# QUANTIFYING THE URBAN WATER SUPPLY IMPACTS OF CLIMATE CHANGE

*by*

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## ***Contents***



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## EXECUTIVE SUMMARY

The difference in timing between water supply and urban water demand in Southern California 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 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. The reservoir system in San Diego, California is used as a case study. Uncertainties in climatic forcing and projected demand scenarios are considered by the models. We find that the climate change scenarios will be more costly to the city than scenarios using historical hydrologic parameters. The magnitude of the costs and the specific optimal policy are sensitive to projected population growth and the accuracy to which our model can predict spills.

# TABLE OF CONTENTS

# I. Introduction

## A. Background

The objective of the present study is to examine the economic implications of a changing climate for an individual storage reservoir or a system of such reservoirs. The main contribution that this interdisciplinary project provides is to introduce a framework that can be applied to any reservoir system for evaluating the costs and benefits of existing reservoir storage. Despite a recognition and awareness of the impending problems climate change poses to water systems, little research has studied the economic costs and benefits of using existing water storage facilities to address future climate change[1].

It is recognized that by 2100, climate change "could fundamentally disrupt California's water rights system[2]". There are several reasons for this. A critical development is that higher temperatures are leading to earlier and more rapid runoff. Snowpack in the Sierra Nevada could decrease by 90% by the end of the 21st century under high temperature scenarios. This has implications for all of California, because Sierra Nevada meltwater is delivered throughout the entire state by an extensive system of aqueducts and reservoirs, and the Sierra snow pack currently provides a natural reservoir of water equal to about half of the constructed reservoirs throughout the state[3].

Global climate models (GCM's) are predicting modest decreases in winter precipitation[4] by the end of the century in the state. This problem is exacerbated by negative correlation between the supply of water and the demand for water. Rising sea levels could lead to the infiltration of salt water in the levee system in the San Francisco Bay Delta region, which would contaminate a large freshwater source of drinking water. Furthermore, higher temperatures will lead to increased evaporation from reservoirs and will result in increased irrigation in agriculture. Increased evaporation may also alter the frequency and intensity of precipitation. The results could be disastrous if these anticipated changes are not considered in water planning efforts. California's water systems are already under great stress with the existing climate and population. Population growth will compound strain on the system by increasing demand[5].

One approach advocated to deal with these issues explores how managers can use climate and hydrology forecasts to improve the operation and management of existing reservoirs[6]. However, limits exist to the gains that can be realized from improved management, because existing reservoirs were designed to accommodate historical hydrologic and runoff distributions. Longer term solutions require evaluating whether existing reservoir capacity is sufficient for meeting demands under altered climate and population conditions and, for those cases that it is not found sufficient, proposing viable alternatives for meeting demands.

Urban water reservoir storage has economic value for two basic reasons: *(a)* the timing difference that exists between the availability of water supply and the timing of the urban water demand, and *(b)* the natural climatic variability of water supply. The first reason implies that reservoir

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[1] Fisher and Rubio 1997 derive a theoretical model that shows the optimal level of investment in water storage when maximizing the net present value of social benefits. They find that a larger variance in precipitation indicates that greater water storage is desirable.
[2] Hayhoe et al 2004.
[3] Statistics in this paragraph were obtained from *Climate Action Team Report to the Governor and Legislature*, section 4.3.
[4] Hayhoe et al 2004.
[5] The population of the state is projected to increase from 34 million people in 2000 to 55 million people by 2050. See State of California, Department of Finance.
[6] See Carpenter and Georgakakos 2001 and Yao and Georgakakos 2001.

storage has value because it makes the water supply available to meet demand over multiple periods in a year, and the second reason implies that reservoirs have value due to a motive for precautionary savings. Inventory is valuable for urban water supply in California because most of the runoff occurs in the winter while demand is highest in the summer. In addition, interannual variability of water supply is great and is affected by large scale climate processes such as El-Niño Southern Oscillation (ENSO) and Pacific Decadal Oscillation (PDO).

We choose the urban water reservoir system of San Diego, California to evaluate the effectiveness of a reservoir system at coping with climate change for a number of reasons. One reason is that the nine reservoirs that the city owns are operated together for the sole purpose of urban water supply, which makes the investment decisions tractable. Secondly, the runoff into the basin that feeds the reservoirs is natural and it is not influenced by upstream regulated releases from other reservoirs. Third, the city imports water from the Metropolitan Water District of Southern California (MWD) through the San Diego County Water Authority (SDCWA). SDCWA is vulnerable to low deliveries from MWD under MWD's preferential rights allocation during periods of drought. A fourth reason is that the financial condition of the city has put public expenditures at a premium, and makes city officials particularly interested in fiscally prudent steps that they can take to ameliorate possible climate change impacts. Fifth, the benefits of additional storage can be determined through the existing urban water reliability literature for the region.

The framework we adopt for this planning study originates in the capacity expansion literature[7]. These models consider optimal ways to add capacity in the presence of fixed costs when demand is growing at varying rates. The critical piece of information required for determining the amount of storage necessary is the relationship of the temporal cycles of supply and demand[8]. If supply and demand are both trending upwards over time, additional capacity will not necessarily be needed unless the rates at which they grow are significantly different over time.

## B. Literature Review

### 1. Hydrology Literature

A literature exists on measuring the impacts of climate change on water resources in California[9], although large potential water supply changes resulting from climate change are by no means unique to the western United States[10]. Recent work[11] in California suggests that the impacts of climate change on California are going to be significant, particularly later in the 21st century. A general finding of this work is that precipitation changes will not be dramatic and that impacts will be greater later in the century than earlier in the century. In this work, we chose to explore scenarios in San Diego until 2030 under the rationale that evaluating capacity expansion projects later in the century are going to be subjected to excessive uncertainty. We chose this timescale because it corresponds to existing planning horizons for urban water managers. Furthermore, even if precipitation changes are not dramatic, population, evaporation and demand changes have the potential to be significant, and the effectiveness of a particular reservoir system at coping with climate change impacts cannot be known a priori unless properly evaluated.

We adopt a hydrologic model that has many of the desirable features outlined in Dracup et al 2005 for studying climate change issues. First, the model is descriptive (simulation based) and not prescriptive (optimization based). This allows us to see what the climate change impacts would be under current reservoir operating practices. We then consider alternate scenarios once

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[7] Loucks et al 1981 contains a discussion of this literature.
[8] Rodrigo et al contain a lengthy discussion of how capacity impacts reliability in their reliability study done for MWD.
[9] This literature is surveyed in Dracup et al 2005 and in Dracup and Vicuna 2006.
[10] See Barnett et al 2005.
[11] See Vicuna et al 2006.

the baseline is established. Secondly, the model has hydrologic flexibility that enables us to evaluate how it might perform under various climate scenarios and uncertainties. It is not constrained to historical climate scenarios. Third, the model accurately depicts the existing reservoir operations and policies. Fourth, the model encompasses a smaller spatial area than typically examined in climate change studies. This is critical because capability of reservoir storage at mitigating climate change is going to depend upon basin level hydrologic characteristics as well as the operating management of the particular reservoir. Smaller scale studies are advantageous because there exists great heterogeneity of water rights and sources amongst urban water districts in California.

Anticipating water supply changes at the basin level from projected future climate forcing scenarios is beset with uncertainty. First, the future level of greenhouse gas (GHG) emissions is unknowable. Secondly, there is uncertainty in determining how increased GHG emissions impact precipitation at a global level. GCM's have arisen in an attempt to predict the impact that the increase of GHG emissions will have on processes such as precipitation. GCM's consist of a system of non-linear equations that deterministically model the coupled dynamics between the ocean, the atmosphere and the land surface based on the principles of physics. Although such complex models can exhibit chaotic behavior from varying initial conditions[12], it is accepted that GCM's provide credible representations of climate on a seasonal basis for large areas[13].

Additional uncertainty exists when the GCM model outputs are downscaled into small areas, and uncertainty exists when the researcher takes model output and uses that to ascertain basin level responses to climate change. Regional uncertainty is introduced because the equations that measure climate variability may be coarse horizontally, while regional behavior can be influenced by local conditions that are at too small of a scale for GCM's to capture[14].

The effectiveness of new storage in an existing system is limited due to the losses associated with evaporation. Evaporation is a function of surface area, so larger reservoirs become less effective at conforming supply to demand because of this. Climate change could lead to a troubling situation in which higher temperatures alter runoff patterns, which would ostensibly necessitate the need for more storage, but higher temperatures also imply higher evapotranspiration, rendering capacity expansion less effective. Basin and reservoir specific models are the only method of evaluating this tradeoff.

## 2. Economics Literature

There are two main reasons that make evaluating adaptive institutional responses to climate change difficult[15]. One reason concerns overall uncertainty surrounding climate change. A second reason is that climate change could have its greatest impact in markets that are already imperfect or distorted[16], which makes the burden on economists for finding optimal policies more challenging.

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[12] *Climate Change 2001: The Scientific Basis*, Chapter 7.
[13] *Climate Change 2001: The Scientific Basis*, Chapter 8.
[14] *Climate Change 2001: The Scientific Basis*, Chapter 10.
[15] Goulder and Pizer 2006.
[16] A private market is referred to as "perfectly competitive" in economics when there are a sufficient number of producers such that the price of the good equals marginal cost. Urban water supply has characteristics of a natural monopoly (large fixed costs and low variable costs), and because water is deemed an essential good by public officials, urban water is supplied either by the municipality or by a regulated utility. Economists refer to regulated markets as "imperfect" when utilities do not set price equal to marginal cost. Frequent practice for water utilities is to set price equal to the historical average cost of providing water. This is generally below the marginal cost of providing water. Refer to Hartwick and Olewiler 1998, chapter 3.

Evaluating capacity expansion projects for urban water supply can be described as finding a first-best policy in a second best setting. A second best situation already exists because urban water rates are usually set inefficiently[17] by municipalities, with the city of San Diego being no exception. San Diego charges a monthly base fee for access to the system which varies by end users. Rates for single family homes are set at an increasing block rate[18]. Commercial and multi-family units pay a flat rate regardless of how much water they consume. There is a multitude of reasons why urban water rates are not set efficiently – one of the most prevalent is for equity purposes[19].

Research by economists on urban water reliability has measured consumers' willingness to pay for water reliability[20]. Because reservoir storage, and hence urban water reliability, is a non-marketed good, contingent valuation[21] is an appropriate approach to use in order to ascertain the value that society places upon that good. This is a critical piece of information to know accurately if one were concerned about optimizing social welfare when evaluating potential reservoir capacity additions.

Adding capacity is not the only solution water managers can resort to in order to avoid shortages. Water managers have various tools at their disposal that can influence the shape of both supply and demand. One option managers have is to change water rates in order to make the time path of demand conform with supply. Crew and Kleindorfer (1986) conjecture that adaptive, seasonal pricing can lead to smaller capacity requirements, yet they do not conclusively prove this. This can be achieved by charging less for water in the winter and more in the summer. If this approach was adopted in practice it would likely have to be accompanied by rebates since water utilities are usually prohibited from earning revenue above the costs of supply.

To understand the seasonal components of demand, it is helpful to disaggregate water into two basic end uses: indoor and outdoor. Demand for water for indoor use needs, such as drinking, cooking, and washing, is fairly consistent year round and is not very responsive to changes in precipitation, temperature, or price[22]. Outdoor use, which includes lawn and plant watering, swimming pools, and car washing, is far more responsive to changes in precipitation, temperature, and price[23]. It is estimated that 32% of urban water use in California is for residential indoor purposes and 21% is for residential outdoor purposes[24].

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[17] Markets in economics are deemed "Pareto efficient" when they maximize the sum of societal welfare, which is consumer surplus plus producer surplus. This occurs when the price of a good equals marginal cost. As explained earlier, this does not occur in urban water markets. Any welfare improving benefit involving urban water supply would be deemed "second best" if it did not correct the preexisting pricing distortion.

[18] This was the rate structure for the city set on October 1, 2004.

[19] Water consumption is regressive in that poorer families spend a larger percentage of their income on water than wealthier families.

[20] Reports include Carson 1991, Barakat & Chamberlain Inc. 1994, Howe et al 1994, and Griffin and Mjelde 2000.

[21] Contingent valuation is a survey technique in which individuals are directly asked how much they would be willing to pay or accept in response to a hypothetical change in quantity for goods that are not typically bought and sold in private markets. The answer represents the area under the income-compensated, or Hicksian, demand curve that determines how much an individual would be willing to pay or accept for the change in the quantity of a good while holding utility constant. See Carson 2000 for details.

[22] Mansur and Olmstead find that indoor use is driven almost exclusively by income and family size.

[23] Mansur and Olmstead find that indoor use is price inelastic and that outdoor use is price elastic in both wet seasons and arid seasons. They also state that "essentially all of the strong seasonal variation we observe in total water consumption is attributable to outdoor use."

[24] Gleick et al 2004. The remainder of urban water use is disaggregated in the following way: 27% of water is used for commercial/institutional purposes, 10% is used for industrial purposes, and 10% is unaccounted for water.

Outdoor use is customarily targeted by managers during times of shortage, and is traditionally targeted through command and control approaches[25]. Indoor use, commercial and industrial water uses are rarely curtailed. Urban water demand is increasing with temperature and decreasing with precipitation. The changes within a year are driven by temperature and precipitation, while differences in levels between years are driven primarily by changes in precipitation[26], which exhibits much higher variability between years then annual mean temperature.

# II. Hydrologic Model

## A. San Diego Background and Reservoir Data

The city of San Diego relies upon local runoff to meet 10-20% of its water demand and imports the residual demand[27]. It operates nine reservoirs with a total capacity of 415,000 acre feet (AF). The sole objective of the reservoirs is for urban water deliveries. Managers are not required to consider flood control or recreational objectives when making operational decisions. In this work, we assume that the reservoirs are perfectly connected, or that the system of reservoirs is equivalent to one giant reservoir[28].

There are three basic ways for water to enter the system for the city. First, the city can import treated water via pipelines directly into their water system. San Diego relies upon treated water for approximately 20% of its supply. Treated water is more expensive to purchase than untreated water, and since San Diego is sufficiently large it has built its own treatment plants. Secondly, the city can import untreated water directly into its treatment centers, bypassing the storage-reservoir system completely. The third source of water for the city is from the storage-reservoir system[29]. The reservoirs accept untreated imports and local runoff. Losses also occur in the reservoir system due to evaporation and spills. The reservoir system provides three basic benefits for the city: *(a)* the city can use the storage to build inventory during winter months when they receive a $70/AF discount on imported water[30], *(b)* insure the city against unanticipated shortages from droughts, earthquakes, or terrorist attacks and *(c)* it can capture local runoff. We have obtained monthly data for each reservoir since the reservoir commenced operations. Figure 1 presents a schematic of the San Diego reservoir system[31].

