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A SIMPLE FRAMEWORK FOR INCORPORATING SEASONAL STREAMFLOW FORECASTS INTO EXISTING WATER RESOURCE MANAGEMENT PRACTICES[1]

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ABSTRACT: Climate-based streamflow forecasting, coupled with an adaptive reservoir operation policy, can potentially improve decisions by water suppliers and watershed stakeholders. However, water suppliers are often wary of straying too far from their current management practices, and prefer forecasts that can be incorporated into existing system modeling tools. This paper presents a simple framework for utilizing streamflow forecasts that works within an existing management structure. Climate predictors are used to develop seasonal inflow forecasts. These are used to specify operating rules that connect to the probability of future (end of season) reservoir states, rather than to the current storage, as is done now. By considering both current storage and anticipated inflow, the likelihood of meeting management goals can be improved. The upper Delaware River Basin in the northeastern United States is used to demonstrate the basic idea. Physically plausible climate-based forecasts of March-April reservoir inflow are developed. Existing simulation tools and rule curves for the system are used to convert the inflow forecasts to reservoir level forecasts. Operating policies are revised during the forecast period to release less water during forecasts of low reservoir level. Hindcast simulations demonstrate reductions of 1.6% in the number of drought emergency days, which is a key performance measure. Forecasts with different levels of skill are examined to explore their utility.

(KEY TERMS: climate variability; drought; water allocation; forecasting; streamflow; reservoir management; water policy.)

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INTRODUCTION

Climate-based seasonal streamflow forecasting, coupled with an adaptive reservoir operation policy, can improve decisions by water suppliers and watershed stakeholders (Kim and Palmer, 1997). Knowledge of future water supplies can be useful for equitably allocating water deliveries between urban, industrial, and agricultural users, as well as providing adequate releases for environmental and ecological needs. When the predicted flood risk is high, reservoir releases can be augmented to increase reservoir void space for flood mitigation. When the predicted drought risk is high, forecasts can be used as part of a formal or informal hedging and drought planning strategy to limit water supply risk.

A number of regional water resource decision-support experiments which incorporate streamflow forecasts have been attempted in recent years. In

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northern California, water suppliers have developed the Integrated Forecast and Reservoir Management system (Georgakakos *et al.*, 2005). The system derives management decisions from a combination of forecast models with varying time scales, from multi-decadal to hourly. In southern Florida, water purveyors manage Lake Okeechobee with the aid of a seasonal streamflow forecast tool. Forecasts are developed 6 to 12 months in advance and then coupled with a decision tree rather than a traditional hydrologic rule curve to determine appropriate reservoir releases (Obeysekera *et al.*, 2007). The Seattle Public Utility District uses seasonal forecasts from snowpack and maritime Pacific conditions in their reservoir release policy. Seasonal forecasts are issued and then used to enact a dynamic rule curve that dictates reservoir releases (Basketfield, 2005). These and other experiments constitute a growing set of decision-support applications. For example, in 2005 Seattle successfully hedged against drought following forecasts of an anomalously low flood season.

While these examples are both innovative and effective, the widespread incorporation of streamflow forecasts into standard reservoir management practice faces considerable challenges. Most of these applications consider idealized decision frameworks that are not directly cognizant of the operational management framework that is being used. This limits adoption of the innovations, as it is difficult to assess the utility or skill of the forecasts directly in the existing management context. The conservative nature of most water managers, coupled with a shared decision-making structure across multiple government agencies, inhibits fundamental changes in management practices. Typically, water managers are interested in the benefits of seasonal streamflow forecasting, provided that they work within their established management structure, are easy to incorporate into existing system modeling tools, and require little if any human intervention (NRC, 2005). Yet at the same time, they want decision-support systems that are flexible and can deal with a variety of different climatic scenarios. How best to achieve this is still an open question. Here, we explore a limited case study for the use of probabilistic streamflow forecasts with existing management structures in the setting of the upper Delaware River Basin (DRB) in the northeastern United States (U.S.).

SETTING AND NEEDS

The DRB is a 35,000 km^2 area stretching from upstate New York to Delaware Bay (see Figure 1), with a total reservoir storage capacity of roughly 1.5 Bm^3. Consumptive water use in the basin is dominated by New York City (NYC), which is entitled to 3 Mm^3/day supplied from three major water supply reservoirs in the upper DRB (Cannonsville, Pepacton, and Neversink) (see Figure 1). New Jersey is also entitled to 0.4 Mm^3/day withdrawn from the lower portion of the Delaware River. Nonconsumptive uses are highly valued, and include fishing, boating, and rafting (Hydrologics, 2004). The annual value of cold water fishing in the Upper Delaware region is estimated at US$30 million (Maharaj *et al.*, 1998). Upper and middle portions of the river have been classified as Special Protection Waters, and most of the main stem upstream of Trenton, New Jersey, is included in the National Wild and Scenic Rivers System.

River basin management is overseen by the Delaware River Basin Commission (DRBC), which consists of representatives from its four bordering states and the federal government. The DRBC, in conjunction with the New York City Department of Environmental Protection (NYCDEP), manages releases from the three upper DRB reservoirs using rule curves derived from historical data. As shown in Figure 2, there are four curves that delineate five reservoir storage state zones. The top curve represents a flood threshold level for the system, while the bottom three curves represent drought threshold levels for the system. The corresponding storage state zones are designated L1 to L5, representing flood, normal, drought watch, drought warning, and drought emergency conditions, respectively. Furthermore, the L1 flood zone is divided into three emergency release subzones for flood events.

The operational mission of the rule curves is to maintain adequate storage at all times to ensure NYC's 3 Mm^3/day supply, by controlling each reservoir's downstream flow release. Each day, the combined storage of the reservoirs is determined, and where this storage lies in relation to the rule curves dictates the release rate for the reservoirs. The basic management policy is to keep the rule curves fixed, but allow for periodic revision of the release rates associated with each storage zone. Seasonal release rates for a recently implemented Flexible Flow Management Policy (FFMP) (DRBC, 2007) are shown in Table 1.

A problem with this rule curve paradigm is that reservoir management lags system stresses, i.e., release rates are not adjusted until after flood or drought thresholds are exceeded. Also, while the current rule curves may be effective at ensuring NYC's water supply, they arguably do so at the expense of downstream stakeholders. NYC tries to keep reservoir levels at or near capacity to reduce drought risk. This leads to periodic "spills," which negatively impact a renowned downstream trout fishery that

FIGURE 1. The Upper Delaware River Basin (source: http://www.drbc.net).

