

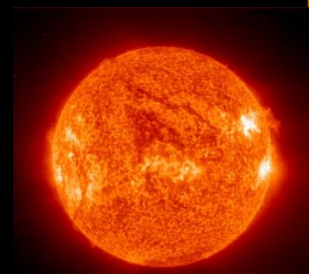
Climate Change: Implications for Reservoir Management and Hydroelectricity in California

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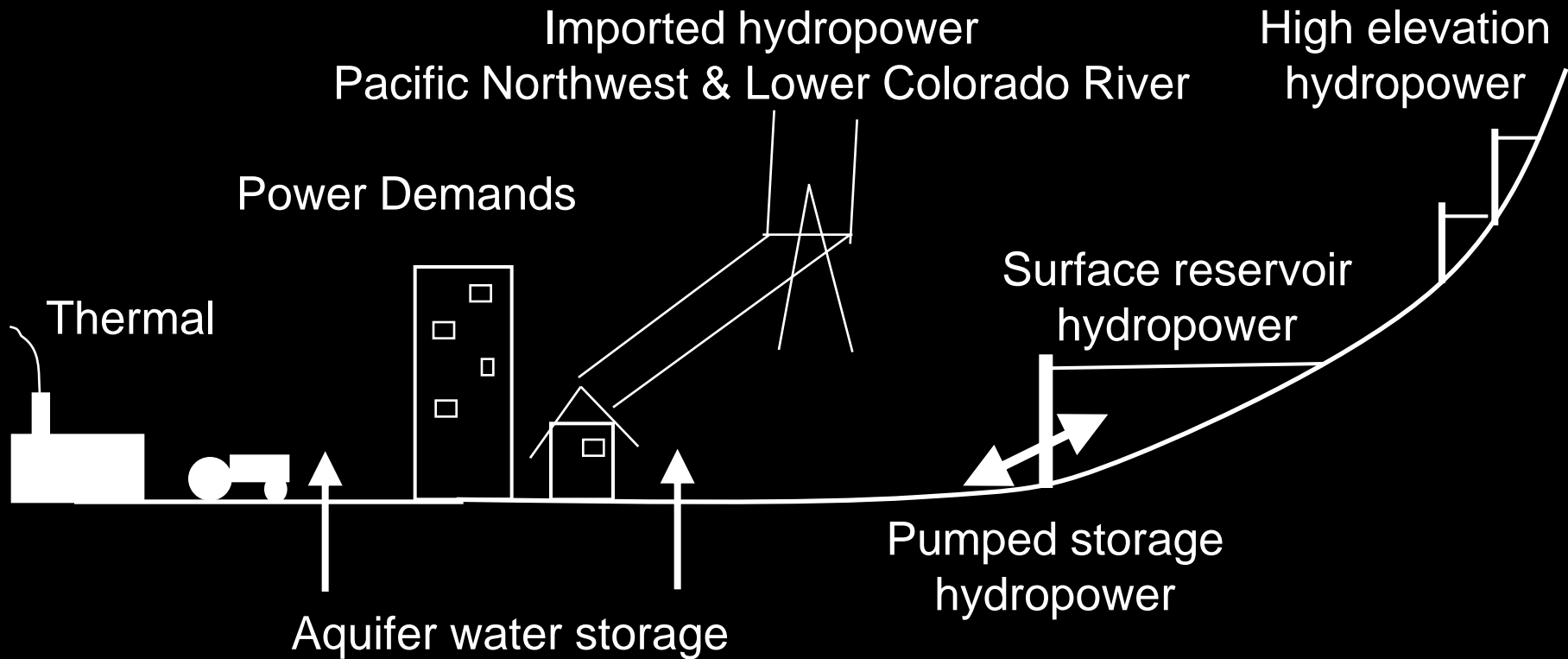
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Outline

- Hydropower in California
- Effects on Low Elevation System (CALVIN)
- Effects on High Elevation System (EBHOM)
- Results
- Limitations!
- Next Step?
- Conclusions

Hydropower Systems



Hydropower and California

1,000 GWH/yr, 2004

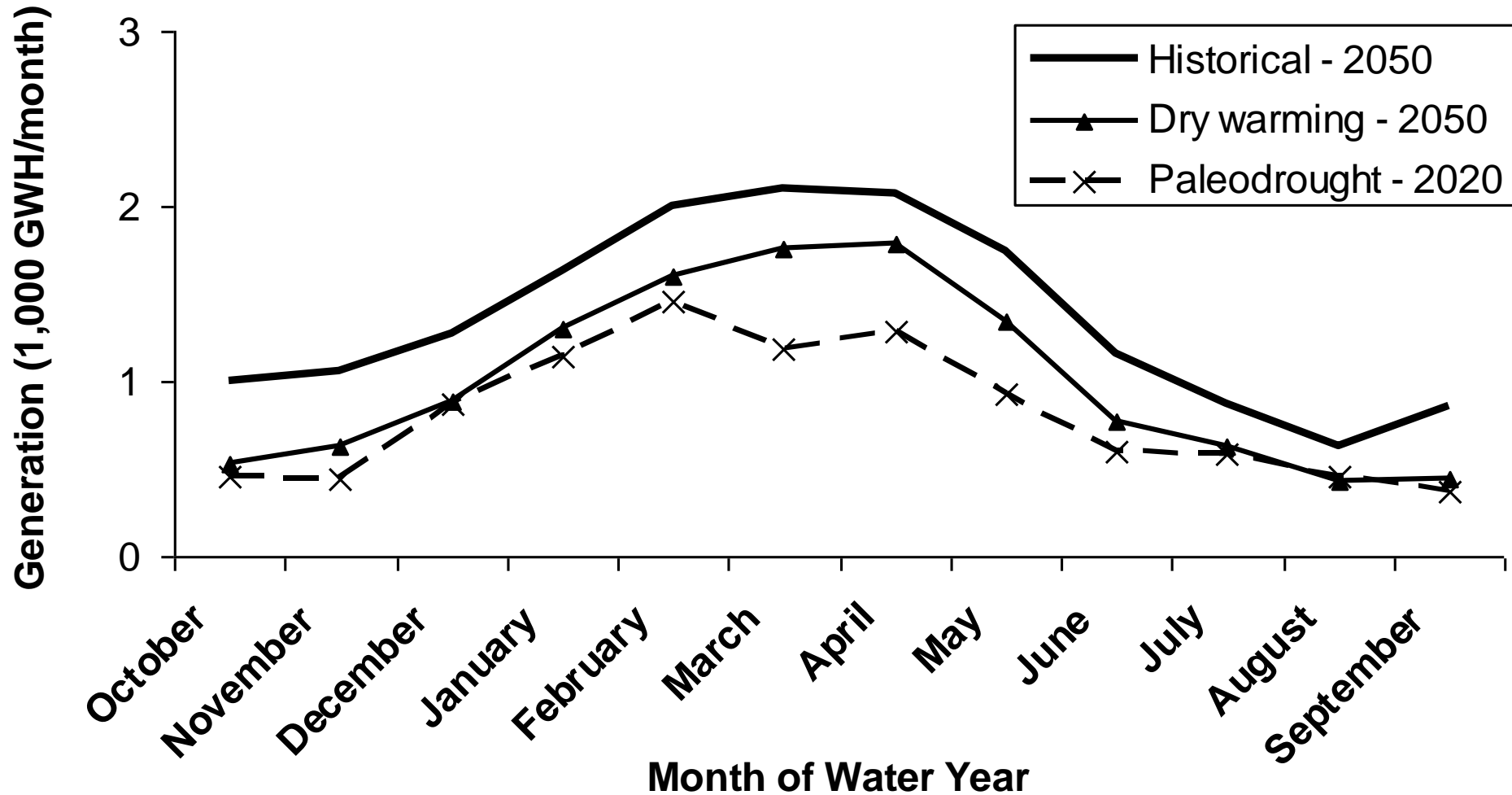
Hydropower Total	45.4
<hr/>	
In-state Hydropower	34.4
High Elevation*	25.3
Low Elevation*	9.1
Pumped Storage	?
Imported Hydropower	11
PNW	9.5
LCR	1.5
<hr/>	
Thermal	205.2
Other renewables	24.5
Total	275.1

* Estimated Sources: CEC; McCann 2005

Climate Effects on Hydropower

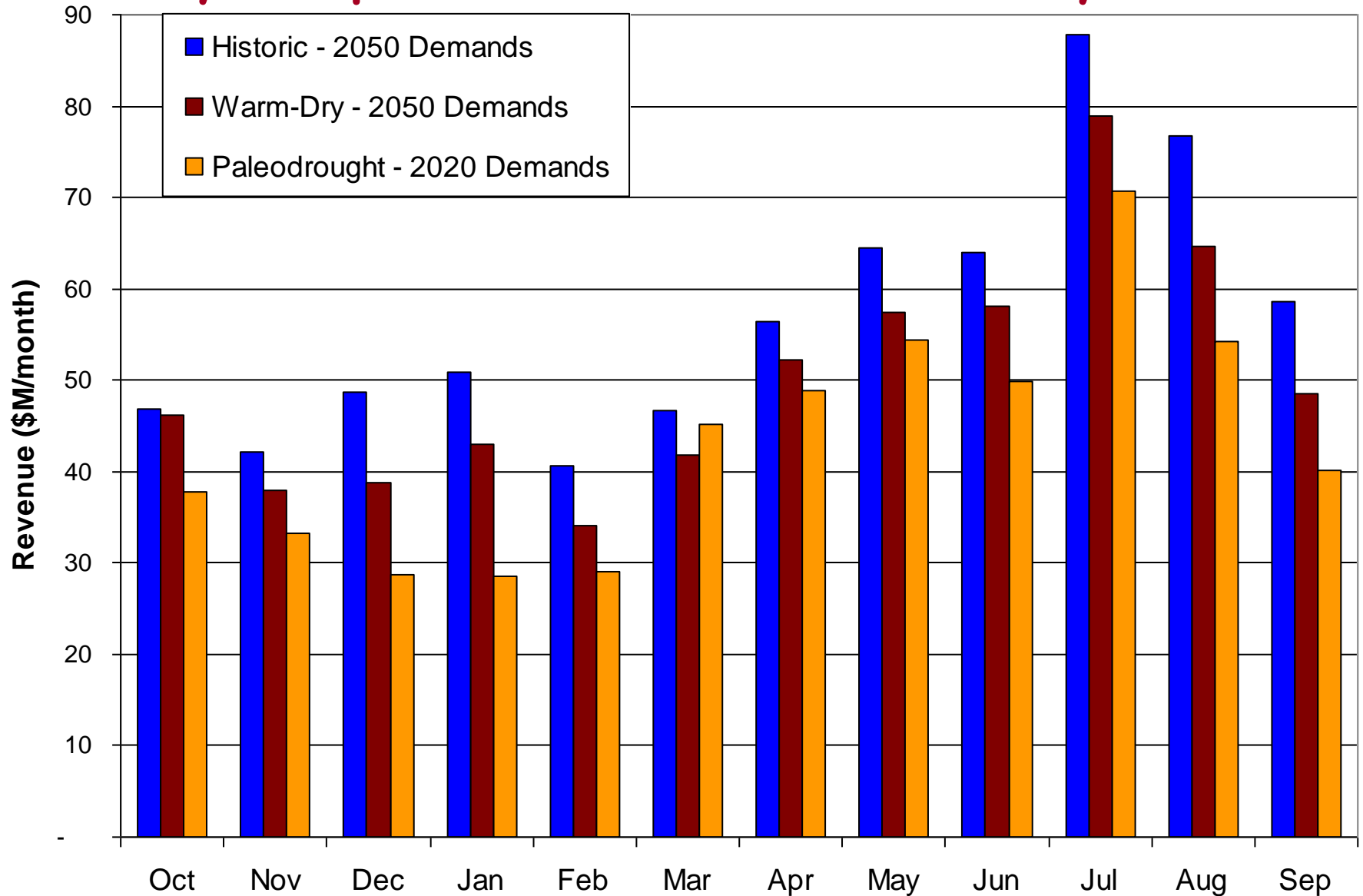
1. Energy demand
2. Timing of water availability
3. Quantity of water available
4. Availability of hydropower to import
5. Thermal generation efficiency
6. Sensitivity of environment to hydro operations