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[25] Examples of this include adopting technologies or curtailing certain uses on specific days.

[26] Mansur and Olmstead find that water demand for indoor use does not vary by season, but that outdoor use does. They also find that, on average, outdoor demand during a dry year is five times larger than indoor demand during a wet year.

[27] Readers interested in background information on how the city imports water should refer to *The 2005 City of San Diego Urban Water Management Plan*.

[28] Treatment plant capacity and pipeline capacity constrain connectivity, and for certain periods, this assumption may be invalid. San Diego County Water Authority (SDCWA) reliability studies exist (*Regional Water Facilities Master Plan*, December 2002) with greater detail regarding inter-reservoir and treatment plant transfers. These SDCWA reliability studies, however, do not consider the impacts of future climate scenarios (they use historical data) and do not consider the economic cost-benefit tradeoffs when evaluating the need for future storage. In this light, our study can be viewed as a planning study complement to the SDCWA detailed reliability studies.

[29] The city relies upon the reservoir system for about 15-20% its water supply, although this percentage can vary greatly over the course of the year. The remaining 60-65% of water bypasses the reservoirs and is imported directly into treatment centers.

[30] Water is discounted in the winter because pipeline capacity becomes constrained in the summer.

[31] The SDCWA states in the 2005 Management Plan that "water use records indicate that local reservoirs are generally operated to maximize the use of local supplies in wet and normal years in order to reduce the need for imported water purchases. While this mode of reservoir operation reduces losses due to evaporation and spills, it also results in increased demands for water during dry years when imported water is more likely to be in short supply." Our model, described below, captures this operating strategy.

## B. The *bd* Model

The hydrologic model used here is a modification of the simple annual *abcd* model presented in Rogers and Fiering 1990. The model is a series of equations that simulate conservation of water volume for a regulated watershed on a monthly time scale, which is commensurate with available data. Significant modifications to the *abcd* model are the inclusion of imports into the system and the elimination of groundwater aquifers, since the city water supply does not rely on well pumping. The reader is referred to Figure 2, which provides a schematic overview of how the model operates.

Uncertainty in the model output is generated through the propagation of uncertainty in precipitation and imports. This is done by simulating precipitation through Monte Carlo sampling from monthly precipitation distributions (see the next section) and incorporating import uncertainty (see section D). A total of 1,000 ensemble members were generated for every monthly time step.

The hydrologic model can be expressed in the following algorithmic form:

{1a} $$outflow_{k,t} = \min\{d_i * \alpha * capacity_t, d_i * q_{k,t}\}$$

{1b} $$storage_{k,t+1} = \min\{(1-d_i) * \alpha * capacity_t, (1-d_i) * q_{k,t}\}$$

where

{1c} $$q_{k,t} = storage_{k,t} + imported_{k,t} - lost\_water_{k,t} + (1-b_j) * precipitation_{k,t} - evaporation_{k,t}$$

In these equations, $t$ is the time index denoting one month, $k$ is an 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. $q_{k,t}$ is the stock of water for month $t$ and ensemble member $k$.

Every month, the city releases a certain percentage (denoted by $d$) of the water in storage. The water that is not released then becomes the storage for the following period. A capacity constraint exists so that the amount of water in stock in the reservoir does not exceed the amount of water that the system is capable of holding. If the stock of water exceeds this amount, then the excess water is lost through spillage. In this monthly formulation, the capacity is taken to be a function of the actual reservoir capacity (denoted by *capacity* in the previous equations) times a multiplier $\alpha$. 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 occurred.

Assuming that monthly precipitation is distributed uniformly over the natural drainage basin of the city reservoir system[32] and that runoff is a linear function of precipitation for monthly aggregate quantities, for each realization of precipitation we can use:

{1d} $$runoff_t \equiv (1-b_j) * precipitation_t$$

[32] The aggregate size of the watersheds draining into the city's reservoirs is 590,509 acres.

as used in Equation (1c), where $b$ is a parameter. This implies that only a fraction of precipitation every period enters the reservoir, and that the rest is lost to evapotranspiration or percolation to deep groundwater storage in the upstream drainage basin. The parameters $d$, $b$ and $\alpha$ are calibrated to fit historical data.

Water volume in storage lost for reasons other than evaporation and spills (such as leaks) was fixed and was not adjusted for the historical simulations. For the climate scenarios, we assume that the only possible way to lose stored water was through either evaporation or spills. For the historical simulations, the initial storage level in the model for January 1948 was set equal to the actual amount of water that the city held in storage at the beginning of January 1948.

## B1. Hydrologic Model Parameter Estimation

The model uses two values for the parameter $b$ - one for the winter months and the other for the summer months[33]. We find these parameters by comparing actual precipitation with actual runoff data. We employ a random sampling method for parameter estimation. We establish a range of possible values of $b$ and impose a uniform probability distribution upon this range. Using a random number generator, we chose the pair of $b$'s that led to the smallest mean square error when compared to the runoff data. The model also has twelve values for the parameter $d$ - one for each month. We find the value of $d$ for each month by taking the average fractional release of the reservoir by volume over the period of operation for the reservoir[34]. See table 1 for the historical precipitation parameters.

Figure 3a shows a time series of cumulative total historical releases from the reservoirs - denoted by the black "x's" – against a cumulative ensemble of 1,000 model-simulated releases[35]. Figure 3b shows the monthly time series of observed actual releases plotted against the 10$^{th}$ and 90$^{th}$ percentile ensemble releases for each month. Both figures show that ensemble releases accurately model historical releases.

## B2. Precipitation

We create monthly precipitation 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 throughout the city and that monthly precipitation distributions are not changing over the historical time period. We assume that non-zero precipitation in one month is independent of non-zero precipitation in adjacent months[36].

We fit the distributions to the sample of non-zero precipitation. However, summer months have a high proportion of months with no precipitation (intermittence). The simulations did incorporate the chance of a dry month as follows. A number from a uniform [0,1] distribution was randomly selected for each month. If the number was less than the estimated fraction of zero precipitation observations for the given month, we assign zero precipitation for that month. If not, we obtain

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[33] We define winter months to include November through March and summer months to include April through October.
[34] We attempted to estimate this parameter using regressions but the resultant slope parameters were not statistically significant, which justifies taking the average to estimate monthly $d$ values.
[35] The model has two different $bd$ parameter sets. We use one set of parameters to model the system from 1948 through 1977, and use another set of parameters for 1978 to the present. Using one set of parameters from 1948 to the present led to an inaccurate fit of the historical data due to significant data transients. The later set of parameters were used in the climate scenarios.
[36] This assumption is supported by the observation that correlations between consecutive monthly precipitation amounts were all less than 31% in absolute value.

precipitation for that month by randomly sampling from the best-fit monthly distribution for non-zero precipitation amounts.

Persistence does exist for months of zero precipitation for summer and fall months. We assume that zero precipitation in these months follow a Markov process. We create different probability distributions for the probability of zero occurrence so that the probability of zero precipitation in a given month is conditioned on whether or not zero precipitation occurred in the previous month. The conditional distributions are presented in Table 2.

Table 3 shows the results from the Kolmogorov-Smirnoff test of fitting distributions to monthly non-zero precipitation data. The hypothesis test indicates whether or not the cumulative distribution function of the monthly data points is statistically significantly different from the specified distribution with given parameters. Thus, a p-value of less than 0.05 indicates that a greater than 95% probability exists that the true distribution of the data is not the specified distribution used in the test. The parameters chosen were the maximum likelihood estimates from the monthly data.

Two parameter gamma distributions[37] are used for October through April and two parameter lognormal distributions[38] are used for May through September. The September data is shown to be statistically different from a lognormal distribution with 95% confidence. We assume that September has a lognormal distribution to conform to the distributions of the previous months because the test statistic and cutoff values are close in magnitude[39].

## B3. Imports

Import uncertainty is included because uncertainty will exist in future years regarding both the supply and demand of imports to the city. Import levels and population levels both trend upward over time. We model annual imports on a per capita basis in order to account for this. White's test for heteroskedasticity was run and was insignificant, so no correction was made for this possible concern. However, serial correlation was present. To correct for this, the following equation was estimated and included in the simulations, with the estimation results reported in Table 4:

{2}

$$\frac{annual\_imports_t}{population_t} = \gamma_1 + \gamma_2 annual\_precip_t + \gamma_3 \frac{annual\_imports_{t-1}}{population_{t-1}} + \gamma_4 annual\_precip_{t-1} + \varepsilon_t$$

[37] The probability distribution for a gamma distribution is $f(x \mid \alpha, \beta) = \frac{x^{\alpha-1} e^{-\frac{x}{\beta}}}{\Gamma(\alpha)\beta^{\alpha}}$ where parameter 1, $\alpha$, influences the shape or peak of the distribution and where parameter 2, $\beta$, influences the scale or spread of the distribution.

[38] The probability distribution for a lognormal distribution is $f(x \mid \mu, \sigma^2) = \frac{e^{-\frac{(\log x - \mu)^2}{(2\sigma^2)}}}{\sqrt{2\pi}\sigma x}$ where parameter 1, $\mu$, and parameter 2, $\sigma^2$, imply that if $X$ is a random variable, then $\log X \sim N(\mu, \sigma^2)$.

[39] The p-value is 0.046.

We assume that $\varepsilon_t$ is independently and identically distributed with mean zero and variance $\sigma^2$ [40]. The results show an R-squared of 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, were all statistically significant at the 99% confidence level with the expected signs.

The above equation predicts aggregate imports to the city in a given year, where $t$ in {2} represents one year. This leaves two issues unresolved: what percentage of the total imports did the city place into the reservoir system (versus using directly without storing it), and how was this allocated on a monthly basis? How and on what basis these decisions were historically made by the city are unknowable to the researchers. However, some patterns emerged from the historical data. First, a higher percentage of imports were placed in reservoirs throughout the 1950's-70's than now. Secondly, more imports were placed into reservoirs in the winter than in the summer. Using this information, we create four gamma distributions of the percentages of total imports placed into reservoirs: summer and winter from 1960-77, and summer and winter from 1978-2003. Prior to 1960, we use average percentages because the amount of imports being placed into reservoirs was extremely high in this period. For the climate runs, we use the distributions from the period 1978-2003. Table 5 presents the parameters.

## B4. Spills

Spills occur as a result of reservoir inflow while reservoir content is at capacity. We define the parameter $\alpha$ as the highest percentage of capacity that the system can hold without spills occurring. We calculate $\alpha$ as the fraction of the summed total threshold storage level from the historical data, which we find as the average of the storage level at the beginning of the month and the storage level at the end of the month for the system as a whole for when a spill occurred, divided by the summed total amount of capacity in the system when the spill occurred. This threshold level is the new capacity constraint for which spills occur in the future scenarios. In the model, spillage would occur if the current water in storage plus the net inflow of water during the period is greater than $\alpha$ times the current capacity of the system (see equations 1a and 1b). Figure 4 shows historical spills for the city.

The monthly data we have for the city's reservoirs does not allow accurate modeling of monthly spills when the sum of ensemble monthly spills from 1948-2003 (with a fitted value of $\alpha = 0.807$) are compared to total realized spills that occurred in the San Diego reservoir system. Higher temporal resolution data, such as daily or hourly, is necessary to resolve spills that may occur any time within a month. Also, spills can result in the system if water cannot be transferred between reservoirs. The spill amount sums from the ensemble runs are all smaller than the total amount spilled historically. We estimate a second value for the spill parameter $\alpha$ of 0.4 so that the median total volume of spills from the ensemble sums equals the observed total spills. Both values of $\alpha$ are included in the sensitivity analysis to be discussed later.

## B5. Evaporation

We model evaporation using the Thornthwaite equation[41] for monthly potential evaporation estimation. 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. The formula for potential evaporation, expressed in centimeters per month, is:

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[40] We consider an alternate specification by taking the natural log of the dependent variable and regressing it on the independent variables. This equation did not noticeably alter the outflow from the historical data.

[41] The equations and adjustment factors are included in Bras 1987.

{3} $$PE = 1.62 * g * \left(\frac{10 * T}{I}\right)^{a}$$

where

{4} $$a = 67.5 * 10^{-8} * I^{3} - 77.1 * 10^{-6} * I^{2} + 0.0179 * I + 0.492$$

and

{5} $$I = \sum_{m=1}^{12} \left(\frac{t_m}{5}\right)^{1.51}$$

$I$ is the annual heat index, $T$ is the mean monthly temperature[42] measured in degrees Celsius, $t$ is mean monthly temperature in degrees Fahrenheit, and $g$ is an adjustment factor (a function of month and latitude) to account for the fact that sunshine is not always available 12 hours per day and not all months are 30 days in duration.

We estimate the surface area of the reservoir system necessary for the computation of free water surface evaporation (potential evaporation over a water body) as follows. First, both the surface area and the capacity of the reservoir when full are known. Secondly, all of the reservoirs were assumed to have a conic shape[43]. The surface area of a reservoir with volume $V$ is:

{6} $$A = \pi * R^{2}$$

where $R$ is the radius. Using the formulas for a cone, we also know that:

{7} $$R = R_c * \left(\frac{V}{V_c}\right)^{\frac{1}{3}} = \left(\frac{A_c}{\pi}\right)^{\frac{1}{2}} * \left(\frac{V}{V_c}\right)^{\frac{1}{3}}$$

where $A_c$ and $V_c$ are the area and volume of the reservoir when full, respectively, and $V$ is the volume of the reservoir for which we want to
compute surface area. So:

{8} $$A = \pi * \left(\left(\frac{A_c}{\pi}\right)^{\frac{1}{2}} * \left(\frac{V}{V_c}\right)^{\frac{1}{3}}\right)^{2} = A_c * \left(\frac{V}{V_c}\right)^{\frac{2}{3}}$$

We find $V$ every period by determining the amount of water in storage at
the beginning of the period and then distributing that water proportionally by capacity amongst all of the reservoirs that were operating at the time.

So, for every period, evaporation equals:

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[42] Historical temperature data for the city was obtained through measurements at Lindbergh Field from 1948 through 2003 taken by the National Weather Service.

[43] We consider (but do not report) a sensitivity assuming that the reservoir is shaped as a rectangular prism. We find that the results to the conic assumption are almost identical.

{9} $evaporation = PE * (\sum_{i=1}^{6} A_i)$

where $i$ denotes the specific reservoir and $PE$ is potential evaporation.

