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Effect of scenario assumptions on climate change risk estimates in a water resource system

Ke Li[1,2,3], Jingyao Qi[1,*], Casey Brown[3], Julia Ryan[3]

[1]State Key Lab of Urban Water Resource and Environment, Harbin Institute of Technology, Harbin 150090, PR China
[2]Key Laboratory of Songliao Aquatic Environment, Ministry of Education, Jilin Jianzhu University, Changchun 130118, PR China
[3]Department of Civil and Environmental Engineering, University of Massachusetts Amherst, Massachusetts 01002, USA

ABSTRACT: The common approach in evaluating the impacts of climate change on a water resource system begins with downscaling general circulation model (GCM) projections, estimating resultant streamflow via a hydrological model, and assessing impacts with a water resource system model. An alternative methodology, described as 'decision scaling,' links a bottom-up approach with climate information including GCM projections through a decision analysis framework. One advantage of this approach is that the effects of different assumptions related to the processing of climate simulations can be directly characterized. This paper demonstrates the usefulness of the decision-scaling methodology by examining how probability distribution function choice influences the modeling of climate-change-impact uncertainty, and how, in turn, this affects projections of water supply systems. The approach is demonstrated in an analysis of the risk of climate change impacts on a large water supply system located in central Massachusetts, USA.

KEY WORDS: Climate change · Water resource system · General circulation model · Risk estimates

1. INTRODUCTION

There is mounting evidence that climate changes due to anthropogenic activities may have a significant impact on hydrology and water resources, which has, as a result, triggered considerable interest in the risk posed to water supply systems. There have been many studies that use projections of climate change to assess the impacts that such scenarios (A1B etc. in IPCC) have on specific systems (e.g. VanRheenen et al. 2004, Sulis et al. 2012, Ficklin et al. 2013). While these studies can estimate the impacts of a particular scenario with regard to a water system, they are less useful for defining risk, which requires an estimated probability of the impacts.

The most common approach to estimating the potential hydrological impacts of climate change is to use climate variables derived from downscaled general circulation model (GCM) projections to drive hydrology models, the output of which is input to water system models. This method has been applied by a number of researchers (e.g. Hamlet & Lettenmaier 1999, VanRheenen et al. 2004, Wiley & Palmer 2008, Pulido-Velazquez et al. 2011, Tsai & Huang 2011, Teng et al. 2012, Weiland et al. 2012). Hamlet & Lettenmaier (1999) used this approach to diagnose the effects of climate change on water resources in the Columbia River Basin. Van Rheenen et al. (2004) adopted statistical downscaling of an ensemble of GCM projections to drive a daily hydrologic model for studying the impact of climate change on water resources in the San Joaquin River Basin. Wiley & Palmer (2008) estimated the impact of climate on the municipal water supply system in Puget Sound of the Pacific Northwest through a 3-stage modeling approach consisting of general circulation, hydrology and water resource system simulation models. Pulido-Velazquez et al. (2011) applied the downscaled data derived from GCM projections into AQUATOOL, a Decision Support System (DSS) that

*Corresponding author: qjy_hit@yahoo.cn

facilitates the definition of monthly conjunctive-use management models at a basin scale, to optimize the strategies to reduce the impact of climate change in the Serpis River Basin.

Most of the time, GCM projections are typically used as scenario generators as described by Lempert et al. (2006); however, they have drawbacks in that capacity. (1) Typically the number of scenarios that can be downscaled from GCM projections is few, especially compared to what can be done stochastically. (2) They explore only the minimum bound on the maximum range of possible future climate change, which is far from ideal for investigating impacts of climate change (Wilks 1992, Stainforth et al. 2007).

Therefore, there is a growing interest in using stochastic models which can generate wider climate scenarios and were commonly applied to assess risk in water resource systems prior to the use of GCM projections (Brown & Wilby 2012). Stochastic weather generation allows the simulation of long records of weather that are consistent with climate means such as may be elicited from GCM projections or otherwise specified. Stochastic models have been used as a statistical downscaling approach to study the potential climate change impacts (e.g. Wilks 1992, 1999, Semenov & Barrow 1997, Kilsby et al. 2007). Semenov & Barrow (1997) considered using GCM projections as a scenario generator to perturb the parameters of the stochastic weather generator LARS-WG to investigate the climate change impacts on crop productions in Europe. Kilsby et al. (2007) developed a daily weather generator, a stochastic model, whose parameters are updated by scenarios generated by GCM projections. Since stochastic models can sample a much wider range of possible scenarios, and GCM projections are the best attempts to respond to increasing greenhouse gas emissions through physical models, the combination of the stochastic model and GCM projections seems reasonable and appealing. Nonetheless, this method is still limited by the range of changes derived from GCM projections, which do not explore the full plausible range of climate changes, especially in terms of variability.

There are some conceptual concerns with the most commonly used approaches. (1) All use of GCM projections requires bias corrections to produce data that are remotely plausible. The bias correction is essentially a stationary linear model based usually on only 2 data points (e.g. historical mean of observations and the mean of a GCM simulation of the historical period) that is applied to a highly nonlinear model of a highly nonlinear system. The bias correction methods typically used are not cross-validated. This results in a major concern in the use of GCM projections for estimating specific future conditions. (2) The incompatible spatial scales between river basins and GCM projections require downscaling and validation before applying them to the evaluation of climate change impacts (e.g. Pilling & Jones 2002, Christensen & Lettenmaier 2007). This results in higher resolution data but potentially adds concern regarding the fidelity of the process.

Additionally, an open question in the use of climate projections in climate risk assessment is the treatment of changes in variability. It is well known that GCM projections often perform less well at variability statistics than they do for mean climate of variables such as precipitation and temperature (Eden et al. 2012). However, a recent study by Deser et al. (2012) shows that even with a perfect model, the internal variability of the Earth's climate system dominates at local scales that are relevant to water resources planning and management. That is, the uncertainty due to variability at the local scale is larger than the effect of the mean global climate changes, and that uncertainty cannot be reduced through downscaling.

Most current studies simply resort to the predicted mean climate change from GCM projections, and are blended with assumptions about the variability, which may be taken from past observations (Maurer & Duffy 2005). Some statistical downscaling approaches such as the 'delta method' simply use the historical trace of precipitation and temperature and apply a scaling factor based on mean changes from future projections (Hay et al. 2000). This is limiting for impact assessments given that changes in variability are typically recognized as climate concerns. Other statistical methods, such as the bias-correction and spatial disaggregation (BCSD; Knutti et al. 2006), derive variability changes from GCM projections. However, given the biases from the GCM projections, there is concern that such biases in variability, which are not explicitly corrected, would result in biases in estimation of climate risk (Brown & Wilby 2012).

