, one could use the estimates of Prob($S_T < S_T^*$) to forecast the end of September storage conditions. For instance, if Prob($S_T < S_T^*$) estimated from forecasts is greater than the Prob($S_T < S_T^*$) estimated from climatology, then restrictions on water supply flows might be required to increase the probability of achieving the target storage. Two different approaches are suggested to invoke restrictions to improve the end of the season target storage conditions: (1) specify the restriction percent to quantify the reduced risk of not meeting the target storage (Fig. 6) or (2) specify the desired reduction in the risk of not meeting the target storage to obtain the corresponding restriction percent (Fig. 7).

The analyses presented here consider restrictions that could be invoked on water supply releases with the water quality flows corresponding to drought-condition release (2.8 cms). Restrictions on water supply releases could be specified if forecast-based estimates of Prob($S_T < S_T^*$) are greater than that of climatological estimates of Prob($S_T < S_T^*$). Thus, if Prob($S_T < S_T^*$) from a given streamflow forecasting model [Fig. 5(b)] is between 0.5 and 0.6, 0.6 and 0.7, and 0.7 and 0.8, then a restriction fraction of 10, 20, and 30% was applied on the quantified water supply release in Fig. 2. Fig. 6(a) shows the reduction in the estimates of Prob($S_T < S_T^*$) after applying restrictions based on the estimates of Prob($S_T < S_T^*$) in Fig. 5(b) (no restrictions). Based on the restricted

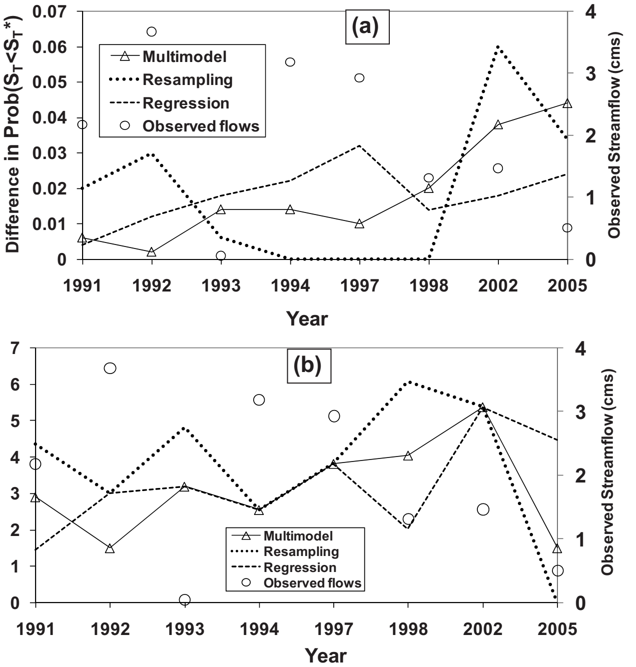

Fig. 6. Performance of streamflow forecasts in reducing the risk of not attaining end of the season target storage (a) under different restriction levels and in improving the end of the season target stage (upon validating with observed flows) (b). September storage difference is obtained from the simulated additional September storage that would have occurred under restricted water supply flows by simulating with the observed flows. Restrictions are obtained based on the estimates of Prob($S_T \leq S_T^*$) with 10, 20, and 30% restriction if the estimates of Prob($S_T \leq S_T^*$) are between 0.5 and 0.6, 0.6 and 0.7, and 0.7 and 0.8, respectively. All the years shown here are below-normal years.