## C. Bulk Reliability Diagrams for Simulations

We create bulk reliability diagrams to demonstrate how well the frequency distribution of outflow from the model matches the frequency distribution of actual outflow. We compute decile frequencies for the model outflow from the simulations and the historical data, and plot them against each other in a bulk reliability diagram plot (Figure 5). We also plot the 45-degree line of perfect correspondence as a reference. The results show that the model tends to underpredict somewhat the low frequency of outflows but predicts adequately the higher outflow occurrence frequencies (greater than 0.5).

## D. Climate Data

We obtain two variables from GCM's as input into the hydrologic model: surface air (screen) temperature and surface precipitation. We use data for the period 2004-2030 and from three climate models (CGCM2, HadCM3 and ECHAM4) to allow for multiple climate change scenarios[44]. We obtained this data from the IPCC Data Distribution Centre.

All three models have a “control” scenario in which they assume that greenhouse gas (GHG) emissions remained 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 GHG's over the future period of simulation. Please refer to Figures 6, 7, 8, and 9 for annual precipitation totals from the historical San Diego observations and from each of the three GCMs for grid nodes that contain San Diego. The data in the figures indicate that grid-point model simulations are substantially lower than the regional historical observations. Furthermore, no consistent differences between control and GHG scenarios are apparent at the annual level for the future period examined (until 2030).

The regional output from GCMs is in a grid format. The resolution varies by model, but in general it is several degrees latitude by several degrees longitude[45]. For this study, the screen temperature and precipitation output from each GCM for 2004-2030 was obtained for the grid point encompassing San Diego. We estimate future distributions of precipitation and temperature by assuming that the distributions using the historical data have the same shape as the distributions that would prevail in the future, and that only the distributional parameters change.

We find new parameters for precipitation by obtaining the mean and variance of the monthly data from 2004 through 2030 for both the “control” run and “greenhouse gas” run. We calculate 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 calculate climate change monthly means and variances for the San Diego basin by multiplying the historical means and variances by the mean and variance ratios that were obtained from the climate data. We calculate new parameters for the precipitation distribution (gamma or lognormal) directly for each month from the estimated mean and variance.

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[44] See Frederick 1997.

[45] The ECHAM4 data comes in 128*64 grid points (2.8125 degrees longitude by approximately 2.775 degrees latitude). HadCM3 data is in 96*73 grid points (3.75 degrees longitude by 2.5 degrees latitude). The CGCM2 output is in 97*48 grid points (approximately 3.75 degrees longitude by 3.75 degrees latitude).

We define the probability of zero precipitation occurrence for data points that are smaller than a given threshold (e.g., 1 mm/month). We do not choose zero because the simulation results from the models are only available as monthly averages. We obtain new zero precipitation percentages by adding the percentage of the time zero precipitation occurred in the historical data to the absolute difference between zero percentages from the greenhouse gas run and the control run. We use percentage differences in the few instances where using the absolute difference led to a negative number. Tables 6, 7, and 8 display the new means, variances, and distributions for each of the climate scenarios.

We adjust temperature data by subtracting the control temperature from the greenhouse gas temperature. We add this difference to the average monthly temperature from the historical temperature data. Figure 10 plots the average annual temperature from each of the climate scenarios against the mean annual historical temperature. It is apparent that there is a trend in all models for increasing temperature and that current simulated temperatures for 2006 are substantially warmer than the historical average.

## E. Capacity Effectiveness Indicators

The reservoir system in San Diego serves two basic functions: a consumption smoothing function and a precautionary savings function. In this section, we describe how two indicators of storage effectiveness are developed. An objective of this section is to estimate a target consumption the city wants to meet. This is necessary for a reliability analysis to be conducted. A second objective is to determine the amount of emergency storage the city is required to hold at a given point in time. To do this, the city projects future consumption targets. Knowing what projection the city makes will allow us to evaluate whether or not the emergency storage requirement is satisfied.

## E1. Reliability Measurements

A consumption target must be calculated for each month in order to measure reliability. Municipal water demand is an increasing function of precipitation deficit, since precipitation is a substitute for outdoor uses of water. This relationship exacerbates the pressure on water managers, because urban water supply availability is positively correlated with precipitation. Reliability analysis must account for this relationship in view of uncertainties in supply and demand. Figure 11 plots the historical seasonal pattern of water consumption in San Diego.

First, we use monthly historical data to obtain the relationship between per capita water consumption, precipitation, and temperature. We include lagged variables in this specification to control for serial correlation. Heteroskedasticity was not present in this regression. The estimation results for the following regression are presented in Table 9:

$$\{10\}\ \frac{mon\_cons_t}{pop_t} = \gamma_1 + \gamma_2 precip_t + \gamma_3 \frac{mon\_cons_{t-1}}{pop_{t-1}} + \gamma_4 precip_{t-1} + \gamma_5 temp_t + \sum_{i=1}^{11} D_i * mon\_dum_i + \varepsilon_t$$

We estimate {10} using OLS on monthly consumption from the city from 1999-2004. Although we have a long time series of annual data from the city, the monthly time series is shorter. Using monthly coefficient estimates allows us to determine how the amplitude of monthly consumption might change over time in response to changing climate variables. Monthly indicator variables for January through November are included to control for month effects[46].

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[46] In the event of a rare, large precipitation, the target consumption can actually become negative. In the event that this happened, the target consumption was set equal to one. This is defensible because the target consumption is an index

The coefficient estimates for precipitation, lagged per capita consumption, lagged precipitation, and temperature are all statistically significant with the appropriate signs. The parameter estimates for the monthly dummy variables for the fall and winter months are insignificant, but the coefficients for the spring and summer months are significant with the expected positive coefficients. The R-squared for the regression is 0.96, which indicates that the model has sufficient explanatory power.

Price is not included as an independent variable in the forecasting equation because the researchers do not have the appropriate data to estimate price elasticities. However, the elasticity of water prices have been estimated in Olmstead, Hanemann, and Stavins using data in which San Diego was one of the ten cities in their sample. We use this price elasticity to account for the result that an increase in reservoir infrastructure would increase rates in order to pay for the investment. We assume that the rates would increase by the percentage of anticipated in average cost that the expansion would create. The increased rates would decrease demand by the elasticity reported in the Olmstead, Hanemann, and Stavins paper[47].

We use population forecasts from SANDAG[48] in order to use this equation for the future climate scenarios. These are the same forecasts used by SDCWA in their reliability studies. SANDAG does not provide confidence intervals for their forecasts, so in order to consider alternate population scenarios, adjustments were made. We consider three population scenarios: projected, high, and low[49].

Because not all of the city's water consumption is met through the reservoir system, target consumption must be allocated between demand to be satisfied by reservoir water and demand satisfied by non-reservoir water. From 1999-2004, the reservoirs were responsible for satisfying approximately 25% of demand in the summer and less than 10% of demand in the winter. There is a high degree of variability in this percentage for the same month in different years, and the reasons for this variability are not clear from the data. To account for this, we draw a number from a uniform distribution at each time set between the minimum percentage and the maximum percentage for that month over this period, and use that number as the percentage of total monthly consumption that must be met through the reservoir system. We are assuming that the city will meet water demand with the same percentages from their reservoirs as they did historically in order for this approach to be valid for the future period analysis.

## E2. Emergency Storage Targets

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for reliability purposes, and in the event of a rainstorm that could induce flooding, the city would not have to worry about meeting reliability.

[47] We assume that the rates would increase for nine years after the investment. For the smaller investment (50,000 AF) we assume that rates increase 4% and for the larger investment we assume that rates increase 5.6%.

[48] SANDAG is a regional planning agency for San Diego. The population projections were taken from *Population, Housing and Employment by Jurisdiction*, Table 1. Since the forecasts are available on a decadal basis, we obtain intermediate years through linear interpolation.

[49] One population scenario assumed that the SANDAG projections are correct. The SANDAG population growth rates from 2000-2010 assume an annual growth rate of 1.1%. A "low" scenario assumes that the population grows at a slower rate until 2010 (0.8%) and a "high" scenario assumes that the population grows at a higher rate than forecasted until 2010 (1.4%). The SANDAG projections assume that population will grow by 12% from 2000-2010, 10% from 2010-2020, and 9.9% from 2020-2030. Our high scenario projects 14.9% growth by 2010 and our low scenario projects 9.1% growth by 2010. In order to obtain percentage growth rates for 2020 and 2030, we assumed that population grew at the same relative percentages in the high and low cases as they did in the SANDAG projections. In other words, for the high case, population growth was assumed to grow 12.5% from 2010-20 and 12.3% from 2020-30, and for the low case population growth was assumed to grow at a 7.6% rate from 2010-20 and 7.5% from 2020-30. Intermediate years were filled in through linear interpolation.

We measure emergency storage effectiveness by counting for a given simulated month how many times the existing storage was less than the target forecast. We then calculate the percentage of times that the storage failed to satisfy emergency storage requirements. We obtain information about future demand from a SDCWA reliability study[50]. SDCWA already has a demand forecast at the member agency level that they use for planning. The demand forecasts use the assumption that water rates remain constant in the future. The 50% demand forecast is used in the climate scenarios[51]. Since the demand data for the city of San Diego is available for every five years, demand during the intermediate years is estimated through linear interpolation. We adjust the data so that high population and low population scenarios are also available. We find monthly storage targets by summing up the next 7.2 months of anticipated consumption[52].

## F. Evaluation of Climate Change Impacts

We conduct the reliability analysis for the purposes of answering the following question: given historical operating policy, is the existing reservoir capacity sufficient for the city to both meet urban water demand and to maintain emergency storage requirements? The simulations conducted for the climate scenarios and for the years 2004-2030 are identical to the historical simulations, except that we are using GCM data and evaluating performance. We set the release parameter $d$ to 0.025 using rule curve percentages. We chose this level because it corresponds to how the city operated their reservoir system historically.

Once we set $d$ equal to 0.025, we make monthly adjustments because releases have occurred at different levels in different months. We find the release percentage for a given month by multiplying $d$ by the ratio of the percentage release for a given month to the average percentage release for all months of the year. We use this approach because we can easily set $d$ to levels that were not used historically in order to evaluate performance for different operating policies.

We use the precipitation and temperature data from the GCM's as input in place of the actual historical time series. The 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 run a set of sensitivity scenarios to determine if the existing infrastructure is sufficient to meet reliability targets and emergency storage requirements under existing operating policy. We run the following sets of simulations for each of the four climate scenarios. First, we simulate precipitation. We then use this simulated precipitation data as input into all of the different sensitivity scenarios within that particular climate scenario. We do this so that the impacts of capacity expansion can be isolated without the concern of changes in the underlying precipitation data.

## G. Sensitivities

We consider several sensitivities under each climate scenario. A "base" case is run, in which capacity expansion is evaluated with regard to historical operating procedures, historical importing patterns, and projected population growth. 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

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[50] San Diego County Water Authority, *Regional Water Facilities Master Plan*, Draft, December 2002.

[51] This a probabilistic measure that assumes that 50% of the time, demand will be higher, and 50% of the time it will be lower.

[52] The current operating policy of the city is to have the anticipated consumption for the next 7.2 months, or 6/10 of the year, currently in storage.

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 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 a percentage drawn from a uniform distribution of 0 to 6% of total annual imports[53].

We run a sensitivity to alter the release rule by changing $d$ from 0.025 to 0.05. We explore the sensitivity of all the results to the spill parameter $\alpha$ 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. A reason for doing this is that higher temperatures are going to result in more fires[54]. Runoff would increase since the burned vegetation would not absorb the water[55]. Two final sensitivities are designed to evaluate current management practice. In one instance, we assume that imports are solely a function of population growth and are independent of climate variables[56]. An alternate sensitivity considers the current importing strategy of importing but places a cap on imports so that during dry years it is not feasible for the city to import as much as they desire.

# III. Economic Model

We adopt the objective that the city wants to meet water consumption targets at the average cost of providing water. We do this for several reasons. First, it is the objective that water agencies adopt[57]. The existence of a literature on water reliability enables us to quantify climate change impacts, which is the overarching objective of the research. All of the water reliability papers cited adopt the aforementioned objective. This implies that we are taking the existing water rates as exogenous. This will allow us to use the willingness to pay to avoid a shortage as the social cost associated with a shortage.

We assume that the city has three choices for adding capacity: 0 AF, 50,000 AF, or 100,000 AF. Additionally, we assume that two time periods exist when capacity can be added. The first is after nine years, or 1/3 of the sample period, and the second option is after eighteen years, or 2/3 of the sample period.

We formulate the optimization model as follows:

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

where

(12a) $$O_1 = L(K,W) + S(K,W) + \beta E_W V_{t+1}(K,W)$$

(12b) $$O_2 = \theta * (50000)^{\vartheta} + L(K,W) + S(K,W) + \beta E_W V_{t+1}(K + 50000, W)$$

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[53] We choose these percentages because 3% is the average monthly mean percentage if we place the same volume of imports into reservoirs as in the other sensitivities.

[54] Westerling et al 2006 discuss how increased temperature, particularly in the spring and summer, leads to more fire.

[55] Fires are more likely to occur as a result of droughts, so this phenomenon is more probable for the drier GCM scenarios.

[56] We assume that annual imports are 5.1% of the current population as this is the average annual import total in the historical record.

[57] The study by Carson was done for MWD.

(12c) $O_3 = \theta * (100000)^{\vartheta} + L(K,W) + S(K,W) + \beta E_W V_{t+1}(K + 100000, W)$

with terminal condition

{13} $V_{T+1}(K,W) = 0$

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 capacity stock, $\beta$ is the discount factor, $W$ is a stochastic state variable designed to represent weather (and is analogous to the "aridity" variable in Griffin and Mjelde), and $\theta$ and $\vartheta$ are economic parameters that capture returns to scale for investment costs. The distribution that $W$ takes is given by our hydrologic model. The expectation operator $E$ has a subscript to denote the source of future uncertainty. "Aridity" levels in the hydrologic model are uncertain and are generated through Monte Carlo sampling. 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 shortage occurs. We would anticipate that reliability would be improved, and hence economic losses associated with water shortages reduced, as the capacity stock increases. 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 subscript $t$ in the economic model above does not correspond to the same time step as in the hydrologic model, which was one month. The value that additional capacity provides must be evaluated over a longer time period. Our simulations are setting this time step at nine years. We assign the costs for additional investment to the period prior to the investment being available for use. The model is the dynamic analog of a static model presented in Griffin and Mjelde. They minimize the sum of current investment capacity costs plus the discounted future shortage losses that is experienced when the demand for water exceeds the supply of water. Our model extends their model by allowing for more than one period of investment.