An alternative approach is to use the stochastic weather generator as a tool for identifying climate vulnerabilities, and then GCM projections to estimate the relative probability of the climate changes that relate to the vulnerabilities. This approach, which is described by the term decision-scaling, has the additional benefit of allowing an explicit comparison of different assumptions related to climate changes on the vulnerabilities of the system (Brown et al. 2012). For example, a variety of changes in interannual variability of climate conditions could be explored to identify the range of variability change that a water resource system can manage before performance degrades. Then, a climate science based analysis could be conducted to assess whether such variability changes are plausible. There is a growing number of studies that use such vulnerability-based approaches (e.g. Dessai et al. 2009, Lempert 2010, Prudhomme et al. 2010, Pielke et al. 2012), although the use of stochastic weather generators is relatively unique.

In this study, the decision-scaling methodology is used to assess the impacts on water supply reliability risks from changes in variability, which are identified using historical variability, versus GCM-derived variability, versus parametrically altered variability. The methodology is presented in the following section, including the description of the stochastic weather generator used in this study, and then it is applied to the assessment of climate change impacts on the Quabbin-Wachusett water resource system in central Massachusetts, USA. It should be noted that this water resource system is used simply to demonstrate the methodology, and this does not represent an actual climate risk assessment of the system.

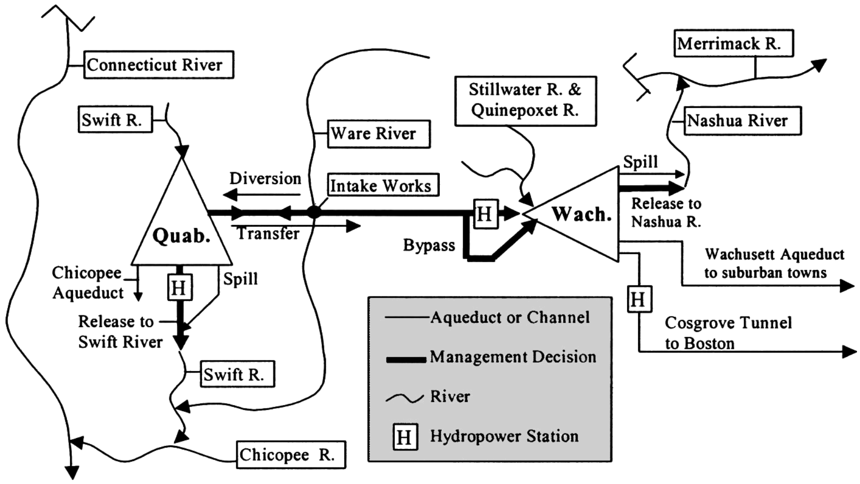

Fig. 1. Massachusetts Water Resources Authority (MWRA) water supply system (Fisher & Palmer 1995). Reservoirs (represented by triangles) — Quab.: Quabbin; Wach.: Wachusett

2. METHODS

The general approach assessing the vulnerablity of a water resource system to climate change consists of the following 3 steps (as described in Brown et al. 2012):

(1) Hazard identification. Description of the system, the metrics or indicators used for evaluating performance (e.g. cost benefit analysis, system reliability, etc.), and thresholds related to acceptable and unacceptable performance.

(2) Risk discovery. Perturbation of climate conditions to characterize the system response and discover the climate conditions that cause hazards. In the present analysis, a stochastic model is used to sample a broad range of possible climate changes. The analysis results in the elicitation of a 'climate response function,' which is the response of the performance indicators to changes in climate. If required, the response surface can be formally fit with a surrogate model for further analysis.

(3) Estimate climate-related risk. Once the problematic climate conditions have been identified, climate information is drawn from GCM projections or other sources to estimate relative probabilities for the different climate states as defined by the performance metrics.

A previous study used parametrically varied climate means and historical variability to demonstrate the climate risk assessment process (Brown et al. 2012). In this study, a stochastic simulation model of streamflow is created to generate a wide range of changes in mean climate and climate variability. This broader sampling of possible climate changes (mean and higher moments) has the potential to identify climate risks that may not be identified using typical top-down approaches. Resulting estimates of climate risk to a typical water supply system are compared with what might be estimated using top-down approaches.

2.1. Study basin and MWRA model

The Massachusetts Water Resources Authority (MWRA) water supply system, which consists of 2 reservoirs as shown in Fig. 1, has a total drainage area of 760.3 km^2 and a storage capacity of 1806 million cubic meters (MCM), with 1002.7 MCM active storage. Quabbin Reservoir, located 130 km west of Boston, has a 481.4 km^2 drainage area and stores up to 1560 MCM of water with 966 MCM active storage. The Wachusett Reservoir, 90 km west of Boston, has a 278.9 km^2 drainage area, up to 246 MCM of water storage capacity, and 36.7 MCM active storage (Westphal et al. 2003). The water system supplies a

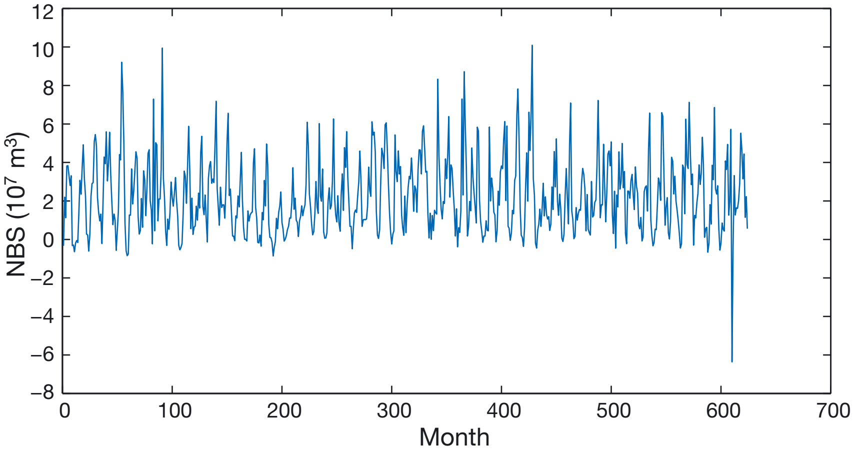

Fig. 2. Historical net basin supplies (NBS) of the Quabbin Reservoir

population of 2.5 million people and 5500 large industrial users in eastern Massachusetts. The minimum release required from the water system is 1.13 MCM d^{-1} (300 million gallons) on average.

A model of the system was created in the Stella modeling environment. The model is a monthly time-step, basin-scale model based on a node-link network, with source nodes such as reservoirs, aqueducts, rivers, hydropower stations and municipal demand. The primary hydroclimate input to the model includes the inflow into the Quabbin and the Wachusett Reservoirs, direct precipitation and evaporation at the reservoir surfaces. In this analysis, these were aggregated and termed monthly net basin supplies (NBS; inflows minus evaporation). For more details on the model of Quabbin–Wachusett Reservoirs see Fisher & Palmer (1995).