Water Supply Dam Hydropower Seasonal Generation Changes

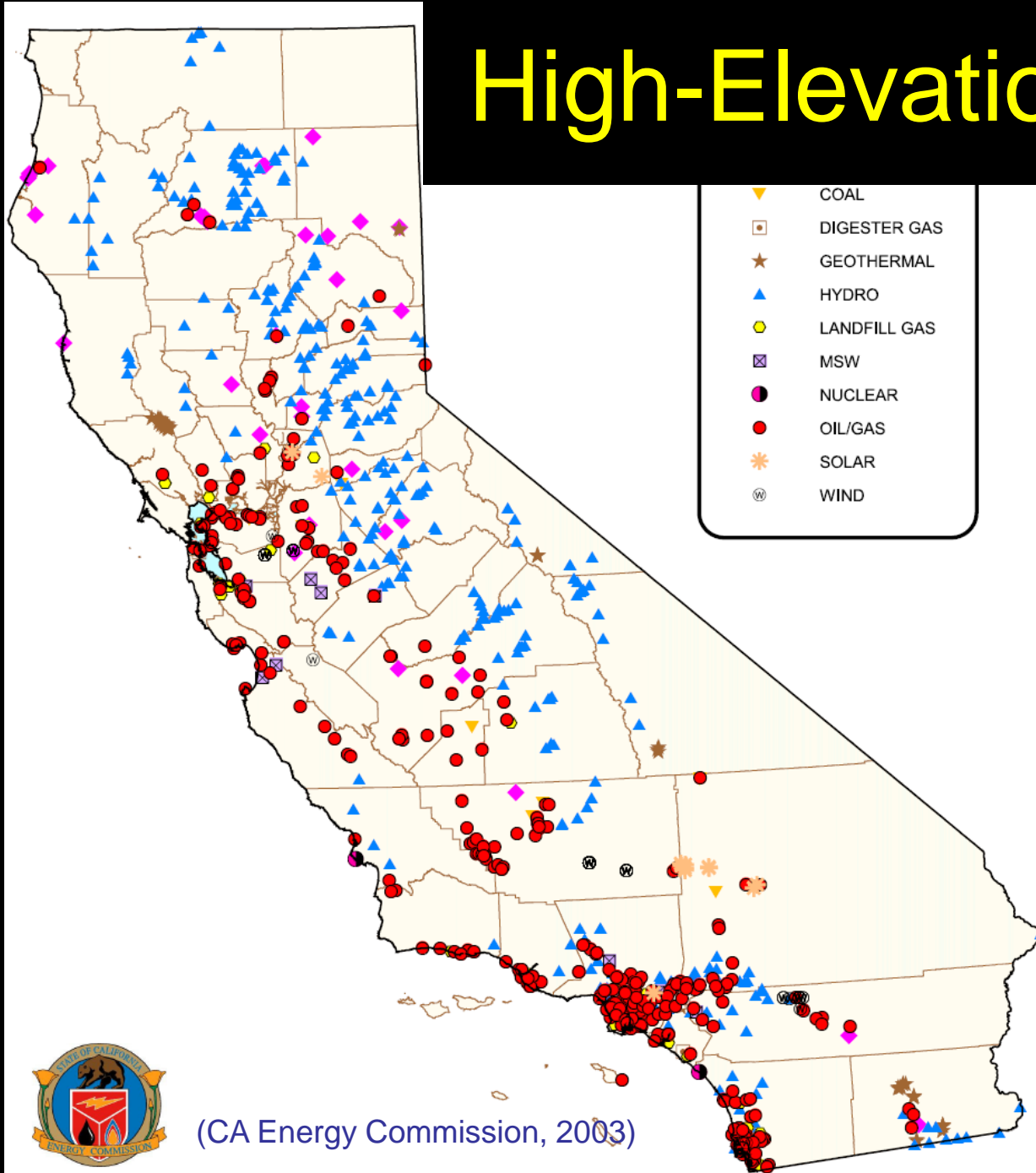


Major water supply reservoirs in CALVIN system optimization model

Average Water Supply Reservoir Hydropower Benefits (\$M/year)



High-Elevation System

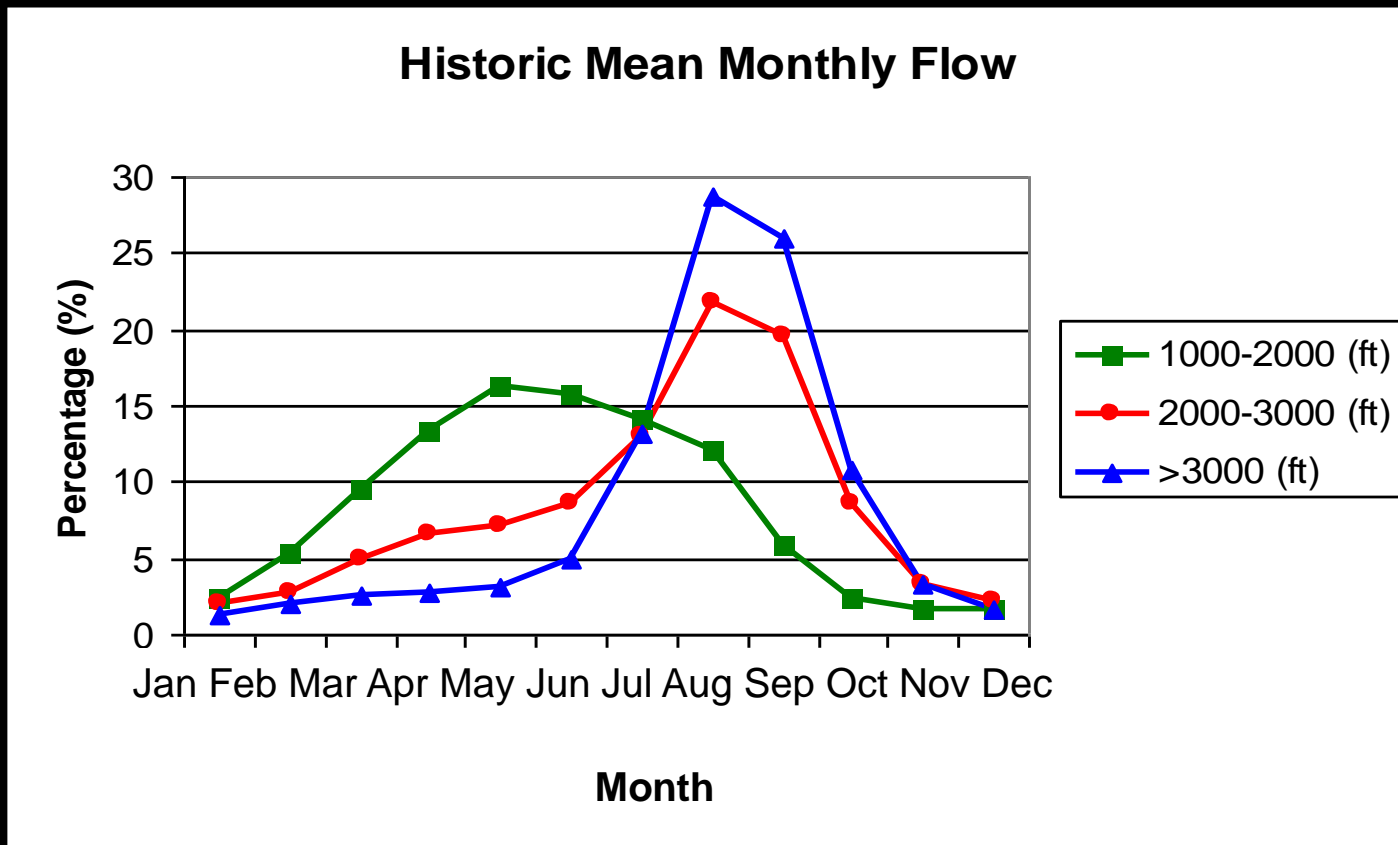


- 156 High-elevation power plants
- Snowpack dependant
- High-head, little head-storage effect
- Limited storage or flow data!!



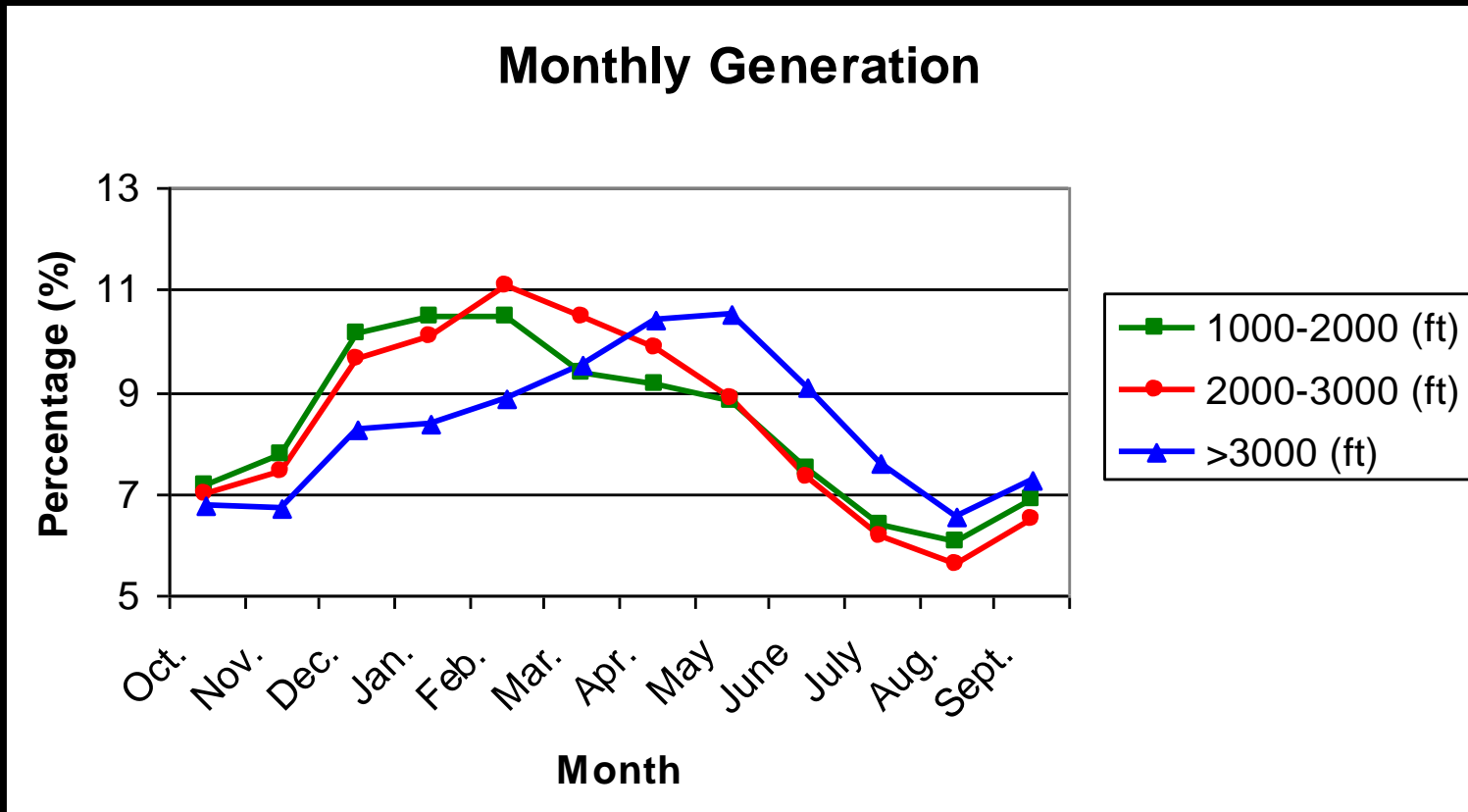
(CA Energy Commission, 2003)

High-Elevation Runoff (Snowpack Effect)