We calibrate the parameters $\theta$ and $\vartheta$ to fit historical construction costs for recently constructed reservoirs in southern California. The Olivenhain Dam, completed in 2003 by the SDCWA, has a storage capacity of 24,000 AF and cost $200 million to build[58]. The 800,000 AF reservoir MWD built at Diamond Valley cost approximately $2 billion[59]. These lead to parameter values of 265,925 for $\theta$ and 0.66 for $\vartheta$. The costs listed are the private costs of construction and do not include external costs[60]. The benefits of additional construction will extend beyond 2030. In order to account for this, we charge them 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:

$$annualized\_\cos t = \frac{r * I}{1 - (1/(1+r))^n}$$

[58] Statistics obtained from a Fact Sheet located on the SDCWA website.
[59] Frederick and Schwarz 2000.
[60] External costs associated with reservoirs are well documented and include beach erosion, adverse impacts on fish, and displacement behind the reservoir. Refer to Duflo and Pande 2006 for the socioeconomic costs associated with reservoir construction in India. However, the reservoirs in San Diego also provide external benefits in the form of recreation. The reservoirs in San Diego allow boating, fishing, and have picnic areas for the public.

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

We use the results from Barakat & Chamberlin 1994 as measures of consumer's willingness to pay for water reliability. The study was conducted over the largest urban water districts in California (including the city of San Diego). The key findings of the report include: customers are willing to pay more to avoid less frequent, larger shortages than they are for smaller shortages of higher frequency; customers are willing to pay significant amounts to avoid small shortages and may make a greater distinction between 'no shortage' and 'shortage' than between different shortage scenarios; and the willingness to pay to avoid shortages shows decreasing returns in both the magnitude and frequency of the shortage. Table 10 shows the willingness to pay to avoid water shortages for California residents in large urban water areas[61]. The results are consistent with the economic notion of loss aversion since preferences are convex in losses.

We implement a formula to calculate willingness to pay for shortages based upon the results from the reported study in the following manner. First, we calculate the magnitudes of each of the shortages by dividing the difference between the consumption target and the outflow by the consumption target[62]. We set negative values equal to zero. Next, we count the number of monthly shortages over a five year block in particular categories[63]. The willingness to pay to avoid shortages cannot be viewed in independent monthly time blocks since that disregards the role that the frequency of a shortage has in determining willingness to pay. For each ensemble sequence, we apply a formula to account for the willingness to pay for shortages in that particular category, and then sum up the shortages over each category[64]. After this, the economic losses are averaged across ensembles. This gives us the expected utility, or von Neumann - Morgenstern utility, associated with consumers' willingness to pay to avoid shortages. The expected utility for our representative consumer is then multiplied by the number of households in order to obtain an aggregate willingness to pay for the city to avoid the shortage and are also discounted. The impact that future shortages will have upon an investment policy are ambiguous – they are weighted less because they are discounted, yet at the same time they carry greater weight because the population will be larger in the future.

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. Although it still possible after this calculation that the historically imported water was consumed prior to the spill occurring, spill and evaporation losses can also represent water that the city did not have to purchase in the future. A complicating factor is that if it is stored then it subject to future evaporation, so if this justification is used for penalizing spills then the total volume is overstated.

[61] The data reported in the text are shown unadjusted for inflation. We adjust the data for inflation when making calculations because the survey occurred in the second half of 1993.
[62] We divide the percentage shortage by 4 since the reservoir shortages only represent a percentage of total shortages for demand for the city.
[63] The categories chosen are 1-10%, 10-20%, 20-30%, 30-40%, 40-50%, and shortages greater than 50%.
[64] The formula we choose is ln(no. of shortages+1)*cost/ln(2). The term cost is 15, 18, 20, 22, 25 and 27 for each of the previously mentioned categories. This formula is desirable because it exhibits diminishing willingness to pay for each additional shortage in the time period.

We sum the total volume of penalized lost water for each ensemble, and then we average over ensembles. We then multiply the number by $360[65] to convert it into monetary units. We choose this value for the penalty because it is the rate that SDCWA charges for one AF of untreated imported water.

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. In general terms, retrofitting older reservoirs is considered first instead of constructing new reservoirs for a variety of reasons[66]. We assume that our volume expansions occur at the El Capitan Reservoir, which is the largest reservoir that the city operates.

# IV. Results

The results from the scenarios are included in tables 11 and 12a-12i. The first section of table 11 shows the optimal (least cost) investment policy that is warranted for each sensitivity[67]. The second section of the table lists the cost that is associated with each of the optimal policies listed above. Even though the optimal policies may be identical between the historical data and GCM data, the costs to San Diego citizens could be different between climate scenarios.

Tables 12a-12i provide the backup data that is summarized in table 11. The first subsection, titled 'shortage costs', provides the economic cost of the reliability shortfall (in millions of dollars) for each capacity expansion scenario. The second subsection quantifies the economic cost of the spilled and evaporated water. The subsection titled 'total costs' is the sum of the construction cost, costs of spills and evaporation, and shortage costs. The remainder of the section will summarize the findings by the model sensitivity that was selected.

## Base

We see in table 12a that the costs associated with anticipated water shortages and optimal policy varied by scenario. The three climate change scenarios all required more capacity than the historical scenario in order to minimize costs. The optimal policy for the Canadian and Hadley scenarios was to add 50,000 AF in each period and the optimal policy for the Echam scenario was to add 100,000 AF in the first period and then 50,000 AF in the second period whereas the optimal policy for the historical scenario was to add 50,000 AF in the second period only. The costs associated with water lost to spills and evaporation are relatively similar between the scenarios. Furthermore, increasing capacity only has a modest ability to mitigate losses associated with spills and evaporation. However, we see that increasing capacity can have a much larger effect on reducing reliability shortages. This is more effective for the climate change scenarios, where the reliability losses are higher, than for the scenario with the historical climate which had smaller reliability losses.

## Winter Imports

Table 12b shows that the costs associated with increased spills and evaporation go up significantly in this scenario and that the impacts of adding storage only reduce those costs modestly. This result occurs because the importing pattern is changing without a corresponding

[65] See http://www.sdcwa.org/news/finances.phtml#current, accessed April 9, 2006.
[66] Some of the reasons include: it is usually cheaper, because small increases in height can lead to large increases in volume; it is quicker to retrofit an old reservoir; and existing reservoirs generally occupy the most ideal grounds for reservoir location.
[67] A column with '50-0' listed under the optimal policy means that it is optimal to add 50,000 AF of storage in the first period and then to add no storage in the second investment period. The other columns have analogous interpretations.

change in operating requirements. However, adding capacity did lead to large reductions in shortage costs for all of the scenarios. The optimal policy in this sensitivity is identical to the base case for three of the four scenarios even though the costs in this sensitivity are far higher. The optimal policy in the Echam scenario was to add 100,000 AF in the first period.

## High Population

We find that higher population growth puts greater stress on the reservoir system. Fortunately, capacity expansion can mitigate these costs. The optimal policy is to add 100,000 AF in the first period in the historical scenario. The optimal policy for the Canadian and Hadley scenarios is to add 100,000 AF in the first period and 50,000 AF in the second period while the optimal policy for the Echam scenario is to add 100,000 AF in each period. The costs associated with higher than projected population growth are higher than base case in all four climate scenarios.

## Low Population

The low population sensitivity results in both lower costs and less investment than the base case in all four climate scenarios. Table 12d shows that the optimal policy for the historical, Canadian, and Hadley climate parameters is to add 50,000 AF in the second period[68] and that the optimal policy for the Echam scenario is to add 100,000 AF in the first investment period. We find that the costs associated with spills and losses are not very dependent on population growth and that the differences in costs between the population growth scenarios is driven by shortage costs.

## Higher Release

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. We do not present the emergency storage requirement results since they do not explicitly enter the objective function, but we did find that they were violated under this scenario about 5-10% of the time. In other sensitivities, such as the base case, emergency storage requirements were virtually never violated. We see in table 12e that capacity requirements are heavily influenced by emergency storage considerations. 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. However, emergency storage requirements exist for reasons not included in our model (such as a potential earthquake), so we do not evaluate whether the emergency storage requirements are worth maintaining or not.

## Increased Spillage

The optimal policy for all climate scenarios is to add 100,000 AF in each period. This is the maximum allowed investment that our model considers. In this 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 11 that this is the most expensive scenario.

## Fire Induced Runoff

[68] The optimal policy for the Hadley scenario was to add either 50,000 AF or 100,000 AF in the second period.

This sensitivity is very favorable for the city due to the increase in runoff. We see in table 12g that the optimal policy is to add 50,000 AF in both periods for the climate change scenarios and to add 50,000 AF in the second period with the historical parameters. Capacity expansion was not effective at limiting spills and evaporation. This is because the city is not penalized for spilling unpurchased water based on the formula defined earlier.

This type of situation, where fire increases runoff, would be more likely to arise after dry periods. This type of variability is not captured in our model, since we assume that runoff is consistently high throughout the entire simulation regardless of historical rainfall patterns. The costs to the city here are cheaper than they were in the base case (of course, we are not considering the costs that a fire might induce).

### Modified Importing Patterns

The two scenarios (tables 12h and 12i) where importing patterns were modified led to the same optimal policy as the base case. The costs of each of these two scenarios were similar to the base case but slightly higher. We would anticipate that this would be true for both scenarios because both could lead to instances where there was insufficient water imported during dry years than relative to the base case.

## V. Conclusion

We find in Table 11 that the costs associated with the climate change scenarios are higher than the historical scenario in every sensitivity for every climate change scenario except for the winter scenario. Generally speaking, the Canadian data is the most favorable of the three climate change scenarios. We find that even over a short time horizon, the costs associated with climate change are in the hundreds of millions of dollars. Because of uncertainty surrounding certain issues, to be discussed below, we cannot recommend a specific investment strategy for the city. However, the magnitude of the costs associated with the optimal policy indicates that further study in reducing the unresolved uncertainty is warranted.

First, we find that obtaining a better understanding of the distribution of future population projections is necessary. The optimal amount of capacity to add during the climate change scenarios varied sharply depending on anticipated population growth. Unfortunately, we cannot assign a priori probabilities to each of the scenarios, and SANDAG does not currently include confidence intervals in their projections. If distributions are known, Monte Carlo analysis could also be conducted with respect to this variable in the simulations.

Secondly, 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. A more detailed modeling of the reservoir system could also be considered in deciding how effective the existing capacity is at containing spills. This includes examining the interconnectedness of the reservoirs or exploring how management and operation could be improved through the use of forecasts. Additionally, we find that capacity choice depends on importing strategy. If city officials alter their importing strategy permanently they will simultaneously need to reassess the viability of the existing infrastructure.

Thus far in the climate change literature on water resources, the majority of the attention has been focused on systems where hydrologic changes will be predominately driven by how changes in snowmelt impact runoff timing. San Diego is impacted by snowmelt changes through changes in import availability. Local runoff will not be impacted by this. However, we still found significant effects even while keeping imports consistent with historical patterns, which is a conservative assumption. If we had included a model of the delivery system of the water wholesale market, then the climate change scenario costs would likely have been much larger.

The changes that are shown for the city are primarily driven by the first order effects of temperature, and temperature is one of the variables that GCM's predict most accurately. Thus, a concluding lesson is that systems that do not heavily rely directly on snowmelt runoff also deserve attention in future climate change studies in California.

