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Quantifying the Urban Water Supply Impacts of Climate Change

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Abstract The difference in timing between water supply and urban water demand necessitates water storage. Existing reservoirs were designed based upon hydrologic data from a given historical period, and, given recent evidence for climatic change, may be insufficient to meet demand under future climate change scenarios. The focus of this study is to present a generally applicable methodology to assess the ability of existing storage to meet urban water demand under present and projected future climatic scenarios, and to determine the effectiveness of storage capacity expansions. Uncertainties in climatic forcing and projected demand scenarios are considered explicitly by the models. The reservoir system in San Diego, California is used as a case study. We find that the climate change scenarios will be more costly to the city than scenarios using historical hydrologic parameters. The magnitude of the expected costs and the optimal investment policy are sensitive to projected population growth and the accuracy to which our model can predict spills.

Keywords Climate change adaptation · Reservoir storage expansion · Urban water reliability · Land surface hydrology · Water planning

1 Introduction

1.1 Background

The recently released Fourth Assessment Report of the Intergovernmental Panel for Climate Change (Rosenzweig et al. 2007) states with high confidence that climate change is strongly affecting snow dependent systems and that emerging evidence exists that climate

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induced changes in water resources are occurring around the world. The observed and anticipated climatic changes are expected to lead to early melting of snowpacks due to temperature increases (e.g., Dettinger and Cayan 1995, Xu 2000), which will alter runoff patterns in cold and mountainous regions; increasing evaporation with implications for significant changes in runoff variability (e.g., Manabe et al. 2004); altering both the intensity and frequency of precipitation with implications for changes in the occurrence of floods and flash floods (e.g., Trenberth et al. 2007); and increasing seasonal demands for urban water, hydropower, and irrigation while in many cases reducing water supply (e.g., Kundzewicz et al. 2007). All these impacts will significantly affect water supply around the world (e.g., Arnell 1999), and water management strategies must adapt to the changing climate in order to avoid expensive water shortages.

The objective of this study is to formulate a methodology that may be used to examine the economic implications of a changing climate for an urban area that depends on storage reservoirs and water imports for its water supply, and to consider the effectiveness of expanding reservoir storage as a means of adaptation. An important aspect of this work is the explicit treatment of uncertainty throughout the system components. Despite a recognition and awareness of the impending problems climate change poses to water systems, water management and decision making in California (and elsewhere around the world) has yet to incorporate quantitative climate change information in operations and planning (Purkey et al. 2007). In addition, little research has studied the economic costs and benefits of expanding existing water storage facilities to adapt to future climate change.

Urban water managers can influence both the demand and supply of water when considering adaptation to climate change. We are examining expanding reservoir storage as a means of adaptation because existing reservoirs are constructed based on historical runoff and demand distributions and may be ineffective at preventing water shortages if the amplitudes of supply and demand change over time under climate change scenarios (e.g., Graham and Georgakakos 2006). Urban water reservoir storage has economic value since it allows agents to transfer water both within and between years from periods when supply is high to periods when demands are high. The effectiveness of expanding reservoir storage as a means of adaptation will be a function of the existing reservoir storage, the climate change impacts on the basin specific hydrologic variables, and reservoir operating rules.

To exemplify our methodology, we choose to study a single municipal water district so that we can design a reservoir model that can analyze adaptation conceptually and accurately. The urban water reservoir system of San Diego, California is suitable to serve as an example because it is in a large urban water district and because it relies extensively on its reservoir system. Desirable features of the model we design and implement, that do not exist with some of the larger reservoir models currently used in California, are: it can accommodate different climate scenarios; it is simulation based with explicit account for hydrologic and other system uncertainties; and it can be used with a set of inputs not limited to the sequence of historical inflows.

Following a short literature review of past studies relevant to this work, we discuss our methodology in Section 2 through the presentation of the water balance formulation and parameterizations. The models for uncertainty characterization as well as the climate model information used in this work are also presented in that section. Section 3 formulates the adaptation strategy as a reservoir capacity expansion program with estimation of the economic parameters. The results of our simulations and sensitivity study are discussed in Section 4, with conclusions and recommendations for future research constituting Section 5. Nomenclature is included in the Appendix.

1.2 Literature Review

A literature exists that explores the adverse impacts that climate change will cause on water supply and demand throughout the world. These studies have examined implications on a worldwide basis, such as Barnett et al. (2005), and also on a regional scale, including studies in China (Xu et al. 2004), Canada (Simonovic and Li 2004), Japan (Islam et al. 2005), Korea (Georgakakos et al. 2005) and New Zealand (Ruth et al. 2007). Specifically, these problems are expected to be significant in the western United States (Barnett et al. 2004; Dracup et al. 2005; Hayhoe et al. 2004). Large reservoir models have been designed to evaluate the impacts of climate change on water resources in California, and Dracup et al. (2005) contains a discussion of the drawbacks of some of these larger models. In addition to lacking desirable modeling features (discussed earlier), the larger models have coarse representation of individual water districts. This is problematic as heterogeneity exists for water rights and population growth for water districts, even for ones in close proximity to each other spatially.

Adaptive strategies in the western United States have thus far focused on improving reservoir management (Carpenter and Georgakakos 2001; Yao and Georgakakos 2001; Vanrheenen et al. 2004) by incorporating climate forecasts and projections. To the best of our knowledge, other forms of adaptation to potential climatic change under increasing populations have not received significant attention. Our study extends this research by focusing on the economic effectiveness of reservoir storage capacity expansion as a means of adaptation to climatic change. Similar studies include Ruth et al. (2007), which discusses adaptive responses to climate change for a single water district in New Zeland, and Semadeni-Davies (2004), who examines the need for infrastructure expansion for urban sewerage networks in regions affected by snow melt changes. However, unlike the present study, these works do not incorporate economic criteria when considering adaptation. Pertinent to the adequacy of storage capacity under an uncertain water supply, Fisher and Rubio (1997) derive a theoretical model that shows that increased uncertainty in projections leads to higher level of reservoir storage in the long term.

The present paper complements the existing literature by examining stochastic urban water supply and demand under projected climatic and population changes in economic terms, and by formulating an adaptation solution through capacity expansion. The innovative aspects of this study consist of the economic focus, the incorporation of uncertainty, the development of capacity expansion as an adaptation approach for urban water supply-demand problems, and the application to actual data from a water district in semi-arid southern California.

