



Sustainable water resource management under hydrological uncertainty

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[1] A proper understanding of the sources and effects of uncertainty is needed to achieve the goals of reliability and sustainability in water resource management and planning. Many studies have focused on uncertainties relating to climate inputs (e.g., precipitation and temperature), as well as those related to supply and demand relationships. In the end-to-end projection of the hydrological impacts of climate variability, however, hydrological uncertainties have often been ignored or addressed indirectly. In this paper, we demonstrate the importance of hydrological uncertainties for reliable water resources management. We assess the uncertainties associated with hydrological inputs, parameters, and model structural uncertainties using an integrated Bayesian uncertainty estimator framework. Subsequently, these uncertainties are propagated through a simple reservoir management model in order to evaluate how various operational rules impact the characteristics of the downstream uncertainties, such as the width of the uncertainty bounds. By considering different operational rules, we examine how hydrological uncertainties impact reliability, resilience, and vulnerability of the management system. The results of this study suggest that a combination of operational rules (i.e., an adaptive operational approach) is the most reliable and sustainable overall management strategy.

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1. Introduction

[2] During the past decade there has been a surge in the development of techniques for assessing various sources of uncertainty associated with hydrological forecasts [e.g., *Beven and Binley*, 1992; *Kuczera and Parent*, 1998; *Vrugt et al.*, 2003; *Maier and Ascoug*, 2006; *Ajami et al.*, 2007]. Despite this progress, links between estimated hydrological uncertainties and water resources management uncertainties have not been extensively explored. Investigation of such linkages is especially important since it is not clear how uncertainty in scenario projections might affect the formulation of robust operational rules for reservoir management. This can directly impact the outcome of water resources planning and management studies, especially climate change studies that use climate forecasts (such as precipitation and temperature) to force hydrological models and consequently project the impact of climate change on managing water resources [e.g., *Chao*, 1999; *Maurer and Duffy*, 2005; *Vicuna et al.*, 2007]. None of these studies specifically account for the uncertainties associated with the hydrological modeling step, including model parameters and model structural uncertainties. Reliable hydrologic

predictions with estimates of associated uncertainties can provide decision makers with information that allows them to incorporate risk in decision making and therefore mitigate some of the social, economical and environmental impact of poor and conservative operational rules.

[3] *Georgakakos et al.* [1998] generated an ensemble of inflow forecasts for a reservoir by using a Monte Carlo approach that generated plausible atmospheric-forcing ensembles based on historical climate variability. Using this approach they estimated measures of hydrologic forecast uncertainty assuming they had generated enough climate ensembles to capture all the possible streamflow inputs to the reservoir. They found that uncertainty projection is very important for effective decision making and water resources management. However, they did not assess any other sources of uncertainty such as hydrologic model structural and parameter uncertainty that would impact the inputs to the reservoir. Later, *Yao and Georgakakos* [2001] assessed the sensitivity of reservoir performance under various historical and climate scenarios. They went a step further than *Georgakakos et al.* [1998] and in addition to climate-driven ensembles (GCM-conditioned ESPs), they used historical analog extended streamflow prediction (analog ESP), hydrologic ESP (which uses physical representation of Folsom watershed), operational forecast and finally perfect forecast to create streamflow ensembles which were propagated through the Folsom reservoir. They found that the ensemble reliability and forecast spread are two important factors that need to be used in decision making for effective reservoir management and better handling the associated risk. *Yao and Georgakakos* [2001] did not quantify and assess various sources of uncertainties that

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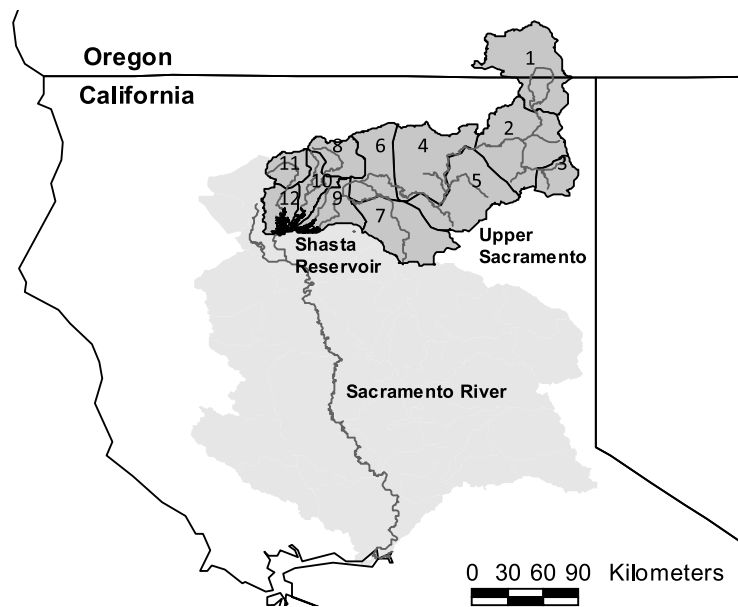


Figure 1. The 12 catchments of the Upper Sacramento that contribute to the upper Shasta reservoir (40.8068 latitude, -121.3808 longitude, 1483 m altitude).

impacts inflow to the reservoir, explicitly. They generated a set of ensembles of streamflow inputs to the reservoir and attempted to indirectly address some of the hydrological uncertainties such as input (by including GCM-conditioned ESPs and hydrologic ESP), parameter and state uncertainty (by using a stochastic framework), however they did not account for hydrologic model structural uncertainty. Both these studies [Georgakakos *et al.*, 1998; Yao and Georgakakos, 2001] attempted to address in different ways the importance of assessing various sources of hydrological uncertainties for more efficient water resource management, however they did not use an integrated approach to quantify overall and end-to-end hydrological uncertainties that impact streamflow inputs to the reservoir. Another common approach to studying how hydrological variability affects water supply reliability is to use a historical sequence of measured hydrological variables [e.g., Brekke *et al.*, 2004; Cai and Rosegrant, 2004]. This approach avoids the uncertainty introduced from using a hydrological model, but is seriously limited by use of a relatively short record and still suffers from an inherent measurement uncertainty. Further, given climate change and some other factors, history will not repeat itself, and the use of historical information can lead to the development of inefficient and ineffective water management strategies.