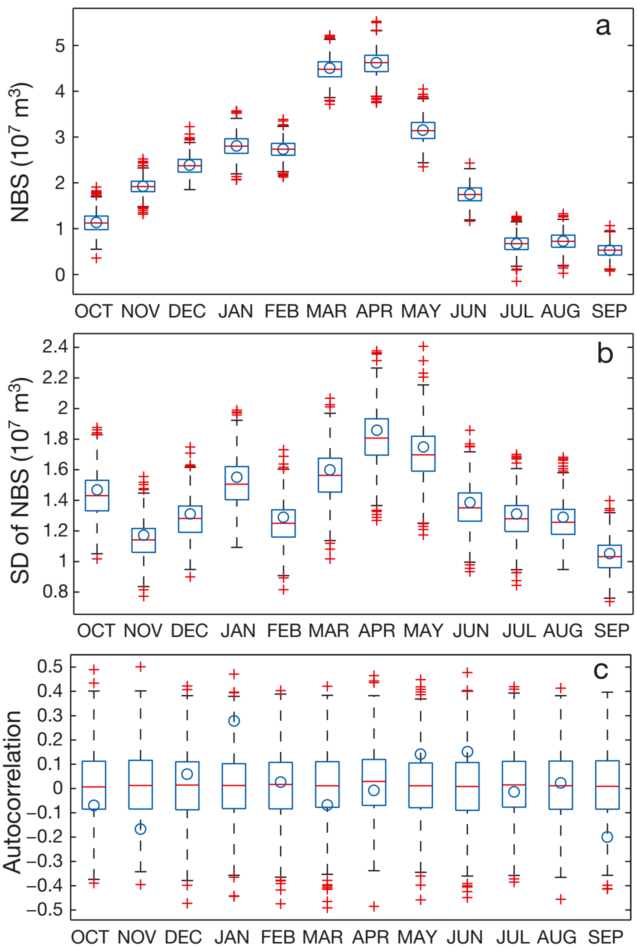

Fig. 3. Comparison of monthly net basin supplies (NBS) statistics for the Quabbin Reservoir: (a) mean, (b) SD, (c) autocorrelation at lag 1 yr. The boxplot represents the value obtained from the flow simulations — central line: median, box: 25th and 75th percentiles, whiskers: values outside the upper and lower quartiles, red crosses: extreme values. Circles: historical data

2.2. Stochastic simulation for risk assessment

Stochastic simulation has been widely used in hydrology and water resources to generate synthetic streamflow sequences for the analysis of complex water resource systems. Time series modeling has been applied to the evaluation of the possibilities of extreme events, forecasting hydrologic events, and risk assessment of reability within water resource systems (e.g. Rasmussen et al. 1996, Vogel & Shallcross 1996, Sun & Furbish 1997, Venema et al. 1997, Tesfaye et al. 2006).

Time series modeling requires that the process is stationary or at least weakly stationary, and that there is no obvious periodic behavior in mean, standard deviation (SD) and skewness (Salas & Obeysekera 1992). The partial plot of the NBS in the Quabbin Reservoir containing 52 yr of data from October 1948 to September 2000 in Fig. 2 shows a very strong periodic behavior with respect to months. As illustrated in Fig. 3, the seasonal cycle is apparent in the main statistical characteristics including monthly NBS mean, SD skewness and autocorrelation. One approach for removing this periodic correlation structure is periodic autoregressive moving average (PARMA) model, which is an extension of the commonly used ARMA model, and has been proposed for inflow simulations, with the seasonal fluctuations in the main statistical characteristics (Rasmussen et al.

1996, Tesfaye et al. 2006, Anderson et al. 2007, Sveinsson et al. 2007). Due to a higher number of parameters to be estimated, the parameter estimation for PARMA models is comparatively more complex than that for ARMA models. The focus in this study is to use time series modeling only to produce reliable simulations of monthly NBS. Fitting an appropriate ARMA model to generate synthetic series after removing the seasonality in series through normalization, as an alternative to PARMA, is much simpler:

$$X_{ks+i} = \frac{\mathrm{NBS}_{ks+i} - \bar{u}_i}{\sigma_i} \quad (1)$$

where X is the series after normalization, $s = 12$ mo; $i = i$th mo, for $i = 1, 2, 3\ldots 12$; k = number of years, an integer; $\bar{u}_i = i$th month mean, $\sigma_i = i$th month SD. After the series were normalized, the ARMA (p, q) was applied to:

$$X_{ks+i} - \sum_{j=1}^{p} \varphi_{ks+i}(j) X_{ks+i-j} = \varepsilon_{ks+i} + \sum_{j=1}^{q} \theta_{ks+i}(j) \varepsilon_{ks+i-j} \quad (2)$$

where ε is a sequence of random variables with mean zero and SD τ, such that $\varepsilon \sim N(0, \tau^2)$. The autoregressive parameters φ_{ks+i} and the moving average parameters θ_{ks+i} were estimated by the Yule-Walker method (Gersch 1970). Finally, the synthetic series could be generated by the inversion of the Eq. (1). Akaike information criteria (AIC) were used to select p, q:

$$\mathrm{AIC} = \log(V) + \frac{2d}{N} \quad (3)$$

where V = variance of model residuals, $d = p + q$ (the number of estimated parameters in the ARMA model), N = length of historical data. Table 1 shows the AIC for p from 1 to 5 and q from 1 to 5 in the ARMA model. The AIC of ARMA (1, 4) yields the minimum value so $p = 1$ and $q = 4$ are preferred in this case.

To evaluate the performance of the model, a 50 000 yr monthly stochastic time series of the NBS in the Quabbin Reservoir was generated through the aforementioned model based on historical data (October 1949 to September 2000). The stochastic series was segmented into 50 yr windows. For each window, the statistics were calculated: each NBS mean and annual NBS mean, with their SD, skewness and autocorrelation at 1 yr lag.

The boxplots in Fig. 3 compare the main monthly statistical characteristics (monthly mean, SD and autocorrelation at 1 yr lag) of the synthetic time series obtained by this simulation procedure, to historical data. It is apparent that monthly mean and SD of the synthetic time series are very similar to historical data, while monthly autocorrelation (lag 1) also resembles historical data except in January, May, June, September, and November. In particular, the time series modeling is able to approximately represent the annual statistical characteristics as shown in Fig. 4a–d, which, similarily, compares historical data to the synthetic data. It was accepted that the model reproduced the essential statistical characteristics, indicating that the model is reliable for generating synthetic series of the NBS in the Quabbin Reservoir, and can be applied to the water resource system for evaluating the effects of climate change on the system.