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# VII. Figures

**Figure 1** – Water Transfers in the City of San Diego

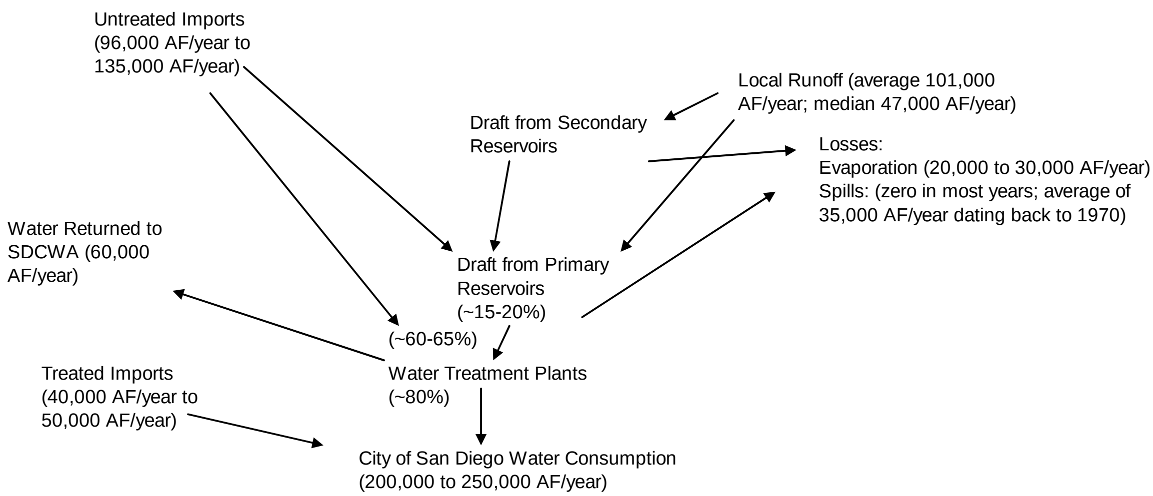


**Figure 2** – Schematic of Reservoir System Model

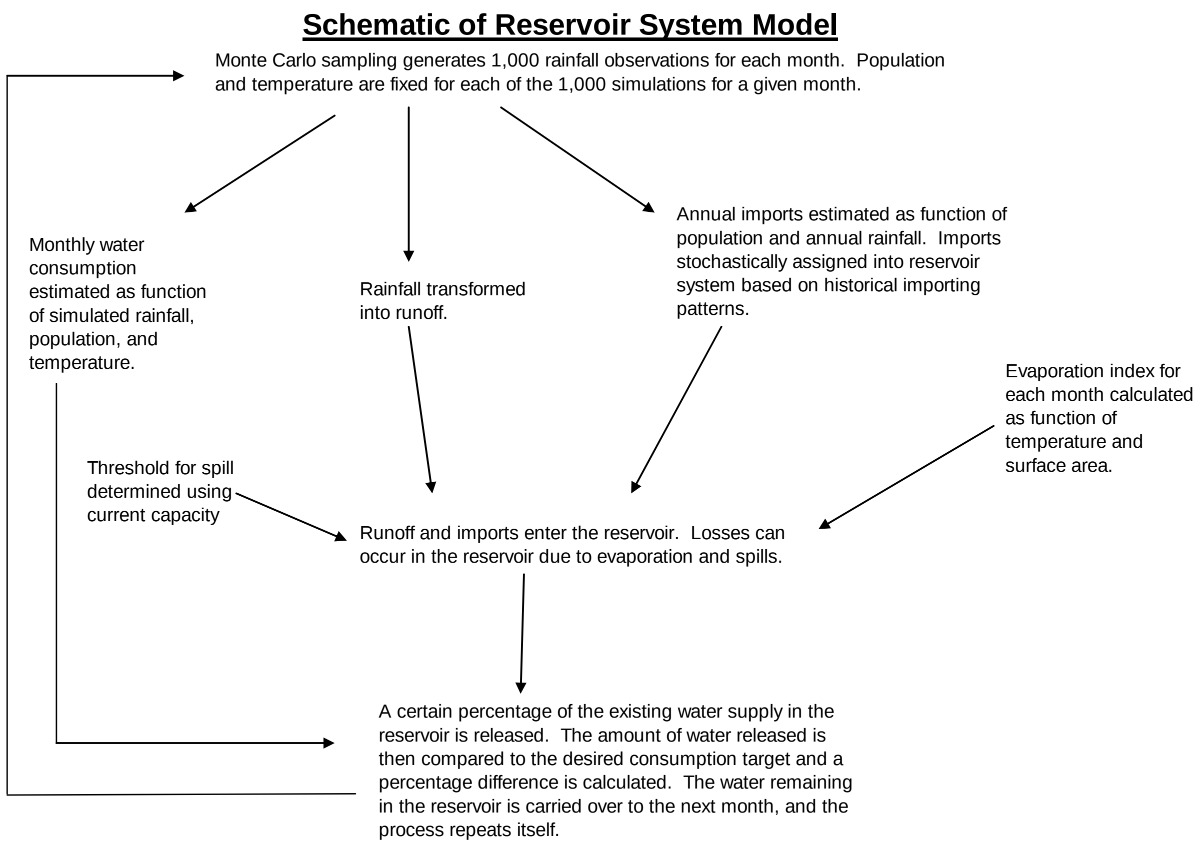


**Figure 3a** – San Diego Reservoir Cumulative Releases:  January 1948 – December 2003

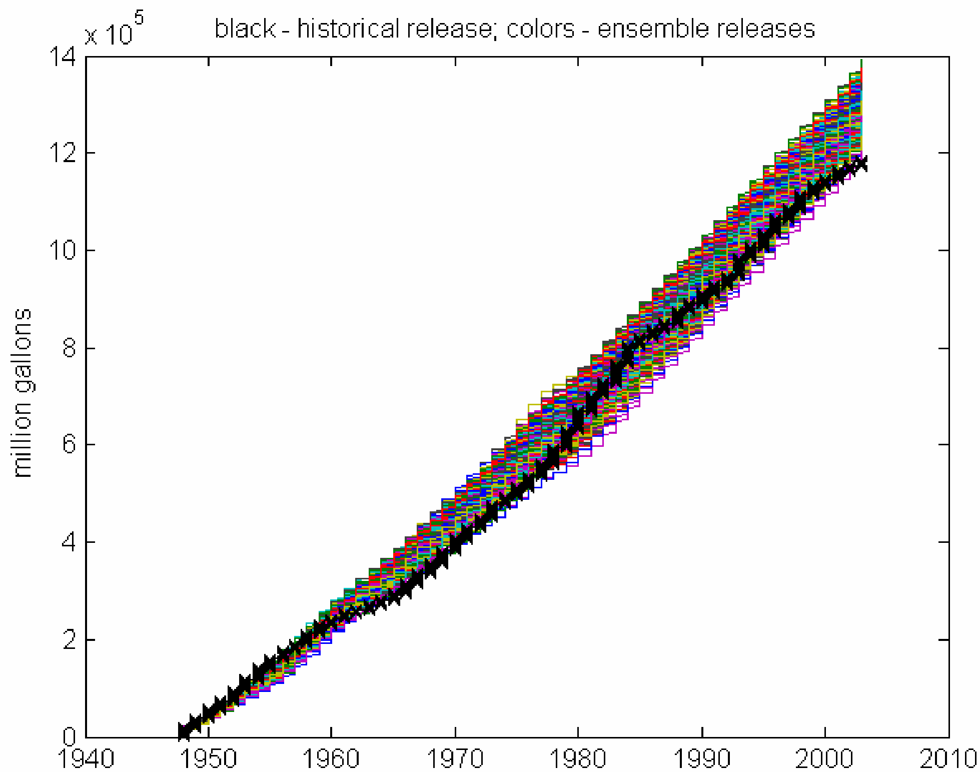


**Figure 3b** – San Diego Reservoir 10th and 90th Percentiles vs. Historical Draft: January 1948 – December 2003

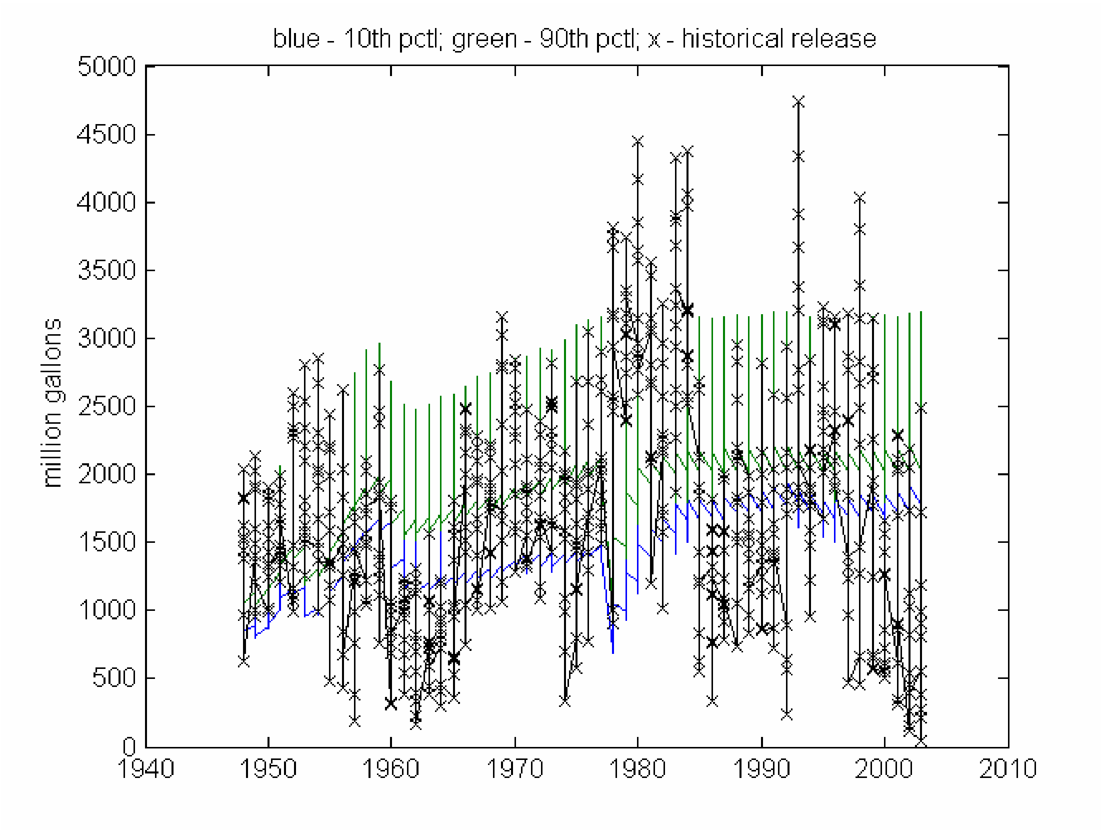


**Figure 4** – Historical Spills

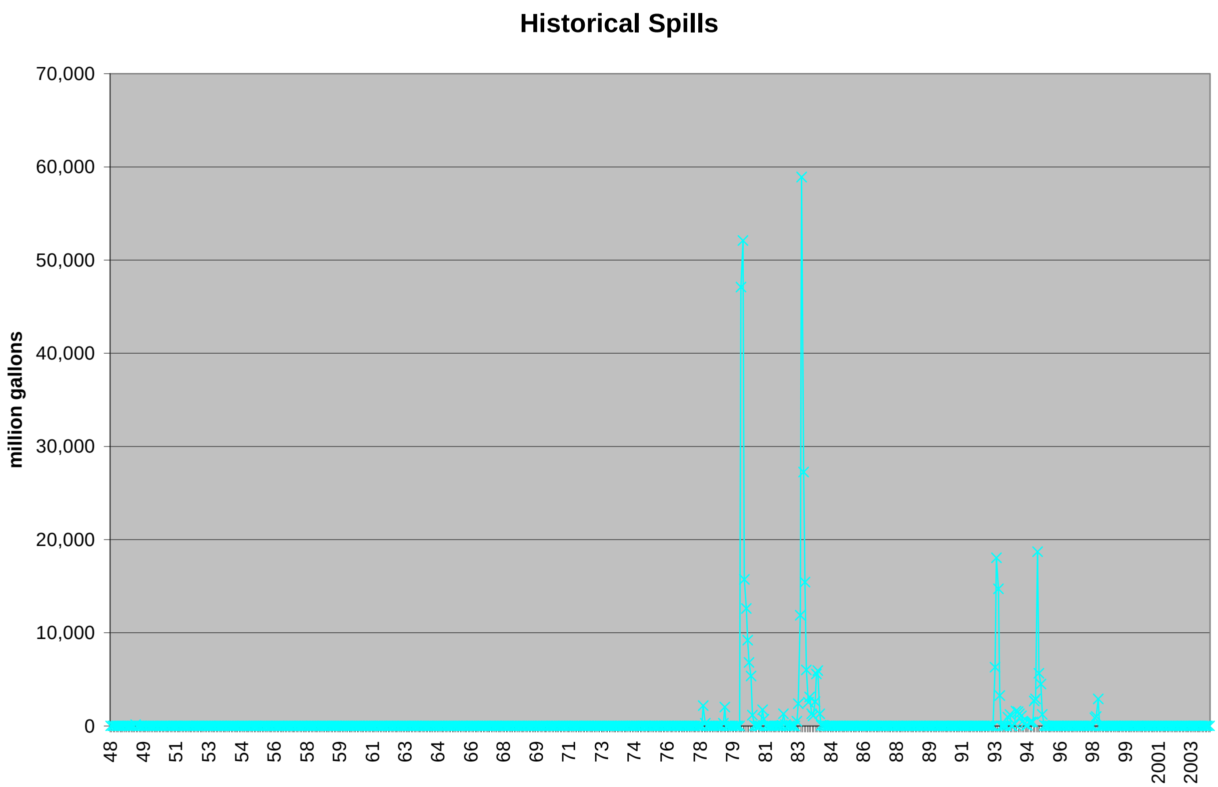


**Figure 5** – Bulk Reliability Diagram and outflow histograms

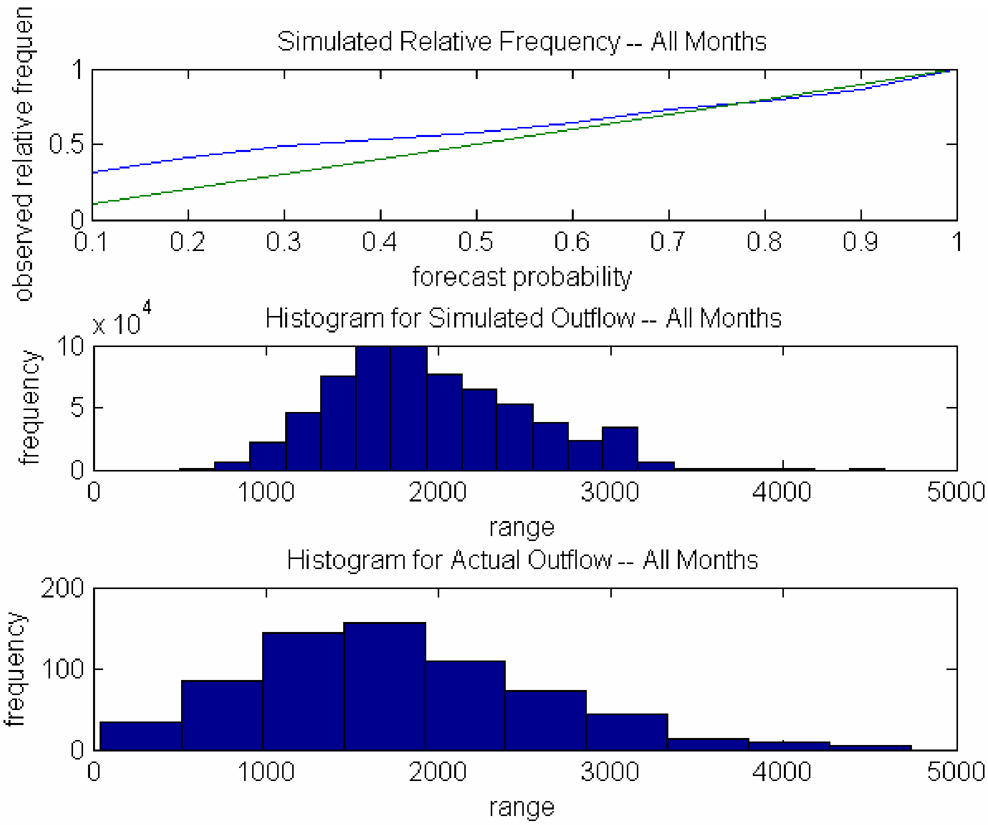


**Figure 6** – Historical Rainfall for City of San Diego

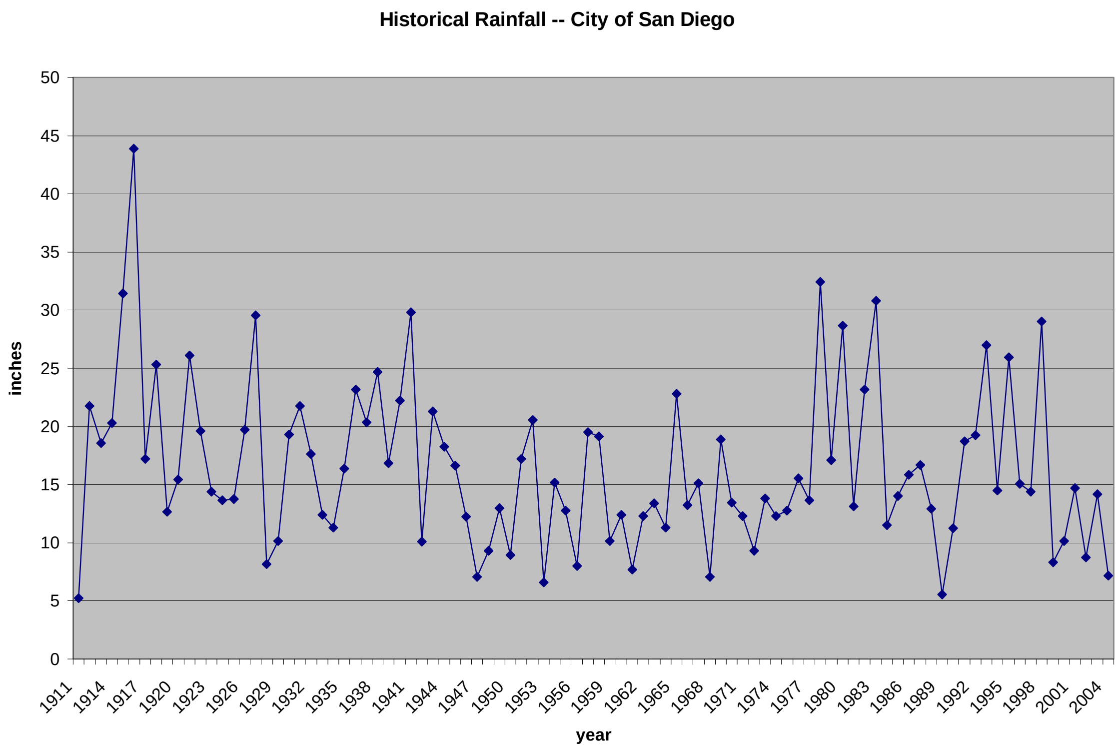


**Figure 7** – ECHAM4 Annual Precipitation at San Diego Grid Point

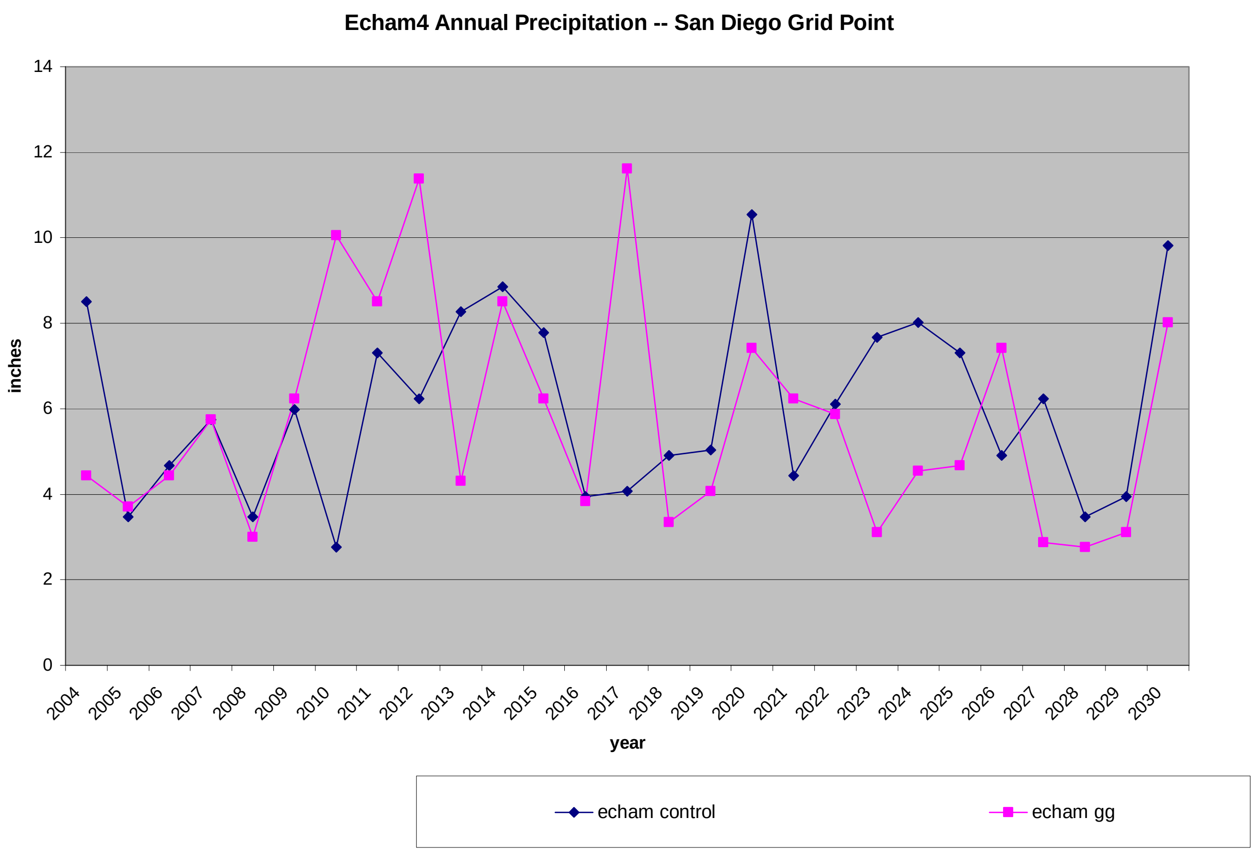


**Figure 8** – HADCM3 Annual Precipitation at San Diego Gridpoint

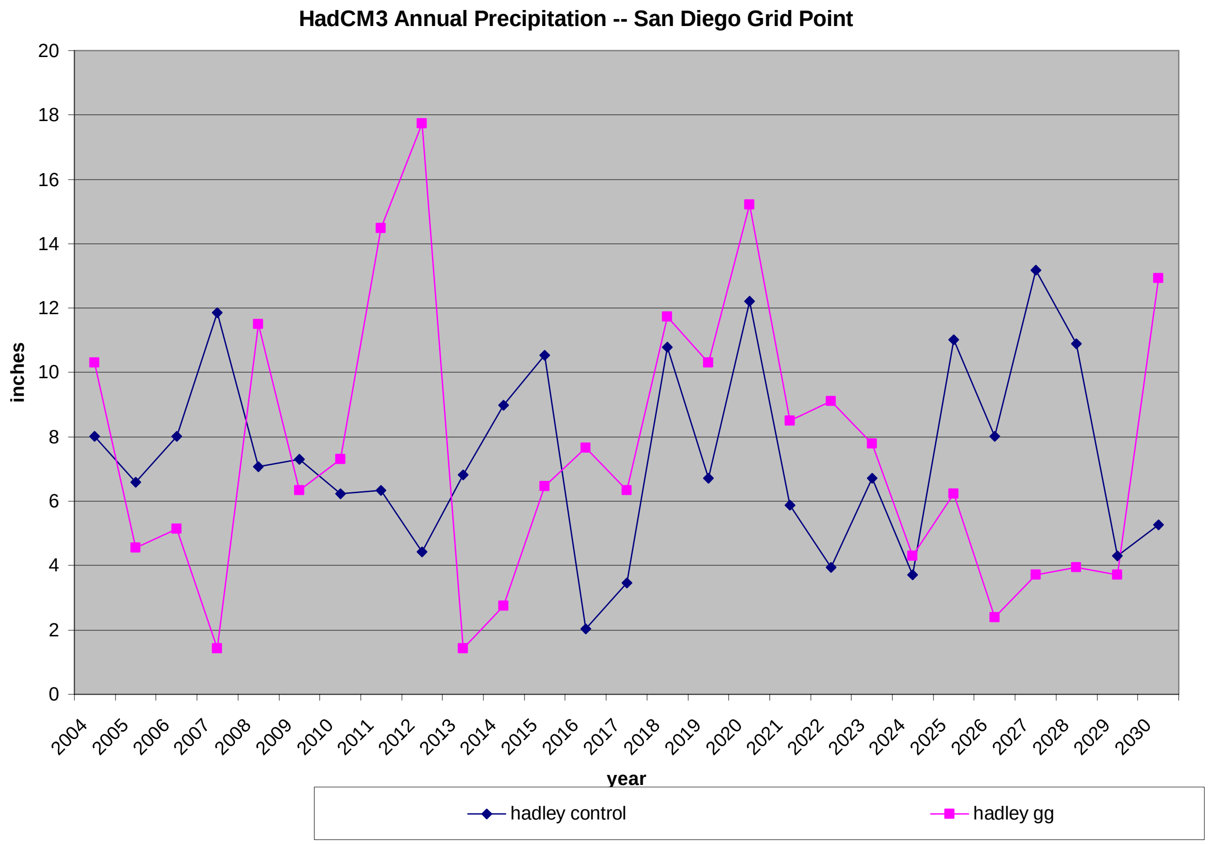


**Figure 9** – CGCM2 Annual Precipitation at San Diego Grid Point

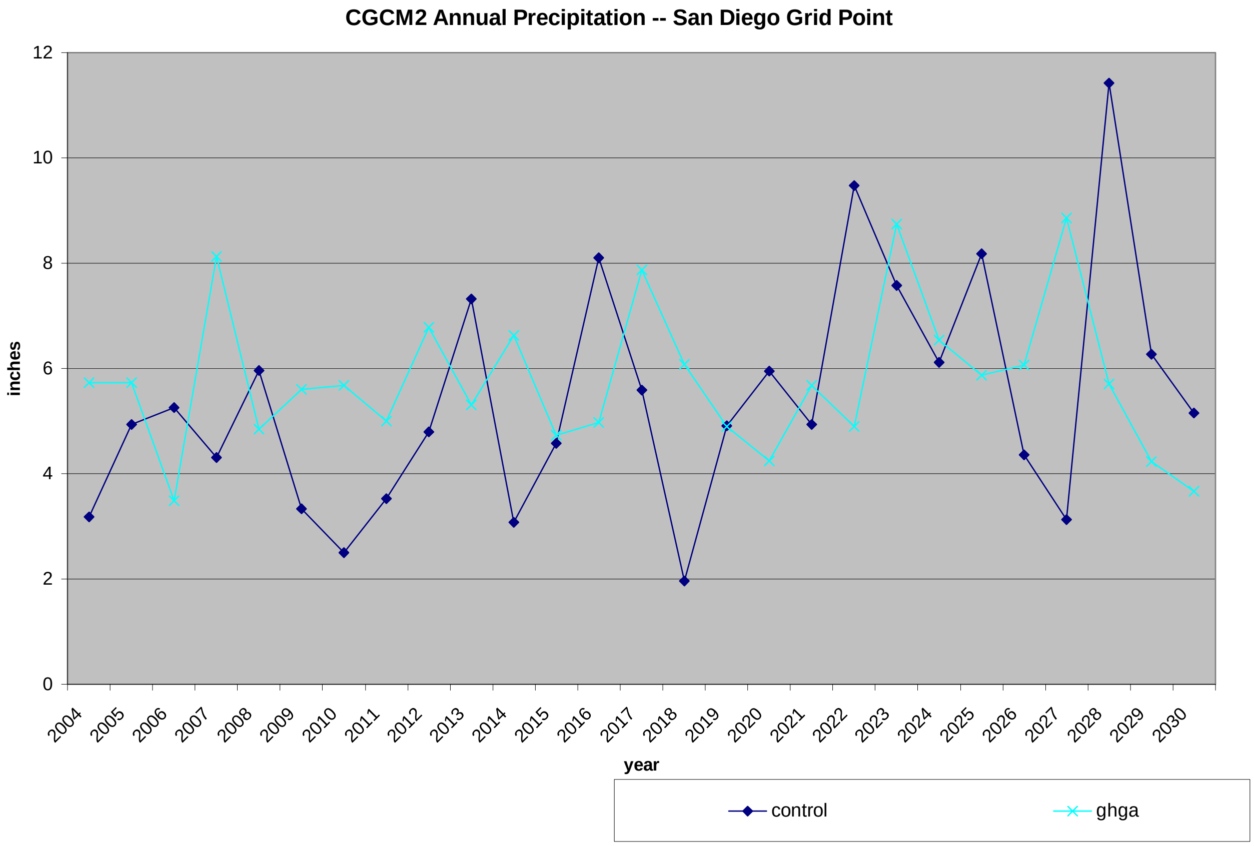


**Figure 10** – Average Annual Temperature:  2006-2030

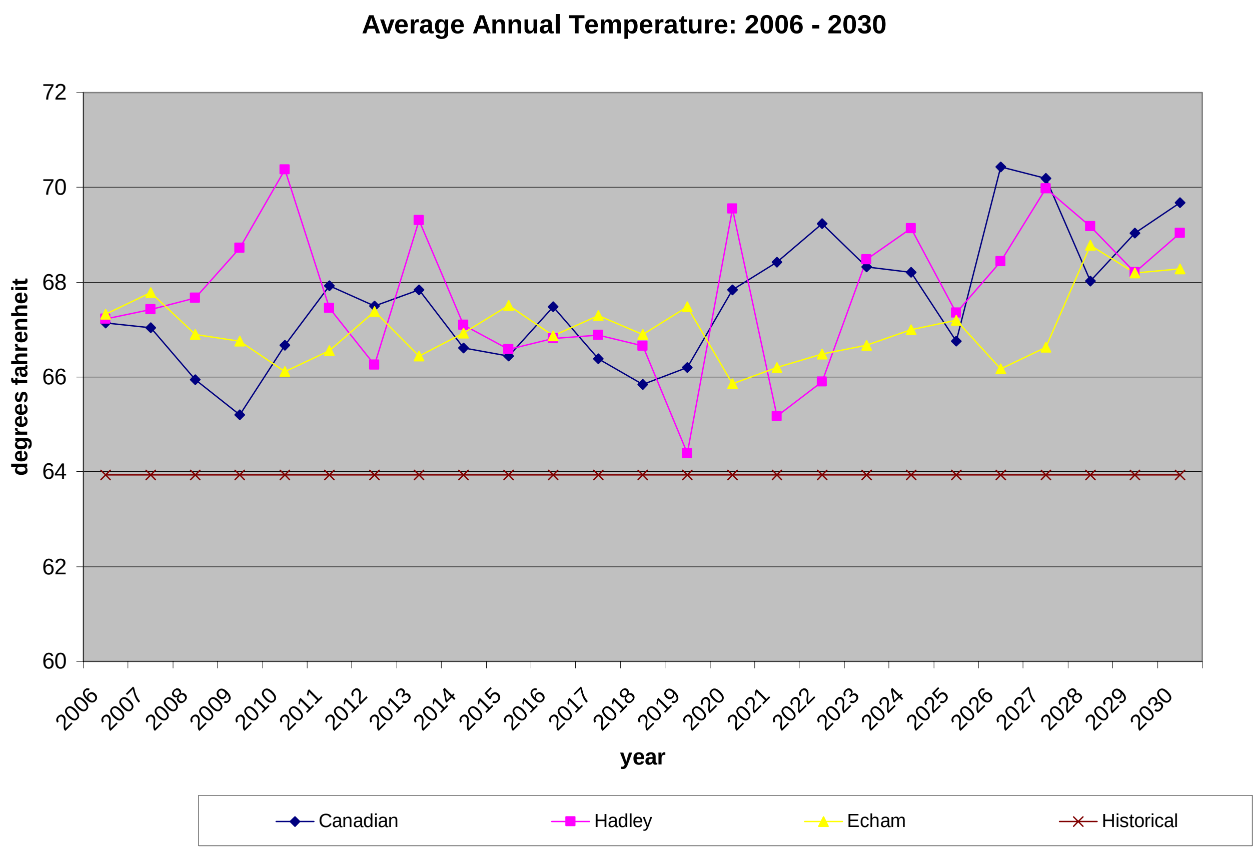
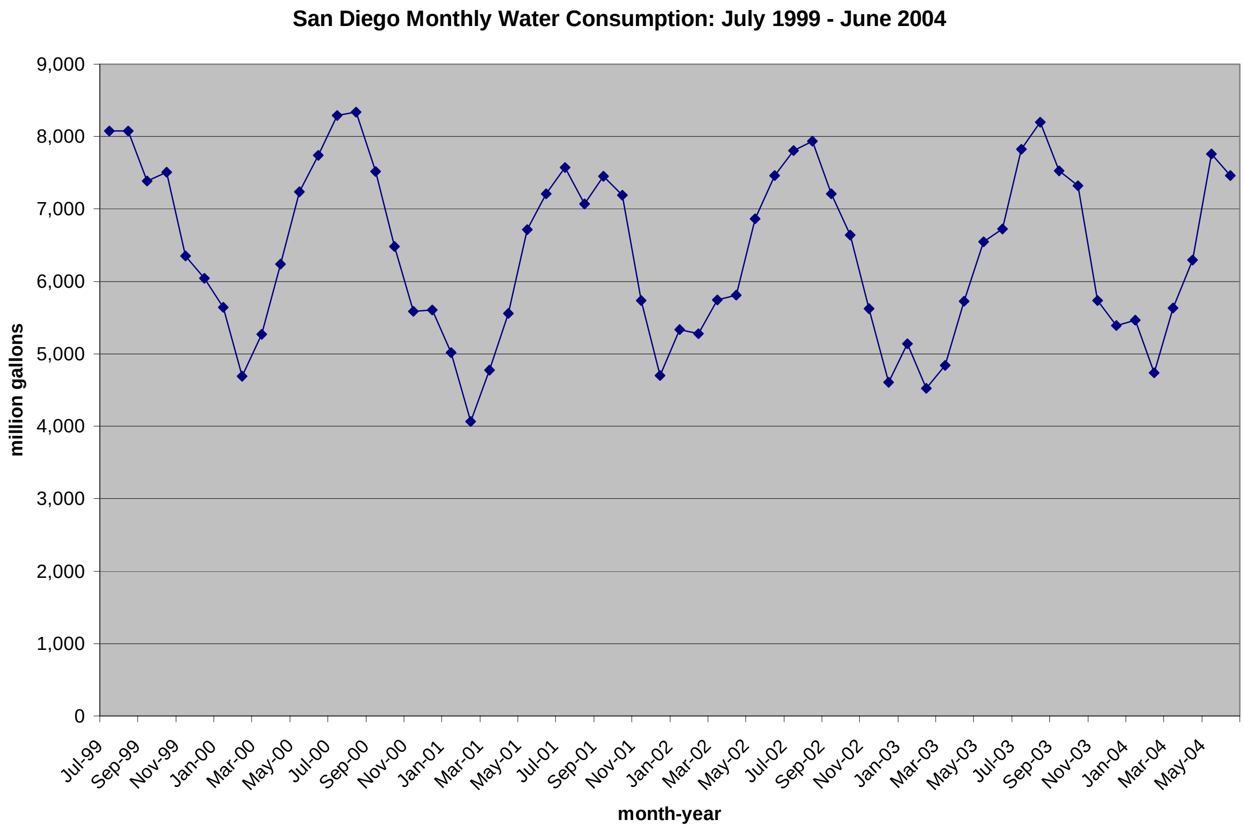


**Figure 11** – San Diego Monthly Water Consumption: July 1999 – July 2004



## VIII. Tables

**Table 1** – Parameter Estimates for *abcd* Model

| | 1948-77 | 1978-2003 |
|---|---|---|
| | D | |
| JAN | 0.044 | 0.021 |
| FEB | 0.041 | 0.018 |
| MAR | 0.042 | 0.019 |
| APR | 0.047 | 0.019 |
| MAY | 0.050 | 0.025 |
| JUN | 0.050 | 0.028 |
| JUL | 0.061 | 0.034 |
| AUG | 0.066 | 0.034 |
| SEP | 0.057 | 0.031 |
| OCT | 0.048 | 0.025 |
| NOV | 0.043 | 0.026 |
| DEC | 0.042 | 0.023 |
| | B | |
| SUMMER | 0.969 | 0.856 |
| WINTER | 0.959 | 0.901 |
| | Alpha | |
| | 0.807 | 0.807 |

**Table 2** – Conditional Distributiones for Zero Precipitation

| Month | Marginal Frequency of Zero Rainfall | Marginal Frequency of 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 3** – Rainfall Distribution Parameters

| | n | % zeros | Distribution | Parameter 1 | Parameter 2 | KS p-value |
|---|---|---|---|---|---|---|
| January | 620 | 1.7% | Gamma (α,β) | 1.049 | 2.832 | 0.104 |
| February | 621 | 2.1% | Gamma (α,β) | 1.195 | 2.613 | 0.334 |
| March | 617 | 2.8% | Gamma (α,β) | 1.228 | 2.409 | 0.182 |
| April | 609 | 4.2% | Gamma (α,β) | 1.080 | 1.296 | 0.636 |
| May | 520 | 18.2% | Lognormal ($\mu,\sigma^2$) | 0.731 | 0.713 | 0.135 |
| June | 308 | 51.6% | Lognormal ($\mu,\sigma^2$) | -2.155 | 1.255 | 0.320 |
| July | 264 | 58.5% | Lognormal ($\mu,\sigma^2$) | -2.225 | 1.293 | 0.323 |
| August | 271 | 57.5% | Lognormal ($\mu,\sigma^2$) | -1.742 | 1.506 | 0.383 |
| September* | 366 | 42.5% | Lognormal ($\mu,\sigma^2$) | 0.677 | 0.740 | 0.046 |
| October | 502 | 20.2% | Gamma (α,β) | 0.857 | 0.886 | 0.126 |
| November | 582 | 7.5% | Gamma (α,β) | 1.082 | 1.489 | 0.086 |
| December | 620 | 1.4% | Gamma (α,β) | 1.141 | 2.093 | 0.270 |