[4] In this paper we study the characteristics of hydrological uncertainties as they are propagated through a water resource management system. A state-of-the-art Bayesian framework called integrated Bayesian uncertainty estimator (IBUNE) [Ajami *et al.*, 2007], was used to quantify input, parameter and hydrological model structural uncertainties. Subsequently, the simulated streamflow ensembles are used to force a hypothetical reservoir system to evaluate the impacts of operational rules on the way hydrological uncertainties are propagated through a water resources system. We show how the characteristics of uncertainty

change as the reservoir is operated on the basis of different sets of operational rules.

2. Methods

2.1. Study Site

[5] For this study we used data for the watersheds that contribute to the Shasta reservoir in the upper portion of the Sacramento River, California (Figure 1). This upper portion of the watershed was subdivided into twelve subcatchments that contribute to Shasta, with a monthly climate time series derived from the $1/8^\circ$ gridded daily time series computed as an average of all grid cell values within the individual catchment [Maurer *et al.*, 2002]. The Shasta reservoir serves multiple purposes including flood control, irrigation, municipal and industrial water supplies, and hydropower generation [Environmental Protection Agency, 2005].

[6] Monthly precipitation was calculated as the sum of the daily values for the period 1962 through 1994. Demand data and other climate variable, including temperature, wind speed and humidity were each specified as monthly values for each catchment. The climatology of the Upper Sacramento River is dominated by winter snowfall and dry, warm summers with little or no precipitation.

2.2. Integrated Assessment of Hydrological Uncertainty

[7] Hydrologic models are simple mathematical conceptualizations of complex and spatially distributed watershed processes that can be used to provide estimates of current and future hydrologic events. The reliability of these models depends on proper parameter and state estimation; however, errors inherent in meteorological and hydrological observations, model states, model parameters, and model structure ultimately introduce bias and uncertainty into the application. When models are applied for hydrologic prediction to be used as reservoir inputs, incomplete accounting of these

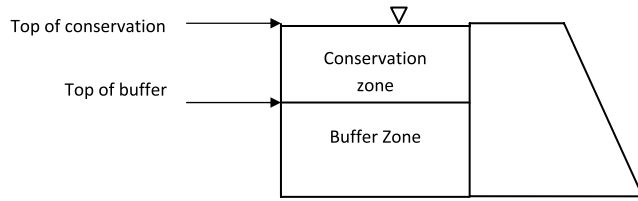


Figure 2. Schematic of hypothetical reservoir.

uncertainties may lead to unreliable and inefficient management of our water resources.

[8] Various hydrological models, regardless of their complexity, suffer from parameter and model structural uncertainties, therefore under the same input forcing perform differently and result in different streamflow predictions [Reed *et al.*, 2004]. The problem of computing streamflow under conditions of input, model structure, and parameter uncertainty can be formulated as

$$y_{k,t} = f(I_t, \theta_k, M_k, t), \quad (1)$$

where $y_{k,t}$ represents streamflow estimate under model K at time t , I_t is input (e.g., precipitation) at time t , θ_k is parameters of the model K , M_k is the model under study from the pool of models and t is time.

[9] We use IBUNE [Ajami *et al.*, 2007] to account for the various sources of uncertainty. To account for model structural uncertainty we study and combine three hydrologic models, the Sacramento Soil Moisture Accounting model (SAC-SMA, 13 parameters [Burnash *et al.*, 1973]), the Simple Water Balance model (SWB, five parameters [Schaake *et al.*, 1996]) and the Hydrological Model (HYMOD, five parameters [Boyle, 2001]). For each model K (M_k) we need to assess uncertainty associated with the model parameter estimation $p_k(\theta|y_{obs}, y_{k,t}, M_k)$ considering observed streamflow data, y_{obs} and consequently the probability of correctness of the estimated streamflow using that model, $p_k(y_{k,t}|\theta, y_{obs}, M_k)$. To account for input forcing uncertainty, we introduce an input error model in the form of multipliers, $I_t = \varphi_t I_t^{obs}$, $\varphi_t \sim N(m_\varphi, \sigma_\varphi)$. We assume that the multipliers φ_t at each time step are drawn from some identical normal distributions with unknown mean (m_φ) and standard deviation (σ_φ). The unknown mean and standard deviation are added to the list of hydrological model parameters to be estimated using a probabilistic parameter estimation method such as shuffle complex evolution Metropolis (SCEM) [Vrugt *et al.*, 2003].

[10] The climatological data (1962–1994) were used as the forcing data for the abovementioned three different hydrological models. The models are run in simulation mode using all the available data. IBUNE first estimates the parameters of the three models and assesses the uncertainty associated with the model parameters and the input forcing using SCEM [Vrugt *et al.*, 2003]. Later IBUNE accounts for model structural uncertainty in streamflow simulation by combining, the estimated streamflow generated by the individual hydrological models using the Bayesian model averaging approach. Bayesian model averaging (BMA) [Hoeting *et al.*, 1999] is a probabilistic multimodel combination technique that combines models

on the assumption that at each particular time step, there is only one best ensemble member or model but we do not know which one. BMA assigns weights to each model. These weights represent the likelihood of each model being a correct model and are defined on the basis of overall performance of each model in representing observed streamflow. The final product of this step of IBUNE is a set of streamflow ensembles that represent the most probable streamflow estimate at each time step with its associated uncertainty from input (precipitation error), model parameter estimation, and model structural deficiencies (more details on IBUNE are given by Ajami *et al.* [2007]). These streamflow ensembles then are used as an input to our management model. The accuracy of the estimated uncertainty bounds using IBUNE are measured by the percentage of observations falling within these bounds while they stay as narrow as possible. If the estimated uncertainty bounds are narrow but do not capture observation points they are not taken to be accurate because they underestimate the overall uncertainty in the system. Also if the estimated uncertainty bounds capture all the observation points because they are too wide, their precision is questionable because they overestimate the uncertainty in the system. If none of the models that are being used capture a certain event there is a high chance that the combination will not capture that event either. Therefore missing some of events may be a result of underestimation of model structural uncertainty in the system. This shortcoming could be addressed by considering additional hydrologic models with different capacities and complexity levels in the model pool. This type of adjustment is beyond the scope of this paper and will not be discussed further. For further discussion on the matter, readers are encouraged to review the work by Ajami *et al.* [2007].