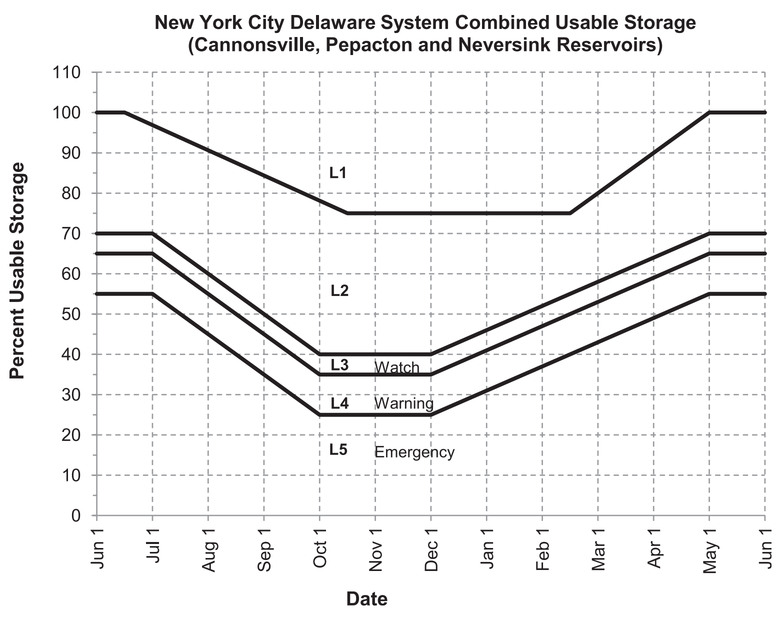

FIGURE 2. Rule Curves and Storage Zones (L1, L2, L3, L4, L5) Governing the Directed Release From the New York City Water Supply Reservoirs (source: http://www.drbc.net).

needs a steady flow of cold water, but is frequently starved for water under the current operation. Downstream residents are also negatively impacted as full reservoirs have minimal void space for absorbing elevated flows during major storms. Even though they are not designed as flood control reservoirs, the recent occurrence of several flood events has prompted residents in the downstream floodplain to call for the reservoirs to be used for flood mitigation. These rigid constraints on the allocation of water in the DRB have contributed to conflicts among users and stakeholders.

TABLE 1. Flexible Flow Management Plan for New York City Water Supply Reservoirs in the Upper Delaware River Basin. Directed reservoir releases in ft^3/s are specified daily for each storage zone, to maintain adequate storage for ensuring New York City's supply.

	Winter		Spring	Summer			Fall	
	Dec. 1-Mar. 31	**Apr. 1-Apr. 30**	**May 1-May 31**	**Jun. 1-Jun. 15**	**Jun. 16-Jun. 30**	**Jul. 1-Aug. 31**	**Sep. 1-Sep. 30**	**Oct. 1-Nov. 30**
Cannonsville storage zone								
L1-a	1,500	1,500	*	*	1,500	1,500	1,500	1,500
L1-b	250	*	*	*	*	350	275	250
L1-c	110	110	225	275	275	275	140	110
L2	80	80	215	260	260	260	115	80
L3	70	70	100	175	175	175	95	70
L4	55	55	75	130	130	130	55	60
L5	50	50	50	120	120	120	50	50
Pepacton storage zone								
L1-a	700	700	*	*	700	700	700	700
L1-b	185	*	*	*	*	250	200	185
L1-c	85	85	120	150	150	150	100	85
L2	65	65	110	140	140	140	85	60
L3	55	55	80	100	100	100	55	55
L4	45	45	50	85	85	85	40	40
L5	40	40	40	80	80	80	30	30
Neversink storage zone								
L1-a	190	190	*	*	190	190	190	190
L1-b	100	*	*	*	*	125	85	95
L1-c	65	65	90	110	110	110	75	60
L2	45	45	85	100	100	100	70	45
L3	40	40	50	75	75	75	40	40
L4	35	35	40	60	60	60	30	30
L5	30	30	30	55	55	55	25	25

*Storage zone does not apply during this period. Releases will be made in accordance with zone L1-c.

We propose a framework for using probabilistic forecasts to modify the existing rule curve management structure in a way that could equitably benefit all stakeholders, and thereby influence the entire management process positively. Climate predictors are used to develop seasonal streamflow forecasts (SSFs) for the upper DRB. The forecasts are incorporated into a modified set of rule curve-directed release rates, while using an existing reservoir system model for scenario analysis and simulation. The rule curve modification considers operation such that the trigger to invoke a rule curve is a predicted end of season reservoir state with a sufficiently high probability rather than the current stage. The initial modification presented here considers primarily the reduction in drought risk and its impacts. Modifications to consider both flood and drought performance measures are discussed.

The DRB stakeholders are potentially receptive to the incorporation of climate information into their existing practices. The DRBC recognizes that stakeholder conflicts can be addressed by introducing innovative approaches to water resources management in the basin. For example, a subcommittee on Ecological Flows was created in 2003 to more explicitly consider conservation needs, which has facilitated the development of the FFMP that helps protect the fishery without substantially increasing drought risk. Interim measures have been enacted to maintain snowpack and event-based voids in the reservoirs under specific circumstances for flood mitigation (Collier, 2006). Finally, the DRBC has acknowledged the relevance of climate change to the DRB, and the need to consider future climate change scenarios probabilistically, for effective long-term planning (Fromuth and Quinodoz, 2001). Members of the DRBC have expressed an interest in using SSFs to complement their operational decision making, and conservation groups have also expressed support for such an approach (Gong *et al.*, 2006).

The existing reservoir simulation model uses a daily time step. So, one needs a mechanism to develop not just probabilistic forecasts of the total seasonal inflow into the reservoirs but also the disaggregation of these forecasts into daily flow sequences. The approach considered here is to generate an ensemble seasonal forecast from the conditional probability distribution, and to then disaggregate each ensemble member into a daily sequence. Each daily sequence can then be run through a system simulation model using a specified operating rule, and the end of period reservoir storage and any other desired performance statistics can then be computed and assembled into an empirical probability distribution of that statistic. This overall approach is developed in the next section.