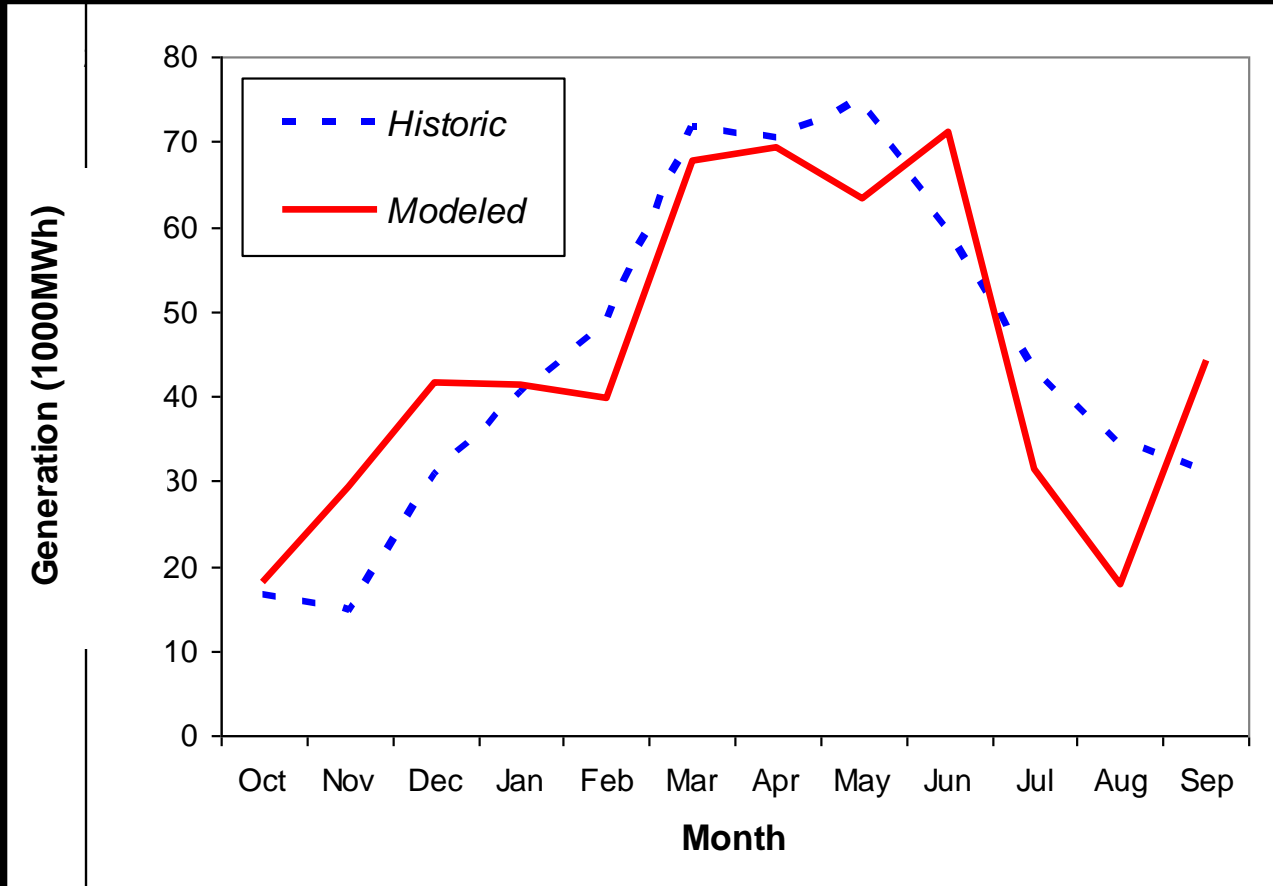
$$runPercent(i) = \frac{average_Runoff(i)}{average_Annual_Runoff}$$

High-Elevation Generation (Snowpack Effect)



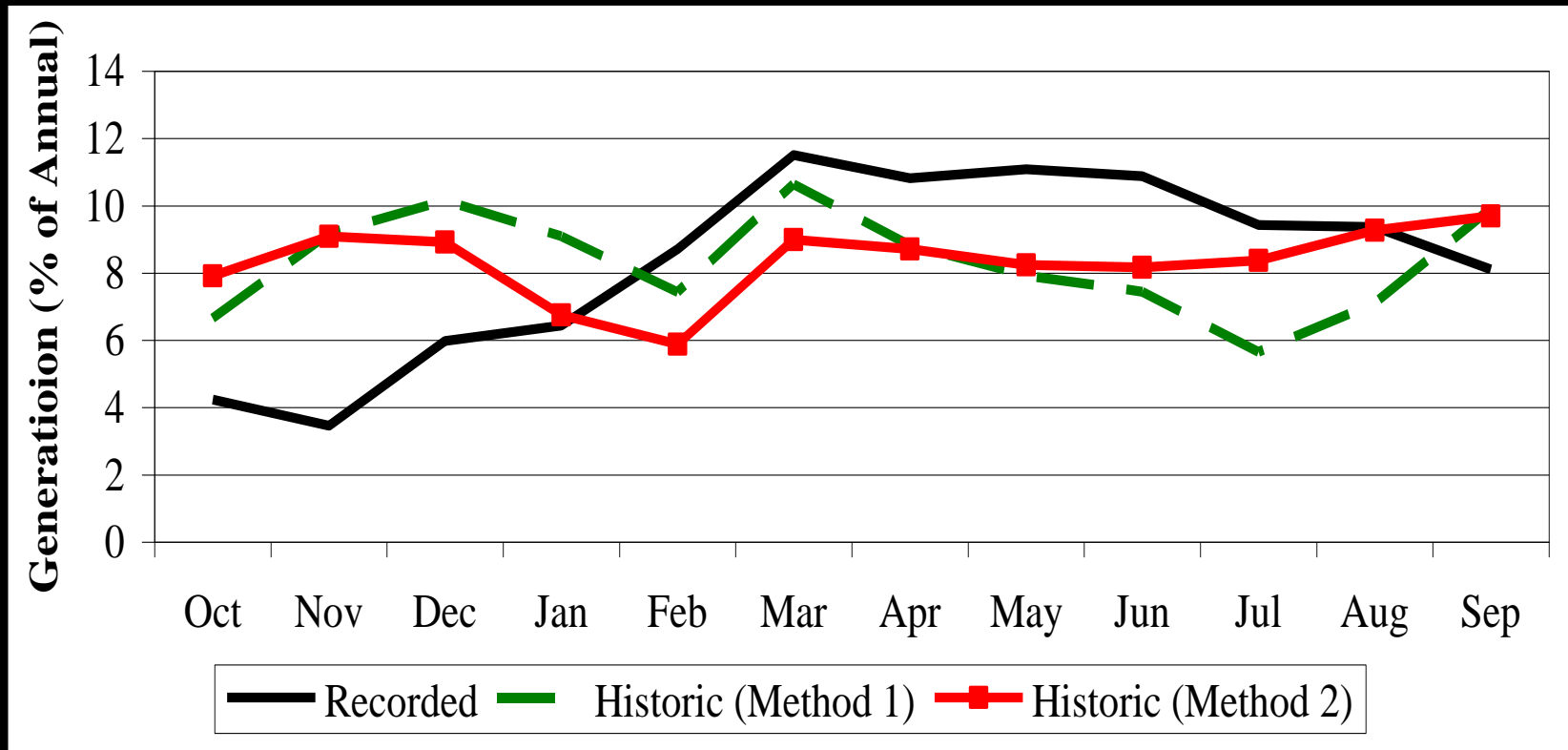
$$genPercent(i) = \frac{average_generation(i)}{average_Annual_generation}$$

White Rock



Historic monthly electricity generation and optimized monthly electricity generation (by EBHOM) in an average year

SMUD System



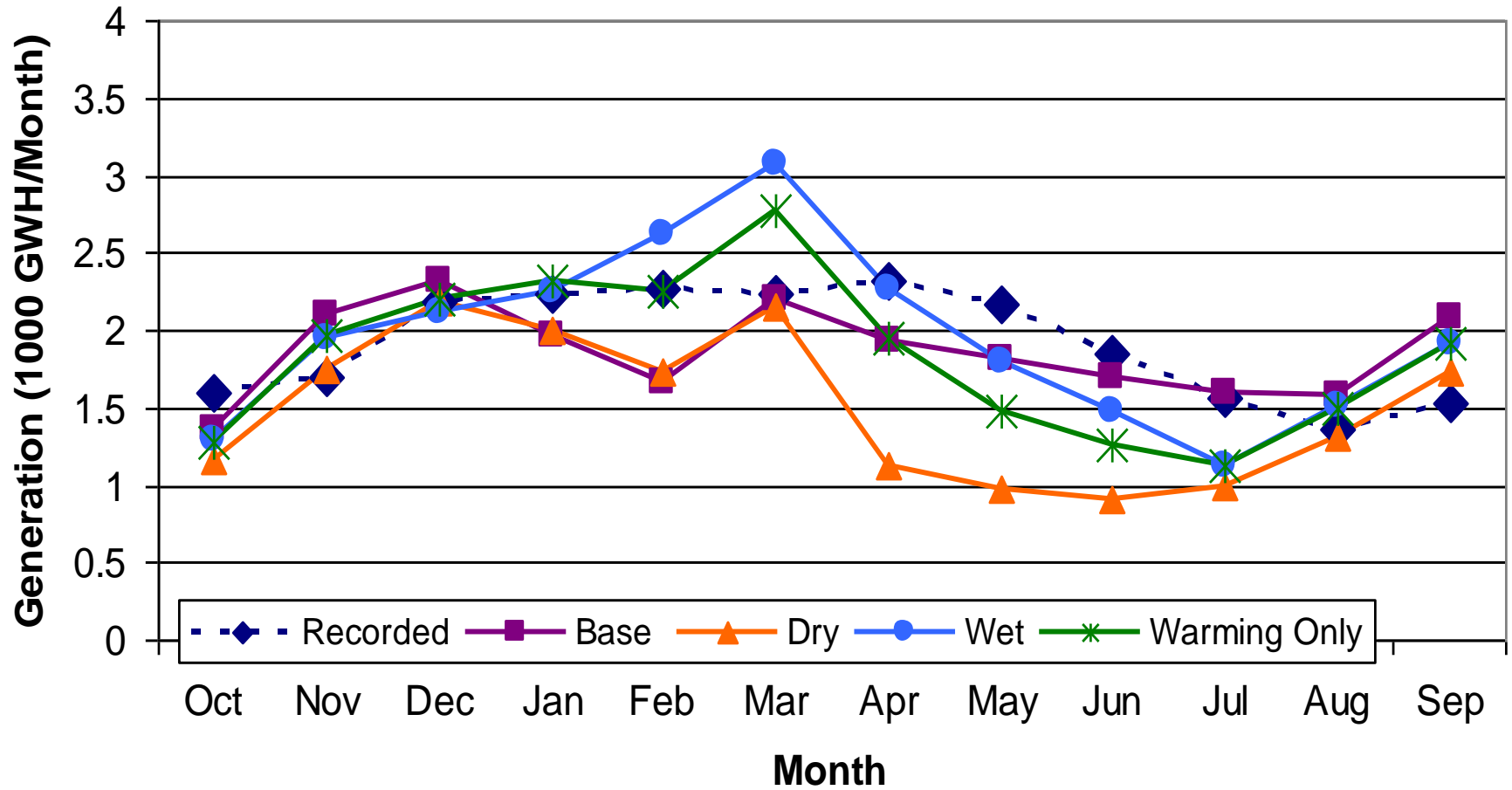
Comparison of EBHOM and traditional optimization applied to SMUD system