2.3. Reservoir Operation and Management Scenarios

[11] We developed a simple water management model to represent the water resources system for the Shasta reservoir. The model solves the supply and demand equilibrium through simulation. For this study the model divides the reservoir storage into a conservation zone and a buffer zone (Figure 2). For simplicity we did not introduce any flood control or inactive zones for this study. We allow the reservoir to release water freely from the conservation zone to meet the demand in full. When the storage level falls into the buffer zone the release is restricted on the basis of a prespecified coefficient that defines the percentage of water that is available for release each month from the buffer zone. The buffer zone coefficient is a subjective construct, defined by managers and operators. We examine the impact of different management scenarios on supply and demand equilibrium by applying various buffer zone coefficients, including 5%, 10%, 20%, 30%, 40% and 50%. The maximum capacity of the reservoir (top of the conservation zone) and the top of the buffer zone for this study are defined to be 5982 and 3330 million cubic meters, respectively.

2.4. Reliability, Resilience, and Vulnerability

[12] Reliability, resilience and vulnerability (RRV) are used here as indices to evaluate the performance of a water resources system in meeting demand [Hashimoto *et al.*, 1982; Fowler *et al.*, 2003]. A criterion, C , is defined for the

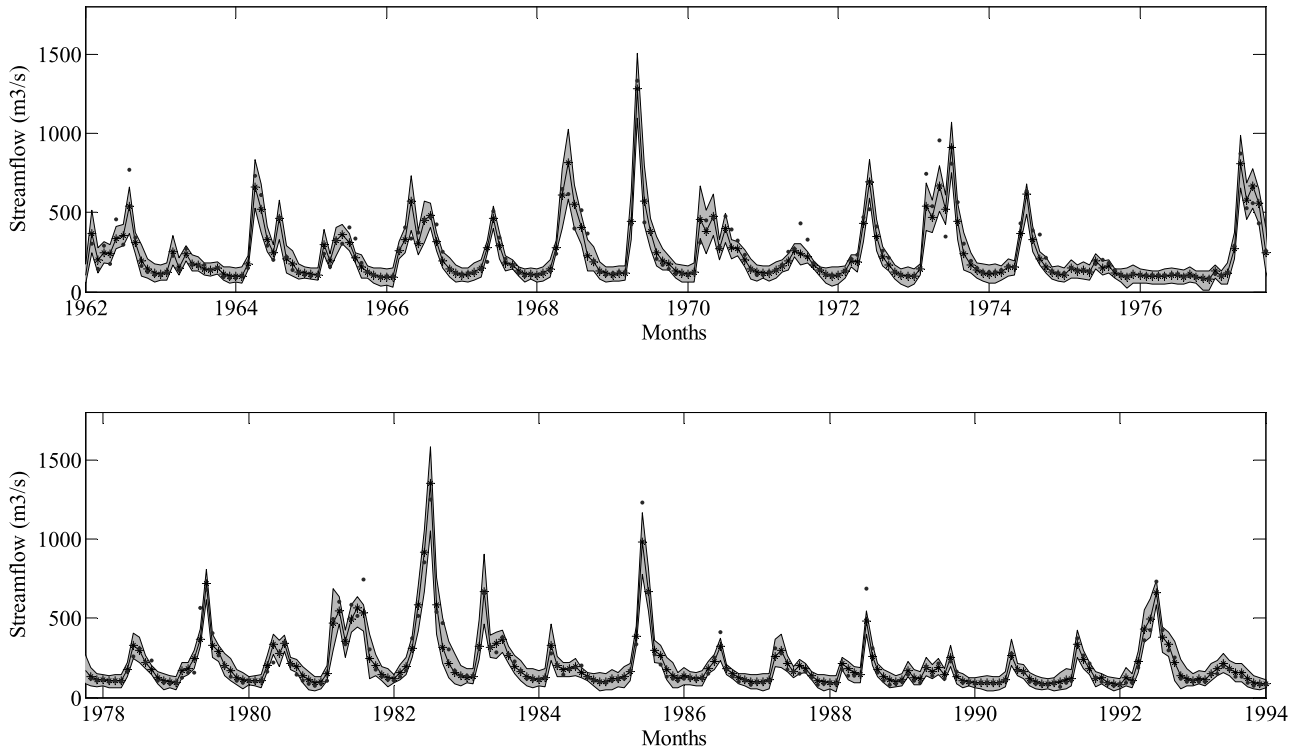


Figure 3. Streamflow predictions and the 95% uncertainty bounds associated with input, model parameters, and model structural uncertainty, assessed by IBUNE.

water supply sources where an unsatisfactory condition occurs when the specified demand is not met. Here, we expect that the reservoir will supply 100% of the demand downstream, therefore C_t is defined as the total demand that needs to be met at every time step. The time series of monthly demand coverage, X_t , are evaluated. Index Z_t signifies a satisfactory or unsatisfactory state of the system. On the basis of our definition of C_t , if all the demand is met the system is in a satisfactory (S) state and Z_t is one, otherwise in an unsatisfactory (U) state and Z_t is zero [Hashimoto *et al.*, 1982]:

$$Z_t = \begin{cases} 1, & \text{if } X_t \in S \\ 0, & \text{if } X_t \in U. \end{cases} \quad (2)$$

An index, W_t , is defined to capture the transitions between satisfactory and unsatisfactory states [Hashimoto *et al.*, 1982]:

$$W_t = \begin{cases} 1, & \text{if } X_t \in U \text{ and } X_{t+1} \in S \\ 0, & \text{otherwise.} \end{cases} \quad (3)$$

Hashimoto *et al.* [1982] treat reliability as a binary measure using index Z_t . In other words, the system either satisfies the predefined criterion for meeting demand and is not penalized, or does not satisfy the criterion and is penalized. Here in this study, we measure reliability on the basis of whether the system meets the prespecified demand criterion and if not, what percentage of the demand has been met (or

not been met) over the desired period (a year or the entire simulation period):

$$\text{Reliability } C_R = \frac{\sum_{i=1}^T X_i}{\sum_{i=1}^T C_i}. \quad (4)$$