2 Water Balance Model and Climate Information

2.1 The Water Balance Model

We modify the *abcd* model presented in Rogers and Fiering (1990) for application to the San Diego's reservoir system. The formulated model is a series of equations that simulate the conservation of water volume for a regulated watershed on a monthly time scale. A significant modification to the *abcd* model that is necessary for our methodology is the inclusion of imports into the system of water balance equations. With this modification the model represents a generally applicable tool for the purposes of climate change adaptation studies in urban environments in semi-arid or arid regions. We adopt a monthly time scale because of the time interval of the available historical data for the application region, and of the time interval of the climate model information used as discussed in subsequent sections. Sensitivity analysis is conducted for water balance components that may require higher resolution for more accurate representation (i.e., reservoir spills).

The City of San Diego, like many other cities in semi arid regions, relies upon local runoff to meet 10–20% of its water demand and imports the residual demand. It operates nine reservoirs with a total capacity of 512 million cubic meters. The sole objective of the reservoirs is for urban water deliveries. We assume that the reservoirs are perfectly connected in the model, although at times this assumption may not be true in practice due to pipeline constraints. The *abcd* model component that simulates groundwater withdrawals is not used as no such withdrawals exist.

Figure 1 provides a schematic overview of the components of the water balance model as applied to the case study and their interconnections. Precipitation and temperature constitute the climatic forcing of the water balance model. Precipitation estimates serve as input to the local runoff model component of the water balance model, for the estimation of expected imports, and for the estimation of expected urban water consumption targets. Temperature estimates are used for the determination of water consumption and reservoir evaporation. Urban population estimates are also used for the estimation of expected imports and water consumption. Water in reservoir storage is replenished by local runoff and imports. It is depleted by evaporation from the water surface in the reservoirs, releases to meet expected water consumption and any losses due to enforced spillage to avoid overtopping.

The model mathematical formulation is shown next in discrete form for a typical month t. To keep variable symbols to a minimum, the equations are generalized to show dependence on the kth ensemble member of the uncertain weather variables (as discussed in Section 2.1.2):

$$Q_{k,t} = \min\left\{d_i \alpha K, d_i v_{k,t}\right\} \tag{1}$$

$$V_{k,t+1} = \min\left\{(1-d_i)\alpha K, (1-d_i)v_{k,t}\right\} \tag{2}$$

where

$$v_{k,t} = V_{k,t} + I_{k,t} + \left(1-b_j\right)P_{k,t} - E_{k,t} \tag{3}$$

In these equations, t is the time index for a monthly time interval of computations, k is the ensemble-member index, j is a season index to indicate parameter dependence on season, and i is a monthly index to indicate parameter dependence on a particular month. Q, P, I, and E denote monthly volumetric flow quantities: reservoir release, basin precipitation, water imports, and total reservoir water surface evaporation. $V_{k,t}$ denotes the water volume in reservoir system storage at the beginning of month t and for ensemble member k. The symbol $v_{k,t}$ represents the stock of water at the end of month t and for ensemble member k.

Every month, the city releases a certain fraction d of the water in storage. The water that is not released becomes storage for the following period. A capacity constraint exists so that the amount of water in the reservoir does not exceed the amount of water that the system is capable of holding. If the water stock exceeds this amount at the end of month t then the excess water is lost through spillage, enforced to avoid overtopping and structural damage.

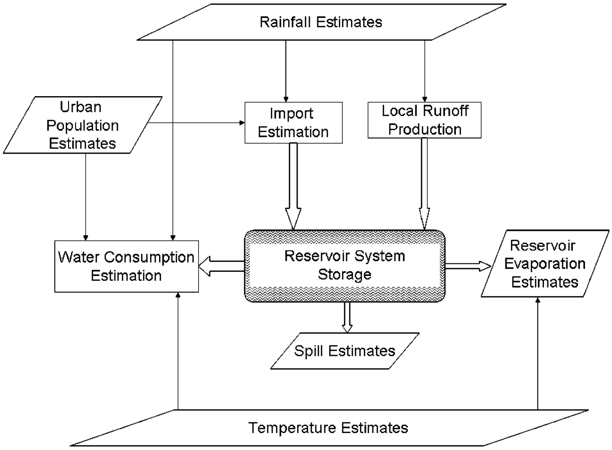


Fig. 1 Schematic of water balance model and interactions as applied to the case study

In this monthly formulation, the spillage capacity is taken to be a function of the actual reservoir capacity (denoted by K in the previous equations) times a multiplier α (<1). A multiplier of less than one is used because daily or hourly accounting is not possible with the existing data, and this information is necessary to approximate the precise conditions at which a spill occurs.

Assuming that monthly precipitation is distributed uniformly over the natural drainage basin of the city reservoir system and that runoff is a linear function of precipitation for monthly aggregate quantities, for each realization of precipitation we use:

$$R_{k,t} = \left(1 - b_j\right) P_{k,t} \tag{4}$$

This expression is implicit in Eq. 3, where b_j is a parameter depending on season j. This implies that only a fraction of precipitation enters the reservoir each period, and that the rest is lost to evapotranspiration or percolation to deep groundwater storage in the upstream drainage basin. The parameters d_i, b_j and α are calibrated to fit historical data.

These precipitation assumptions are reasonable since this is a small urban basin relative to the large spatial and temporal resolution associated with climate change projections. Also, in view of the significant uncertainty in precipitation and temperature projections for future climates (e.g., Koutsoyiannis et al. 2007), assuming a linear relationship between regional monthly runoff and precipitation is reasonable while it yields parsimonious and easily calibrated models. Furthermore, and typical for semi-arid urban environments, import volumes from outside the urban basin are as important or even more important than local-basin runoff volumes, thus reducing the sensitivity of the overall analysis to the rainfall-runoff relationship.

2.1.1 Hydrologic Model Parameter Estimation

Parameter b depends on season with two parameter values defined: one for the winter months, which we define as November through March; and the other for the summer months, defined as April through October. We find these parameters by comparing actual precipitation with actual runoff data. We employ a random sampling method for parameter estimation. We impose a uniform probability distribution $U(0,1)$ upon the possible range of values for b. Using a random number generator, we choose the pair of b values that lead to the smallest mean square error when compared to the runoff data. We adopt this convention as precipitation and runoff are not perfectly correlated to due soil characteristics such as porosity and moisture content, and these deviations may occur in either a positive or negative direction.