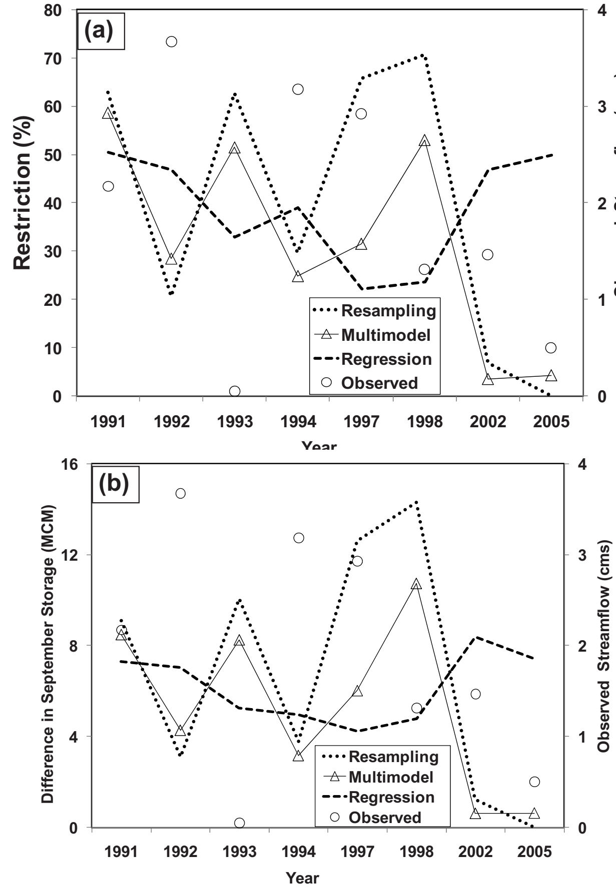

Fig. 7. Performance of streamflow forecasts in suggesting restriction for the prescribed level of reduction in the risk (5%) of not attaining end of the season target storage (a) and in improving the end of the season target stage (b) (upon validating with observed flows) for the obtained restriction in (a)

water supply target, the difference in September storage are obtained [Fig. 6(b)] by simulating the restricted water supply releases and water quality releases with the observed flows.

From Fig. 6(a), it can clearly be seen that resampled flows being bootstrapped from observed flows do not show any appreciable decrease in the estimates of Prob($S_T < S_T^*$). It is important to note that, for year 2005, the estimate of Prob($S_T < S_T^*$) from the resampling model is less than that of climatology and hence the model suggests no restriction. This is indicated by the limited difference in the end of September storage, as restriction could not be applied based on the estimated Prob($S_T < S_T^*$), which indicates a missed target by the resampling model. As expected, differences in the end of September reservoir storage with and without restricted water supply releases clearly show that more water is stored by invoking restrictions, which should in turn improve the resilience of the system during the fall season. *For instance, the improved storage in September 2002 due to restrictions is sufficient enough to supply water for an additional 45 days in the fall season*.

Comparing the performance of different streamflow forecasts in improving the end of September storage conditions, multimodel forecasts seem to perform consistently better because of its ability to predict the below-normal storage conditions better. From Fig. 6(b), regression suggests invoking restrictions in 2005, which is in line with the flows being below normal, but regression model suggests invoking restriction in year 2004 [see Fig. 5(b)], which is incorrect as the observed flows belong to above-normal category. Thus, we would have invoked restrictions in year 2004, resulting in end of September storage over the 76.7 m rule curve target level. Based on the difference in estimates of Prob($S_T < S_T^*$) and the end of September storage conditions obtained by invoking different restriction levels, multimodel streamflow forecasts appear to reduce false alarms by suggesting restrictions only during below-normal inflow years.