Now, if the periods of unsatisfactory state X_t are J_1, \dots, J_N then resilience and vulnerability are defined as follows [Hashimoto *et al.*, 1982; Fowler *et al.*, 2003], where T is the total length of the time series:

$$\text{Resilience } C_{RS} = \frac{\sum_{t=1}^T W_t}{T - \sum_{t=1}^T Z_t} \quad (5)$$

$$\text{Vulnerability } C_V = \max \left\{ \sum_{t \in J_i} C - X_t, \quad i = 1 \dots N \right\}. \quad (6)$$

Here, reliability, C_R , measures the percentage of the demand that has been met and resilience, C_{RS} , indicates the recovery speed of the system from the state of failure (unsatisfactory). Reliability and resilience are both positive measures (the higher, the better). Vulnerability, C_V , is a measure of the extent of failure which here has been shown as the maximum shortfall among all the continuous failure or unsatisfactory

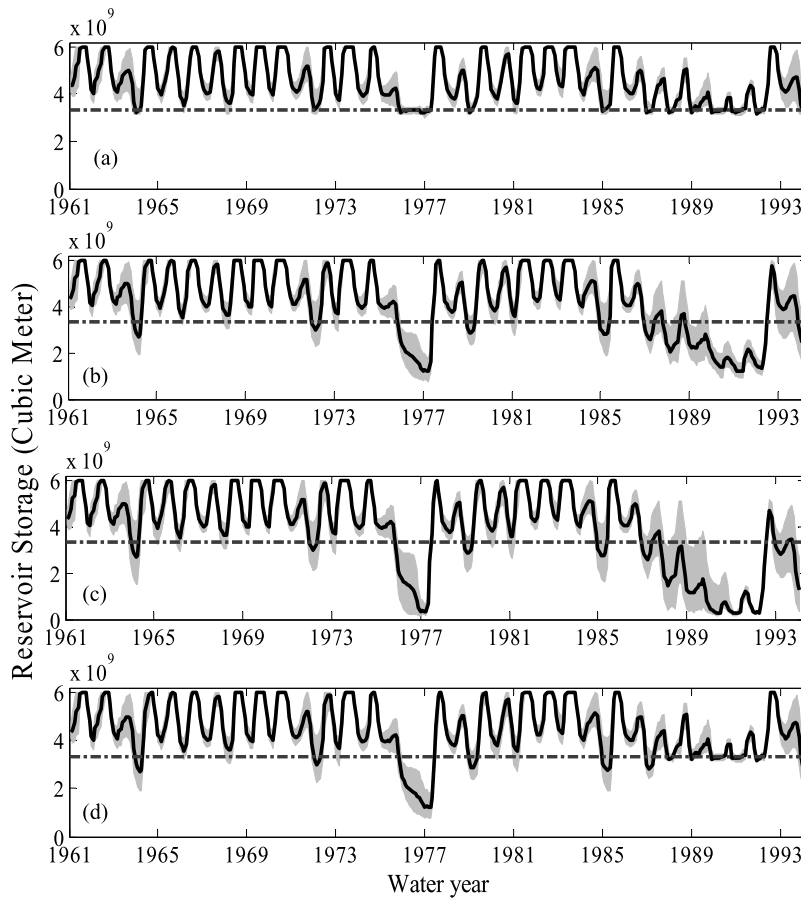


Figure 4. Reservoir storage capacity under various conditions. The gray shading represents the hydrological uncertainties which have been propagated through the reservoir: (a) 5% buffer zone coefficient, (b) 20% buffer zone coefficient, (c) 50% buffer zone coefficient, and (d) adaptive scenario (5% and 20%).

periods. In other words, if there are n unsatisfactory periods, on the basis of equation (6), we first calculate the sum of shortfall over each period and then select the highest of these values as vulnerability. This value shows how poorly the system can perform during an unsatisfactory period in meeting the demand. Vulnerability is a negative measure (the smaller, the better). For more details on these measures, the reader is referred to *Hashimoto et al.* [1982] and *Fowler et al.* [2003].

[13] An efficient management and operational strategy should improve the reliability and resilience of the system while reducing vulnerability. Reliability and vulnerability are inversely related. As reliability of the system increases, the vulnerability of the system lessens. However, this relationship is not direct and linear; trade-off decisions often need to be made in an attempt to accommodate both factors and to find an acceptable balance between reliability and vulnerability of the system.

[14] To evaluate overall performance of the system under various operational rules, we can calculate sustainability measure [Loucks, 1997] by combining reliability, resilience and vulnerability indices as follows:

$$S = \text{Reliability} * \text{Resilience} * (1 - \text{Relative Vulnerability}), \quad (7)$$

where reliability and resilience are calculated earlier on the basis of equations (4) and (5). Relative vulnerability represents dimensionless vulnerability measure and is defined as follows:

$$\text{Relative Vulnerability} = \frac{C_V}{\sum_{t \in J_n} X_t}, \quad (8)$$

where C_V is calculated using equation (6), J_n refers to the unsatisfactory period that C_V represents and X_t is demand at time step t . The multiplication in equation (7) gives added weight to the statistical measure that has the lowest value, therefore does not overestimate the system's performance. Sustainability is a positive measure as well, the higher the better. This index reflects the overall performance of the system considering the RRV measures.