The release parameter d takes an average value of 0.025 when the available reservoir rule curves are used. We make monthly adjustments to the value of d because releases have occurred at different levels in different months. We find the release fraction for a given month of the year by multiplying d by the ratio of the release for that month to the average release for all months of the year.

Spills occur as a result of reservoir inflow while reservoir content is at capacity. We define the parameter α as the highest percentage of capacity that the system can hold without spills occurring. For model simulations, αK denotes the capacity constraint for which spills occur. In the absence of hourly or even daily data, a reasonable approach to estimate a value for α from the historical record is to use:

$$\alpha = 0.5\sum\nolimits_{t=1}^{T_N} \left(V_t + V_{t+1}\right) \Big/ \sum\nolimits_{t=1}^{T_N} K \qquad (5)$$

where t denotes a month for which historical spills occurred, and T_N is the total number of months with spills. Application of Eq. 5 with the historical data (1948–2003) gives an estimate of 0.807 for α. This estimate tends to underestimate the total spill volume over the historical record. For this reason, we obtain a second estimate for the value of α that preserves the historically observed total spill volume and use this new estimate in the sensitivity analysis with respect to spills (presented in the Results section). This new estimate of α (denoted by α') is equal to 0.4 and it yields a higher spill volume in accordance with the historical record.

2.1.2 Precipitation

Precipitation stochasticity must be incorporated for urban water supply planning. We incorporate uncertainty in monthly precipitation over the entire catchment of the urban water supply system of reservoirs through the development of monthly precipitation distributions. We create these distributions by pooling all available historical precipitation data from all the reservoir drainage areas by month and fitting a frequency distribution to the sample. We assume that precipitation patterns are identical at all of the reservoir drainage basins and that monthly precipitation distributions are not changing over the historical time period. On the basis of preliminary analysis for the case study, we further assume that non-zero precipitation in one month is independent of non-zero precipitation in adjacent months.

We fit the distributions to the sample of non-zero precipitation. However, summer months have a high proportion of months with no precipitation. The simulations incorporate the chance of a dry month as follows. A random sample $u_{t,k}$ is drawn from a uniform distribution $U(0,1)$ for each month. If the sample is less than the estimated fraction of zero precipitation observations for the given month, we assign zero precipitation for that month. If not, we obtain precipitation for that month by randomly sampling from the best-fit monthly distribution for non-zero precipitation amounts.

Persistence exists for summer and fall months for zero precipitation amounts. We assume that zero precipitation in these months follows a Markov lag-1 process. We create different probability distributions for the probability of zero precipitation occurrences so that the probability of zero precipitation in a given month is conditioned on whether or not zero precipitation occurred in the previous month. We present the sample frequencies of the unconditional and conditional distributions for the case study in Table 1.

Table 2 shows the historical precipitation statistics and results from the Kolmogorov-Smirnoff (KS) test of fitting distributions to monthly non-zero precipitation data. The values of the parameters chosen are the maximum likelihood estimates from the historical monthly data. We use two-parameter gamma distributions for October through April and two-parameter lognormal distributions for May through September. In Table 2, p denotes the shape of the gamma and the mean of the lognormal distributions, while q denotes the scale of the gamma and the variance of the lognormal distributions.

2.1.3 Imports

To proceed with the analysis of the urban water system under potential climatic change it is necessary to develop models to estimate imports. Future imports into the city are uncertain because of their dependence on precipitation and population growth. The historical operating policy of the city is maximize the capture of local runoff during wet years. This strategy minimizes losses to spills and evaporation but increases vulnerability during dry years due to the possibility of paying extra to acquire imports. Alternate importing strategies are considered as a sensitivity. We estimate annual import volume, I_y^a, for year y based on the following regression equation. Table 3 shows the parameter values and regression statistics.

$$\frac{I_y^a}{p_y^a} = \gamma_0 + \gamma_1 P_y^a + \gamma_2 \frac{I_{y-1}^a}{p_{y-1}^a} + \gamma_3 P_{y-1}^a + \varepsilon_y \qquad (6)$$

where γ_l (l=0,1,2,3) are regression parameters, p_y^a represents the urban population in year y, P_y^a represents the precipitation volume in year y, and ε_y is the zero-mean, normally distributed residual error of the regression. The r-squared for the regression is 0.78, which indicates that the specified regression is capturing a significant part of the variation in per capita imports. The parameter estimates, shown in the first column in Table 3, are all statistically significant at the 99% confidence level with the expected signs. On the basis of

Table 1 Sample unconditional and conditional frequencies for precipitation

Month	Marginal frequency (zero rainfall; %)	Marginal frequency (non-zero rainfall; %)	Sample conditional frequency (zero/zero; %)	Sample conditional frequency (zero/non-zero; %)	Sample conditional frequency (non-zero/zero; %)	Sample conditional frequency (non-zero/non-zero; %)
May	18.2	81.8	56.9	43.1	50.4	49.6
June	51.6	48.4	57.6	42.4	59.4	40.6
July	58.5	41.5	63.7	36.3	48.9	51.1
August	57.5	42.5	47.5	52.5	37.6	62.4
September	42.5	57.5	25.1	74.9	18.0	82.0
October	20.2	79.8	11.0	89.0	6.6	93.4
November	7.5	92.5	8.5	91.5	0.9	99.1

Table 2 Precipitation statistics for historical data

Month	Number (n)	Percent zeros	Distribution	p^{a}	q^{b}	KS p-value
January	620	1.7	Gamma (p,q)	1.049	2.832	0.104
February	621	2.1	Gamma (p,q)	1.195	2.613	0.334
March	617	2.8	Gamma (p,q)	1.228	2.409	0.182
April	609	4.2	Gamma (p,q)	1.080	1.296	0.636
May	520	18.2	Lognormal (p,q)	0.731	0.713	0.135
June	308	51.6	Lognormal (p,q)	−2.155	1.255	0.320
July	264	58.5	Lognormal (p,q)	−2.225	1.293	0.323
August	271	57.5	Lognormal (p,q)	−1.742	1.506	0.383
September	366	42.5	Lognormal (p,q)	0.677	0.740	0.046
October	502	20.2	Gamma (p,q)	0.857	0.886	0.126
November	582	7.5	Gamma (p,q)	1.082	1.489	0.086
December	620	1.4	Gamma (p,q)	1.141	2.093	0.270

[a] Denotes the shape parameter for the Gamma and the mean parameter for the Lognormal distributions

[b] Denotes the scale parameter for the Gamma and the variance parameter for the Lognormal distributions

historical data analysis, from the annual import estimates we create gamma distributions of the percentages of total imports placed into reservoirs for the summer and winter. For the climate runs, we use the distributions as estimated from the period 1978–2003. (O'Hara and Georgakakos 2006) provide the analysis and the parameter values for those distributions.