*September was also tested against exponential and gamma distributions and was found significantly different from those as well. The lognormal had the highest KS p-value.

**Table 4** – Import Regression Results

Years: 1960-2003

| Dependent Variable: per capita imports | OLS Parameter Estimate | Standard Error | t-Statistic | p-value |
|---|---|---|---|---|
| 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 standard error.

**Table 5** – Import Percentage Distributions

| | Distribution | Alpha | Beta | KS p-value |
|---|---|---|---|---|
| Summer 1960-1977 | gamma | 1.171 | 0.019 | 0.432 |
| Winter 1960-1977 | gamma | 2.244 | 0.023 | 0.138 |
| Summer 1978-2003 | gamma | 1.607 | 0.008 | 0.233 |
| Winter 1978-2003 | gamma | 1.620 | 0.013 | 0.827 |

**Table 6** – ECHAM Precipitation Parameters

| | New Mean | New Variance | New Parameter 1 | New Parameter 2 | New 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% |

**Table 7** – Hadley Precipitation Parameters

| | New Mean | New Variance | New Parameter 1 | New Parameter 2 | New 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 8** – Canadian Precipitation Parameters

| | New Mean | New Variance | New Parameter 1 | New Parameter 2 | New 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% |

**Table 9** – Per Capita Consumption Regression Results

Included observations: 59

| Dependent Variable: Per Capita Consumption | OLS Parameter Estimate | t-Statistic | p-value |
|---|---|---|---|
| Constant | 0.0003 | 0.31 | 0.76 |
| Rain | -0.0002 | -4.38 | 0.00 |
| Temperature | 0.0000 | 2.29 | 0.03 |
| Lag Rain | -0.0001 | -2.26 | 0.03 |
| Lag Per Capita Cons. | 0.4312 | 4.11 | 0.00 |
| Jan Dummy | 0.0002 | 1.19 | 0.24 |
| Feb Dummy | 0.0001 | 0.34 | 0.74 |
| Mar Dummy | 0.0006 | 3.09 | 0.00 |
| Apr Dummy | 0.0006 | 3.73 | 0.00 |
| May Dummy | 0.0009 | 5.06 | 0.00 |
| Jun Dummy | 0.0006 | 2.58 | 0.01 |
| Jul Dummy | 0.0008 | 3.16 | 0.00 |
| Aug Dummy | 0.0006 | 2.17 | 0.04 |
| Sep Dummy | 0.0003 | 1.03 | 0.31 |
| Oct Dummy | 0.0003 | 1.14 | 0.26 |
| Nov Dummy | -0.0002 | -1.37 | 0.18 |
| | | | |
| R-squared | 0.962 | | |

**Table 10 –** Willingness to Pay to Avoid Water Shortages for California Customers

Mean Monthly Willingness to Pay, Table ES-1 (additional $/month)

| | 1 occurrence every 30 years | 1 occurrence every 20 years | 1 occurrence every 10 years | 1 occurrence every 5 years | 1 occurrence every 3 years |
|---|---|---|---|---|---|
| 10% | | | 11.63 | 11.98 | 12.12 |
| 20% | 11.62 | 12.33 | 13.06 | | |
| 30% | 13.05 | 13.80 | 14.57 | | |
| 40% | 14.56 | 15.34 | 16.13 | | |
| 50% | 16.15 | 16.92 | | | |

**Table 11** – Climate Change Results Summary Table

| Scenario | | | | | Optimal Policy | | | |
|---|---|---|---|---|---|---|---|---|
| **Population Growth** | **Import Scenario** | **d** | **alpha** | **b** | **Historical** | **Canadian** | **Echam** | **Hadley** |
| Projected | Historical | 0.025 | 0.807 | 0.86,0.9 | 0-50 | 50-50 | 100-50 | 50-50 |
| Projected | **Winter** | 0.025 | 0.807 | 0.86,0.9 | 0-50 | 50-50 | 100-0 | 50-50 |
| **High** | Historical | 0.025 | 0.807 | 0.86,0.9 | 100-0 | 100-50 | 100-100 | 100-50 |