High-Elevation Model Results

137 of 156 hydropower plants

1984 – 1998 period

Monthly Generation

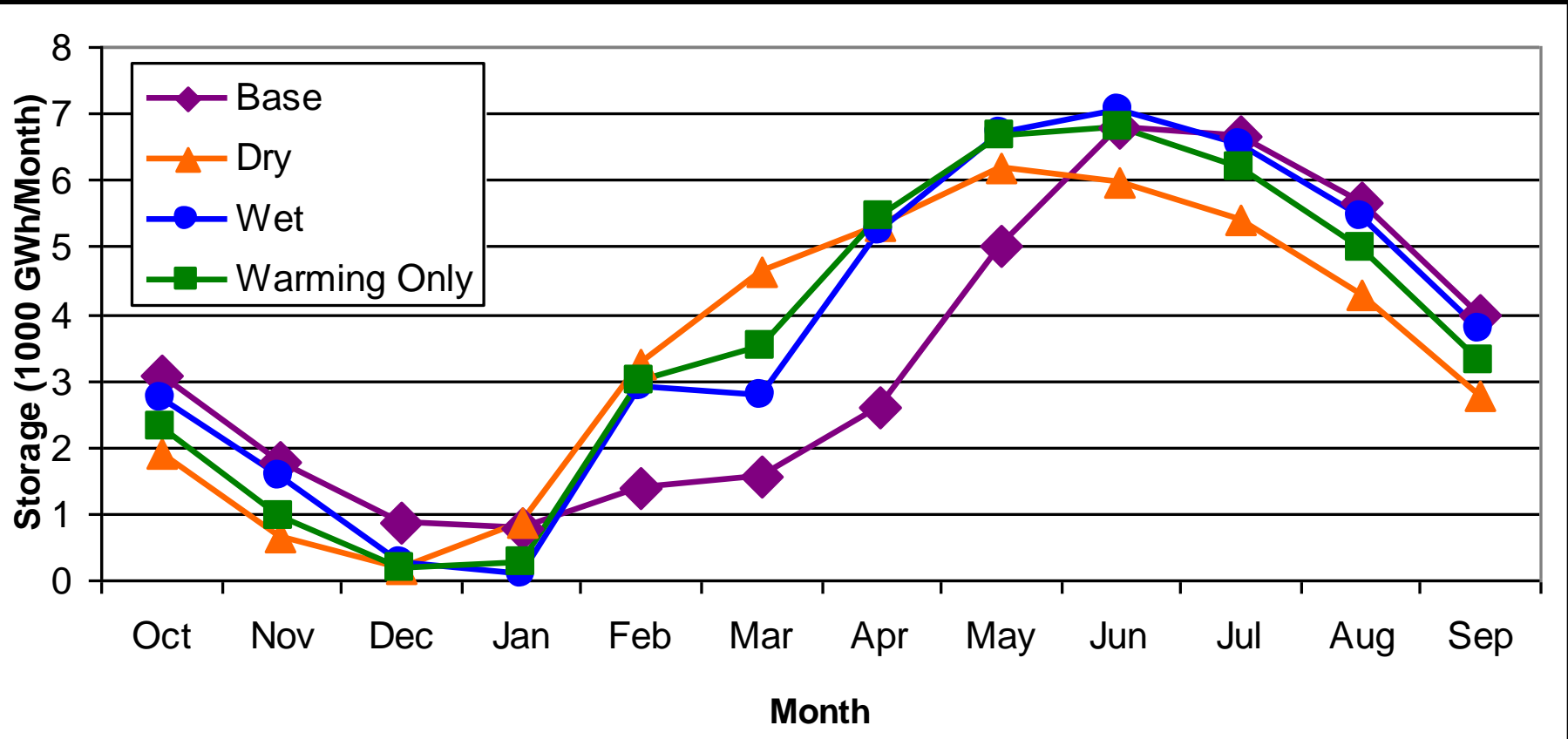


Model Results

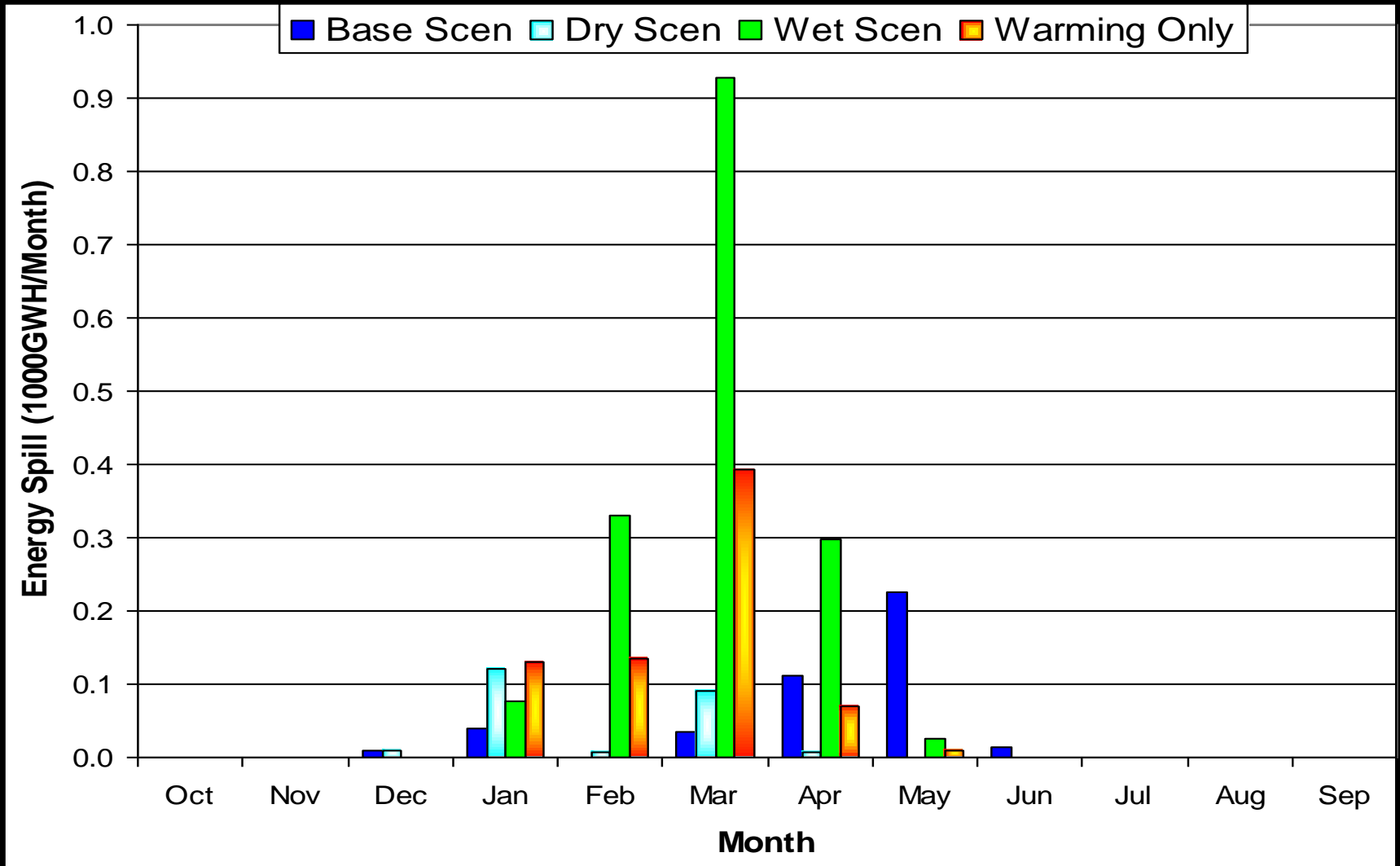
	Scenario			
	<i>Base</i>	<i>Dry</i>	<i>Wet</i>	<i>Warming-Only</i>
Generation (1000 GWH/yr)	22.3	18.0	23.4	22.0
Generation Change with Respect to the Base Case (%)		- 19.3	+ 4.8	- 1.4
Spill (MWH/yr)	433	224	1,661	735
Spill Change with Respect to the Base Case (%)		- 46.0	+ 283.9	+ 58.8
Revenue (Million \$/yr)	1,449	1,271	1,483	1,435
Revenue Change with Respect to the Base Case (%)		- 12.3	+ 2.3	- 0.9

average of results over 1984-1998 period

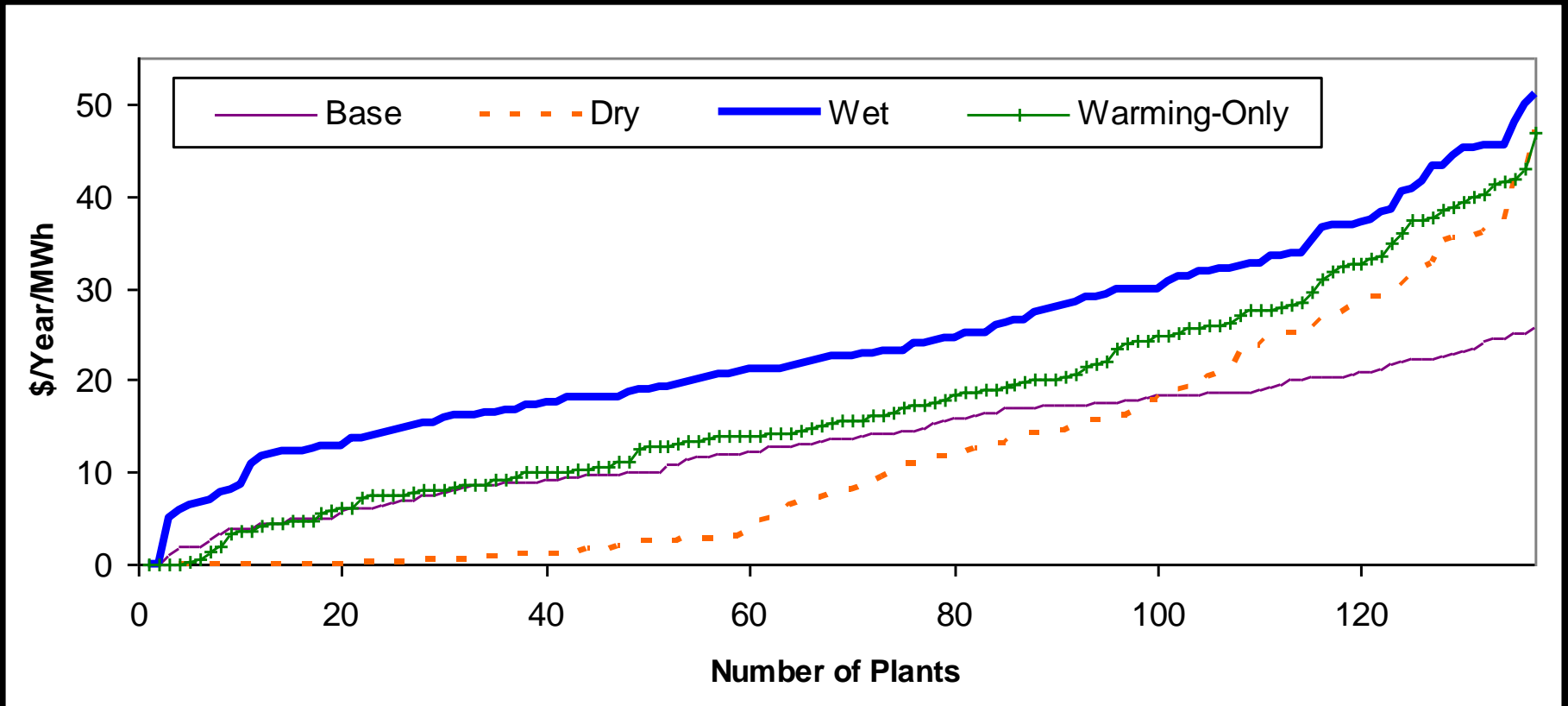
Average total end-of-month energy storage (1984-1998)



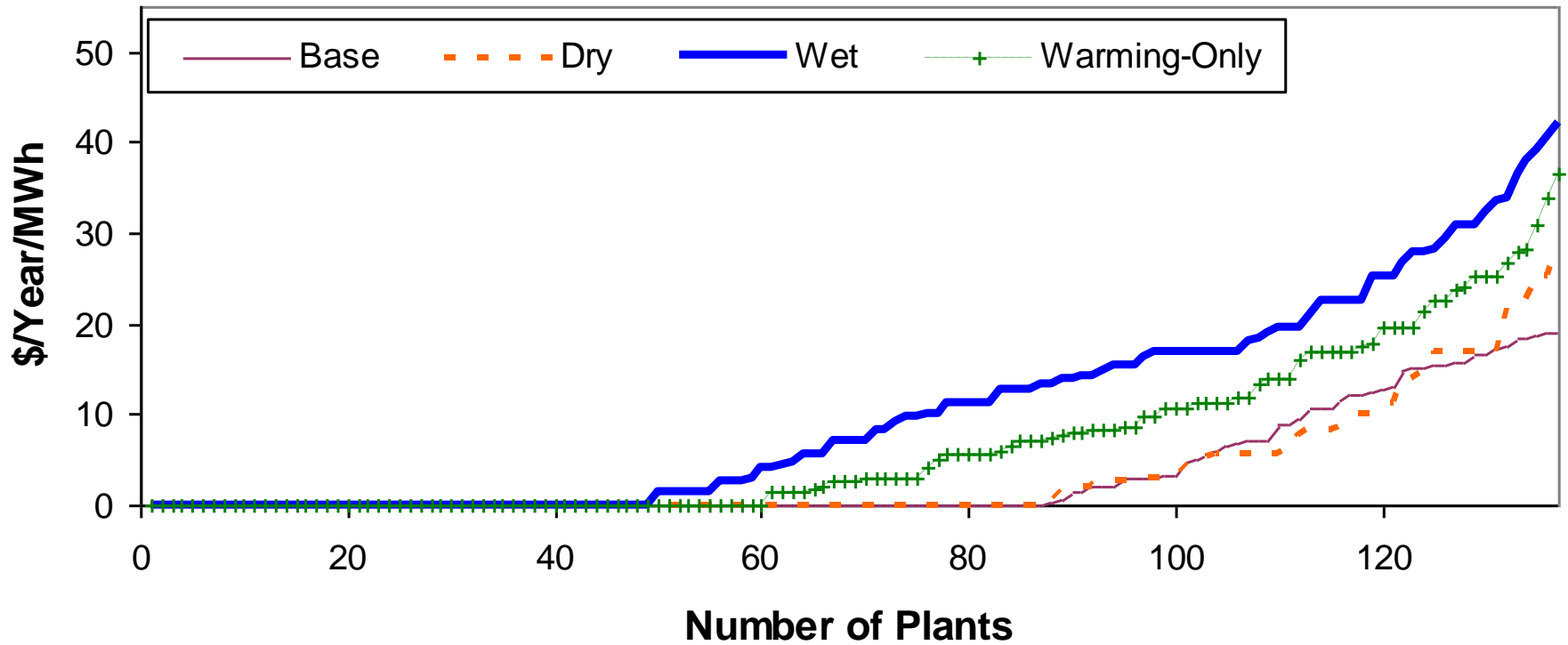
Average monthly energy spill (1984-1998)



Benefit of Storage Capacity Expansion



Benefit of Generation Capacity Expansion



Limitations of EBHOM

- NSM Limitations
- Few stream gauges
- Coarse elevation ranges
- Hydrologic variability
- Perturbation ratios
- Energy demand/price changes
- Deterministic (perfect foresight)
- No Environmental Constraints

Overall Conclusions

- Sierra loses snowpack, the natural reservoir.
- Storage works. Generation changes more with total runoff than seasonal runoff shift.
- Problems for smaller high-elevation reservoirs - more spills even without change in total runoff
- Drier climate causes more problems than wetter climate causes benefits.
- Revenue reduction may be economically insufficient to justify expanding storage or generation capacity.