CONCEPTUAL APPROACH

Goals and Objectives

The existing rule curves are based on an estimate of the storage required on specific dates to meet the maximum cumulative deficit from supply, anticipated looking forward from that date during the critical dry period in the historical record. Operational decisions are therefore based on the current system state and assumed future "worst case" low inflow conditions. This is not necessarily the approach that leads to the most efficient utilization of flows, even for a reservoir system operated for seasonal storage, as is the case for this system. The NYC operating rule actually keeps the reservoir storage well above the rule curve levels in most years, with drought warning, watch, or emergency declared if different levels associated with the rule curve are reached. Recognizing that this reservoir system is primarily operated as a seasonal storage system, using a probabilistic streamflow forecast with current storage conditions provides the opportunity to evaluate the probability of the maximum cumulative deficit over the current season that could ensue under normal or modified release policies. This information can be utilized to offer a more liberal release policy for environmental flows or for a measure of flood control. Thus, with a skillful forecast it may be possible to provide additional performance for additional uses without increasing the risk of NYC supply. Demonstrating that this may be feasible is the goal of this study.

The specific objective is the design and application of an incremental modification of the existing rule curve-based operation, to use a probabilistic forecast of seasonal inflows and their disaggregation into daily sequences, with a specification of a trigger based on the probability distribution of future storage. The intent is to use such an approach with any ensemble forecast, including perhaps a climatological forecast. An associated objective is to evaluate the performance of the rule curve modifications developed, and the effectiveness of the SSFs.

Framework

The general conceptual framework is organized into a sequence of steps illustrated in Figure 3, and described below.

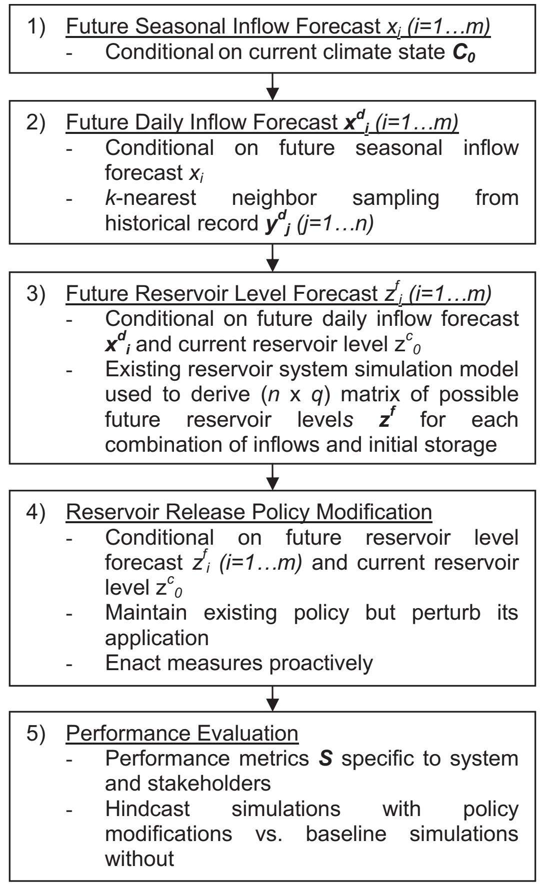

FIGURE 3. Conceptual Framework for Improving Reservoir Management Using Probabilistic Seasonal Reservoir Inflow Forecasts.

Future Seasonal Inflow Forecast. An m member ensemble forecast of future season inflow x_i ($i = 1, \ldots, m$) given the current season observation of climate state $\boldsymbol{C_0}$ is first developed. This corresponds to m random samples from the conditional probability density function (PDF) $f_{x\mid\boldsymbol{C}}(x_i \mid \boldsymbol{C_0})$. The vector quantity $\boldsymbol{C_0}$ can be represented by standard climate indices [e.g., El Nino-Southern Oscillation (ENSO)] or regional fields of atmospheric or surface parameters (e.g., zonal windspeeds over the Gulf of Mexico), or rainfall forecasts from a General Circulation Model of the Ocean and Atmosphere. By incorporating current season climate information, the conditional PDF $f_{x\mid\boldsymbol{C}}(x_i \mid \boldsymbol{C_0})$ improves upon the practice of drawing a sample from n observed values of future season inflow y_j ($j = 1, \ldots, n$) over the n year historical record, treating each of these values as equally likely for the upcoming season. A skillful forecast x_i conditioned on current season climate observations is an important first step for this framework.

Future Daily Inflow Forecast. Convert the future seasonal inflow forecast into a future daily inflow forecast sequence entering the reservoir. Each seasonal forecast ensemble member is compared against the historical record of future season streamflow values to identify a subset of years that most closely match the seasonal forecast value. One of the years is randomly selected, and the daily streamflow values over the forecast period for the selected year are taken as one ensemble member of the future daily inflow forecast. Specifically, obtain a probabilistic forecast of future daily inflow with m ensemble members $\boldsymbol{x^d_i}$ ($i = 1, \ldots, m$) given the SSF x_i, which amounts to m random samples from the conditional PDF $f_{\boldsymbol{x}^d | x}(\boldsymbol{x^d_i} \mid x_i)$. For each seasonal forecast ensemble member x_i, use a k-nearest neighbor approach to randomly draw from the k-nearest y_j values, with a kernel function that gives higher probability to closer values (Lall and Sharma, 1996). For the selected y_j, assign its observed daily inflow timeseries $\boldsymbol{y^d_j}$ as the corresponding daily ensemble member $\boldsymbol{x^d_i}$ for that seasonal x_i value.

Future Reservoir Level Forecast. Use the future daily reservoir inflow forecast sequence to obtain a reservoir level forecast for the end of the forecast season. Specifically, obtain a probabilistic forecast of future reservoir level with m ensemble members z^f_i ($i = 1, \ldots, m$), which amounts to m random samples from the conditional PDF $f_{z^f | x^d, z^c}(z^f_i \mid \boldsymbol{x^d_i}, z^c_0)$. Using an existing simulation model for the reservoir system at hand, assemble *a priori* an $(n \times q)$ matrix $\boldsymbol{z^f}$ of possible future reservoir levels, where each matrix element z^f_{jl} results from one reservoir system model simulation with a unique pair of boundary and initial conditions. Inflow boundary conditions span the n years of observed daily inflow $\boldsymbol{y^d_j}$, and reservoir level initial conditions span q uniformly distributed values z^c_l ($l = 1, \ldots, q$), where the z^c_l value closest to the actual observed reservoir level is taken as z^c_0. Then for each daily ensemble member $\boldsymbol{x^d_i}$, use its corresponding observed $\boldsymbol{y^d_j}$ along with z^c_0 to read the corresponding future reservoir level ensemble member z^f_i from the matrix $\boldsymbol{z^f}$.