Table 1. Akaike information criteria (AIC) for the autoregressive moving average, ARMA (p, q)

	q 1	q 2	q 3	q 4	q 5
p 1	−0.09339	−0.09029	−0.09325	−0.09515	−0.09043
p 2	−0.09027	−0.09379	−0.09388	−0.09260	−0.08981
p 3	−0.09494	−0.09294	−0.09020	−0.08872	−0.08584
p 4	−0.09089	−0.09025	−0.08714	−0.08391	−0.08295
p 5	−0.08666	−0.08548	−0.08550	−0.08083	−0.08484

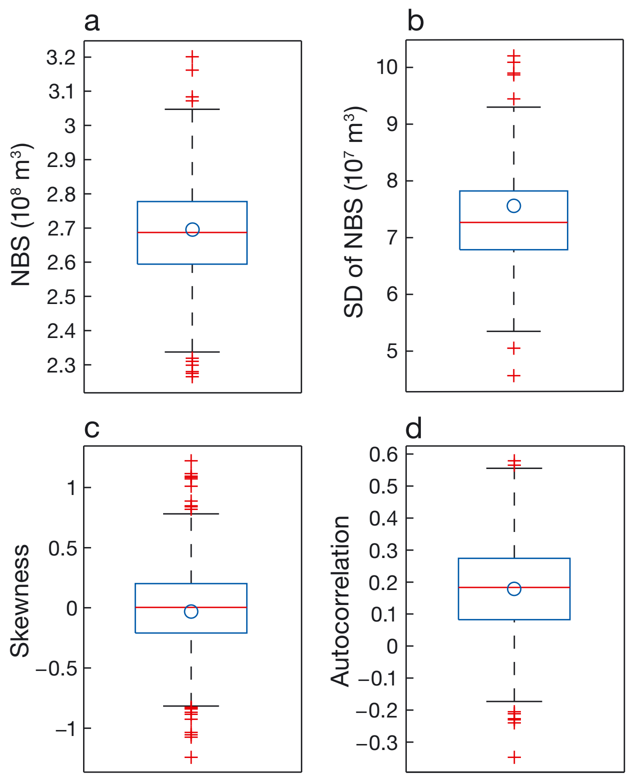

Fig. 4. Comparison of annual net basin supplies (NBS) statistics for the Quabbin Reservoir: (a) mean, (b) SD, (c) skewness, (d) autocorrelation at lag 1 yr. See Fig. 3 for boxplot description

3. RESULTS AND DISCUSSION

3.1. Identification of climate hazard and thresholds

In this study, a reliability indicator (Hashimoto et al. 1982a,b), which has been successfully applied to assess the climate change impacts on water resource systems (e.g. Frederick et al. 1997, Vogel et al. 1999a, Maier et al. 2001, Vano et al. 2010), is used as a performance indicator for evaluating the water resource system under the influence of climate change:

$$\begin{aligned} &\text{If } X_t \geq C \text{ then } X_t \in S \text{ and } Z_t = 1 \\ &\text{else } X_t \in U \text{ and } Z_t = 0 \end{aligned} \tag{4}$$

$$C_\mathrm{R} = \frac{\sum_{t=1}^{T} z_t}{T} \tag{5}$$

where C is the safe yield criterion (~1.3 MCM d^{-1} for the reservoir system in the present study), S represents 'satisfactory' yield (water yield $\geq C$), Z_t is the fraction of the time period, from period $t = 1$ to $t = T$, during which the reservoir system water supply is satisfactory, U represents 'unsatisfactory' yield, and C_R is reservoir reliability (water supply can meet the required demand for 95% of the time). The safe yield is used in all demand calculations. Although demand was above C prior to 1992, it has now decreased to a level well below the C, due to an aggressive water conservation program. In this study, the threshold of the reliability was set at 95% as a general planning standard, as suggested by Modarres et al. (1999) and required by the MWRA. It indicates whether the climate conditions linked to the performance indicator (described in Section 3.2) are acceptable or unacceptable.

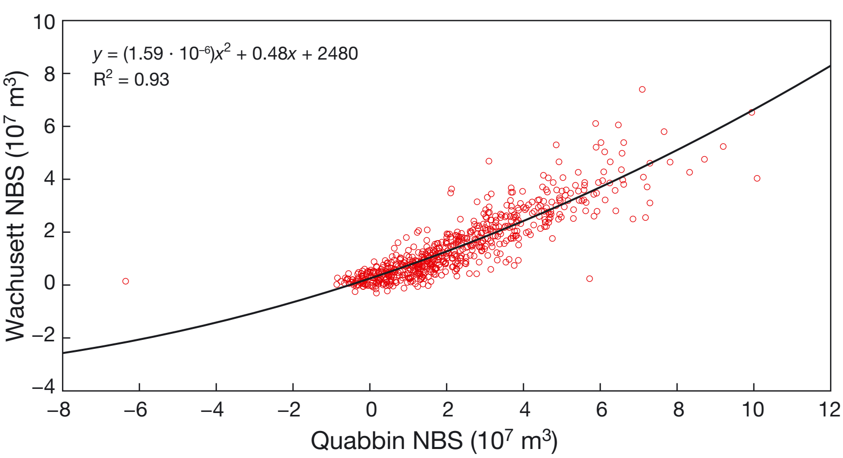

Fig. 5. Relationship between net basin supplies (NBS) of Quabbin and Wachusett Reservoirs

3.2. Risk discovery

The synthetic inflow generated by the time series model explained in Section 2.2 allows the testing of the water supply system for a greater variety of inflow scenarios than those that occurred historically. Although it does not reflect the real climate conditions actually occurring, it can allow us to identify climate states which cause risk. More details are given below (this subsection).

3.2.1. Identification of climate hazard and thresholds

In order to evaluate the effect of changes in mean climate, the mean monthly state of NBS was adjusted in the synthetic model. Then 6 chains of 50000 yr stochastic monthly NBS, which are based on 100, 95, 90, 85, 80, and 70% of historical monthly NBS mean data $\bar{u}_i$ of the Quabbin Reservoir, were generated separately by using the time series modeling described in Section 2.2. The corresponding monthly NBS of the Wachusett Reservoir can be calculated based on the quadratic equation as shown in Fig. 5 and is used for the climate sensitivity analysis of the system. The 6 chains of 50000 yr simulation can then be broken into 30 yr analysis windows, which are used to fit the temporal scale to the outputs of GCM projections in Section 3.3, and as input to the MWRA model, representing periods of the mean climate.

For each analysis window, both the monthly and annual statistics of NBS are calculated, including mean, SD, and autocorrelation at 1 yr lag. In this study, the non-automatic backward stepwise regression is used to discard those predictor variables of secondary importance that do not improve the goodness-of-fit, while keeping the key predictor variables in the model. The data analysis revealed that annual mean and SD explained the vast majority of the variance ($R^2 = 0.93$) in the reliability for each 30 yr window. It is in line with the relationship between reliability of US reservoirs and these statistical variables (Vogel & Bolognese 1995). Of importance here is the relationship between the performance indicator and the statistics of climate variables that are robust enough to derive the climate response function, which can then be adopted to identify the problematic climate states.