Next Steps?

- Climate change effects on energy demand/ price
- More detailed high-elevation studies

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Estimated Impacts of Climate Warming on California's High-Elevation Hydropower

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Abstract

California's high-elevation hydropower system is composed of more than 150 power plants, most with modest reservoir storage capacity, which supply roughly 74 percent of California's in-state hydropower. This system was designed to take advantage of snowpack, a natural reservoir. The expected shift of runoff peak from spring to winter as a result of snowpack reduction due to climate warming might have important effects on power generation and revenues in California. Thus, with climate warming, the adaptability of the high-elevation hydropower system is in question. With so many hydropower plants in California, estimation of climate warming effects by conventional simulation or optimization methods would be tedious and expensive. An Energy-Based Hydropower Optimization Model (EBHOM), estimated from 15 years of generation data for 137 hydropower plants, was developed to facilitate practical climate change and other low-resolution system-wide hydropower studies. Employing recent historic hourly energy

prices, the model is used to explore energy generation in California for three climate warming scenarios (dry warming, wet warming, and warming only) over 15 years, representing a range of hydrologic conditions. While dry warming and warming-only climate changes reduce average hydropower revenues, wet warming could increase revenue. The available storage and generation capacities help compensate for snowpack losses to some extent. Storage capacity expansion and to a lesser extent generation capacity expansion both increase revenues. However, such expansions might not be cost-effective.

Keywords: climate warming, climate change, hydropower, optimization, Energy-Based Optimization Model (EBHOM), No-Spill Method (NSM), California, operation.

1. Introduction

Warming is expected over the 21st century, with current projections of a global increase of 1.5°C to 6°C by 2100 (Pew Center on Global Climate Change 2006). The potential effects of climate change on California have been widely discussed from a variety of perspectives (Lettenmaier et al. 1990; Lettenmaier and Sheer 1991; Aguado et al. 1992; Cayan et al. 1993; Stine 1994; Dettinger and Cayan 1995; Haston and Michaelsen 1997; Gleick and Chalecki 1999; Gleick 2000; Meko et al. 2001; IPCC 2001; Carpenter and Georgakakos 2001; Snyder et al. 2002; Lund et al. 2003; Miller et al. 2003; VanRheenen et al. 2004; Brekke et al. 2004; Dettinger et al. 2004; Zhu 2004; Zhu et al. 2005; Tanaka et al. 2006; Medellin et al. 2008).

Much of California has cool, wet winters and warm, dry summers, and a resulting water supply which is poorly distributed in both time and space (Zhu et al. 2005). On average, 75 percent of the annual precipitation of 584 mm occurs between November and March, while urban and agricultural demands are highest during the summer and lowest during the winter. Spatially, more than 70 percent of California's 88 billion cubic meters (bcm) average annual runoff occur in the northern part of the state (CDWR 1998). Temperature changes due to climate change can affect the amount and timing of runoff. Climate warming is expected to shift the seasonal runoff to the wet winter months with less snowmelt runoff during spring. Such a shift might hamper California's ability to store water and generate electricity for the spring and summer months if the available storage capacity is insufficient. Currently, California's large winter snowpack (often considered the largest surface water reservoir in California) melts in the spring and early summer, replenishing water supplies during these drier months. This runoff is used for irrigation, urban supplies, hydropower production, and other purposes.

An increase in temperature decreases snowpack and would shift some precipitation from snow to rain, reducing accumulated snowpack and melting it sooner. The available stream flow from snowmelt or rain can either pass the turbines immediately to generate electricity or be stored in reservoirs to produce hydropower later. The amount of water stored is limited by storage capacity. More storage capacity allows more stored water which leads to less immediate generation and more hydropower generation later when energy prices are greater. Turbine capacity also limits hydropower generation.

California relies on hydropower for 9 to 30 percent of the electricity used in the state, depending on hydrologic conditions, averaging 15 percent (Aspen Environmental Group and M. Cubed 2005). Hydroelectricity's low cost, near-zero emissions, and ability to be dispatched quickly for peak loads are particularly valuable. As climate change affects temperature and runoff, future hydrologic conditions will affect hydropower generation. Some studies have addressed the effects of climate change on hydropower generation in California, but such analyses have been largely restricted to large lower-elevation water supply reservoirs (Lund et al. 2003; VanRheenen et al. 2004; Tanaka et al. 2006), one moderate hydropower system (Vicuna et al. 2008), or have ignored the available storage capacity at high-elevation (Madani and Lund, 2007a; b). There is still a lack of knowledge about the global warming effects on statewide hydroelectricity generation by high-elevation facilities and the adaptability of California's high-elevation hydropower system to hydrologic changes.

2. California's High-Elevation Hydropower System

Current regulators of California hydropower are snowpack and reservoirs. Snowpack is controlled by nature, and reservoirs by man. As temperatures increase, the water stored in snowpack will be released earlier in the year. The vast majority of reservoir storage capacity, over 17 million acre-feet (MAF), lies below 1,000 feet elevation, while most in-state hydropower generation capacity is at higher elevations (Aspen Environmental Group and M. Cubed 2005) and mostly in northern California. Lower elevation storage

capacity is used mostly for water storage and flood control, and also produce a notable amount of hydropower. Roughly 74 percent of in-state generated hydropower is supplied by high-elevation units although only about 30 percent of in-state usable reservoir capacity is situated at high-elevation (Aspen Environmental Group and M. Cubed 2005).

The high-elevation hydropower system has less manmade storage and may be vulnerable to climate change if storage capacity cannot accommodate reduced snowpack. Most low elevation hydropower plants (below 1,000 feet) benefit from larger storage capacities and will be affected less than high-elevation hydropower generation (Tanaka et al., 2006). Energy storage and generation capacity limits at high elevation will affect the adaptability of high-elevation hydropower systems. This study investigates the potential effects of climate warming on high-elevation hydropower generation in California and the adaptability of the statewide high-elevation system as a result of changes in hydrology by application of the Energy-Based Hydropower Optimization Model (EBHOM) developed by Madani and Lund (submitted) for California's high-elevation hydropower system.

3. Method

One hundred thirty-seven high-elevation hydropower plants (above 1,000 feet) in California were identified in this study for which the historical monthly generation data were complete for the 15 year 1984 to 1998 period. Studying individual changes in generation patterns as a result of climate change for more than 130 plants by conventional simulation and optimization models would be costly and tedious, especially when basic

required information such as stream flows, turbine capacities, storage operating capacities, and energy storage capacity at each reservoir are not readily available for each individual plant. Thus, this study investigates the climate change effects and adaptations through application of the Energy-Based Hydropower Optimization Model (EBHOM) (Madani and Lund, submitted) which is based on energy flows and storage instead of water volume balances. EBHOM is a monthly-based optimization model which requires all input variables including monthly runoff, storage capacity, and generation capacity in energy units. Generally, EBHOM can be applied in any hydropower system operation study where there is relatively little effect of storage on head and there is an interest in the big picture of the system and details are of lesser importance. Madani et al. (2008) found EBHOM reliable for climate change studies by comparing the results of EBHOM's and a traditional hydropower optimization model of the Sacramento Municipal Utility District (SMUD) reservoir system developed by Vicuna et al. (2008). Both models produced similar results.

Since runoff patterns vary by elevation, three elevation ranges were considered (1,000-2000 feet, 2000-3000 feet, and above 3000 feet). Runoff data were obtained for several U.S. Geological Survey (USGS) gauges representing these elevation ranges, selected in consultation with the former California Department of Water Resources (DWR) chief hydrologist. Monthly runoff distributions were found for each elevation range (Figure 1). This figure shows the value of snowpack to the system. Runoff peaks later at higher elevations where snowpack is larger and lasts longer. Average historic monthly generation data were perturbed using monthly runoff perturbation ratios of three climate

change scenarios, the Dry Warm Scenario (GFDL A2-39), the Wet Warm Scenario (PCM A2-39) (as described by Vicuña et al., 2005), and the Warming-Only Scenario. A perturbation ratio is the ratio of the value of the flow (e.g., average monthly stream flow over the specific period) under a particular scenario (e.g. PCM A2-39) to the corresponding value of the same variable in the same month under baseline (historic) conditions. The perturbation ratios were adjusted for each elevation range. Dry and Wet climate warming scenarios result in 20 percent less and 10 percent more annual runoff at each elevation band, respectively. The warming-only scenario has the historical annual inflow volume, shifting only seasonal timing of flows differently for each elevation band. The ratios were applied to each month of historical runoff to create a climate change hydrology over a multi-year sequence. Figure 2 shows how runoff distributions change for different elevation ranges and climate scenarios. This enables investigation of overall system adaptability and how each hydropower plant might perform over a range of years with climate warming.

The available energy storage capacity at each power plant was estimated based on the No Spill Method (NSM) as explained in Madani and Lund (submitted) and tested in Madani et al. (2008). EBHOM was designed for net revenue maximization. In California, most hydropower plants are operated predominantly for net revenue maximization. EBHOM is applicable to systems in which the reservoir is used only for seasonal (as opposed to over-year) hydropower generation. Also, it requires a “high-head” condition where storage does not significantly affect hydropower head. EBHOM is solved in Microsoft Excel with “What’sBest”, a commercial solver package for Microsoft Excel. EBHOM’s

formulation can be linear (Madani and Lund, 2007b) or non-linear (Madani and Lund, 2008). The non-linear EBHOM is solved by linear programming through piecewise linearization of the concave revenue function (Madani and Lund, submitted). Linear EBHOM does not capture the effects of off-peak and on-peak energy prices on operations well. Thus, the non-linear EBHOM was used here in which, off-peak and on-peak energy prices are captured, using a method which considers the non-linear relationship between monthly generation and monthly revenue based on recorded hourly prices (Madani and Lund, submitted). Real time hourly hydroelectricity prices for 2005 (California ISO OASIS, 2007) were used in this study.

For each year from 1984 to 1988, EBHOM was run to estimate optimal monthly reservoir storage and energy generation decisions for the 137 power plants. The model was run for four different hydrologic scenarios including the base case (Historic) hydrology and three climate change hydrologies (Dry Warming, Wet Warming, and Warming-Only). Since the model optimizes decisions one year at a time, 15 years of results were used to model variations in performance over the 1984 to 1998 period. Assuming no over-year storage, release decisions in each year are independent. Figure 3 shows the range of the estimated energy storage and generation capacities of the studied high-elevation hydropower plants. The annual energy storage capacities of most of the studied power plants are at least 1.3 times larger than their monthly generation capacity, which provides some flexibility in operations. For these power plants, active storage capacity exceeds one month of generation capacity.