A key simplifying procedure for this conceptual framework is to represent each future daily inflow ensemble member $\boldsymbol{x^d_i}$ using the observed daily inflow timeseries from a specific historical year $\boldsymbol{y^d_j}$. Without utilizing the historical timeseries, there is no means of reliably disaggregating future seasonal inflows to daily inflows. Furthermore, this technique allows for a finite set of $(n \times q)$ reservoir system simulations to be run once, before any forecasts are ever made. As each daily streamflow sequence considered is one of the historical set, this evaluation needs to be done only once. Effectively we give each historical year a conditional probability of occurrence given the current climate conditions, and then compute the probability distribution of end of period storage considering an initial storage and the daily sequence from a specific historical year which is sampled with the desired probability. The matrix $\boldsymbol{z^f}$ encompasses the entire spectrum of possible future reservoir levels, and replaces the burden of simulating the reservoir system response to each of m ensemble members with a simple lookup table approach.

Reservoir Release Policy Modification. Use the future reservoir level forecast z^f_i ($i = 1, \ldots, m$) to determine reservoir release rates during the forecast period. The basic decision rule is that if $p(z^f < z^*) \geq p^*$ then release at rate $r = f(z^f, z^c_0)$, where z^* is a future rule curve action threshold, p^* is a critical probability of z^* exceedance, and r represents modified release rates informed by predicted critical future conditions. The set of rule curves and release rates associated with the existing operational policy is maintained, but the r value specified for each storage zone is adjusted to enact measures proactively if p^* is exceeded, rather than reactively if and when the rule curves are actually exceeded.

Performance Evaluation. This proposed framework includes a set of decision parameters z^*, p^*, and r that are specific to the reservoir system and its management objectives. Similarly, one or more performance metrics $\boldsymbol{S}$ can be developed that are of key interest to the specific system and its stakeholders. Effective metrics concisely and quantitatively assess the hydrological, economic, or societal benefits achieved by the applied framework. $\boldsymbol{S}$ may be multivariate if the reservoir system can serve multiple functions, and may differ across reservoir systems depending on their intended purposes. Hence each application of this framework will have unique attributes, so there is a need to work closely with system managers and stakeholders to develop a meaningful application.

Regardless of the specified $\boldsymbol{S}$ for a system, the effectiveness of this proposed framework is easily evaluated by comparing $\boldsymbol{S}$ for hindcast simulations with the forecasts and policy modifications, to baseline simulations without them. Hindcasts using different SSF techniques can also be compared to evaluate the ability of the SSFs to provide new and useful information.

UPPER DELAWARE RIVER BASIN CASE STUDY

A case study of our proposed conceptual framework is developed for the upper DRB. To demonstrate the overall framework clearly and succinctly, this application considers a limited management objective of releasing less water when forecasted future reservoir levels are low, so as to minimize drought risk for NYC. Only the spring "fill season" is considered, when modest filling may be an indicator of subsequent summer drought.

Future Inflow and Reservoir Level Forecasts

The SSF developed for the upper DRB consists of forecasted March-April (MA) average reservoir inflow, issued on the preceding February 28. The MA season has physically based potential for exhibiting streamflow predictability. Average streamflow during this season exhibits the greatest magnitude and interannual variability, which suggests winter snowpack storage and spring snowmelt as a causal factor. The winter season is particularly responsive to large-scale climatic phenomena such as ENSO and the North Atlantic Oscillation (NAO), so preceding winter atmospheric and oceanic states are another potential source of predictability (Barlow *et al.*, 2000; Bradbury *et al.*, 2002).

A multivariate linear regression model is built for forecasting MA reservoir inflow, using n = 57 years of streamflow observations from 1949 to 2005, at United States Geological Survey (USGS) station 01413500, located just upstream of the Pepacton Reservoir. USGS stations upstream of the Cannonsville and Neversink reservoirs have shorter periods of record, and are highly correlated with the Pepacton streamflow record ($r \geq 0.9$), so forecasts made for Pepacton inflow are scaled and applied to the other two reservoirs as well.

Numerous candidate predictor variables are considered, including preceding winter streamflows, climatic teleconnection indices (e.g., NINO3, NINO12, NAO), local snow depth (SND) from the United States Historical Climatology Network (Williams *et al.*, 2004), sea surface temperatures (SST) from the Hadley Centre SST dataset (HadSST2) (Rayner *et al.*, 2006), and remote sea level pressure (SLP) and zonal wind (ZW) from NCEP/NCAR Reanalysis (Kalnay, 1996). Five influential predictors are identified from among the candidates using univariate correlation analysis followed by stepwise multiple linear regression: February average local SND, January-February average (JF) SST off the Pacific coast of the U.S., JF SLP over the Gulf of Mexico, and JF 700 hPa ZW over the Great Lakes and the Gulf of Mexico. Figure 4 shows the gridpoint correlations between MA inflow and the SST, SLP, and ZW predictor fields, including regions over which the gridpoint correlations were averaged to obtain the predictor variable for the forecast model. Individual predictor variable correlation magnitudes with MA inflow ranged from 0.32 to 0.61.