The multiple logistic regression function, a general linear model (McCullagh & Nelder 1989, Neter et al. 1996, Montgomery 2008), was used in this study as the climate response function to predict the reliability as a function of changes in climate:

$$\text{Reliability} = \frac{1}{1+\exp(-\beta X)} \tag{6}$$

An input vector is multiplied by a vector of regression coefficient, β:

$$\beta X = \beta_0 + \beta_1 X_1 + \cdots \beta_n X_n \tag{7}$$

The advantage of this is that it can transform the linear combination of predictor variables from the real number range of [−∞:∞] to the range of [0:1], which is equal to the range of reliability. The method of maximum likelihood was used to estimate the parameters in Eq. (7). Annual mean and SD of NBS were predictors in this equation. The coefficients are listed in Table 2 ($R^2 = 0.82$).

3.2.2. Sensitivity to climate changes in NBS mean and variability

Fig. 6 shows the resulting climate response function as a function of changes in annual NBS mean and SD. The *x*- and *y*-axis are the percent change in annual NBS mean and SD, respectively. As can be seen from the figure, the reliability function is very sensitive to annual NBS mean and falls rapidly when annual NBS mean decreases. Annual NBS SD has a relatively lower impact on the reliability compared to annual NBS mean, but is still significant and usually apparent. In a certain range, a lower SD increases reliability and a higher SD gives lower reliability. When annual NBS SD falls to 20% of historical data and annual NBS mean is <10% of historical data, reliability falls below the 95% threshold. While annual NBS SD increases to >40% of historical data and to <95% observed annual NBS mean, reliability will also be <95%.

Table 2. Information from the logistic regression procedure. See Eq. (7). NBS: net basin supplies

Predictor variables	Coefficient	SE	p
Constant	−13.51	0.0153	0.0001
Annual NBS mean	6.61×10^{-5}	8.63×10^{-8}	0.0001
Annual NBS SD	-1.05×10^{-5}	2.04×10^{-7}	0.0001

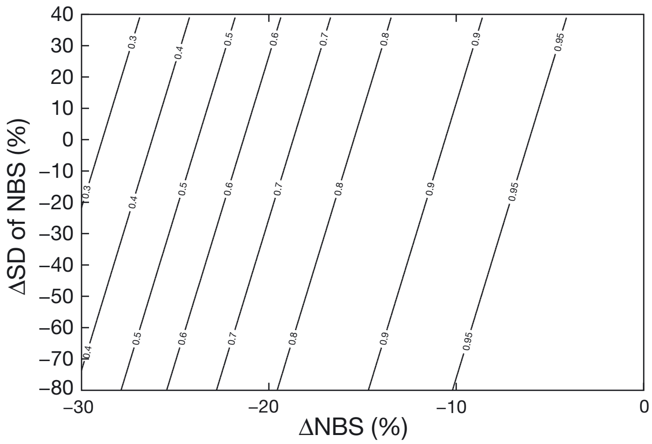

Fig. 6. Contour lines of reliability as a function of annual mean and SD of net basin supplies (NBS)

3.3. Estimation of climate informed risk

The previous step identified problematic climate conditions. This step uses GCM projections to estimate risks: that is, probabilities of those hazardous conditions. In this case, the projections of temperature and precipitation downloaded from the WCRP–CMIP3 (Bias Corrected and Downscaled World Climate Research Coupled Model Intercomparison Project phase 3) multi-model dataset for scenarios A2, A1B and B1 (Table 3) were used (Maurer et al. 2002). A log-linear regression model has been successfully applied to estimate stream flow in the northeastern US (Vogel et al. 1999b). A simple regression derived

Table 3. General circulation model (GCM) projections adopted in this paper and applied to scenarios A1B, A2, B1

	Projection run numbers A2	A1B	B1
bccr_bcm2_0	1	1	1
cccma_cgcm3_1	1–5	1–5	1–5
cnrm_cm3	1	1	1
csiro_mk3_0	1	1	1
gfdl_cm2_0	1	1	1
gfdl_cm2_1	1	1	1
giss_model_e_r	1	2, 4	1
inmcm3_0	1	1	1
ipsl_cm4	1	1	1
miroc3_2_medres	1–3	1–3	1–3
miub_echo_g	1–3	1–3	1–3
mpi_echam5	1–3	1–3	1–3
mri_cgcm2_3_2a	1–5	1–5	1–5
ncar_ccsm3_0	1–4	1–3, 5–7	1–7
ncar_pcm1	1–4	1–4	2, 3
ukmo_hadcm3	1	1	1
Total runs per ensemble	36	39	37

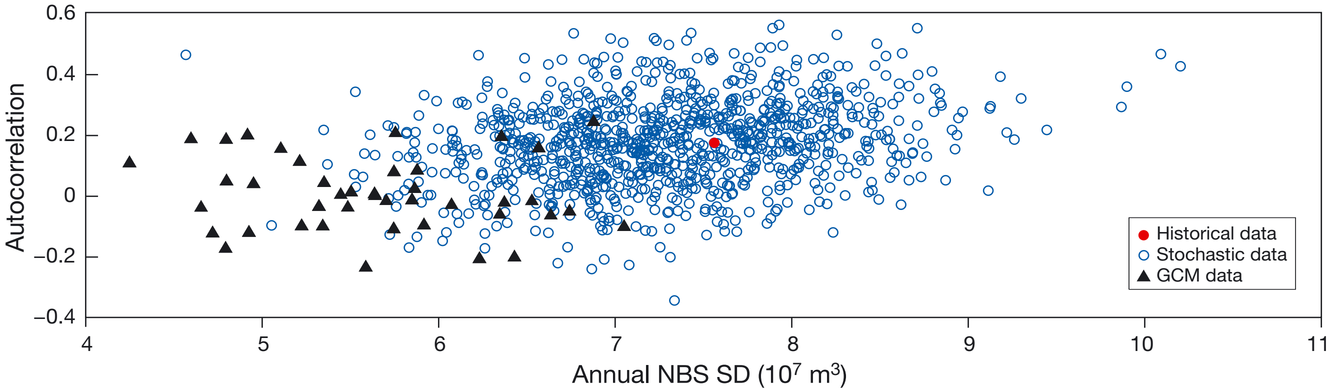

Fig. 7. Comparison of annual autocorrelation (lag 1 yr) and SD of net basin supplies (NBS) from general circulation models, stochastic model and historical observations

from historical data, based on mean annual temperature and precipitation, was developed to simulate the NBS of Quabbin Reservoir ($R^2 = 0.87$) for the purposes of this example (see Eq. 8). The model was fit using ordinary least squares regression. The use of regression introduces the problem of extrapolation in the response of NBS to climate changes when climate projections are used. For a more comprehensive analysis of a particular location's hydrologic response to climate change, a physically-based hydrological model should be used, although that also requires extrapolation on the part of the hydrologic model:

$$\mathrm{NBS} = -18\,693.2T + 347P + 110\,049 \quad (8)$$

where T = annual temperature and P = annual precipitation.