3. Results

3.1. Change in Characteristics of the Uncertainty

[15] The IBUNE procedure resulted in a simulation of time-variant probability distributions of streamflow (Figure 3). The IBUNE uncertainty bounds associated with input, parameter and model structural uncertainty, are re-

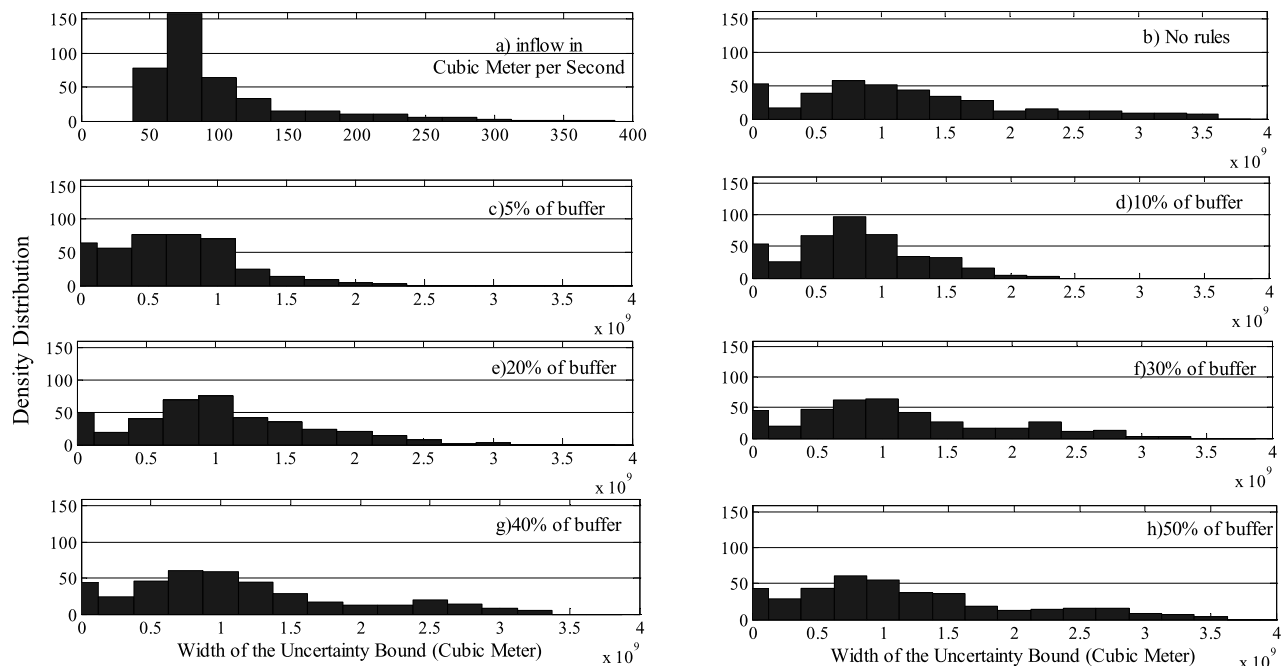


Figure 5. Distribution of the width of the reservoir storage uncertainty bounds under different operational rules.

sonably narrow while almost 95% of the observation points fall within the 95% forecast range (Figure 3). The uncertainty bounds fail to capture some of the peak values (Figure 3). We are using monthly streamflow values so the peak flows do not represent flood events and missing them in the uncertainty bounds does not mean that the hydrologic models failed for our purposes.

[16] The streamflow input realizations (5000 ensembles), which were simulated on the basis of assessed hydrological uncertainties, are propagated through our simple reservoir system. The characteristics of these hydrological uncertainties change as they are propagated through the reservoir at each time step on the basis of the operational rules (Figure 4). We observed that the uncertainty bounds for reservoir storage generally widen. Also we can see that compared to the streamflow input uncertainty bound distribution (Figure 5a), the distribution of the width of the reservoir storage uncertainty bounds is bimodal. The bimodality in the distribution is the result of two facts: (1) the reservoir capacity limitations and (2) buffer zone coefficient. The first mode in Figures 5b–5h is created when the storage level hits its maximum capacity (top of the conservation zone). Regardless of streamflow input level, there is no more space available in the reservoir to store the water, therefore, all the streamflow ensembles result in a single storage level or storage levels with negligible differences. As we impose various operational rules the second center of mass becomes more dominant in the probability distribution (Figure 5). These operational rules, as mentioned earlier, include the percentage of water in the buffer zone which is available to meet the demand downstream. Because the reservoir acts as an accumulator, the widening of the uncertainty bounds is inevitable during periods of declining storage. Therefore, even when there are no rules in place the width of the uncertainty bounds widens compared to

streamflow input (Figures 5a and 5b). Because reservoir has capacity limitation, even under the no rules scenario (Figure 5b), we can see a very weak second mode in the distribution of the width of reservoir storage capacity uncertainty bounds. Once the rules are put into place, the probability distribution sustains its bimodal shape and the center of mass moves between 0.75 and 1 million cubic meters (Figures 5c–5f). As the buffer coefficient (i.e., the available free water from the buffer zone) increases to meet the demand, the distribution again takes its original shape (no rules in place, Figures 5g and 5h) and the uncertainty bounds widen some more. Once 30% of the water in the buffer zone becomes available to meet the demand the distribution of the uncertainty bounds begins to revert to a very weak bimodal distribution. By the time half of the water in the buffer zone is available for release ($C = 0.5$), the uncertainty distribution essentially returns to that of the “no operational rules” scenario (Figure 5).

[17] Examination of the width of the propagated hydrological uncertainty bounds for unmet demand shows behavior opposite to reservoir storage capacity (Table 1). As the width of the uncertainty bounds enlarges with increase in released water, the width of the uncertainty bounds for unmet demand becomes narrower. This is expected since more water becomes available to meet the demand. The width of the uncertainty bounds for unmet demand drops by more than 50% as the buffer coefficient increases from 5% to 20%. Increases in the buffer coefficient beyond 20% do not significantly change the uncertainty bounds for unmet demand (Table 1). This is expected since most of the demand is met during normal years by taking 20% of the water from the buffer zone and there is no need for additional water. However during dry years by increasing the buffer zone coefficient to more than 20%, regardless of whether more water becomes available to meet demand,

Table 1. Average Width of Uncertainty Bounds for Different Variables Under Various Release Scenarios^a

	5%	10%	20%	30%	40%	50%
Streamflow	2.60E+08	2.60E+08	2.60E+08	2.60E+08	2.60E+08	2.60E+08
Reservoir storage	6.46E+08	7.70E+08	9.99E+08	1.09E+09	1.11E+09	1.14E+09
Unmet demand	7.11E+07	4.43E+07	3.17E+07	2.88E+07	2.99E+07	3.06E+07

^aUnits are in million m³.

considerable deficiency continues to exist in storage and consequently, cannot alleviate unmet demand. Therefore, no significant improvement (tightening) is seen in the width of the uncertainty bounds for the unmet demand as we increase the buffer zone coefficient (Table 1).