2.1.4 Evaporation

We model monthly potential evaporation (PE) using the Thornthwaite equation for monthly potential evaporation estimation (see formulation in standard texts such as Bras 1987). We assume evapotranspiration from the drainage areas is insignificant when compared to the surface area evaporation from the city reservoirs, which occurs at the potential rate.

Estimates of the surface area of the reservoir system are necessary for the computation of free water surface evaporation (potential evaporation over a water body). Approximate estimates may be obtained from the known capacity K^i and *corresponding* lake surface area A^i_v of reservoir i in the urban reservoir system of study. This may be accomplished through the approximation of the shape of the reservoir lake with a regular shape (we

Table 3 Import regression results for 1960–2003

Parameters	OLS parameter estimate	Standard error	t-statistic	p-value*
Regression constant	0.0246	0.0046	5.37	0.000
Annual rainfall	−0.0003	0.0001	−3.46	0.001
Lagged per capita imports	0.7285	0.0740	9.85	0.000
Lagged annual rainfall	−0.0003	0.0001	−3.40	0.002
r-squared	0.782			

*The p-value denotes the probability that the parameter estimate is statistically different than zero. The t-statistic is the parameter estimate divided by the SE produced similar results for a cone and a rectangular prism). For a conic shape, the surface area A_v^i of reservoir i with volume V ($<K^i$) is:

$$A_V^i = A_K^i \left(V/K^i\right)^{2/3} \tag{7}$$

We find V for each reservoir at the beginning of a given month by distributing the total volume computed from Eq. 2 proportionally based on capacity amongst all of the reservoirs. For a given month, reservoir system evaporation is then obtained from:

$$E = (\mathrm{PE})\left(\sum\nolimits_{i=1}^{6} A_V^i\right) \tag{8}$$

where i is a reservoir index.

2.1.5 Model Validation Using Historical Data

Figure 2 shows the 5th and 95th percentile of predicted model historical (1948 – 2003) cumulative releases from the San Diego urban reservoir system simulated by Monte Carlo sampling from the precipitation distributions. The corresponding observed release during this period is also shown with the black line denoted with the symbol *x*. Figure 2 demonstrates that the ensemble releases contain the historical releases throughout the period while they maintain low variance. To further evaluate performance, we construct the bulk reliability diagram to demonstrate how well the frequency distribution of predicted historical releases by the model matches the frequency distribution of actual historical releases. This is denoted in the upper panel of Fig. 3 with a dashed line. Perfect performance, which would arise if the probability distribution of historical outflows from the model exactly matched the probability distribution of actual historical outflows, is shown by the 45° line in the same upper panel as a benchmark and is represented by a solid line. The unconditional sample frequency distributions of simulated and actual releases are also shown in the lower panels of Fig. 3 for reference. The results show that the model tends to somewhat over predict the low frequency of outflows but predicts adequately the higher outflow occurrence frequencies (>0.5).

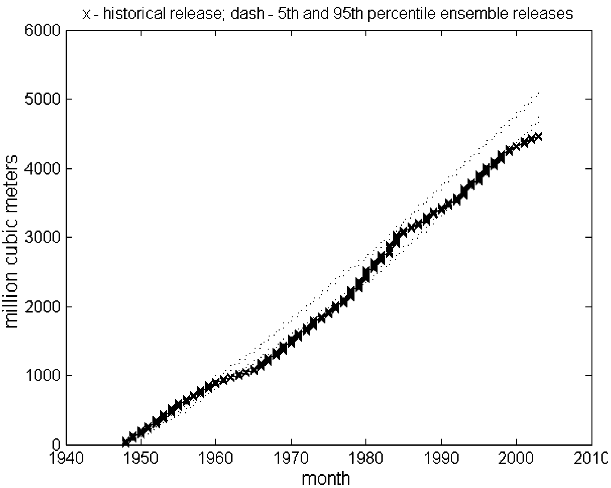
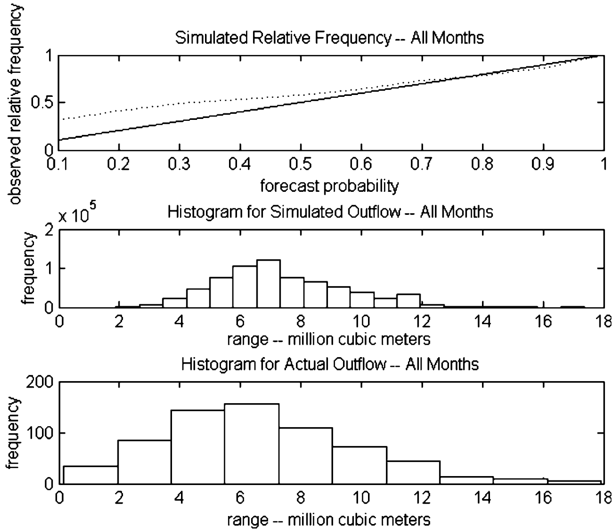


Fig. 2 Ensemble realizations of 5th and 95th percentile cumulative simulated release from the San Diego reservoir system (*dashed lines*) *versus* corresponding cumulative observed release (points denoted by '*x*') for the period: January 1948–December 2003

Fig. 3 Bulk Reliability Diagram (*top panel*) and histograms for simulated (*middle panel*) and actual release outflow (*bottom panel*). See text for a more detailed description of the panels



2.2 Climate Model Data and Future Water Balance Model Forcing

To simulate the water balance model for future climates, we use readily available output from Global Climate Models (GCMs) pertaining to monthly surface air (screen) temperature and precipitation. The output corresponds to the GCM grid point encompassing San Diego and was obtained form the Intergovernmental Panel for Climate Change (IPCC) Data Distribution Centre. We use data for the period 2006–2030 from three climate models to allow for multiple climate change scenarios. The models are: CGCM2 (Canadian Model), HadCM3 (Hadley Model) and ECHAM4 (Echam Model). We choose to explore scenarios in San Diego until 2030 since this timescale corresponds to existing planning horizons for urban water managers.