These five predictors represent physically plausible regional mechanisms for influencing MA streamflow in the upper DRB (Hartley and Keables, 1998; Bradbury *et al.*, 2003; Miller *et al.*, 2006). Seasonal storage and melting of local winter snowpack plays an obvious role in the volume of spring discharge. ZW over the eastern U.S. are related to winter storm tracks which deposit snow in the DRB. Positive (negative) ZW correlations over the Gulf of Mexico (Great Lakes) in Figure 4 are consistent with winter cyclonic activity originating near the Gulf of Mexico and transporting moisture northeast into the DRB region. Negative SLP correlations over the Gulf of Mexico in Figure 4 are also indicative of this cyclonic activity. Finally, positive SST correlations off the Pacific coast of the U.S. in Figure 4 suggest that the subtropical

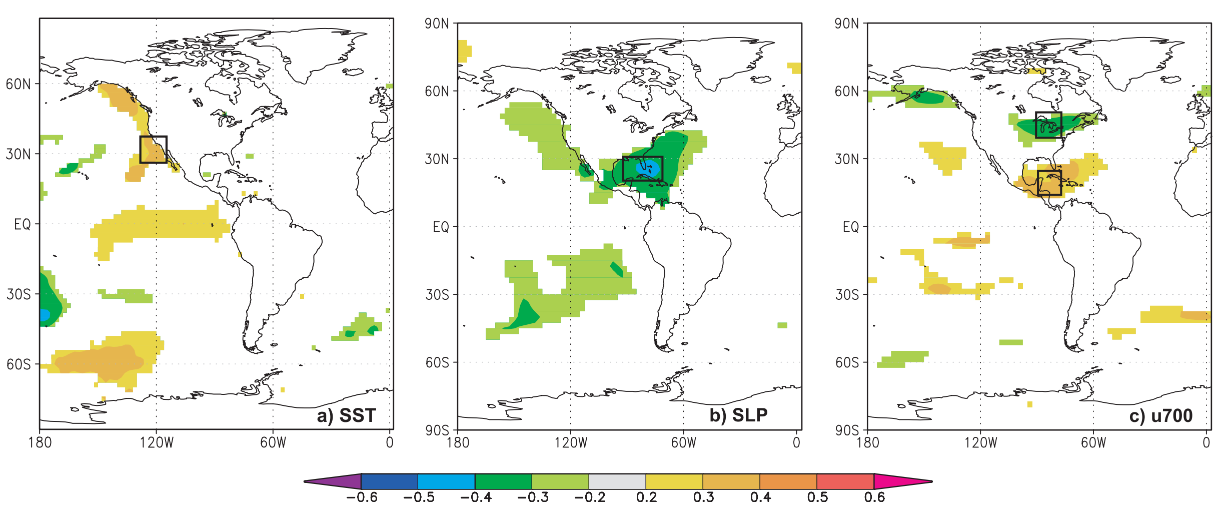

FIGURE 4. Linear Correlations Between MA Average Reservoir Inflow and Preceding January-February Average Atmospheric Fields of (a) Sea Surface Temperature, (b) Sea Level Pressure, and (c) 700 hPa Zonal Wind. Boxes indicate geographic regions for climate predictor variables.

Pacific provides moisture that gets transported to the DRB region via the subtropical jet stream.

The resulting seasonal forecast model explains 54% of the variance in observed MA inflow, and can be expressed mathematically as:

$$x_i = \beta_0 + \beta_1 C_1 + \beta_2 C_2 + \beta_3 C_3 + \beta_4 C_4 + \beta_5 C_5 + \varepsilon \qquad (1)$$

where x_i is the forecast MA seasonal inflow, $\boldsymbol{\beta} = \beta_0, \beta_1, \ldots, \beta_5$ are the regression parameters, $\boldsymbol{C_0} = C_1, C_2, \ldots, C_5$ are the five winter climate predictors, and $\varepsilon = N(0, \sigma_\varepsilon^2)$ is a randomly sampled error term. A semiparametric model as in Souza Filho and Lall (2003) could also be used, if the assumption of normality or the linearity assumption in (1) were an issue. Disaggregation to a MA daily inflow forecast $\boldsymbol{x^d}_{\boldsymbol{i}}$ using $k = 1$ nearest-neighbor sampling was used in the applications for simplicity, using the historical dataset of USGS streamflow observations for $\boldsymbol{y^d}_{\boldsymbol{j}}$.

The DRBC and associated government agencies use the OASIS software package (Hydrologics, 2001) to simulate daily flows through the upper DRB system. This upper DRB model was first developed in 2002, and has since been continuously refined and used in both a planning and operational capacity. It is used here to obtain the $(n \times q)$ matrix of April 30 reservoir levels $\boldsymbol{z^f}$ shown in Figure 5, where $q = 20$ uniformly distributed reservoir level initial conditions $z^c{}_l$. The April 30 reservoir level forecast $z^f{}_i$ is drawn from this $\boldsymbol{z^f}$. $m = 100$ ensemble members are sampled on February 28 to generate the probabilistic MA inflow and April 30 reservoir level forecasts.

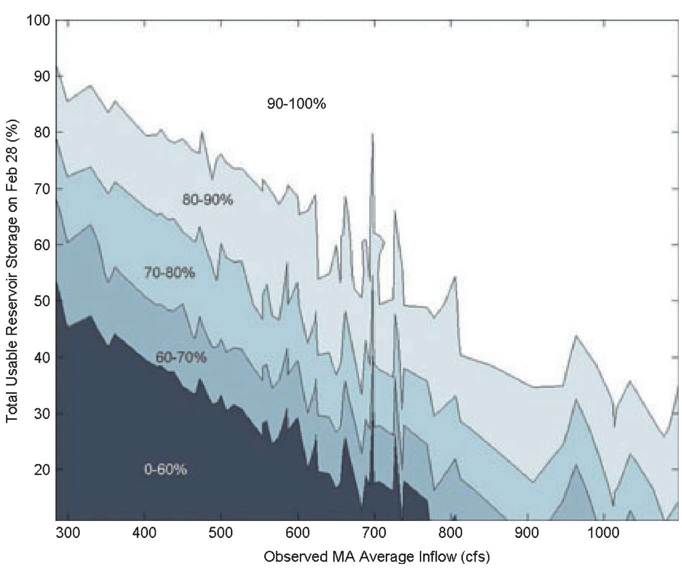

FIGURE 5. OASIS Simulation Matrix Indicating Usable Storage (percent of combined capacity) on April 30, as a Function of February 28 Usable Storage Initial Condition and Observed MA Average Inflow Boundary Condition.

Reservoir Release Policy Modification

For this case study, reservoir release rates are modified when the forecast of April 30 reservoir levels fall below $z^* = 80\%$ of usable storage, with probability $p^* \geq 0.8$, i.e., $p(z^f < 80\%) \geq 0.8$. The existing rule curves trigger drought watch conditions on April 30 if usable storage falls below 70%, so here preemptive action occurs if the forecast April 30 conditions fall below the more conservative threshold of 80% usable storage. However, preemptive action only occurs if the probabilistic forecast indicates a high likelihood ($p^* \geq 0.8$) of falling below this threshold. Both the level and the probability were chosen just for illustration here.