4. Results

Table 1 indicates how energy generation, energy spill and annual revenue change with climate scenarios. Revenue is greatest for the Wet scenario and least for the Dry scenario. Although annual inflow is 10 percent higher than the Base case for the Wet scenario, revenue is only about 2 percent higher than the Base scenario when optimized operations are applied. This is due to storage capacity limits, the system being designed to take advantage of historical snowpack, and monthly energy prices following the historical generation pattern. Thus, although generation is almost 5 percent higher under the Wet scenario, revenue is only 2 percent higher. Energy spill is greatest under the Wet scenario due to limited storage and generation capacities.

When total annual inflow does not change for the Warming-Only scenario (shifting only runoff timing), total revenue is reduced by about 1 percent due to limited storage capacity and some limited generation capacity, and spills greatly increase over the Base case. The timing of snowmelt and the form of precipitation (as snow or rain), in addition to total runoff volume, significantly affect generation patterns and overall quantity and value. When storage capacity cannot store the peak flow from snowpack melt for release in high-value months, revenues are reduced as a result of energy spill or generation in months when energy prices are not the highest. However, some storage capacity is available to handle the extra winter runoff under a warmer climate. This provides some flexibility in operations to store winter water to be released when energy demand is higher. As a result, although annual inflow under the Dry scenario is 20 percent less than

in the Base case, Dry scenario revenues are reduced by about 12 percent even though the energy generation reduction under this scenario is greater than 19 percent. Energy spills under this scenario increase relative to the Base case during peak runoff months, causing some off-peak generation losses.

4.1. Generation Changes with Climate Warming

Figure 4 shows average monthly energy generation for 1984 to 1998 hydrologic conditions, modified for different climate changes. Results are summed from all 137 power plants modeled in this study. Generally, model results suggest less generation in months with lower average energy prices to store energy for months with higher energy prices. Summer generation always is less than the Base case under all three climate warming scenarios. Generation under the Wet and Warming-Only scenarios is higher than the Base scenario from January to April due to increased runoff peaks and limited capacity to store this shift in peak runoff. If more storage capacity were available, there would be less likelihood of water bypassing turbines (“spills”) from January to April. Instead, this water would be stored and released in summer, reducing generation in late winter and early spring to increase summer generation (when prices are higher). Generation under the Dry scenario is almost always less than generation under the Base scenario. From January to March, when the runoff peaks occur, Dry scenario generation is close to Base scenario generation.

Figure 5 shows the frequency of optimized monthly generation for each month over the 15 year period (1984-1998) summed for all units, under different climate hydrologies. Dry climate warming results in considerably less generation than Base generation in over 85 percent of months over the 15 year period, with almost similar levels occurring in the remaining 10 to 25 percent of the months. Under the Wet and Warming-Only scenarios, generation is slightly less than or equal to the base case 80 percent of the time. It greatly exceeds Base generation 20 percent of the time. If more storage capacity were available, generation frequency curves under Wet and Warming-Only scenarios could be closer to the Base scenario, with higher revenues. Generation curves under Wet and Warming-Only scenarios exceed the Base case 20 percent of the time when storage capacity cannot store more wet winter flows for summer and spring generation, forcing operators to release up to the turbine capacity or spill excess flows as reservoirs fill in January to April.

4.2. Reservoir Storage Changes with Climate Warming

Figure 6 shows how average end-of-month energy storage in all reservoirs combined changes with climate when reservoirs are operated for energy revenues only. Under the Base scenario, reservoirs reach their minimum storage level by the end of January to prepare to capture expected inflow from winter precipitation and later spring snowmelt. On average, reservoirs are full by June and gradually emptied for energy generation over the summer when energy prices are higher and there is little natural inflow. Under historical conditions, refill starts in January and drawdown starts in June. Although

climate warming results do not appear to change these cycles much, snowpack loss generally increases average reservoir storage (stored energy) between February and May than in the Base case. With dry climate warming, energy storage peaks earlier and drawdown begins a month earlier.

4.3. Energy Spills with Climate Warming

Figure 7 shows the frequency of total monthly energy spill from the system for the study period when the system is optimized for revenue maximization. Energy spill results from runoff that can be neither stored nor sent through turbines because of limited capacities. Energy spill is the equivalent energy value of the available runoff water which cannot contribute to energy production at each site. Energy is spilled by the system in 30 percent of months under all climate scenarios, including the Base scenario. However, the magnitude of spills increases for Wet and Warming-Only scenarios, and decreases for the Dry scenario. Existing storage capacity cannot compensate for the loss of snowpack during wetter years, and overall earlier snow melt, but appears able to compensate in drier years.

What is calculated as energy spill in this study is the increased historic energy spill, because annual historical generation (actual recorded output of the system) in each year during 1984 to 1994 period was used as the annual energy input to calibrate the hydropower system model, for which spill data are unavailable. However, the calculated energy spill under the historic scenario is only 0.002 percent of total generation.

Figure 8 shows the distribution of total average monthly energy spill under different climate scenarios. Under the historic climate scenario, energy spills occur from December to June when inflow to the system peaks. The changes in the magnitude and timing of spills under different climate warming scenarios indicate the importance of runoff inflow timing and magnitude to the performance of this system.

Figure 9 plots the frequency curve of total annual spill from the system for the study period. Energy does not spill under the Base scenario for most years. Annual energy spill frequency and magnitude both increase with Wet and Warming-Only scenarios and decrease with Dry warming. As more precipitation falls as rain than snow and snow melts sooner at high elevation under climate warming, annual energy spills increase in both size and frequency as monthly runoff distribution patterns and annual volumes no longer match well with existing storage and generation capacities. Most energy spill occurs under the Wet scenario, in more than 80 percent of years. Under the Warming-Only and Dry scenarios, energy spills in more than 70 and 50 percent of years, respectively.

4.4. Revenue and Energy Price Patterns under Climate Warming

Figure 10 indicates the climate warming effects on monthly average price for generated energy. Climate warming generally increases average energy prices in more than 60 percent of months. As expected, the rise in prices is highest with dry climate warming

(given the non-linear relationship between electricity price and generation quantity). Under this scenario prices are higher than the base case more than 90 percent of the time. Average received energy price frequency curves for Wet and Warming-Only scenarios show similar behavior, highlighting the importance of runoff timing over quantity for optimal system operations.

Figure 11 shows the effects of climate warming on the frequency of total annual revenues of all 137 hydropower plants studied for the period 1984 to 1998. Although monthly average prices received for generated energy were higher under the Dry scenario, the increase in prices does not compensate for the Dry scenario reduction in total energy generation. Annual revenue under the Wet scenario exceeds Base scenario revenue in 60 percent of years but is almost the same during the rest of the time. Annual revenue under the Warming-Only scenario is similar to the Base scenario.

In this study, the effects of climate warming on energy demand were neglected. To improve the estimations, in future, the effects of climate change on energy demand can be studied by defining different relationships between energy generation quantity and energy price for various scenarios (Madani and Lund, submitted).

4.5. Benefits of expanding energy storage and generation capacity

Figure 12 shows, on average, how energy storage capacity expansion changes hydropower generation revenues under different climate scenarios over the study period

(15 years). This figure indicates the average shadow price of energy storage capacity (the increase in annual revenue per 1 MWh energy storage capacity expansion) for all 137 reservoirs. For instance, increase in annual revenue per 1 MWh energy storage capacity expansion is less than \$5 for 103 of the studied power plants under the Dry scenario. Storage capacity expansion reduces spills and allows for more release in summer when energy prices are higher. Storage capacity expansion can increase average annual revenues for almost all hydropower plants under all climate scenarios, but such expansion might not be justified due to expansion costs. As expected, benefits of capacity expansion are greater for Wet and Warming-Only scenarios. The annual marginal benefit of storage capacity expansion is greatest under the Wet scenario when more energy is available to store. Even with the historical hydrology, expanding storage capacity increases total annual revenues in all years because more storage capacity allows for more flexible operations needed to generate more energy during peak price times. While about 100 hydropower plants benefit more from energy storage capacity expansion under the Base scenario than the Dry scenario, the other 37 hydropower plants benefit more from energy storage capacity expansion under the Dry scenario than the Base scenario.

Figure 13 indicates the average shadow price of energy generation capacity (the increase in annual revenue per 1 MWh of monthly energy generation capacity expansion) for all 137 plants under different climate scenarios. Generation capacity expansion does not increase the annual revenues of about 90 hydropower plants under the Base and Dry scenarios. About 50 of the studied hydropower plants do not need energy generation capacity expansion under all types of climate warming, meaning that those units do not

experience energy spill at all even with warmer climates. Although generation capacity expansion produces benefits, expansion costs might be prohibitive. Similar to storage capacity expansion, benefits of energy generation capacity expansion are higher under Wet and Warming-Only than Base and Dry scenarios. Comparison of Figures 12 and 13 shows that energy storage capacity expansion is typically more beneficial than energy generation capacity expansion if the expansion costs are the same.

5. Limitations

Models are not perfect and optimized results are optimized to particular conditions and objectives. During model development many simplifying assumptions are made which should be considered in interpreting the results. However, simulation and optimization models are useful in studying resource management problems. Here, the results give some insights on how the system works and how it might adapt under different climate warming scenarios.

Calibration of EBHOM for this study (Madani and Lund, submitted) is likely to underestimate energy storage capacities and therefore also underestimate adaptability of the system to climate change. Availability of spill or energy storage capacity data would reduce this source of error.

California is big and variable in hydrology. Assuming the same seasonal pattern for inflows in north and south at the same elevation will cause some inaccuracies. A 1000

feet range covers a great variability in hydrology. Smaller elevation ranges might increase the accuracy of the estimation. Since many power plants are in the 3000-4000 feet elevation range, it might be worthwhile to study this range separately. Also, more gauges might be considered for each elevation range.

As a first step in studying the adaptability of California's high-elevation hydropower system to climate warming, this study looks at flexibility of operations without considering environmental constraints.

Here, energy prices were imposed on each individual power plant. Instead, total demands might be imposed to the system of one hundred thirty-seven plants. This gives more flexibility in operation and reaction of the system. High-elevation plants at lower elevations which receive the peak flows earlier can generate more in earlier months while higher plants generate more, later during the year. Although the timing of flow will change, there is still a difference in flow patterns at different elevation ranges which benefits the system if operated wisely. By integrating operations of individual hydropower systems that span different watersheds and elevation bands, greater operational flexibility to respond to changes in climate, streamflow, and runoff may be possible.

With climate warming, demands are likely to increase in warmer months from higher temperatures. This could affect energy prices. EBHOM employed recorded real-time energy prices for finding revenue curves which define the relation between monthly

energy generation and energy price. The prices used here are from 2005 which do not exactly match energy prices of the 1984 to 1995. This might cause some inaccuracies in EBHOM's estimation of revenues and energy prices. However, this limitation might not affect the other results (generation, spill, and storage) much as the energy price trends are similar over the years of study. Application of price data sets which are longer than one year in future might improve the accuracy of model results.

For this application we assume inflow distributions adhere to a fixed seasonal pattern. Inflow distributions are likely to be more local and vary more between years. Here, the model optimizes revenue based on its perfect information about the year's hydrological pattern. Such management is impossible in practice.

6. Conclusions

In absence of detailed information about the available energy storage capacity at high-elevation in California, this study applied a simple low-resolution approach for estimating the adaptability of California's high-elevation hydropower generation to climate warming. Substituting the estimated energy content of runoff water inflows and storage for these relatively high-head hydropower units and estimating seasonal inflow distribution patterns by elevation band allowed preliminary optimization-driven monthly system operations modeling of more than 137 hydropower plants with various climate changes.

With climate warming, California loses snowpack which has functioned historically as a natural reservoir to delay runoff, but considerable energy storage and generation capacity remaining available. The EBHOM's results show that most extra runoff in winter months from climate warming can be accommodated by the available storage capacity at high-elevation sites for average years. Lower-elevation reservoirs, constructed primarily for water supply, already have substantial re-regulation capacity for seasonal flow adjustments (Tanaka et al. 2006). However, operating rules should change with climate warming to adapt the system to changes in hydrology (Medellin et al. 2008).

Generally, climate warming alone reduces high-elevation hydropower generation and revenue, without changes in total runoff, due solely to changes in seasonal runoff timing. Energy spills increase dramatically under Wet and Warming-Only scenarios with existing storage and generation capacities. More storage capacity would increase revenues but might not be cost effective. Storing water in reservoirs helps shift energy runoff reductions to months with lower energy prices to reduce economic losses. More generation capacity also increases revenues by reducing energy spill. Annual marginal benefits of capacity expansion are higher for storage than for generation. Nevertheless, current storage and generation capacities give the system some flexibility to adapt to climate change. Although the Dry scenario examined in this study has 20 percent less runoff than the base historical hydrology, system-wide, revenues decrease by less than 12 percent through optimally re-operating storage and generation facilities within existing capacity limits. Thus, the current storage and generation capacities can compensate for

some snowpack loss, and for the Wet and Warming-Only scenarios with very little revenue decrease.