All three models have a control scenario in which greenhouse gas (GHG) emissions remain fixed at 1990 levels throughout the entire future period of model simulation. All three also have a standard GHG emission scenario of 1% annual growth in GHGs over the future period of simulation. O'Hara and Georgakakos (2006) perform an analysis of precipitation annual totals and annual average temperatures for various future scenarios for each of the three GCM models and for several grid nodes in the vicinity of San Diego. No consistent differences for precipitation exist at the annual level between control and GHG scenarios for the future period examined. There is, however, a trend in all models for increasing temperature with simulated temperatures for 2006 substantially warmer than the historical average.

We assume that the shape of the historical precipitation distributions is preserved in the future under all climate change scenarios, and that only the distributional parameters change. We find new parameters for precipitation by obtaining the mean and variance of the monthly data from 2006 through 2030 for both the control run and greenhouse gas run. We compute the ratios for each month and for each model by dividing the greenhouse gas mean and variance by the corresponding mean and variance from the control run. This allows us to capture the predicted impacts of climate change on precipitation statistics from each of the models. We then estimate monthly precipitation means and variances for the climate change scenarios in the San Diego basin by multiplying the historical means and variances

Table 4 Precipitation statistics for the ECHAM4 model scenario of climate change (parameters p and q correspond to the fitted distribution of Table 2)

Month	Mean	Variance	p	q	Percent zeros
January	3.73	26.16	0.53	7.02	9.2
February	2.98	9.05	0.98	3.03	13.2
March	2.21	2.79	1.76	1.26	13.9
April	2.19	3.98	1.21	1.82	1.4
May	2.97	13.93	0.61	0.95	21.9
June	0.19	0.11	−2.39	1.42	51.6
July	0.21	0.14	−2.28	1.42	65.9
August	0.24	0.16	−2.11	1.35	68.6
September	2.52	8.77	0.49	0.87	46.2
October	0.49	0.11	2.29	0.21	38.7
November	2.10	3.82	1.16	1.82	11.2
December	2.98	16.60	0.53	5.57	5.1

by the mean and variance ratios that we obtain from the climate data. Lastly we estimate new parameters for the monthly precipitation distribution (gamma or lognormal) directly for each month from the estimated mean and variance.

For model monthly simulations, we define a zero-precipitation month as a month that has a monthly precipitation estimate less than a given threshold (e.g., 1 mm/month). For each month, we calculate the absolute difference between zero percentages from the greenhouse gas scenario and the control scenario for each of the climate change models. We then obtain long-term average zero precipitation percentages for future periods by adding the percentage of the time zero precipitation occurred in a given month of the year in the historical data to this calculated difference. Tables 4, 5, and 6 display the monthly precipitation means, variances, and distributional parameter estimates for each of the climate scenarios and for each month of the year.

A similar procedure was followed to produce future monthly temperature averages. We subtract the control temperature from the greenhouse gas temperature for each month and we then add this difference to the average monthly temperature from the historical temperature data.

Table 5 As in Table 4 but for the Hadley model scenario of climate change

Month	Mean	Variance	p	q	Percent zeros
January	4.12	33.49	0.51	8.12	1.2
February	2.78	7.57	1.02	2.72	5.8
March	2.77	3.62	2.13	1.30	2.8
April	0.95	0.82	1.10	0.87	19.1
May	3.39	13.50	0.83	0.78	33.1
June	0.00	0.00	NA	NA	62.7
July	0.18	0.19	−2.70	1.95	51.1
August	0.30	2.24	−2.82	3.25	38.9
September	2.50	8.94	0.47	0.89	42.5
October	2.59	97.79	0.07	37.71	20.2
November	1.50	1.58	1.44	1.05	22.3
December	2.90	3.03	2.78	1.04	5.1

Table 6 As in Table 4 but for the Canadian model scenario of climate change

Month	Mean	Variance	p	q	Percent zeros
January	4.39	18.50	1.04	4.22	11.6
February	2.51	4.08	1.54	1.63	1.4
March	3.24	7.47	1.41	2.30	5.3
April	1.08	0.65	1.79	0.60	0.5
May	2.03	4.11	0.36	0.69	19.5
June	0.40	1.22	−2.01	2.17	55.3
July	0.16	0.06	−2.46	1.22	37.5
August	0.33	0.30	−1.79	1.34	41.4
September	2.62	5.68	0.66	0.60	27.7
October	0.96	1.50	0.61	1.57	16.5
November	2.30	7.71	0.68	3.36	9.9
December	2.45	7.19	0.84	2.93	1.4

2.3 Water Consumption Target

Controlled releases of stored water are made to meet water demand for the urban area of interest. We need estimates of water consumption targets (see Fig. 1) to simulate this process for historical and future periods and to have a basis for estimating urban system operation costs. Municipal water demand is an increasing function of precipitation deficit, because precipitation is a substitute for outdoor uses of water. We use monthly historical data to obtain the relationship between per capita water consumption, precipitation, and temperature. The formulation of the relevant regression equation is:

$$\frac{C_t}{p_t} = \gamma_0 + \gamma_1 P_t + \gamma_2 T_t + \gamma_3 P_{t-1} + \gamma_4 \frac{C_{t-1}}{p_{t-1}} + \sum_{l=1}^{11} \delta_l D_l + \varepsilon_t \tag{9}$$

where P_t is observed monthly precipitation volume for month t, T_t is monthly average temperature for month t, p_t is the urban population for month t, C_t is the monthly water consumption for month t, D_l (l=1,...,11) are long-term average monthly water consumption per capita estimates for month l of the year, γ_l (l=0,1,2,3,4) and δ_l (l=1,..,12) are regression parameters, and $\boldsymbol{\varepsilon}_t$ represents the regression zero-mean and normally distributed random residual. We include monthly indicator variables for January through November (D_l) to control for month effects.