| **Low** | Historical | 0.025 | 0.807 | 0.86,0.9 | 0-50 | 0-50 | 100-0 | 0-50,0-100 |
| Projected | Historical | **0.05** | 0.807 | 0.86,0.9 | 0-0 | 0-0 | 0-0 | 0-0 |
| Projected | Historical | 0.025 | **0.4** | 0.86,0.9 | 100-100 | 100-100 | 100-100 | 100-100 |
| Projected | Historical | 0.025 | 0.807 | **0.6** | 0-50 | 50-50 | 50-50 | 50-50 |
| Projected | **Pop Only** | 0.025 | 0.807 | 0.86,0.9 | 0-50 | 50-50 | 100-50 | 50-50 |
| Projected | **Capped** | 0.025 | 0.807 | 0.86,0.9 | 0-50 | 50-50 | 100-50 | 50-50 |

| Scenario | | | | | Optimal Minimum Cost | | | |
|---|---|---|---|---|---|---|---|---|
| **Population Growth** | **Import Scenario** | **d** | **alpha** | **b** | **Historical** | **Canadian** | **Echam** | **Hadley** |
| Projected | Historical | 0.025 | 0.807 | 0.86,0.9 | 540 | 635 | 783 | 729 |
| Projected | **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 |
| Projected | Historical | **0.05** | 0.807 | 0.86,0.9 | 14 | 29 | 72 | 91 |
| Projected | Historical | 0.025 | **0.4** | 0.86,0.9 | 6,565 | 7,367 | 7,517 | 7,481 |
| Projected | Historical | 0.025 | 0.807 | **0.6** | 420 | 515 | 604 | 523 |
| Projected | **Pop Only** | 0.025 | 0.807 | 0.86,0.9 | 585 | 681 | 828 | 776 |
| Projected | **Capped** | 0.025 | 0.807 | 0.86,0.9 | 545 | 638 | 794 | 738 |

*Costs are expressed in millions of dollars

**Table 12a** – Backup Data 1

| Population Growth: | Import Scenario: | d: | alpha: | b: |
|---|---|---|---|---|
| projected | historical | 0.025 | 0.807 | 0.86,0.9 |

**Shortage Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 353 | 676 | 869 | 813 |
| 0-50 | 201 | 366 | 608 | 479 |
| 0-100 | 182 | 310 | 529 | 411 |
| 50-0 | 155 | 283 | 492 | 394 |
| 50-50 | 117 | 178 | 363 | 271 |
| 50-100 | 111 | 160 | 326 | 249 |
| 100-0 | 111 | 177 | 345 | 272 |
| 100-50 | 100 | 141 | 280 | 223 |
| 100-100 | 99 | 135 | 265 | 216 |

**Spill Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 286 | 279 | 282 | 270 |
| 0-50 | 274 | 272 | 272 | 264 |
| 0-100 | 257 | 260 | 259 | 256 |
| 50-0 | 254 | 258 | 256 | 254 |
| 50-50 | 233 | 242 | 239 | 242 |
| 50-100 | 213 | 224 | 222 | 231 |
| 100-0 | 210 | 223 | 221 | 229 |
| 100-50 | 188 | 202 | 201 | 214 |
| 100-100 | 170 | 185 | 184 | 202 |

**Total Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 639 | 955 | 1,151 | 1,083 |
| 0-50 | **540** | 704 | 945 | 809 |
| 0-100 | 542 | 673 | 891 | 770 |
| 50-0 | 560 | 692 | 899 | 797 |
| 50-50 | 565 | **635** | 818 | **729** |
| 50-100 | 578 | 638 | 802 | 733 |
| 100-0 | 559 | 637 | 803 | 738 |
| 100-50 | 591 | 645 | **783** | 740 |
| 100-100 | 610 | 661 | 790 | 758 |

**Table 12b –** Backup Data 2

| Population Growth: | Import Scenario: | d: | alpha: | b: |
|---|---|---|---|---|
| projected | winter | 0.025 | 0.807 | 0.86,0.9 |

**Shortage Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 234 | 549 | 638 | 602 |
| 0-50 | 75 | 214 | 334 | 234 |
| 0-100 | 67 | 157 | 258 | 176 |
| 50-0 | 35 | 139 | 219 | 149 |
| 50-50 | 8 | 34 | 97 | 47 |
| 50-100 | 8 | 24 | 86 | 43 |
| 100-0 | 7 | 40 | 100 | 56 |
| 100-50 | 7 | 17 | 74 | 38 |
| 100-100 | 7 | 17 | 74 | 38 |