Limited capacities cannot take full advantage of increased energy runoff under the Wet scenario. The Wet warming scenario examined here has 10 percent more runoff than the historical hydrology, but only 5 percent more generation and 2 percent more average annual revenues. In a Warming-Only scenario with unchanged historical precipitation, generation and revenues decrease by 1.4 and almost 1 percent, respectively.

This study required some simplifying assumptions. Nevertheless, it gives insights and suggests some degree of adaptive capability to climate warming. Future studies should address environmental and other constraints, include demand and price impacts of climate change, and apply refined estimates of varied hydrologic changes from climate change across California.

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Table 1. EBHOM’s results (average of results over 1984-1988 period) for different climate scenarios

	<i>Base</i>	<i>Dry</i>	<i>Wet</i>	<i>Warming-Only</i>
Generation (1000 GWH/yr)	22.3	18.0	23.4	22.0
<i>Generation Change with Respect to the Base Case (%)</i>		- 19.3	+ 4.8	- 1.4
Spill (MWH/yr)	433	224	1,661	735
<i>Spill Change with Respect to the Base Case (%)</i>		- 46.0	+ 283.9	+ 58.8
Revenue (Million \$/yr)	1,449	1,271	1,483	1,435
<i>Revenue Change with Respect to the Base Case (%)</i>		- 12.3	+ 2.3	- 0.9

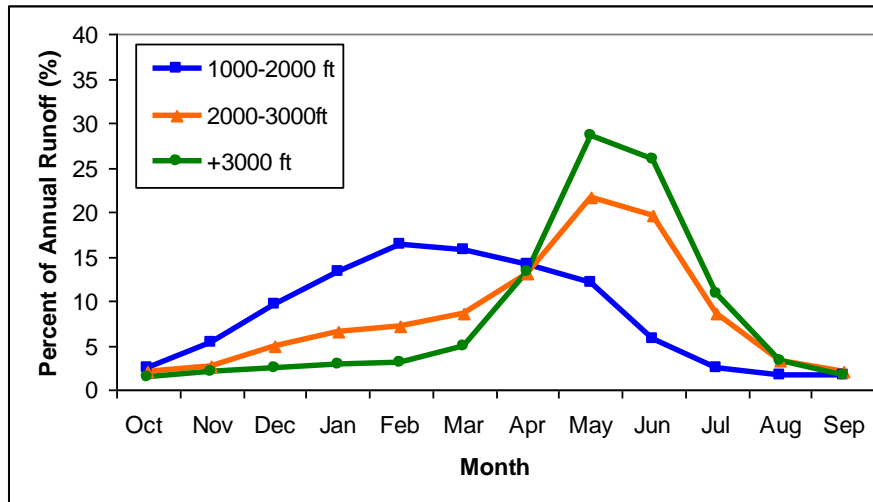
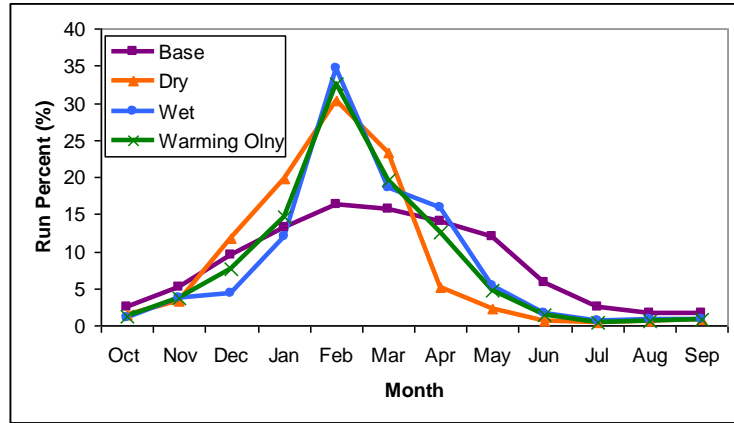
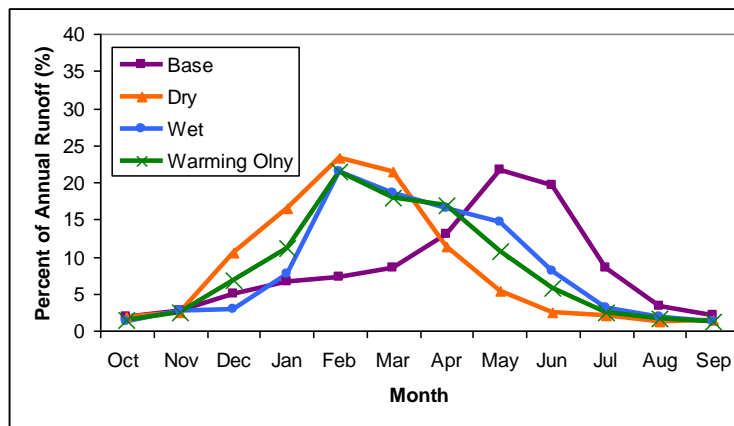


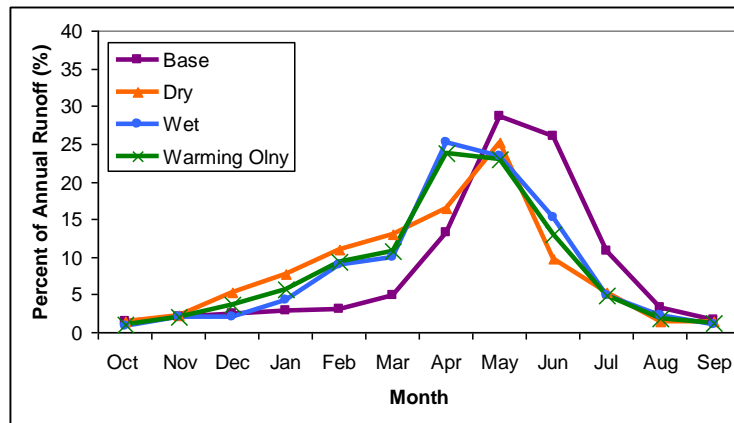
Figure 1. Monthly runoff distributions at different elevation ranges



a) 1000-2000 ft



b) 2000-3000 ft



c) + 3000 ft

Figure 2- Monthly runoff distributions for different climate change scenarios and elevation ranges

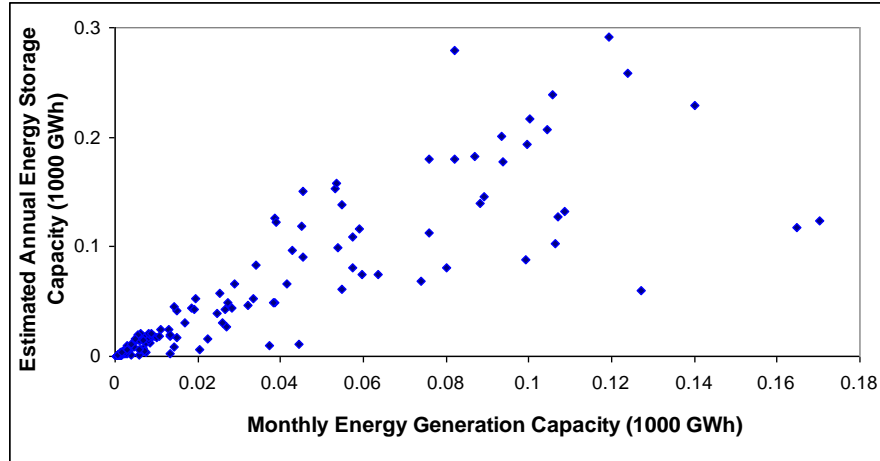


Figure 3. Range of the estimated energy storage and generation capacities of the 137 studied high-elevation hydropower plants in California

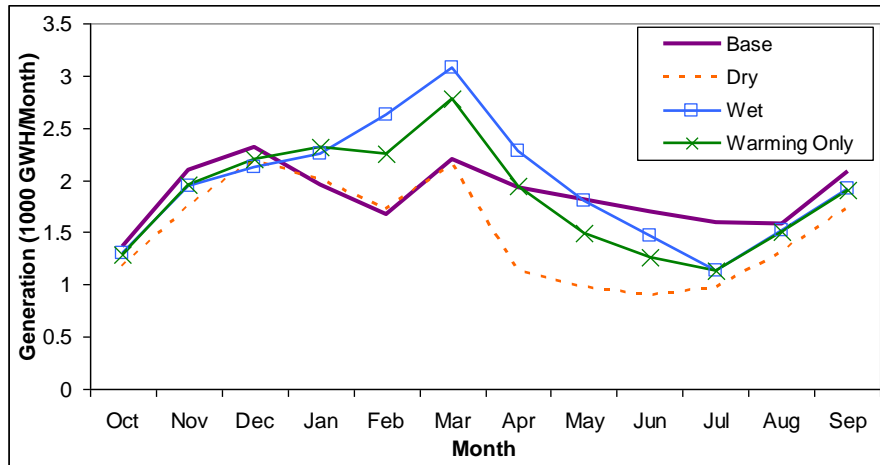


Figure 4. Average monthly generation (1984-1998) under different climate scenarios

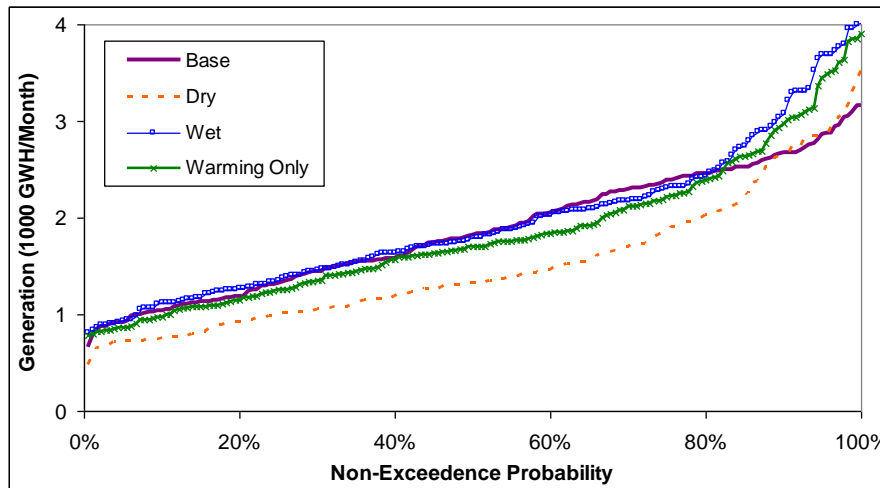


Figure 5. Frequency of optimized monthly generation (1984-1998) under various climate scenarios (all months, all years, all units)

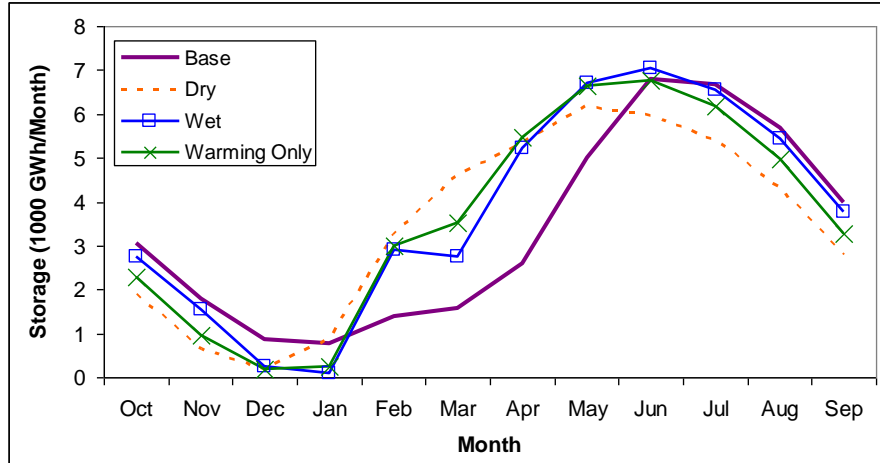


Figure 6. Average total end-of-month energy storage (1984-1998) under different climate scenarios