We present parameter estimation results using monthly data from San Diego and for the period June 1999 through December 2004 in Table 7. The coefficient estimates for precipitation, temperature, lagged precipitation, and lagged per capita consumption are all statistically significant and have the appropriate signs. The parameter estimates δ_l for the monthly variables for the fall and winter months are not statistically significant, but these coefficients for the spring and summer months are significant (significant δ_i coefficients are shown in Table 7). The r-squared for the regression is 0.96, which indicates that the model has sufficient explanatory power.

Water price is not included as an independent variable because the authors do not have the appropriate data to estimate price elasticity. However, we use the price elasticity reported in Olmstead et al. (2006) to reduce demand in the capacity expansion scenarios

Table 7 Regression results for per capita consumption (59 observations; r-squared=0.962)

Parameters	Parameter estimates	t-statistic	p value
γ_0	0.0003	0.31	0.76
γ_1	−0.0002	−4.38	0.00
γ_2	0.0000	2.29	0.03
γ_3	−0.0001	−2.26	0.03
γ_4	0.4312	4.11	0.00
δ_3	0.0006	3.09	0.00
δ_4	0.0006	3.73	0.00
δ_5	0.0009	5.06	0.00
δ_6	0.0006	2.58	0.01
δ_7	0.0008	3.16	0.00
δ_8	0.0006	2.17	0.04

employed later in this work because an increase in reservoir infrastructure would increase rates in order to pay for the investment. We assume that the rates would increase by the anticipated percentage in average cost that the expansion would create.

We refer the interested reader to (O'Hara and Georgakakos 2006) for more details on the formulation.

2.4 Method for the Evaluation of Climate Change Impacts

We conduct simulations of the urban water system for the purpose of answering the following question: Given historical operating policy, is the existing reservoir capacity sufficient to meet urban water demand under climate change scenarios? If not then: Can reservoir capacity expansion and associated costs accommodate projected climatic and population changes? The simulations conducted for the climate change scenarios for the future years 2006–2030 are identical to the historical simulations, except that we adjust the historical precipitation and temperature data by the climate model output as discussed previously (Section 2.2). Simulations labeled "historical" use the historical precipitation distributions and temperature data in a historical analog scenario and are presented as benchmarks for the future simulation period.

We consider several sensitivities under each climate scenario. A "baseline" case is run, in which capacity expansion is evaluated with regard to historical operating procedures, historical importing patterns, and projected population growth. We use population forecasts from SANDAG, a regional planning agency for the city of San Diego, in order to use this equation for the future climate scenarios. SANDAG does not provide confidence intervals for their forecasts, so we run two additional scenarios in which sensitivity to population projections are explored – a "high" population case and a "low" population case. We explore scenarios in which importing patterns are altered solely to winter months (which could be the result of the seasonal import availability changing or as a desire to purchase more imports during off-peak periods). In the winter import scenario, we assume that there is no change in the total volume of water available, but we assume that none of the imported water is placed into the reservoirs in summer months and that the percentage of water placed into the reservoirs during winter months is distributed uniformly to match the historical average mean monthly percentage of the historical import volume placed into reservoirs.

We run a sensitivity to alter the release rule by changing the value of the parameter d from 0.025 to 0.05. We also explore the sensitivity of all the results to the spill parameter α for the reasons outlined in the section on spills. In addition, we consider a scenario in which we modify the runoff parameter by setting b equal to 0.6 in every month. The reason for doing this is to simulate fire effects expected for higher temperatures in the region (Westerling et al. 2006). These effects would mainly consist of increased runoff in burnt areas. Increased fires may further have adverse impacts on water quality, rendering some of the additional runoff unusable, although examining water quality is beyond the scope of the model and is not considered here.

3 Economic Model

Three capacity expansion increments are considered for increasing urban reservoir capacity for the purposes of this analysis: 0 m^3, Δ_l (62 million m^3), or Δ_h (123 million m^3). The two time periods when capacity can be added are after 9 years, or one third of the sample period, and after 18 years, or two thirds of the sample period. These discrete measures are necessitated due to the time necessary to appropriate funds for capacity expansion and to complete the structural work.

We formulate the capacity expansion problem as a recursive mathematical programming program:

$$E_W\{V_t(K,W)\} = \min\{O_1;\ O_2;\ O_3\} \tag{10}$$

where

$$O_1 = L(K,W) + S(K,W) + \beta E_W\{V_{t+\tau}(K,W)\} \tag{11}$$

$$O_2 = \theta(\Delta_l)^{\lambda} + L(K,W) + S(K,W) + \beta E_W\{V_{t+\tau}(K+\Delta_l,W)\} \tag{12}$$

$$O_3 = \theta(\Delta_h)^{\lambda} + L(K,W) + S(K,W) + \beta E_W\{V_{t+\tau}(K+\Delta_h,W)\} \tag{13}$$

with terminal condition

$$E_W\{V_{T+\pi}(K,W)\} = 0 \tag{14}$$

A terminal condition is necessary to initiate the backward recursive technique that is necessary for solving the optimization problem. K is a state variable that denotes the reservoir capacity, β is the discount factor, W is a stochastic state variable representing climate, and θ and λ are economic parameters that capture returns to scale for investment costs. The expectation operator $E_W\{\}$ has a subscript to denote the source of future uncertainty. The power function in the expressions for O_2 and O_3 represents the amount spent on investment in capacity for that period. It is the size of the capacity converted into monetary units by the two previously mentioned economic parameters. The second term, $L(K,W)$, represents the monetary losses associated with rationing and equals zero if no water shortage occurs. As the reservoir capacity increases, it is expected that reliability improves, and, hence, economic losses associated with water shortages are reduced. The term $S(K,W)$ represents the costs associated with spilled water and evaporation. Spilled water and evaporation are costly because they represent purchased water that is lost and unused. The time step τ in the economic model above does not correspond to the monthly time step used in the hydrologic model but corresponds to the 9 year period discrete increment discussed earlier.