A different approach to invoke restrictions is by specifying the desired reduction in the estimate of Prob($S_T < S_T^*$). Fig. 7 provides the suggested restriction percentage from each model [Fig. 7(a)] for 5% reduction in the estimate of Prob($S_T < S_T^*$). Fig. 7(b) shows the difference in the end of September storages between restricted and unrestricted water supply releases for each forecasting model upon simulating with the observed flows. The advantage of this approach is that the restriction percentages are actually specified by the model based on the desired level of reduction in the risk of not meeting the target storage. From Fig. 7(a), we can clearly see that the multimodel streamflow forecasts seem to advocate restrictions that are in between the restriction percentages suggested by resampling and regression models (except 1994 and 2002). For instance, in year 2004, though the flow is below normal, it is very close to the 0.33 percentile (4.2 cms), thus the suggested restriction percentage is less than the restriction suggested by regression and resampling models. Fig. 7(b) illustrates that the difference in end of September storage from the multimodel varies consistently to the change in streamflow potential. For example, in year 2003, the average streamflow is only 0.05 cms, and the restriction suggested by the multimodel is much closer to the resampling model. Of course, the initial storage available in July also plays an important role in estimating the Prob($S_T < S_T^*$), but multimodel forecasts, obtained by combining forecasts from resampling and regression models reduce the model uncertainty and improve the confidence on streamflow forecasts based water allocation by reducing the number of false alarms and missed targets.

Discussion

In developing seasonal water allocation policies, initial storages may ensure 100% reliability of supplying target releases for the intended uses, thereby limiting the utility of climate forecasts. But, ensuring the end of the season target storage (or the operational rule curve) will be met with high probability could offer additional insights for invoking the appropriate level of restrictions during below-normal inflow years. Further, as the water demand increases over the service area (due to urbanization and population growth), the initial storage may no longer ensure 100% reliability, which will necessitate the application of climate forecasts for invoking restrictions. During above-normal inflow years, as the forecasts based Prob($S_T < S_T^*$) will be lower than its climatological probability, forecasts based allocation would avoid unnecessary restrictions if the initial storage is lower than the operational rule curve. On the other hand, if the initial storage is higher than the operational rule curve, then additional release could be considered to reduce the downstream flood risk such that the forecasts based estimates of Prob($S_T < S_T^*$) are equal to its climatological probability.

The retrospective analysis presented in this study could also be utilized to determine the appropriate beginning of the season storage under future increased demand scenarios. Using climatological ensembles, one can estimate the increased beginning of the season storage, S_0, which needs to ensure the current climatological Prob($S_T < S_T^*$) will remain unchanged even under future release scenarios. Similarly, the proposed formulation also could be utilized to develop rule curves that change according to the inflow potential. For instance, in Fig. 6 it is shown that by restricting reservoir releases during below-normal years, the Prob($S_T < S_T^*$) could be increased. To develop rule curves for this scenario, one can specify $S_T = S_T^*$ and obtain previous month target storages that will ensure the restricted releases during the season. It is also important that these rule curves need to be updated regularly based on the updated climate information, which is important towards better prediction of intraseasonal variability in streamflows (Sankarasubramanian et al. 2008).

The main advantage in utilizing multimodel forecasts is in reducing model uncertainty by constituting ensembles from multiple models. In the multimodel combination scheme of Devineni et al. (2008), higher weight is given to the individual model that performs well under similar predictor conditions. For instance, if an individual model performs better during El Nino conditions, then higher number of ensembles is drawn from that particular model under similar predictor conditions. By combining individual models with climatology, one can reduce the overconfidence in individual model forecasts to develop multimodel forecasts that have reduced false alarms and missed targets (Devineni et al. 2008). This study clearly shows that employing such multimodel forecasts for season-ahead water allocation provides a more reliable way to develop appropriate management strategies such as invoking (or not invoking) restrictions during below-normal (above-normal) years. Future studies on climate forecasts application will focus on better management of water supply systems under increased demand potential without resorting to capacity expansion and investments on new systems by considering alternate water uses (e.g., reclaimed water) and trading.

Summary and Conclusions

A reservoir simulation model that uses ensembles of streamflow forecasts is presented and applied for allocating water during the summer season (JAS) from the Falls Lake Reservoir in the Neuse River Basin, N.C. Given the initial storage at the beginning of the season and ensembles of seasonal streamflow forecasts, the simulation model can estimate the reliability of the specified target releases and the end of the season target storage probability.