The preemptive policy modifications $r = f(z^f,\ z^c{}_0)$ utilize the release rates associated with the existing rule curves, but apply rates that correspond with lower storage conditions than indicated for February 28 ($z^c{}_0$), since April 30 storage conditions ($z^f{}_i$) are forecast to be low. For example, if reservoir levels are in the normal (L2) storage zone on February 28, the existing rule curves in Table 1 call for 1.84 m^3/s to be released from the Pepacton Reservoir. But if the April 30 forecast calls for preemptive modifications, then release instead at a lower rate of 1.56 m^3/s according to the drought watch (L3) storage zone. The specific release policy modification varies with February 28 storage zone, as shown in Table 2.

Performance Evaluation

As the operational mission of the upper DRB reservoirs is to ensure NYC's water supply, the primary performance metric of interest to NYCDEP is the number of drought emergency days that occur. The effectiveness of the proposed framework at reducing this metric is evaluated via hindcast simulations of the $n = 57$ year period of record using OASIS. Each year a SSF is issued on February 28, and used to inform any release policy modifications to be applied

TABLE 2. Release Rates for Pepacton Reservoir During MA Forecast Period, With and Without SSF-Based Policy Modifications.

	Reservoir Release Rate (m^3/s)	
February 28 Storage Zone	**Existing Rule Curve Policy**	**SSF-Modified Policy**
L1 (Flood)	2.41	1.56
L2 (Normal)	1.84	1.56
L3 (Drought Watch)	1.56	1.27
L4 (Drought Warning)	1.27	1.13
L5 (Drought Emergency)	1.13	1.13

during the MA forecast period. The unaltered rule curves are used for all subsequent months until the next year's forecast period. Results are compared against a baseline simulation with no SSF and release policy modifications, which yielded 1,253 drought emergency days.

A perfect hindcast simulation is performed in which each year's MA daily inflow hindcast is obtained directly from the observed daily MA inflow record for that year. In essence, actual April 30 reservoir levels are known at the preceding February 28 time of hindcast issuance, and used to determine release policy modifications accordingly. Forecast sampling errors are effectively removed, and the release policy modifications can be evaluated without the ambiguities associated with probabilistic forecast skill. This represents an idealized limiting case where $p(z^f < 80\%) = 0$ or 1, i.e., $p^* \rightarrow 1$. This simulation yielded 1,233 drought emergency days, a decrease of 1.6% from the baseline simulation. Thus the release policy modifications adopted for this limited case study result in modest but tangible water management gains.

A second hindcast simulation is performed which utilizes the multivariate linear regression forecast model with climate predictors described above. The release policy modifications are unchanged from the perfect hindcast, but the effectiveness of this simulation is now subject to the skill of the SSF. This simulation yielded 1,251 drought emergency days, which is virtually unchanged from the baseline simulation. This result suggests that standard linear streamflow forecasts for the upper DRB region may not be sufficient to facilitate the proposed conceptual framework proposed here for incorporating SSFs into existing water resource management practices.

Results Using an Alternative SSF Technique

In an effort to improve forecasting skill, the MA reservoir inflow predictand is refined before assembling the multivariate linear regression model. The intention is to remove factors that influence MA reservoir inflow which are not directly related to preseason observed climate predictors. First, base flow x_b is removed by subtracting out the preceding February flow rate. This is based on the rationale that winter flows are derived primarily from groundwater which persists into spring, while winter climate patterns influence subsequent spring flows more than winter flows directly, via snow storage.

Second, a *k*-means clustering analysis is applied, to identify years with negative or nearly negative base flow-removed streamflow. Such years are classified as "dry" years in which spring flows are dominated by groundwater or base flow conditions which are not designed to be predicted by the climate-based scheme considered here. The remaining years are classified as "normal" years in which flows are dominated by atmospheric inputs that can be predicted by climate. For this case study 11 "dry" years are identified among the 57 year period of record.

We treat the "dry" and "normal" states separately in subsequent model development. For the 11 "dry" years, the simple historical median of the base flow-removed streamflow over all "dry" years is applied. For the 46 "normal" years, a probabilistic multivariate linear regression model x_{n} is developed analogous to the original climate-based forecast model x_i in Equation (1), but for base flow-removed MA streamflow.

The forecast model is completed by determining the probability that the upcoming season will be "normal" (i.e., not "dry"). A multivariate logistic regression analysis is performed, in which a binary MA streamflow timeseries (dry = 0, normal = 1) is regressed against yet another set of winter climate predictors, yielding a probability p_{n} that a particular year's set of predictor values results in a "normal" year. p_{n} acts as a weighting factor for combining the "dry" and "normal" forecasts, after which base flow is added back. The conditional mean of the forecast distribution, can then be identified as x_i:

$$x_i = [(1 - p_{\mathrm{n}})m_{\mathrm{d}} + p_{\mathrm{n}}x_{\mathrm{n}}] + x_b \tag{2}$$

$$x_n = \beta_{n0} + \beta_{n1}C_{n1} + \beta_{n2}C_{n2} + \beta_{n3}C_{n3} + \beta_{n4}C_{n4} + \beta_{n5}C_{n5} \tag{3}$$

$$p_n = \frac{1}{1 + \exp[\beta_{p0} + \beta_{p1}C_{p1} + \beta_{p2}C_{p2} + \beta_{p3}C_{p3} + \beta_{p4}C_{p4} + \beta_{p5}C_{p5}]} \tag{4}$$

where m_{d} is the median value of base flow-removed streamflow during "dry" years; x_{n} is the linear regression based forecast for the "normal" years with regression parameters $\boldsymbol{\beta_{\mathrm{n}}} = \beta_{\mathrm{n}0}, \beta_{\mathrm{n}1}, \ldots, \beta_{\mathrm{n}5}$ and climate predictors $\boldsymbol{C_{\mathrm{n0}}} = C_{\mathrm{n}1}, C_{\mathrm{n}2},, \ldots, C_{\mathrm{n}5}$; p_{n} is the probability of a "normal" year estimated using logistic regression of the binary sequence of normal/dry years, with regression parameters $\boldsymbol{\beta_{\mathrm{p}}} = \beta_{p0}, \beta_{p1}, \ldots, \beta_{p5}$ and climate predictors $\boldsymbol{C_{p0}} = C_{p1}, C_{p2}, \ldots, C_{p5}$. Uncertainty in the forecast distribution can be represented by a convolution of the uncertainty distributions of p_{n} and x_{n}, respectively.