We calibrate the parameters θ and λ to fit historical construction costs for recently constructed reservoirs in southern California. They represent the private costs of construction and do not include external costs or benefits. However, the model is sufficiently general that these could easily be incorporated in basins where these were prominent. The benefits of additional construction will extend beyond 2030. In order to account for this, we charge the city the 'annualized' construction cost for every year that the additional capacity exists in our framework. We assume that the new capacity will last for 50 years. The formula for the annualized investment cost is:

$$c_e = \frac{rC_I}{1 - (1/(1+r))^n} \tag{15}$$

where n is the lifetime of the investment, C_I is the total cost of the investment, and r is the discount rate.

Research by economists on urban water reliability has measured consumers' willingness to pay for water reliability (Carson 1991; Barakat and Chamberlain 1994; Howe et al. 1994; and Griffin and Mjelde 2000). See Carson (2000) for an overview of issues relating to contingent valuation studies. We use the results from Barakat and Chamberlin (1994) to construct an index of consumer's willingness to pay for water reliability as a function of the magnitude and frequency of the shortage. Details of the algorithm for computing the economic costs of a shortage are contained in (O'Hara and Georgakakos 2006). Once the economic losses are computed for each ensemble trace, the economic losses are averaged across ensembles. The expected costs for a representative consumer are then multiplied by the number of urban households in order to obtain an aggregate willingness to pay for the city to avoid the shortage.

We calculate costs associated with spills and evaporation by penalizing the city for losing water through excessive importing. To calculate the penalty for lost water at a specific point in time, we compare the sum of total imported water up to that month in the iteration with the sum of penalized evaporation and spills up to that point. If the latter term is greater, we calculate the volume of water to penalize for spills and evaporation as the difference between the sum of total imported water at the current month and the summed volume of water subject to the spill and evaporation penalty up through the month prior to the current month. Otherwise, we calculate the total volume of water subject to evaporation and spill penalty as the current volume of water that spilled and evaporated in the current month. We then average the total volume of penalized lost water over ensembles, and, lastly, we multiply the total by the rate charged for untreated imported water to convert it into monetary units.

The location of the capacity expansion has to be specified in our model so that we know the additional surface area that the expansion creates. We assume that our volume expansions occur at the largest reservoir that the city operates.

4 Results

The results from all the climate change and population growth scenarios are included in Table 8. The remainder of the section summarizes what is reported in the Table.

Table 8 Climate change results summary table

Population growth	Sensitivity drivers				Historical	Canadian	Echam	Hadley
	Import scenario	*d*	*α*	*b*				
Optimal capacity expansion policy in two stages (Mill m^3)								
Expected	Historical	0.025	0.807	0.86, 0.9	0–62	62–62	123–62	62–62
Expected	Winter	0.025	0.807	0.86, 0.9	0–62	62–62	123–0	62–62
High	Historical	0.025	0.807	0.86, 0.9	123–0	123–62	123–123	123–62
Low	Historical	0.025	0.807	0.86, 0.9	0–62	0–62	123–0	0–62,0–123
Expected	Historical	0.05	0.807	0.86, 0.9	0–0	0–0	0–0	0–0
Expected	Historical	0.025	0.4	0.86, 0.9	123–123	123–123	123–123	123–123
Expected	Historical	0.025	0.807	0.6	0–62	62–62	62–62	62–62
Minimum expected costs (Mill US$)								
Expected	Historical	0.025	0.807	0.86, 0.9	540	635	783	729
Expected	Winter	0.025	0.807	0.86, 0.9	2,974	2,897	3,068	2,872
High	Historical	0.025	0.807	0.86, 0.9	607	700	864	805
Low	Historical	0.025	0.807	0.86, 0.9	465	566	702	648
Expected	Historical	0.05	0.807	0.86, 0.9	14	29	72	91
Expected	Historical	0.025	0.4	0.86, 0.9	6,565	7,367	7,517	7,481
Expected	Historical	0.025	0.807	0.6	420	515	604	523

4.1 Baseline

The expected costs associated with anticipated water shortages and optimal investment policy varies by climate scenario. The three climate change scenarios all required more capacity than the historical scenario in order to minimize expected costs. The optimal investment policy for the Canadian and Hadley scenarios is to add 62 million m^3 in each period and the optimal investment policy for the ECHAM4 scenario is to add 123 million m^3 in the first period and then 62 million m^3 in the second period. The optimal investment policy for the historical scenario is to add 62 million m^3 in the second period only. Increasing capacity is more effective at mitigating water shortages for the climate change scenarios, where the expected reliability losses are higher.

4.2 Winter Imports

Adding reservoir storage capacity leads to large reductions in expected shortage costs for all of the scenarios. The optimal investment policy in this sensitivity is identical to the baseline case for three of the four scenarios even though the expected costs in this sensitivity are far higher. The only climate scenario in which the optimal investment policy changes is the ECHAM4 scenario, in which it is now optimal to add 123 million m^3 in the first period and no capacity in the second period.

4.3 High Population

We find that higher population growth puts greater stress on the reservoir system. Fortunately, capacity expansion can mitigate these costs. The optimal investment policy is to add 123 million m^3 in the first period in the historical scenario. The optimal investment policy for the Canadian and Hadley scenarios is to add 123 million m^3 in the first period and 62 million m^3 in the second period, while the optimal investment policy for the ECHAM4 scenario is to add 123 million m^3 in each period. The expected costs associated with higher than projected population growth are higher than the baseline case for all four climate scenarios.

4.4 Low Population

The low population sensitivity results in both lower expected costs and less optimal investment than the baseline case in all four climate scenarios. The optimal investment policy for the historical, Canadian, and Hadley climate scenarios is to add 62 million m^3 in the second period (the Hadley scenario had a tie between two possibilities). The optimal investment policy for the ECHAM4 scenario is to add 123 million m^3 in the first investment period.

4.5 Higher Release

The city is also required to maintain a fixed amount of water storage for emergency storage requirements. Additional details and results concerning emergency storage requirements are provided in O'Hara and Georgakakos (2006). We find that changing the release parameter from 0.025 to 0.05 makes it difficult to maintain emergency storage requirements regardless of how much capacity is added. If the emergency storage requirements were relaxed we would be able to change the operating policy in order to improve reliability without adding additional capacity.