The customized simulation model for Falls Lake was analyzed using JAS seasonal streamflow forecasts from three models: *parametric regression, semiparametric resampling, and multimodel forecasts (obtained from the former two models)*. The performance of these three models in estimating Prob($S_T < S_T^*$) was evaluated by comparing with the estimates of Prob($S_T < S_T^*$) from climatological ensembles to predict below-normal storage conditions, which could help in invoking restrictions for improving storage conditions at the end of the summer season.

Analyses of Falls Lake using the simulation model without constraining the end of season target storage showed 100% reliability of meeting target releases, implying that the entire seasonal demand could be met purely based on initial storage. This invalidated the utility of streamflow forecasts available for the summer season. However, by constraining the system to meet the end of the season target storage, it is clearly shown that the estimates of Prob($S_T < S_T^*$) from forecasts are higher than the climatology estimates during below-normal summer inflow years and vice versa during above-normal inflow years, thereby indicating the utility of forecasts in invoking restrictions. By invoking restrictions during JAS based on the predicted estimates of Prob($S_T < S_T^*$), the study shows that, upon validating with JAS observed flows, increased storage conditions result in September. Among the three streamflow forecasting models, multimodel streamflow forecasts seem to better predict the change in streamflow potential, thus resulting in reduced false alarms and missed targets in predicting below-normal storage conditions at the end of September. Thus, applying multimodel forecasts would reduce uncertainty from individual models which could lead to better decisions and also could improve public confidence in utilizing seasonal streamflow forecasts for water management application.

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References

Arumugam, S., Sharma, A., and Lall, U. (2003). "Water allocation for multiple uses based on probabilistic reservoir inflow forecasts." *Proc., Int. Association of Hydrological Sciences*, International Association of Hydrological Science, Wallingford, U.K.

Barlow, M., Nigam, S., and Berbery, E. H. (2001). "ENSO, Pacific decadal variability, and US summertime precipitation, drought, and stream flow." *J. Clim.*, 14(9), 2105–2128.

Barnston, A. G., Mason, S. J., Goddard, L., DeWitt, D. G., and Zebiak, S. E. (2003). "Multimodel ensembling in seasonal climate forecasting at IRI." *Bull. Am. Meteorol. Soc.*, 84, 1783–1796.

Dettinger, M. D., and Diaz, H. F. (2000). "Global characteristics of stream flow seasonality and variability." *J Hydrometeorol.*, 1(4), 289–310.

Devineni, D., Sankarasubramanian, A., and Ghosh, S. (2008). "Multi model ensembling of streamflow forecasts: Role of predictor state in developing optimal combinations." *Water Resour. Res.*, 44(9), 1–22.

Doblas-Reyes, F. J., Deque, M., and Piedelievre, J. P. (2000). "Multimodel spread and probabilistic seasonal forecasts in PROVOST." *Q. J. R. Meteorol. Soc.*, 126(567), 2069–2087.

Georgakakos, A. P., Yao, H. M., Mullusky, M. G., and Georgakakos, K. P. (1998). "Impacts of climate variability on the operational forecast and management of the upper Des Moines River basin." *Water Resour. Res.*, 34(4), 799–821.

Guetter, A. K., and Georgakakos, K. P. (1996). "Are the El Niño and La Niña predictors of the Iowa River seasonal flow?" *J. Appl. Meteorol.*, 35(5), 690–705.

Hamlet, A. F., and Lettenmaier, D. P. (1999). "Columbia River streamflow forecasting based on ENSO and PDO climate signals." *J. Water Resour. Plann. Manage.*, 125(6), 333–341.

Hamlet, A. H., Huppert, D., and Lettenmaier, D. P. (2002). "Economic value of long-lead streamflow forecasts for Columbia River hydropower." *J. Water Resour. Plann. Manage.*, 128(2), 91–101.