Note that the climate predictor sets for this model $\boldsymbol{C_{\mathrm{n0}}}$ and $\boldsymbol{C_{p0}}$, and the original seasonal forecast model $\boldsymbol{C_0}$ in Equation (1), are each identified independently via univariate correlation and stepwise multiple linear regression with their respective streamflow predictands x_{n}, p_{n}, and x_i, and yield distinct regression parameter sets $\boldsymbol{\beta_{\mathrm{n}}}$, $\boldsymbol{\beta_p}$, and $\boldsymbol{\beta}$. However, all three climate predictor sets model $\boldsymbol{C_{\mathrm{n0}}}$, $\boldsymbol{C_{p0}}$, and $\boldsymbol{C_0}$ are similar in that they represent the same variables, the same seasons, and similar geographic regions (see Figure 4), as the same basic physical mechanisms drive each predictand. This similarity suggests the integration of Equations (2-4) into a single generalized linear model for parameter estimation and estimation using generalized maximum likelihood.

The seasonal linear regression model x_{n} explains 60% of the variance in observed MA inflow, but only during "normal" years. The final logistic/linear forecast model x_i explains only 16% of the variance in observed MA inflow over the entire period of record. Forecast skill during strongly normal years improves somewhat, but the constraint of using a single representative climatological value for subsurface-dominated years weakens the overall streamflow forecast model.

A third hindcast simulation is performed which utilizes this alternative logistic/linear regression, but maintains the same release policy modifications as for the previous hindcasts. This simulation yielded 1,238 drought emergency days, a decrease of 1.2% from the baseline simulation. This result represents a substantial improvement over the original linear forecast model, and approaches the 1.6% decrease obtained for the perfect hindcast simulation. Thus forecast skill has a clear impact on this sample DRB water management objective.

The improved skill of the logistic/linear regression model is not apparent in the final set of predicted MA inflow x_i, which only explains 16% of the observed variance. However, note that for this case study, policy modifications occur when forecast reservoir levels are low, e.g., when forecast inflows are low. During such conditions base flow is expected to be minimal, so that flows are more likely to be climate-driven, and the forecast model x_i is heavily weighted toward the more skillful "normal" year linear regression model x_{n}. In other words, policy modifications for this sample management objective occur primarily during years in which the SSF skill is relatively high.

CONCLUSIONS

The intent of this study is to develop and demonstrate a general framework for incorporating SSFs into existing reservoir management practice in a readily applicable and broadly accessible manner. The key concepts of this framework include (1) making season-ahead reservoir inflow forecasts based on observed climatic conditions; (2) expediting the reservoir level forecasting process by sampling from an *a priori* set of system simulations that use the historical record to represent potential future conditions; (3) making proactive decisions based on the forecasted future state, instead of reactive decisions based on assumed future critical conditions as embodied in rule curves; and (4) maintaining the existing rule curve structure but perturbing its application.

Framework parameters and performance measures are specific to each reservoir system and its management objectives. A limited case study is conducted for the upper DRB to demonstrate the framework, which focuses on reducing the number of drought emergency days during the spring "fill" season. Physically plausible spring SSFs are developed using climate predictors during the preceding winter season, and translated into spring reservoir levels forecasts using existing DRB system models and rule curves. Forecasts of low reservoir levels prompt a mitigation of the reservoir release rate associated with the rule curve storage zones, as summarized in Table 2. Fifty-seven-year hindcast simulations employing this framework yield reductions in the number of drought emergency days reaching 1.6%, although the results are sensitive to the quality of the forecasts. Nevertheless, this upper DRB application serves as a model by which the proposed SSF incorporation framework can be readily adopted by other water resource systems.

Note that the forecasting skill associated with a simple linear regression model was limited, and refinements to this linear forecast yielded notable improvements in operational performance (i.e., number of drought emergency days) but not in terms of the statistical measure of forecasting skill (i.e., fraction of observed variance explained). This is an important aspect to note as most forecast evaluation methods consider only the usual second-order skill statistics which may not match the relatively asymmetric performance measures in actual reservoir operation. Furthermore, only a single operational performance measure was considered here, and gains may vary depending on the measures actually considered. Nevertheless, more sophisticated techniques involving local or other nonlinear regression models may further improve forecasting skill, and further reduce the occurrence of drought emergency days in the upper DRB reservoirs. Varying the reservoir release policy modification as embodied in the framework decision parameters z^*, p^*, and r may also further reduce drought risk for NYC.

In addition, alternative policy modifications, performance measures, and forecast periods can be considered to address different management objectives. For example, forecasts during the autumn and early winter when reservoir levels are relatively low could be more useful for drought alleviation than forecasts for the spring "fill season." Increasing the lead time of the SSFs would allow more time for policy modifications to take effect and impact reservoir levels regardless of the season, if forecast skill is sufficiently high. Forecasts of high future reservoir levels can be used to trigger policy modifications that increase the occurrence of directed reservoir releases, to benefit downstream fisheries and create reservoir voids for flood mitigation during years when drought risk is low. The proposed framework can easily accommodate any of these variations for the upper DRB, and is flexible enough to potentially inform a broad range of reservoir systems and management objectives.

Finally, the framework presented in this study is aimed at SSFs based on interannual climatic variability, but is not designed to address the water resource management response to anthropogenic climate change. Future global climate conditions could conceivably lead to historically unprecedented seasonal streamflow values for the region being considered. This framework may not sufficiently capture such scenarios as the predicted daily streamflow sequence is obtained by matching the forecasted seasonal streamflow to the historical record. However, it is also possible that anthropogenic climate change will instead affect the frequency of occurrence of extreme streamflow conditions that are still within the historical record. In this case our approach to daily streamflow disaggregation, and our overall framework, would still be applicable, provided that the forecasts accurately represent the changing conditions. In either the interannual variability or the climate change context, a forecast-based approach can lead to potential gains in terms of improved system resilience and adaptation. However, as argued and demonstrated in Sankarasubramanian *et al.* (2009), novel approaches to water allocation and management that go beyond the "perturbation" of the existing management structure demonstrated here may be needed to effect greater societal benefits from seasonal and longer streamflow forecasts.