**Spill Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 2,856 | 2,708 | 2,825 | 2,658 |
| 0-50 | 2,834 | 2,694 | 2,807 | 2,646 |
| 0-100 | 2,807 | 2,672 | 2,784 | 2,630 |
| 50-0 | 2,807 | 2,673 | 2,784 | 2,630 |
| 50-50 | 2,779 | 2,648 | 2,758 | 2,610 |
| 50-100 | 2,750 | 2,621 | 2,730 | 2,587 |
| 100-0 | 2,750 | 2,621 | 2,730 | 2,588 |
| 100-50 | 2,721 | 2,593 | 2,702 | 2,563 |
| 100-100 | 2,691 | 2,564 | 2,673 | 2,537 |

**Total Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 3,090 | 3,257 | 3,463 | 3,260 |
| 0-50 | **2,974** | 2,973 | 3,206 | 2,946 |
| 0-100 | 2,977 | 2,933 | 3,144 | 2,909 |
| 50-0 | 2,993 | 2,962 | 3,153 | 2,929 |
| 50-50 | 3,002 | **2,897** | 3,071 | **2,872** |
| 50-100 | 3,011 | 2,898 | 3,069 | 2,884 |
| 100-0 | 2,995 | 2,899 | **3,068** | 2,881 |
| 100-50 | 3,030 | 2,912 | 3,079 | 2,904 |
| 100-100 | 3,039 | 2,922 | 3,087 | 2,916 |

**Table 12c –** Backup Data 3

| Population Growth: | Import Scenario: | d: | alpha: | b: |
|---|---|---|---|---|
| high | historical | 0.025 | 0.807 | 0.86,0.9 |

**Shortage Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 579 | 1,050 | 1,197 | 1,206 |
| 0-50 | 314 | 593 | 835 | 709 |
| 0-100 | 268 | 481 | 715 | 589 |
| 50-0 | 235 | 448 | 667 | 583 |
| 50-50 | 155 | 256 | 483 | 360 |
| 50-100 | 144 | 217 | 423 | 314 |
| 100-0 | 149 | 257 | 455 | 366 |
| 100-50 | 125 | 187 | 360 | 279 |
| 100-100 | 122 | 173 | 331 | 263 |

**Spill Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 297 | 290 | 293 | 280 |
| 0-50 | 284 | 282 | 282 | 274 |
| 0-100 | 267 | 270 | 269 | 266 |
| 50-0 | 265 | 268 | 267 | 263 |
| 50-50 | 243 | 251 | 249 | 252 |
| 50-100 | 222 | 233 | 231 | 240 |
| 100-0 | 220 | 232 | 230 | 238 |
| 100-50 | 197 | 211 | 209 | 223 |
| 100-100 | 179 | 193 | 192 | 210 |

**Total Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 876 | 1,340 | 1,490 | 1,486 |
| 0-50 | 663 | 940 | 1,182 | 1,048 |
| 0-100 | 638 | 854 | 1,087 | 957 |
| 50-0 | 650 | 866 | 1,084 | 996 |
| 50-50 | 614 | 722 | 948 | 827 |
| 50-100 | 620 | 704 | 908 | 807 |
| 100-0 | **607** | 727 | 923 | 841 |
| 100-50 | 624 | **700** | 872 | **805** |
| 100-100 | 641 | 707 | **864** | 814 |

**Table 12d –** Backup Data 4

| Population Growth: | Import Scenario: | d: | alpha: | b: |
|---|---|---|---|---|
| low | historical | 0.025 | 0.807 | 0.86,0.9 |

**Shortage Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 207 | 420 | 622 | 537 |
| 0-50 | 136 | 239 | 446 | 329 |
| 0-100 | 130 | 213 | 399 | 298 |
| 50-0 | 106 | 184 | 346 | 273 |
| 50-50 | 90 | 131 | 267 | 208 |
| 50-100 | 89 | 123 | 248 | 199 |
| 100-0 | 86 | 129 | 253 | 208 |
| 100-50 | 82 | 113 | 217 | 186 |
| 100-100 | 82 | 109 | 212 | 184 |

**Spill Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 276 | 269 | 272 | 260 |
| 0-50 | 264 | 262 | 262 | 254 |
| 0-100 | 248 | 251 | 249 | 247 |
| 50-0 | 245 | 249 | 247 | 244 |
| 50-50 | 224 | 233 | 230 | 234 |
| 50-100 | 204 | 216 | 214 | 222 |
| 100-0 | 201 | 214 | 212 | 220 |
| 100-50 | 180 | 194 | 193 | 207 |
| 100-100 | 163 | 178 | 177 | 195 |

**Total Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 483 | 690 | 894 | 797 |
| 0-50 | **465** | **566** | 773 | **648** |
| 0-100 | 481 | 567 | 751 | **648** |
| 50-0 | 501 | 583 | 743 | 668 |
| 50-50 | 530 | 580 | 713 | 657 |
| 50-100 | 547 | 593 | 716 | 675 |
| 100-0 | 525 | 581 | **702** | 666 |
| 100-50 | 565 | 609 | 713 | 695 |
| 100-100 | 586 | 628 | 730 | 719 |

**Table 12e –** Backup Data 5

| Population Growth: | Import Scenario: | d: | alpha: | b: |
|---|---|---|---|---|
| projected | historical | 0.05 | 0.807 | 0.86,0.9 |

**Shortage Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 5 | 11 | 46 | 29 |
| 0-50 | 5 | 8 | 33 | 23 |
| 0-100 | 5 | 8 | 31 | 21 |
| 50-0 | 5 | 10 | 38 | 25 |
| 50-50 | 5 | 8 | 27 | 20 |
| 50-100 | 5 | 7 | 25 | 19 |
| 100-0 | 5 | 10 | 36 | 23 |
| 100-50 | 5 | 7 | 25 | 19 |
| 100-100 | 5 | 7 | 23 | 16 |

**Spill Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 9 | 19 | 25 | 62 |
| 0-50 | 7 | 15 | 20 | 55 |
| 0-100 | 6 | 14 | 18 | 52 |
| 50-0 | 3 | 11 | 14 | 48 |
| 50-50 | 3 | 10 | 12 | 44 |
| 50-100 | 3 | 10 | 11 | 42 |
| 100-0 | 3 | 9 | 10 | 40 |
| 100-50 | 2 | 9 | 9 | 38 |
| 100-100 | 2 | 9 | 9 | 37 |

Total Costs (million $)

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | **14** | **29** | **72** | **91** |
| 0-50 | 77 | 89 | 118 | 144 |
| 0-100 | 114 | 125 | 152 | 176 |
| 50-0 | 159 | 172 | 202 | 223 |
| 50-50 | 223 | 234 | 254 | 280 |
| 50-100 | 261 | 271 | 290 | 314 |
| 100-0 | 245 | 256 | 284 | 301 |
| 100-50 | 310 | 319 | 337 | 360 |
| 100-100 | 348 | 356 | 373 | 393 |

**Table 12f –** Backup Data 6

| Population Growth: | Import Scenario: | d: | alpha: | b: |
|---|---|---|---|---|
| projected | historical | 0.025 | 0.4 | 0.86,0.9 |

**Shortage Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 9,784 | 10,844 | 10,924 | 11,062 |
| 0-50 | 8,765 | 9,866 | 9,934 | 10,046 |
| 0-100 | 8,248 | 9,252 | 9,379 | 9,419 |
| 50-0 | 8,012 | 9,023 | 9,106 | 9,183 |
| 50-50 | 7,287 | 8,186 | 8,335 | 8,294 |
| 50-100 | 6,863 | 7,708 | 7,854 | 7,801 |
| 100-0 | 6,942 | 7,804 | 7,958 | 7,942 |
| 100-50 | 6,385 | 7,154 | 7,330 | 7,268 |
| 100-100 | 5,936 | 6,756 | 6,891 | 6,872 |

**Spill Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 288 | 270 | 285 | 268 |
| 0-50 | 288 | 270 | 285 | 268 |
| 0-100 | 288 | 270 | 285 | 268 |
| 50-0 | 288 | 270 | 285 | 268 |
| 50-50 | 288 | 270 | 285 | 268 |
| 50-100 | 288 | 270 | 285 | 268 |
| 100-0 | 288 | 270 | 285 | 268 |
| 100-50 | 288 | 270 | 285 | 268 |
| 100-100 | 288 | 270 | 285 | 268 |

**Total Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 10,072 | 11,114 | 11,209 | 11,330 |
| 0-50 | 9,119 | 10,201 | 10,284 | 10,379 |
| 0-100 | 8,639 | 9,625 | 9,767 | 9,789 |
| 50-0 | 8,450 | 9,443 | 9,542 | 9,601 |
| 50-50 | 7,791 | 8,672 | 8,836 | 8,777 |
| 50-100 | 7,405 | 8,232 | 8,393 | 8,323 |
| 100-0 | 7,468 | 8,312 | 8,481 | 8,447 |
| 100-50 | 6,976 | 7,727 | 7,918 | 7,839 |
| 100-100 | **6,565** | **7,367** | **7,517** | **7,481** |

**Table 12g –** Backup Data 7

| Population Growth: | Import Scenario: | d: | alpha: | b: |
|---|---|---|---|---|
| projected | historical | 0.025 | 0.807 | 0.6 |

**Shortage Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 232 | 536 | 638 | 587 |
| 0-50 | 77 | 214 | 351 | 233 |
| 0-100 | 69 | 159 | 277 | 175 |
| 50-0 | 36 | 140 | 233 | 154 |
| 50-50 | 9 | 38 | 112 | 49 |
| 50-100 | 9 | 27 | 99 | 45 |
| 100-0 | 8 | 41 | 113 | 59 |
| 100-50 | 8 | 18 | 84 | 40 |
| 100-100 | 8 | 18 | 82 | 40 |

**Spill Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 278 | 262 | 276 | 258 |
| 0-50 | 278 | 262 | 276 | 258 |
| 0-100 | 278 | 262 | 276 | 258 |
| 50-0 | 278 | 262 | 276 | 258 |
| 50-50 | 278 | 262 | 276 | 258 |
| 50-100 | 278 | 262 | 276 | 258 |
| 100-0 | 278 | 262 | 276 | 258 |
| 100-50 | 278 | 262 | 276 | 258 |
| 100-100 | 278 | 262 | 276 | 258 |

**Total Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 511 | 798 | 914 | 846 |
| 0-50 | **420** | 541 | 692 | 557 |
| 0-100 | 450 | 524 | 656 | 537 |
| 50-0 | 464 | 552 | 659 | 563 |
| 50-50 | 502 | **515** | **604** | **523** |
| 50-100 | 540 | 542 | 628 | 557 |
| 100-0 | 524 | 541 | 626 | 555 |
| 100-50 | 589 | 583 | 663 | 601 |
| 100-100 | 626 | 620 | 699 | 638 |

**Table 12h –** Backup Data 8

| Population Growth: | Import Scenario: | d: | alpha: | b: |
|---|---|---|---|---|
| projected | population only | 0.025 | 0.807 | 0.86,0.9 |

**Shortage Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 367 | 675 | 872 | 796 |
| 0-50 | 219 | 368 | 614 | 462 |
| 0-100 | 201 | 312 | 535 | 403 |
| 50-0 | 175 | 287 | 496 | 383 |
| 50-50 | 137 | 182 | 372 | 272 |
| 50-100 | 133 | 166 | 342 | 254 |
| 100-0 | 131 | 182 | 355 | 274 |
| 100-50 | 123 | 151 | 297 | 236 |
| 100-100 | 122 | 146 | 285 | 230 |

**Spill Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 314 | 323 | 312 | 318 |
| 0-50 | 301 | 315 | 302 | 311 |
| 0-100 | 284 | 303 | 289 | 303 |
| 50-0 | 281 | 301 | 286 | 301 |
| 50-50 | 259 | 283 | 269 | 288 |
| 50-100 | 238 | 264 | 250 | 276 |
| 100-0 | 236 | 263 | 249 | 274 |
| 100-50 | 212 | 241 | 228 | 258 |
| 100-100 | 193 | 222 | 210 | 244 |

**Total Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 681 | 998 | 1,185 | 1,114 |
| 0-50 | **585** | 749 | 981 | 839 |
| 0-100 | 587 | 718 | 927 | 809 |
| 50-0 | 606 | 739 | 933 | 834 |
| 50-50 | 611 | **681** | 856 | **776** |
| 50-100 | 625 | 684 | 846 | 783 |
| 100-0 | 604 | 683 | 842 | 786 |
| 100-50 | 638 | 695 | **828** | 796 |
| 100-100 | 655 | 708 | 835 | 815 |

**Table 12i –** Backup Data 9

| Population Growth: | Import Scenario: | d: | alpha: | b: |
|---|---|---|---|---|
| projected | capped | 0.025 | 0.807 | 0.86,0.9 |

**Shortage Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 359 | 679 | 881 | 823 |
| 0-50 | 207 | 370 | 620 | 490 |
| 0-100 | 188 | 313 | 542 | 422 |
| 50-0 | 161 | 286 | 504 | 403 |
| 50-50 | 123 | 181 | 375 | 281 |
| 50-100 | 117 | 164 | 338 | 259 |
| 100-0 | 116 | 180 | 356 | 282 |
| 100-50 | 106 | 144 | 292 | 233 |
| 100-100 | 105 | 138 | 277 | 226 |

**Spill Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 286 | 279 | 281 | 269 |
| 0-50 | 273 | 271 | 270 | 263 |
| 0-100 | 256 | 260 | 258 | 255 |
| 50-0 | 254 | 258 | 255 | 253 |
| 50-50 | 232 | 241 | 238 | 241 |
| 50-100 | 212 | 224 | 221 | 230 |
| 100-0 | 210 | 222 | 220 | 228 |
| 100-50 | 187 | 202 | 200 | 214 |
| 100-100 | 170 | 185 | 183 | 201 |

**Total Costs (million $)**

| Expansion Scenario: | Historical | Canadian | Echam | Hadley |
|---|---|---|---|---|
| 0-0 | 644 | 958 | 1,162 | 1,092 |
| 0-50 | **545** | 706 | 956 | 818 |
| 0-100 | 547 | 676 | 902 | 780 |
| 50-0 | 565 | 694 | 909 | 806 |
| 50-50 | 570 | **638** | 828 | **738** |
| 50-100 | 583 | 641 | 813 | 743 |
| 100-0 | 564 | 640 | 814 | 748 |
| 100-50 | 596 | 648 | **794** | 749 |
| 100-100 | 615 | 664 | 801 | 768 |