Hartmann, H. C., Pagano, T. C., Sorooshian, S., and Bales, R. (2002). "Confidence builders—Evaluating seasonal climate forecasts from user perspectives." *Bull. Am. Meteorol. Soc.*, 83(5), 683–698.

Kyriakidis, P. C., Miller, N. L., and Kim, J. (2001). "Uncertainty propagation of regional climate model precipitation forecasts to hydrologic impact assessment." *J Hydrometeorol.*, 2(2), 140–160.

Leung, L. R., Hamlet, A. F., Lettenmaier, D. P., and Kumar, A. (1999). "Simulations of the ENSO hydroclimate signals in the Pacific Northwest Columbia River basin." *Bull. Am. Meteorol. Soc.*, 80(11), 2313–2329.

Lyon, B., Christie-Blick, N., and Gluzberg, Y. (2005). "Water shortages, development, and drought in Rockland County, New York." *J. Am. Water Resour. Assoc.*, 41(6), 1457–1469.

Pagano, T. C., Hartmann, H. C., and Sorooshian, S. (2001). "Using climate forecasts for water management: Arizona and the 1997–1998 El Nino." *J. Am. Water Resour. Assoc.*, 37(5), 1139–1153.

Piechota, T. C., Chiew, F. H. S., Dracup, J. A., and McMahon, T. A. (2001). "Development of exceedance probability streamflow forecast." *J. Hydrol. Eng.*, 6(1), 20–28.

Piechota, T. C., and Dracup, J. A. (1996). "Drought and regional hydrologic variation in the United States: Associations with the El Nino Southern Oscillation." *Water Resour. Res.*, 32(5), 1359–1373.

Regonda, S. K., Rajagopalan, B., Clark, M., and Zagona, E. (2006). "A multimodel ensemble forecast framework: Application to spring seasonal flows in the Gunnison River Basin." *Water Resour. Res.*, 42(9), 1–14.

Ropelewski, C. F., and Halpert, M. S. (1987). "Global and regional scale precipitation patterns associated with the El-Nino southern oscillation." *Mon. Weather Rev.*, 115(8), 1606–1626.

Sankarasubramanian, A., Devineni, N., and Ghosh, S. (2006). "Multi model ensembling based predictor state space: Seasonal forecasts and climate relation." *Miniseries*, Institute of Statistics North Carolina State Univ., Raleigh, N.C.

Sankarasubramanian, A., Lall, U., and Espuneva, S. (2008). "Role of retrospective forecasts of GCMs forced with persisted SST anomalies in operational streamflow forecasts development." *J Hydrometeorol.*, 9(2), 212–227.

Schaake, J., and Larson, L. (1998). "Ensemble streamflow prediction (ESP): Progress and research needs." *Special Symp. on Hydrology*, American Meteorological Society, Boston, J19–J24, 1998.

Sicard, E., Sabatier, R., Niel, H., and Cadier, E. (2002). "A new approach in space-time analysis of multivariate hydrological data: Application to Brazil's Nordeste region rainfall." *Water Resour. Res.*, 38(12), 1319.

Souza, F., and Lall, U. (2003). "Seasonal to interannual ensemble streamflow forecasts for Ceara, Brazil: Applications of a multivariate." *Water Resour. Res.*, 39(11), 1–13.

Steinemann, A. C. (2006). "Using climate forecasts for drought management." *J. Appl. Meteorol.*, 45(10), 1353–1361.

Vorosmarty, C. J., Green, P., Salisbury, J., and Lammers, R. B. (2000). "Global water resources: Vulnerability from climate change acid population growth." *Science*, 289(5477), 284–288.

Weaver, C. J. (2005). "The drought of 1998–2002 in North Carolina–Precipitation and hydrologic conditions." *USGS Scientific Investigations Rep.*, Washington, D.C.

Yao, H., and Georgakakos, A. (2001). "Assessment of Folsom Lake response to historical and potential future climate scenarios. 2—Reservoir management." *J. Hydrol.*, 249(1–4), 176–196.