Fig. 7 shows annual NBS SD and autocorrelation (lag 1 yr) for 1950 to 2000 derived from GCM projections, which are represented as triangles. The solid circle denotes historical NBS and open circles stand for the corresponding statistics of 50 yr windows from the 50000 year chain. From this figure, it is obvious that annual NBS SD drawn from GCM projections is less than historical data and synthetic data. Annual NBS autocorrelations from GCM projections are within the range of the synthetic data.

Annual mean and SD of NBS were calculated for 3 future time periods: 2006–2035, 2036–2065 and 2066–2095. In every case, the average of each 30 yr period was used to estimate annual mean values and SD of NBS in order to reduce the effects of internal model variability in any individual run. These values that represent the mean of the climate in the future were then input to the climate response function as mentioned before. After this, the climate information drawn from GCM projections could be used to assess the probability of those climate changes.

As a means of specifying impacts in terms of risk, the probability distribution of reliability was estimated as a function of the climate change projections. In this study, each GCM run is considered as an equiprobable possible future climate. Based on this assumption, probability is assigned according to the number of runs that fall into each climate state. Thus, the more projections that fall into a climate state, the more likely it is assumed to be. Then the distributions of the reliability from GCM projections can be evaluated through a nonparametric empirical probability distribution given by (Wilks 1995):

$$P = \frac{m}{n+1} \quad (9)$$

where P represents the cumulative probability, m represents the rank of the data (from small to high) and n denotes the total number of the data points. Since GCM projections cannot capture the true annual NBS SD as depicted in the previous section, cumulative probability of reliability under different scenarios were calculated with the historical SD.

Due to climate change, the future annual NBS SD may be greater than that of the current climate state. Since the GCM-based historical estimates of SD were implausibly low, the SD was parametrically varied to explore the effects of increasing variability. Reliability was calculated based on annual NBS mean from GCM projections with 100, 110, 120, 130 and 140% of the historical annual NBS SD. The corresponding probability of problematic climate states (i.e. those causing water supply not to meet demand) in each time period under each scenario with 4 different annual NBS SD are shown in Table 4. As shown in Fig. 8a–c, the probability of a problematic state with all different annual NBS SDs under scenario A2 is below 20% and increases along with the annual NBS standard deviation in the first period. In the

Table 4. Probability of unacceptable reliability (<0.95) for 3 time periods under scenarios A2, A1B and B1, and increasing annual standard deviation. Percent values in column headers: percent of historical SD

Period	Percent of historical SD 100	110	120	130	140
A2					
2006–2035	0.135	0.162	0.162	0.162	0.189
2036–2065	0.216	0.216	0.216	0.216	0.216
2066–2095	0.432	0.459	0.486	0.486	0.513
A1B					
2006–2035	0.100	0.100	0.125	0.125	0.125
2036–2065	0.225	0.275	0.300	0.300	0.300
2066–2095	0.275	0.325	0.375	0.400	0.400
B1					
2006–2035	0.079	0.079	0.079	0.079	0.079
2036–2065	0.105	0.105	0.105	0.105	0.105
2066–2095	0.157	0.157	0.184	0.184	0.211

period 2036–2065, annual NBS SD has little effect on the probability of the problematic state, which is ~20 % with different annual NBS SD. The probability of the problematic state is within the 40 to 50 % range in the last period.

Increasing the NBS SD increases the probability of the problematic state. Fig. 8d–f shows the results of the empirical cumulative distribution with scenario A1B. The probability of a reliability under the acceptable threshold is ~10 % with these annual NBS SDs in the first period. In the second period, the probability of a problematic climate state is ~15 %, with SD driven from GCMs, and increases to about 30 % with 140 % SD of historical data. In the last period, the probabilities of problematic climate states increased from 25 to 40 % along with the SD drawn from GCMs and 140 % historical SD. With scenario B1, all probabilities of problematic climate states are below 20 % in the 3 periods with these annual NBS SDs as shown in

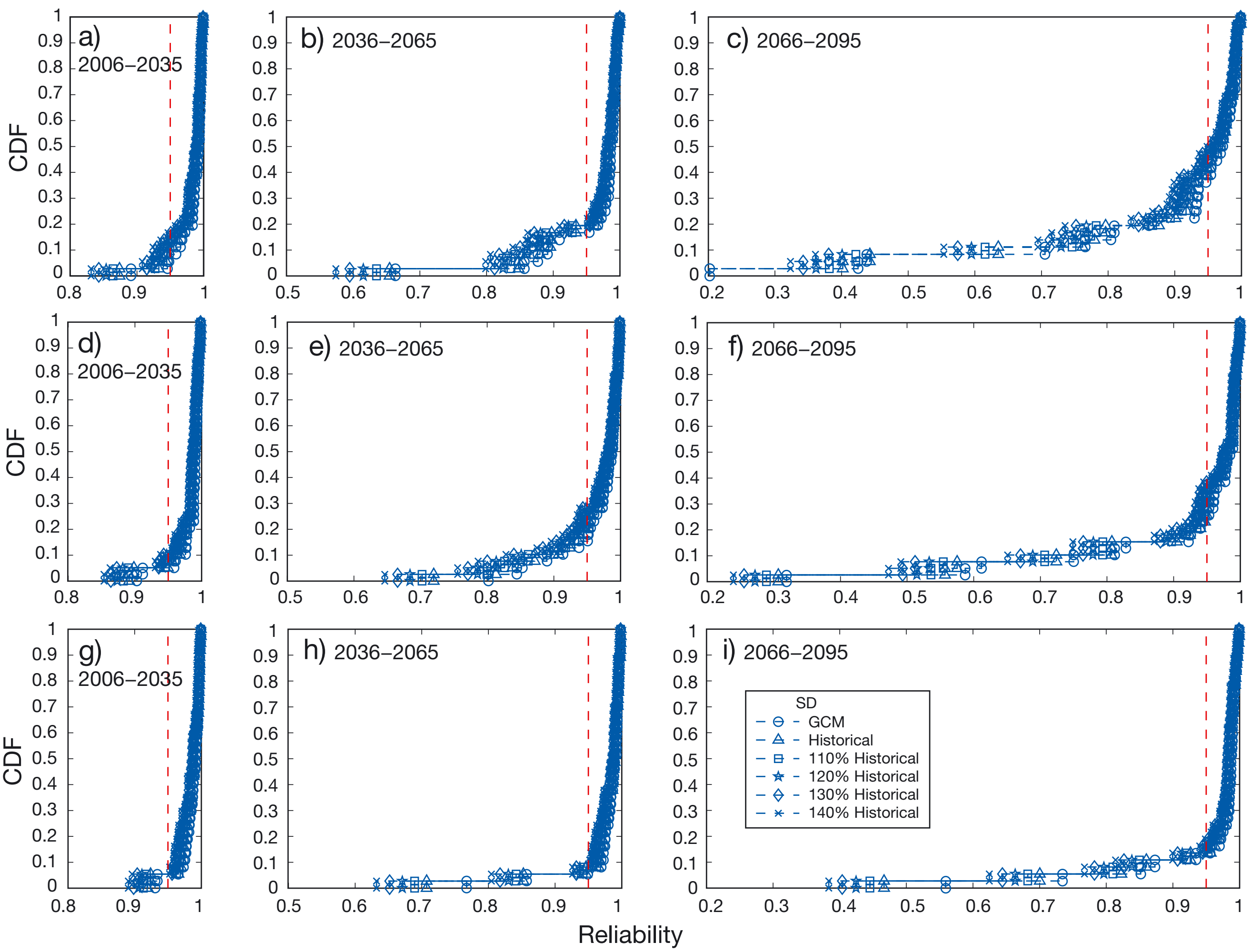

Fig. 8. Cumulative distribution function (CDF) of reliability based on general circulation model (GCM) projections under the (a–c) A2, (d–f) A1B and (g–i) B1 scenarios