3.2. Impacts of Operational Rules on System Reliability, Resilience, and Vulnerability

[18] The overall reliability, resiliency and vulnerability of the system over a 33-year period (1961–1994), was found to be sensitive to the first three operating scenarios which can release 5%, 10% and 20% of available water in the buffer zone to meet the demand (Figures 6a–6c). We found that as more water becomes available to meet the demand the reliability of the system increases and the system becomes less vulnerable (Figures 6a and 6c). However, the slope of these improvements slows down as the available free water from the buffer zone increases. Resiliency does not follow the same trend (Figure 6b). Resiliency measures the relative recovery speed of the system from an unsatisfactory state (equation (4)). As more water becomes available, the unsatisfactory periods are eliminated or shortened. Yet, because resiliency is a relative measure, if the recovery time is long, relative to the total unsatisfactory period, the resiliency decreases even though the reliability of the system improves. Different operating scenarios also lead to variable reliability, vulnerability and resilience uncertainty bounds.

[19] In addition, the results revealed that limiting the available free water in the buffer zone to 5% is a less vulnerable and more resilient management scenario than a 10% scenario (Figures 6a–6c). The results also show that the 5% buffer zone coefficient leads to a more sustainable system compared to 10% (Figure 7a). Studying the reservoir storage capacity and annual RRV measures under both conditions demonstrates that during consecutive drought periods the 10% operation scenario will lead to a slightly more reliable system performance while the vulnerability of the system deteriorates. In analyzing annual RRV measures during the drought period of 1990–1992 (Figure 8) we found that the 5% operation scenario outperforms, or is as good as the other operational scenarios considering reliability, resilience and vulnerability measures, especially during the final years of the drought (1991–1992). Evaluating sustainability of the system during these drought years confirms the superiority of the 5% scenario as we go further in the drought (Figures 7b–7d). Therefore, we considered a combination operational strategy which would use a 5% buffer coefficient during the consecutive drought period (1987–1992), and 20% for all other times (adaptive operational scenario). The results indicate that this combination will lead to a more efficient and less vulnerable (Figures 6

and 8, adaptive scenario) and therefore, more sustainable management strategy (Figure 7).

4. Discussion

[20] Operational rules have a direct impact on the characteristics of hydrological uncertainty propagated through a reservoir system. As more water is maintained in the buffer zone the distribution of the width of uncertainty bounds becomes skewed (Figure 5). The results demonstrate that skewness in the distributions is caused by considerable widening of uncertainty bounds during dry periods (Figure 4, years 1976–1977 and 1989–1992). Under the release scenarios that allow a high percentage of the water in the buffer zone (e.g., buffer coefficient of 40%) to be released to meet the demand at all times, the reservoir storage volume becomes very sensitive to various streamflow ensemble inputs. During dry periods of higher buffer coefficients not enough water accumulates in the reservoir in prior months or years to prevent the reservoir level from dropping significantly, therefore allows the system to go to

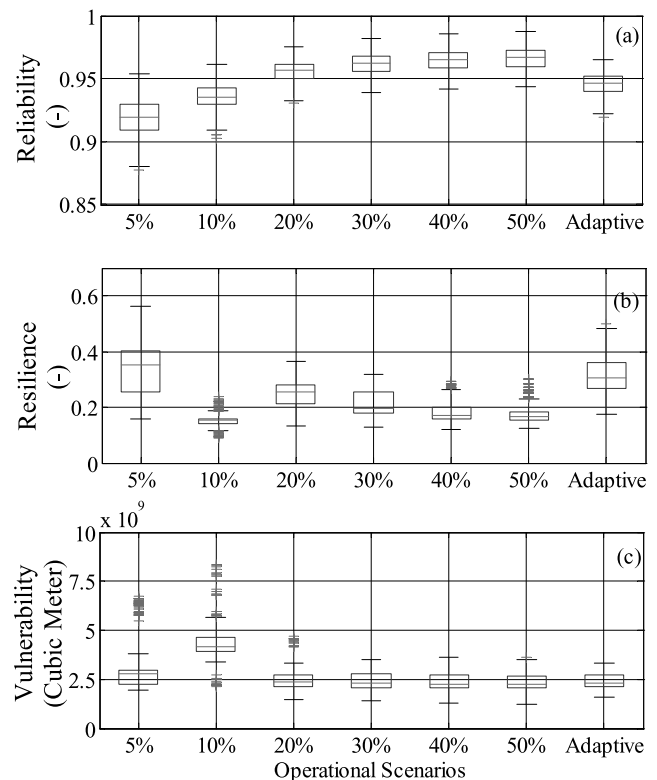


Figure 6. Box-and-whisker plots for ensembles of the overall reliability, resiliency, and vulnerability under various operational scenarios.