4.6 Increased Spillage

The optimal investment policy for all climate scenarios is to add 123 million m^3 in each period. This is the maximum allowed investment that our model considers. In this sensitivity scenario it is difficult for the reservoir system to carry sufficient water due to higher spills. Because the reservoir system is carrying less water, and the release is defined as a percentage of the total amount of water in storage, the releases are far smaller than they need to be in order to maintain reliability requirements. Adding capacity does reduce the losses associated with this scenario, although we see on Table 8 that this is the most expensive scenario.

4.7 Fire Induced Runoff

This sensitivity is very favorable for the city due to the increase in runoff. The optimal investment policy is to add 62 million m^3 in both periods for the climate change scenarios and to add 62 million m^3 in the second period with the historical parameters.

5 Conclusions and Recommendations

The paper formulates a methodology for assessing impacts of climate change and population growth in urban environments and for generating adaptation strategies and associated costs. Uncertainty in climate variables and projected demands and population growth is taken into consideration either explicitly through Monte Carlo simulation or through sensitivity analysis of low and high estimates. The formulations are exemplified through application to the urban area of San Diego, California, that relies on both local runoff and imported water to meet water demand. We use output from three climate models (Canadian, Hadley and Echam) in the case study and examine various scenarios of urban water balance. We use monthly time steps in the analysis, consistent with the available historical supply and demand data, and with the climate change model data.

The innovative aspects of this study consist of the economic focus, the incorporation of uncertainty, the development of capacity expansion as an adaptation approach for urban water supply-demand problems, and the application to actual data from a water district in semi-arid southern California. The approach developed in this work may be applied to other semi-arid urban environments to provide a first look for urban water managers of the potential costs of adapting to uncertain climatic and population changes and identifying the range of possible solutions through capacity expansion. The approach yields a screening tool for conducting hypothetical studies with relatively easily obtained historical and climate change data for specific regions and urban environments.

Water planners face difficult challenges in future years as successful adaptation must be anticipatory due to the time length associated with capital infrastructure investment. Planning is complicated by both weather stochasticity and parametric uncertainty about a changing climate. This study evaluated the effectiveness of a given investment planning strategy under different climate scenarios. However, it is important to recognize that the model is general enough to evaluate storage expansion of different magnitudes, time intervals, and beliefs about future climate change. The model could readily be accommodated to incorporate learning through Bayesian updating of the climate parameters in scenarios involving parametric uncertainty. The model does not make decisions, although model output under various climate realizations could be used in optimization for a given manager's objective function.

Perhaps the most important conclusion of this work is that for urban environments with pronounced seasonal precipitation variability and for which imported water is a significant source of water supply, the expected costs of adaptation to climatic change and population growth are high. Even over a short time horizon, the expected costs associated with climate change are in the hundreds of millions of dollars. The expected costs associated with the climate change scenarios are higher than those of the historical climate scenario for all sensitivities and climate change scenarios except for the winter import sensitivity. Among climate models, the Canadian climate model data produces the lowest expected costs of adaptation for the case study. The loss of snowpack has drawn considerable attention in the western United States and elsewhere as a major concern of climate change. The present study finds that the expected costs of climate change scenarios for urban environments may be high even though the region is not impacted by melting snowpack directly.

The magnitude of the expected costs associated with the optimal investment policy indicates that further study in reducing unresolved uncertainty is warranted. First, obtaining a better understanding of the distribution of future population projections should an important future research target. The optimal amount of capacity to add during the climate change scenarios varied sharply depending on anticipated population growth, underlying the importance of this variable. Second, the uncertainty in the spill parameter needs to be resolved by using higher resolution (either hourly or daily) data. It is clear from the results that the decision on adding capacity will depend on how accurately spills are modeled, and this is an important needed extension to the present case study work.

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Appendix

A_K^i	Surface area of the reservoir i at capacity
A_V^i	Surface area of reservoir i for volume V
b_j	Runoff parameter for season j
c_e	Annualized cost of capacity expansion investment
C_I	Total cost of capacity expansion investment
C_t	Monthly urban water consumption estimate for month t
D_l	Long-term average monthly water consumption per capita estimates for month l of the year
d_i	Reservoir system release parameter for month i of the year
$E_{k,t}$	Evaporation from reservoir system during month t for realization (ensemble member) k
$E\{\}$	Generic expected-value operator
$E_W\{\}$	Expected value operator with respect to uncertainty due to climate variables
I_y^a	Annual imports for year y
$I_{k,t}$	Imported water volume during month t for realization (ensemble member) k
K	Reservoir system capacity
n	Lifetime of investment in years
P_y^a	Annual precipitation volume for year y
PE	Monthly potential evaporation volume
$P_{k,t}$	Precipitation during month t for realization (ensemble member) k
p	Parameter that denotes the shape of the gamma and the mean of the lognormal distributions
p_t	Monthly population estimate for month t
p_y^a	Annual population estimate for year y
q	Parameter that denotes the scale of the Gamma and the variance of the lognormal distributions
$Q_{k,t}$	Reservoir system release during month t for realization (ensemble member) k
r	Discount rate
$R_{k,t}$	Runoff during month t for realization (ensemble member) k
T_N	Total number of months with spills in historical record
T_t	Mean monthly temperature (degrees C) for month t
$u_{t,k}$	Random number generated from the uniform distribution $U(0,1)$ for month t and for realization k
$U(0,1)$	Uniform probability distribution in the interval [0,1]
$v_{k,t}$	Reservoir system stock of water at the end of month t for realization (ensemble member) k; this is an intermediate computational variable
V	Individual-reservoir volume at the beginning of a given month
$V_{k,t}$	Reservoir system volume storage at the beginning of month t for realization (ensemble member) k
W	Denotes dependence on climate variables

Δ_h	High increment of additional capacity
Δ_l	Low increment of additional capacity
O_l	Economic functions in the formulation of the capacity expansion program ($l=1,2,3$)
α	Spillage parameter estimate
α'	Higher spillage parameter estimate
β	Discount factor in the capacity expansion program
γ_l	Regression parameters (l=0,1,2,...)
δ_l	Regression parameters to include month of the year effects (l=1,..,11)
ε_y	Residual error in annual imports regression for year y
θ	Economic model parameter
λ	Economic model parameter

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