Fig. 8g–i. Annual NBS SD does not affect the cumulative distribution as much as in the other 2 scenarios.

This analysis demonstrates a method for exploring plausible changes in the variability of future inflows, which in some cases may reveal higher risks than would be identified using only historical variability. Analyses that are driven by GCM projections often use either variability from the projections, which is typically underestimated, or historical variability. In both cases, the reliability of water supply may be overestimated using such approaches. In this case, the effect is relatively small and likely due to the very large storage volume that this system has relative to demand. As a result, the variability effects are muted. Perhaps surprisingly, the emissions scenario has a significant effect on reliability estimates even prior to 2050, which is contrary to expectations.

The challenge in studies such as these is determining how to interpret the results. As discussed in the introduction, there are numerous studies that use climate change projections to project the impacts on water resource systems. This study attempts to first understand how the system responds to climate changes and to determine what climate changes would cause performance to fall to the point that some adaptive action would be necessary. In this way, it attempts to directly model 'actionable information,' a term commonly referenced as a desirable product of such studies. While the study still relies on climate change projections to provide information regarding the future, the projections can be put into the context of decision-relevant thresholds. In addition, the stochastic approach allows a full and exhaustive sampling of climate change uncertainty, something that climate projections do not provide. In fact, there is concern that in some cases climate projections underestimate the risk of climate change due to bias in the variability in GCM projections that is not corrected in some statistical methods, such as bias-corrected and spatially disaggregated data (BCSD, Brown & Wilby 2012).

Again, these results are simply a demonstration of methods, and should not be construed as the actual estimation of climate risk to the Quabbin–Wachusett system, which in general has a voluminous and secure water supply.

4. LIMITATIONS OF THIS METHODOLOGY

In this application, the decision-scaling methodology used a climate response function to link the decision-relevant performance indicators of climate conditions, and some accuracy is inevitably lost. In addition, in order to simulate changes in NBS directly from climate change projections, a simple regression model was used. However, neither of these modeling choices are inherent limitations of the general methodology. The general limitation to the approach is that the assignment of probabilities to future climate conditions remains a science in progress, and this is a critical step for any approach that intends to assist decision making. The risk estimates only use probability, which is assigned according to the number of runs which fall into each climate state in this study, but other probability assignment methods are not explored. In addition, the methodology is centered on the derivation of climate response from a large sampling of system performance to varying climate conditions. However, in some cases the link between climate and the hydrologic hazard may be weak or unknown. For example, in the case of floods, the stochastic sampling approach will likely indicate increasing flood risk as mean precipitation increases, but the actual response may be subtler than a shifting of the entire distribution. It should be noted that decision scaling is a nascent approach with much room for methodological improvement.

5. CONCLUSION

This study used a vulnerability-based approach to evaluate the climate informed risk of the Quabbin–Wachusett Reservoir systems through time series modeling, combined with the output of climate change projections. The main result of this study demonstrated that annual net basin supply (NBS) SD affects both reliability and the probability of problematic climate states, although the effect is relatively small in comparison to annual NBS mean, likely due to the large ratio of storage to demand in this system. It was found that GCM projections in this region significantly underestimate SD, even after bias correction. As a result, estimation of reliability using such climate change projections may be biased and lead to underestimation of risk. Future NBS variability may be greater than variability of the current climate state due to climate change. The vulnerability-based method developed in this paper can explore the risks associated with change in variability as well as changes to mean conditions that may be derived from GCM projections. At the same time, the probability distribution can be easily updated when new GCM projections and climate information sources are available. Although not presented here, the vulnerability-based method described in this paper can be used for the development and evaluation of hazard risk management strategies under present and future possible climate states.

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LITERATURE CITED

Anderson PL, Tesfaye YG, Meerschaert MM (2007) Fourier-PARMA models and their application to river flows. J Hydrol Eng 12:462–472

Brown C, Wilby RL (2012) An alternate approach to assessing climate risks. Eos Trans AGU 93:401–402

Brown C, Ghile Y, Laverty M, Li K (2012) Decision scaling: linking bottom-up vulnerability analysis with climate projections in the water sector. Water Resour Res 48: W09537, doi:10.1029/2011WR011212W09537

Christensen NS, Lettenmaier DP (2007) A multimodel ensemble approach to assessment of climate change impacts on the hydrology and water resources of the Colorado River Basin. Hydrol Earth Syst Sci 11:1417–1434

Deser C, Knutti R, Solomon S, Phillips AS (2012) Communication of the role of natural variability in future North American climate. Nature Clim Chan 2:775–779

Dessai S, Hulme M, Lempert R, Pielke R Jr (2009) Climate prediction: a limit to adaptation. In: Adger WN, Lorenzoni I, O'Brien KL (eds) Adapting to climate change: thresholds, values, governance. Cambridge University Press, Cambridge, p 64–78

Eden JM, Widmann M, Grawe D, Rast S (2012) Skill, correction, and downscaling of GCM-simulated precipitation. J Clim 25:3970–3984

Ficklin DL, Stewart IT, Maurer EP (2013) Effects of projected climate change on the hydrology in the Mono Lake Basin, California. Clim Change 116:111–131

Fisher SM, Palmer RN (1995) Managing water supplies during drought: the search for triggers. Proc 22nd Annu Nat Conf, Cambridge, MA, p 1001–1004

Frederick KD, Major DC, Stakhiv EZ (1997) Water resources planning principles and evaluation criteria for climate change: summary and conclusions. Clim Change 37: 291–313

Gersch W (1970) Estimation of the autoregressive parameters of a mixed autoregressive moving-average time series. IEEE Trans Automatic Control 15:583–588

Hamlet AF, Lettenmaier DP (1999) Effects of climate change on hydrology and water resources in the Columbia River Basin. J Am Water Resour Assoc 35:1597–1623

Hashimoto T, Loucks DP, Stedinger JR (1982a) Robustness of water-resources systems. Water Resour Res 18:21–26