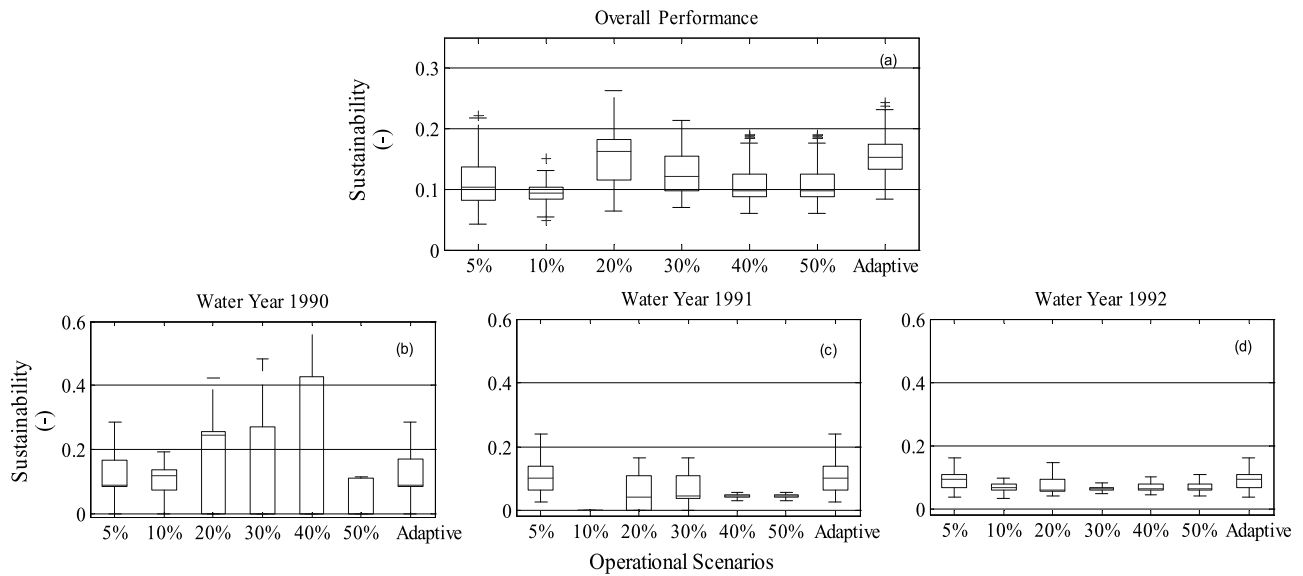


Figure 7. Box-and-whisker plots for ensembles of sustainability measure.

an unsatisfactory state in meeting the demand. This can lead to a very wide range of reservoir response depending on the demand. The considerable drop in reservoir storage for lower inflow values from the simulation ensembles, that happen under such scenarios, can cause some critical problems (such as failing to meet the agricultural and urban water demands or shortages in hydro electricity generation), especially during consecutive dry periods or drought spells when the reservoir does not have enough time to recover from one crisis before the next one arrives.

[21] We found that the distribution of the width of the uncertainty bounds for operational scenarios of 5–30% buffer coefficient is less skewed compared to scenarios with larger buffer coefficient (40% and 50%). When the reservoir

is full (or close to full), the uncertainty bounds are zero (or very insignificant and narrow), creating one center of mass around zero bound width for all scenarios (Figure 5). The second center of the mass around higher values in the bimodal distribution is created by even and uniform widening of the uncertainty bounds throughout the simulation period around the buffer zone boundary line (Figures 4 and 5). This widening mainly happens around the threshold separating the buffer zone from the conservation zone especially for the lower buffer zone coefficients. Reservoir storage at the end of each month depends on the water released to meet the demand, which is a function of demand, inflow to the reservoir during that month, and the initial storage. For example, when stricter operational

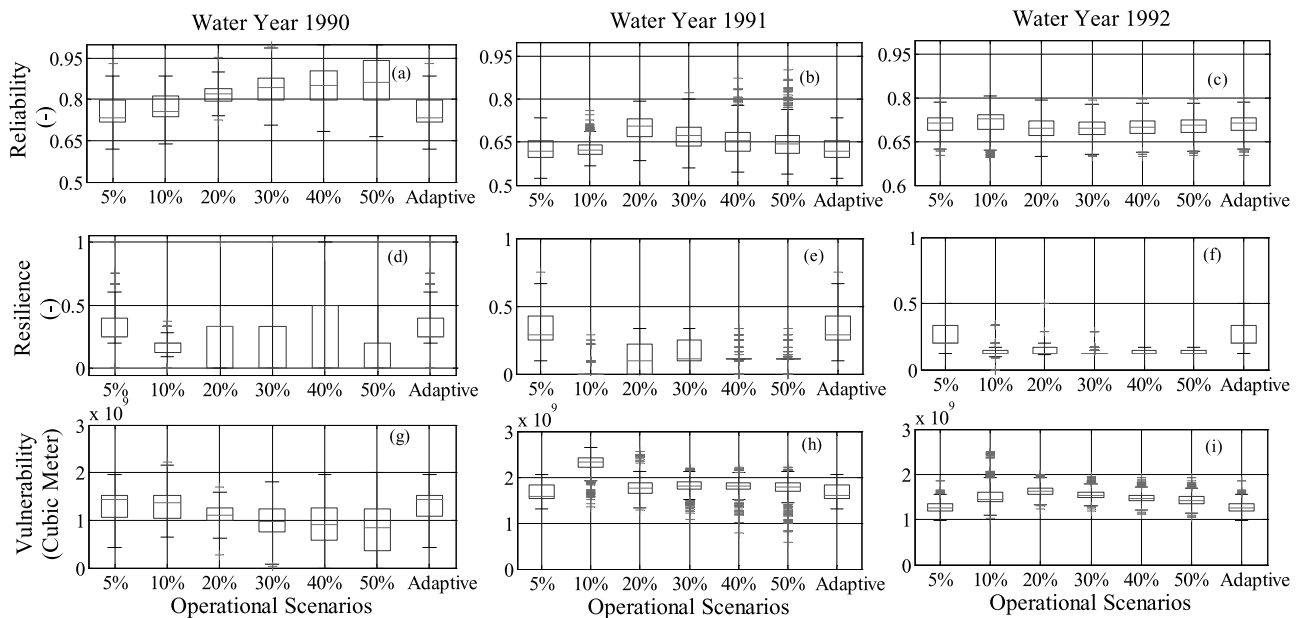


Figure 8. Box-and-whisker plots for ensembles of annual reliability, resilience, and vulnerability under various operational scenarios for drought period of 1990–1992.