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LITERATURE CITED

Barlow, M., S. Nigam, and E.H. Berbery, 2000. ENSO, Pacific Decadal Variability, and U.S. Summertime Precipitation, Drought, and Streamflow. Journal of Climate 14:2105-2128.

Basketfield, D.L., 2005. Managing Seattle's Water Supply in Context: Weather and Climate. US Climate Change Science Program Workshop: Climate Science in Support of Decision Making, Arlington, Virginia, 14-16 November.

Bradbury, J.A., S.L. Dingman, and B.D. Keim, 2002. New England Drought and Relations With Large Scale Atmospheric Circulation Patterns. Journal of the American Water Resources Association 38:1287-1299.

Bradbury, J.A., B.D. Keim, and C.P. Wake, 2003. The Influence of Regional Storm Tracking and Teleconnections on Winter Precipitation in the Northeastern United States. Association of American Geographers 93:544-556.

Collier, C., 2006. Moving Forward to Reduce Flood Vulnerability in the Delaware River Basin. http://www.state.nj.us/drbc/Flood_Website/FloodLossReductionStatement.htm, *accessed* on December 10, 2007.

DRBC, 2007. Flexible Flow Management Program. September 26, 2007. http://www.state.nj.us/drbc/FFMP/index.htm, *accessed* on September 15, 2008.

Fromuth, R.K. and H.A.M. Quinodoz, 2001. Climate Change and the Delaware River Basin. http://www.essc.psu.edu/MARA/events/advisory_Jun01/summary/hernan.htm, *accessed* on December 10, 2007.

Georgakakos, K.P., N.E. Graham, T.M. Carpenter, A.P. Georgakakos, and H. Yao, 2005. Integrating Climate-Hydrology Forecasts and Multi-Objective Reservoir Management for Northern California. EOS 86:122-127.

Gong, G., U. Lall, C. Brown, and P. Kolesar, 2006. Climate-Informed Adaptive Management and Planning to Meet Urban Water Supply and Flood Mitigation Goals in the Delaware River Basin. NOAA Award NA07OAR4310377, Sectoral Applications and Research Program, FY2007, awarded to Columbia University.

Hartley, S., and M.J. Keables, 1998. Synoptic Associations of Winter Climate and Snowfall Variability in New England, USA. International Journal of Climatology 18:281-298.

Hydrologics, 2001. User Manual for OASIS with OCL, Version 3.4.14. December 21, 2001, Hydrologics, Inc., Columbia, Maryland.

Hydrologics, 2004. Strategy for Resolution of Interstate Flow Management Issues in the Delaware River Basin. Prepared for the Delaware River Basin Commission, August 2004. http://www.state.nj.us/drbc/04flowreport/index.htm, *accessed* on October 6, 2007.

Kalnay, E., M. Kanamitsu, R. Kistler, W. Collins, D. Deaven, L. Gandin, M. Iredell, S. Saha, G. White, J. Woollen, Y. Zhu, A. Leetmaa, R. Reynolds, M. Chelliah, W. Ebisuzaki, W. HIggins, J. Janowiak, K. C. Mo, C. Ropelewski, J. Wang, R. Jenne, and D. Joseph, 1996. The NCEP/NCAR 40-Year Reanalysis Project. Bulletin of the American Meteorological Society 77:437-471.

Kim, Y.O. and R.N. Palmer, 1997. Value of Seasonal Flow Forecasts in Bayesian Stochastic Programming. Journal of Water Resources Planning and Management 123:327-335.

Lall, U. and A. Sharma, 1996. A Nearest Neighbor Bootstrap for Time Series Resampling. Water Resources Research 32:679-693.

Maharaj, V., J. McGurrin, and J. Carpenter, 1998. The Economic Impact of Trout Fishing on the Delaware River Tailwaters in

New York. Report Prepared for American Sportfishing and Trout Unlimited. October 1998.

Miller, W.D., D.G. Kimmel, and L.W. Harding, Jr., 2006. Predicting Spring Discharge of the Susquehanna River from a Winter Synoptic Climatology for the Eastern United States. Water Resources Research 42:W05414.

NRC, 2005. Review of CCSP Draft Synthesis and Assessment Product 5.3: Decision-Support Experiments and Evaluations Using Seasonal to Interannual Forecasts and Observational Data. The National Academies Press, Washington, DC, 56 pp.

Obeysekera, J., P. Trimble, C. Neidrauer, C. Pathak, J. VanArman, T. Strowd, and C. Hall, 2007. Appendix 2-2: Consideration of Long-Term Climatic Variability in Regional Modeling for SFWMD Planning and Operations. 2007 South Florida Environmental Report, Florida Department of Environmental Protection and South Florida Water Management District, 47 pp. http://www.sfwmd.gov/sfer/SFER_2007/Appendices/v1_app_2-2.pdf, *accessed* on March 20, 2008.

Rayner, N.A., P. Brohan, D.E. Parker, C.K. Folland, J.J. Kennedy, M. Vanicek, T. Ansell, and S.F.B. Tett, 2006. Improved Analyses of Changes and Uncertainties in Sea Surface Temperature Measured In Situ Since the Mid-Nineteenth Century: The HadSST2 Data Set. Journal of Climate 19:446-469.

Sankarasubramanian, A., U. Lall, F.D. Souza Filho, and A. Sharma, 2009. Improved Water Allocation Utilizing Probabilistic Climate Forecasts: Short Term Water Contracts in a Risk Management Framework. Water Resources Research 45:W11409, doi: 10.1029/2009WR007821.

Souza Filho, F.A. and U. Lall, 2003. Seasonal to Interannual Ensemble Streamflow Forecasts for Ceara, Brazil: Applications of a Mutlivariate, Semi-Parametric Algorithm. Water Resources Research 39:1307-1321.

Williams, C.N., R.S. Vose, D.R. Easterling, and M.J. Menne, 2004. United States Historical Climatology Network Daily Temperature, Precipitation, and Snow Data. ORNL/CDIAC-118, NDP-070. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, Oak Ridge, Tennessee.