Hashimoto T, Stedinger JR, Loucks DP (1982b) Reliability, resiliency, and vulnerability criteria for water-resource system performance evaluation. Water Resour Res 18: 14–20

Hay LE, Wilby RJL, Leavesley GH (2000) A comparison of delta change and downscaled GCM scenarios for three mountainous basins in the United States. J Am Water Resour Assoc 36:387–397

Kilsby C, Jones P, Burton A, Ford A and others (2007) A daily weather generator for use in climate change studies. Environ Model Softw 22:1705–1719

Knutti R, Meehl GA, Allen MR, Stainforth DA (2006) Constraining climate sensitivity from the seasonal cycle in surface temperature. J Clim 19:4224–4233

Lempert R (2010) Robust decision making approach to managing water resource risks. AGU Fall Meet Abstr #H13H-02

Lempert RJ, Groves DG, Popper SW, Bankes SC (2006) A general, analytic method for generating robust strategies and narrative scenarios. Manag Sci 52:514

Maier HR, Lence BJ, Tolson BA, Foschi RO (2001) First-order reliability method for estimating reliability, vulnerability, and resilience. Water Resour Res 37:779–790

Maurer EP, Duffy PB (2005) Uncertainty in projections of streamflow changes due to climate change in California. Geophys Res Lett 32:L03704

Maurer E, Wood A, Adam J, Lettenmaier D, Nijssen B (2002) A long-term hydrologically based dataset of land surface fluxes and states for the conterminous United States. J Clim 15:3237–3251

McCullagh P, Nelder JA (1989) Generalized linear models. Chapman & Hall/CRC, Boca Raton, FL

Modarres M, Kaminskiy M, Krivtsov V (1999) Reliability engineering and risk analysis: a practical guide, Vol 55. CRC Press, New York

Montgomery DC (2008) Design and analysis of experiments. John Wiley & Sons, New York

Neter J, Wasserman W, Kutner MH, Li W (1996) Applied linear statistical models. Irwin, Boston, MA

Pielke RA Sr, Wilby R, Niyogi D, Hossain F and others (2012) Dealing with complexity and extreme events using a bottom-up, resource-based vulnerability perspective. Geophys Monogr Ser 196:345–359

Pilling CG, Jones JAA (2002) The impact of future climate change on seasonal discharge, hydrological processes and extreme flows in the upper Wye experimental catchment, mid-Wales. Hydrol Processes 16:1201–1213

Prudhomme C, Wilby R, Crooks S, Kay A, Reynard N (2010) Scenario-neutral approach to climate change impact studies: application to flood risk. J Hydrol (Amst) 390: 198–209

Pulido-Velazquez D, Garrote L, Andreu J, Martin-Carrasco FJ, Iglesias A (2011) A methodology to diagnose the effect of climate change and to identify adaptive strategies to reduce its impacts in conjunctive-use systems at basin scale. J Hydrol (Amst) 405:110–122

Rasmussen PF, Salas JD, Fagherazzi L, Rassam JC, Bobée B (1996) Estimation and validation of contemporaneous parma models for streamflow simulation. Water Resour Res 32:3151–3160

Salas JD, Obeysekera J (1992) Conceptual basis of seasonal streamflow time series models. J Hydraul Eng 118: 1186–1194

Semenov MA, Barrow EM (1997) Use of a stochastic weather generator in the development of climate change scenarios. Clim Change 35:397–414

Stainforth DA, Allen MR, Tredger ER, Smith LA (2007) Confidence, uncertainty and decision-support relevance in climate predictions. Philos Trans R Soc A 365:2145–2161

Sulis M, Paniconi C, Marrocu M, Huard D, Chaumont D (2012) Hydrologic response to multimodel climate output

using a physically based model of groundwater/surface water interactions. Water Resour Res 48:W12510, doi: 10.1029/2012WR012304
Sun HB, Furbish DJ (1997) Annual precipitation and river discharges in Florida in response to El Niño and La Niña sea surface temperature anomalies. J Hydrol (Amst) 199: 74–87
Sveinsson OGB, Salas JD, Lane WL, Frevert DK (2007) Stochastic analysis, modeling, and simulation (SAMS) version 2007, user's manual. Tech Rep 11, Computing Hydrology Laboratory, Department of Civil and Environmental Engineering, Colorado State University, Fort Collins, CO
Teng J, Vaze J, Chiew FHS, Wang B, Perraud JM (2012) Estimating the relative uncertainties sourced from GCMs and hydrological models in modeling climate change impact on runoff. J Hydrometeorol 13:122–139
Tesfaye YG, Meerschaert MM, Anderson PL (2006) Identification of periodic autoregressive moving average models and their application to the modeling of river flows. Water Resour Res 42:01419, doi: 10.1029/2004WR003772
Tsai AY, Huang WC (2011) Impact of climate change on water resources in Taiwan. TAO 22:507–519
Vano JA, Voisin N, Cuo L, Hamlet AF and others (2010) Climate change impacts on water management in the Puget Sound region, Washington State, USA. Clim Change 102:261–286
VanRheenen NT, Wood AW, Palmer RN, Lettenmaier DP (2004) Potential implications of PCM climate change scenarios for Sacramento–San Joaquin River Basin hydrology and water resources. Clim Change 62:257–281
Venema HD, Schiller EJ, Adamowski K, Thizy JM (1997) A water resources planning response to climate change in the Senegal River Basin. J Environ Manag 49:125–155
Vogel RM, Bolognese RA (1995) Storage–reliability–resilience–yield relations for over-year water supply systems. Water Resour Res 31:645–654
Vogel RM, Shallcross AL (1996) The moving blocks bootstrap versus parametric time series models. Water Resour Res 32:1875–1882
Vogel RM, Lane M, Ravindiran RS, Kirshen P (1999a) Storage reservoir behavior in the United States. J Water Resour Plan Manag 125:245–254
Vogel RM, Wilson I, Daly C (1999b) Regional regression models of annual streamflow for the United States. J Irrig Drain Eng 125:148–157
Weiland FCS, van Beek LPH, Weerts AH, Bierkens MFP (2012) Extracting information from an ensemble of GCMs to reliably assess future global runoff change. J Hydrol (Amst) 412–413:66–75
Westphal KS, Vogel RM, Kirshen P, Chapra SC (2003) Decision support system for adaptive water supply management. J Water Resour Plan Manag 129:165–177
Wiley MW, Palmer RN (2008) Estimating the impacts and uncertainty of climate change on a municipal water supply system. J Water Resour Plan Manag 134: 239–246
Wilks DS (1992) Adapting stochastic weather generation algorithms for climate change studies. Clim Change 22: 67–84
Wilks DS (1995) Statistical methods in the atmospheric sciences, Vol 100. Academic Press, Oxford
Wilks DS (1999) Multisite downscaling of daily precipitation with a stochastic weather generator. Clim Res 11:125–136

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