rules are in place and the buffer zone coefficient is 5% and the level of the reservoir is very close to the threshold, any small change in the inflow or outflow to the reservoir can cause the storage level to fluctuate between the two zones from one time step to the other. In other words, the combination of the inflow ensembles and the release ensembles can lead to some chaotic reaction around the threshold by jumping from one state to the other at different time steps (Figure 4). Since there is limited water available in the buffer zone to be released under the stringent operational rules (5% buffer zone coefficient), the width of the uncertainty bounds becomes very narrow and uniform around the threshold value during the simulation period, which leads to the denser second center of mass in the bimodal distribution (Figures 4 and 5). In contrast, looser operational scenarios have a significant impact on the uncertainty bounds during dry periods since they allow reservoir storage to drop much lower in the buffer zone (Figure 4). This leads to significant widening of the uncertainty bounds and thus, skewness in the final distribution (Figure 5). To put this in perspective, we examined the distribution of the width of the demand uncertainty bounds for the 50% buffer zone coefficient, and found that the widening and therefore skewness that is observed in reservoir storage uncertainty bounds leads to the skewed distribution on the demand side as well. The widening of the demand uncertainty bounds for higher buffer coefficients (30–50%) mainly happens toward the end of 1976–1977 and 1989–1992 drought periods. As the reservoir tries to meet the entire demand during the early years of drought by releasing more water from the buffer zone, the storage level goes significantly down; consequently, there is not enough water in the later years of drought to meet the demand, especially for the ensembles with lower values. It is important to keep in mind that we would like to have narrow and precise uncertainty bounds that capture most of the observed values at all times. This may lead to more efficient and sustainable planning and decrease risk. When the uncertainty bounds become too wide each given time step has many possible events that can take place which can significantly differ from each other. Such wide spread possibilities can increase risk of failure in decision making because it is hard to come up with a set of rules that can handle all possible events. Decision makers can try to manage such cases by using a set of very conservative operational rules that would not fail under most possibilities. Such conservative decision rules can have very inefficient social and economical impacts. Therefore, accuracy and reliability in the hydrological forecast can mitigate such impacts and help decision makers to better handle the risk in decision making.

[22] The overall reliability and vulnerability measures showed considerable sensitivity to the 5% to 20% operational rules. However, as the buffer coefficient is increased (30% to 50%), this sensitivity faded away and not much improvement was observed (neither in the mean value nor in the width of the uncertainty bound) in increasing the available water. As the percentage of available water from the buffer zone is increased from 5% to 10%, both resilience and vulnerability deteriorates while reliability improves. This is contrary to our expectation that the availability of more water from the buffer zone would improve the system performance on the basis of RRV measures, since there is

more water available to meet the demand (Figure 6). We found that this deterioration in the overall system performance can be attributed to the poor performance of the 10% operational scenario considering the resilience and vulnerability, during consecutive drought years (Figure 8). The 5% operational scenario conserves some water by not fully meeting the demand downstream, which helps increase supply during the long drought periods, therefore being able to meet the whole demand after a few months of conservation. Therefore, the 5% operational scenario improves the resilience of the system by shortening the unsatisfactory periods (breaks them into two or three shorter cycles rather than a one long one). This also leads to a reduction in vulnerability compared to the 10% operational scenario. The 5% scenario also performs as well as the other operational scenarios (30–50%) that provide more water to meet the demand during dry periods (Figure 8).

[23] Studying the uncertainty associated with each one of these measures, one can see that the width of the uncertainty bounds on reliability and vulnerability does not change much from one operational rule to the other, especially as we pass the 20% buffer coefficient. It seems that the uncertainty bounds on resilience are the most sensitive to the operational rules. As the amount of available water from the buffer zone increases, resilience deteriorates while the uncertainty bounds narrow down (Figure 6c, comparing 5% to 50% buffer coefficient). To put these into perspective we tested the sustainability measure (Figure 7a). Close investigation of an overall sustainability measure (Figure 7a) depicts that considering 5%, 40% and 50% buffer coefficient almost leads to the same level of sustainability in the system considering their mean and the width of uncertainty bounds. Ten percent and 20 percent operational rules are the least and the most sustainable scenarios, respectively. They also lead to the narrowest (10%) and widest (20%) uncertainty bounds as well. Even though the mean value of the sustainability measure for the 20% operational rule has the highest value, the uncertainty bounds around it are quite wide compared to all other scenarios, not a desirable factor for decision makers because it can lead to development of more conservative and less efficient management rules to deal with the risk.

[24] We found that a trade-off decision needs to be made on the basis of the overall and annual reliability, resilience and vulnerability of the system. The results demonstrate that efficient and sustainable management is achievable through the use of a combination of buffer coefficients (Figures 7) that would lead to high overall reliability while maintaining high resilience and low vulnerability (Figures 6 and 8). Under the existing state of demand, our results indicate that the combination of a 20% release from the buffer zone during the normal and wet years and a 5% release during consecutive dry years, is the most efficient management approach here, considering the RRV measures (Figures 6 and 8) and sustainability index (Figure 7).

[25] The combination scenario (adaptive) also leads to the narrowest uncertainty bounds in the reservoir storage simulations during the critical years of 1989–1992 (Figure 4) and the overall sustainability measure (Figure 7a), which is very important because it makes decision making and planning easier and less uncertain. As demonstrated in the pioneering study of *Burness and Quirk* [1979], and in later

work by Sunding *et al.* [2008], there can be a large economic value associated with reductions in uncertainty about future water supplies. The productivity of water is determined in large part by capital investments that increase the value of water used in production processes. Uncertainty is a disincentive to making such investments; consequently, resolution of uncertainty can improve the efficiency and productivity of water use and help to cope with conditions of scarcity and increasing competition. Also, accurately accounting for various sources of uncertainty can reduce the social and economical impacts of inefficient and unsustainable decision making that is caused by poor knowledge of inherited uncertainty and therefore, inaccuracy of the hydrological forecast.

5. Summary

[26] This paper evaluates the importance of hydrological uncertainty in sustainable and efficient management of water resource systems. The hydrological uncertainties were estimated using the recently developed uncertainty estimation framework integrated Bayesian uncertainty estimator (IBUNE) [Ajami *et al.*, 2007]. These uncertainties were later propagated through a reservoir system and various operational rules were put into place to examine the impact of these rules on the characteristics of hydrological uncertainties. The change in the distribution of the width of uncertainty bounds from streamflow to reservoir storage capacity leads to nonintuitive effects in terms of measures of system performance. On the basis of the presented results, we infer that an adaptive operational approach where the decision maker adjusts the operational rules on the basis of inflow climate forecast and the existing state of reservoir storage at each given time step, can lead to a more efficient and sustainable management of the reservoir. Therefore, improved reservoir management solely depends on accuracy of the climate forecast ensembles that would lead to more accurate hydrological forecasts and effective use of these ensembles. Hence, accurately accounting for various sources of uncertainty that influence our forecasted inflow to the reservoir provides better and more precise information to decision makers and will help them operate a water resource system in a more sustainable, socially and economically efficient way.

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