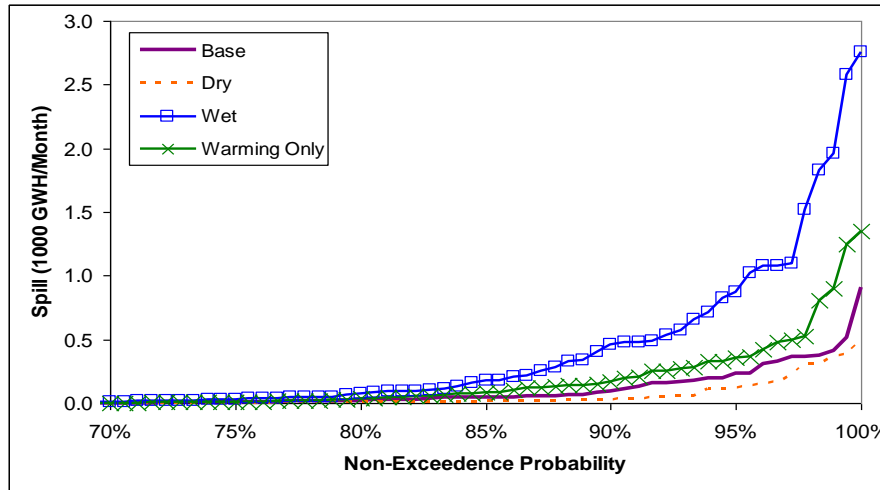


Figure 7. Frequency of total monthly energy spill (1984-1998) under different climate scenarios (all months, all years, all units)

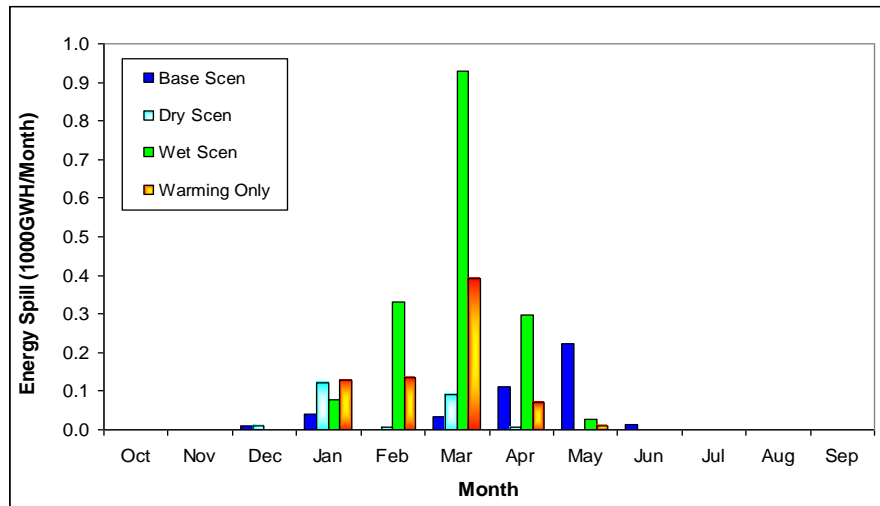


Figure 8. Average monthly total energy spill (1984-1998) under different climate scenarios

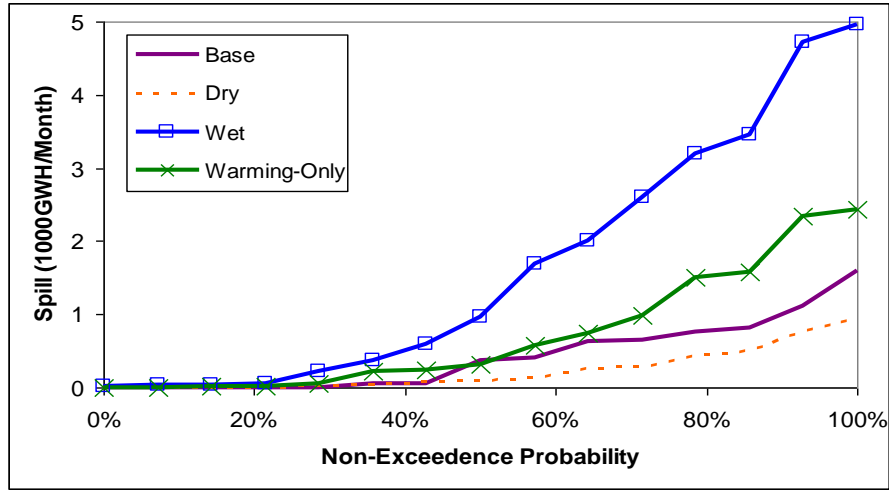


Figure 9. Frequency of total annual energy spill (1984-1998) under different climate scenarios (all years, all units)

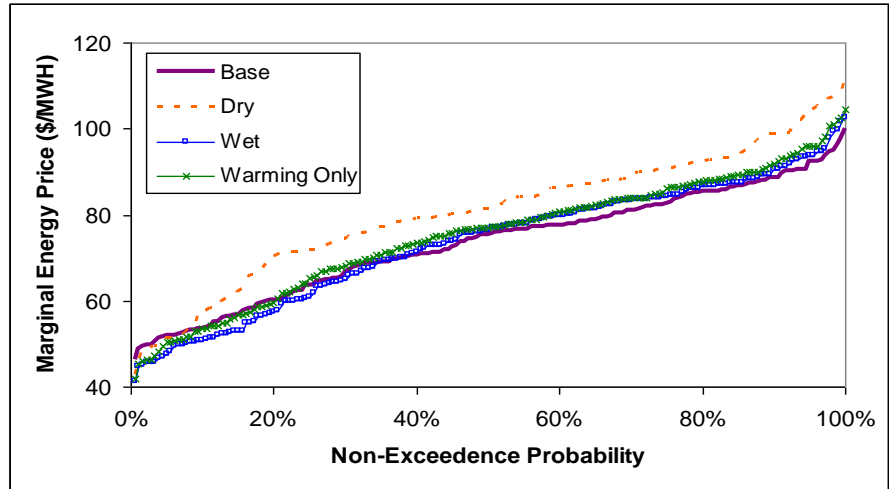


Figure 10. Frequency of monthly energy price (1984-1998) under different climate warming scenarios (all months, all years, all units)

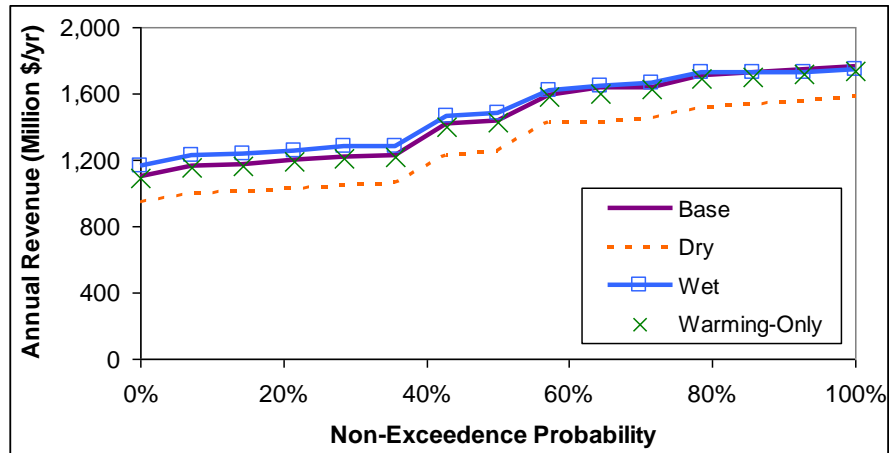


Figure 11. Frequency of total annual revenue (1984-1998) under different climate scenarios (all years, all units)

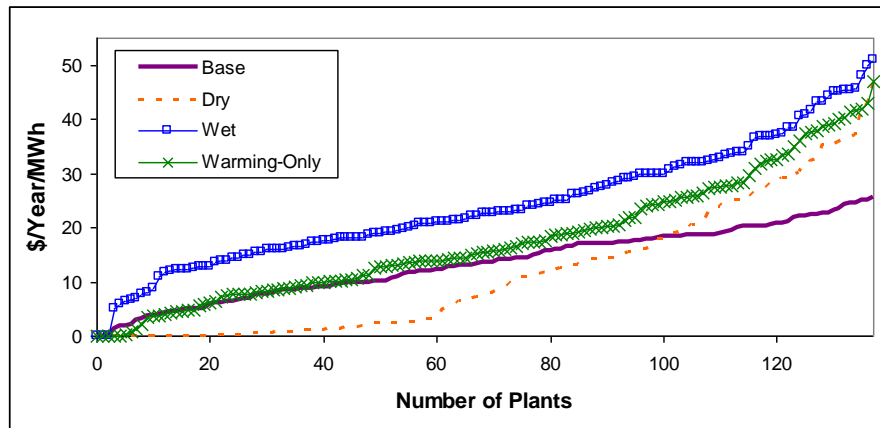


Figure 12. Average shadow price of energy storage capacity of 137 hydropower units in California in the 1984-1998 period under different climate scenarios

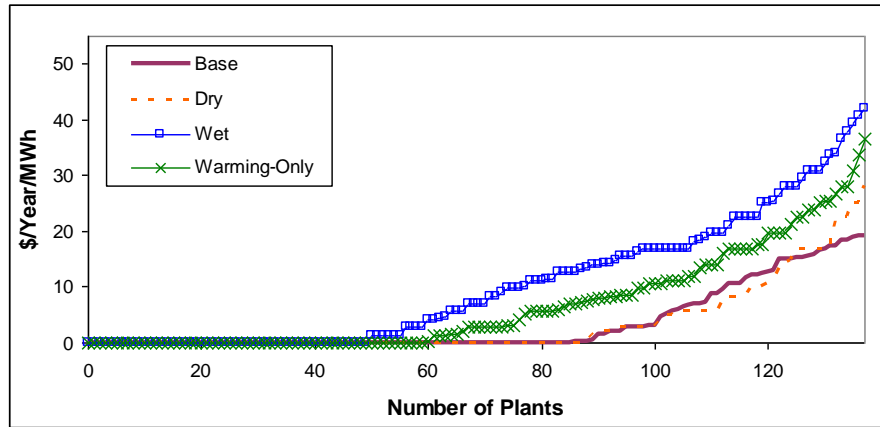


Figure 13. Average shadow price of energy generation capacity of 137 hydropower units in California in the 1984-1998 period under different climate scenarios

1 **Modeling California’s High-Elevation Hydropower Systems in Energy Units**

2
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8 **Abstract**

9 This paper presents a novel approach for modeling of high-elevation hydropower systems.
10 Conservation of energy and energy flows (rather than water volume or mass flows) are used as
11 the basis for modeling more than 130 high-elevation high-head hydropower sites throughout
12 California. The unusual energy basis for reservoir modeling allows for development of
13 hydropower operations models for a large number of plants to estimate large-scale system
14 behavior without the expense and time needed to develop traditional streamflow and reservoir
15 volume-based models in absence of storage capacity, penstock head, and efficacy information.
16 Potential applications of the developed Energy-Based Hydropower Optimization Model
17 (EBHOM) include examination of the effects of climate change and energy prices on system-
18 wide generation and hydropower revenues.

19
20 **Keywords:** hydropower, high-elevation, electricity, optimization, reservoir operation, climate
21 change, California.

24 **1. Introduction**

25 Hydroelectric power's low cost, near-zero pollution emissions, and ability to quickly respond to
26 peak loads make it a valuable renewable energy source. In the mid-1990s, hydropower was
27 about 19 percent of world's total electricity generation (Lehner et al., 2005). Worldwide
28 hydroelectric generation from 1990 to 2020 could grow at an annual rate between 2.3 to 3.6
29 percent (European Commission, 2000; Lehner et al., 2005).

30

31 Depending on hydrologic conditions, hydropower provides 5 to 10 percent of the electricity used
32 in the United States (National Energy Education Development Project, 2007) and almost 75
33 percent of the nation's electricity from all renewable sources (EIA, 2005; Wilbanks et al., 2007).
34 No electricity generation source is cheaper than hydropower. While it costs almost 4 cents and 2
35 cents to generate one kilowatt-hour (kWh) of electricity at coal plants and nuclear plants,
36 respectively, hydropower generation typically costs only about 1 cent per kWh (National Energy
37 Education Development Project, 2007).

38

39 About 75,000 megawatts of hydropower generation capacity exist in the U.S., equivalent
40 capacity to 70 large nuclear power plants (National Energy Education Development Project,
41 2007). More than half of U.S. hydroelectric capacity is in the western states of Washington,
42 California and Oregon, with approximately 27 percent in Washington (EIA, 2007).
43 Hydropower facilities in the U.S. are diverse. Facilities range from multi-purpose dams with
44 large reservoirs to small run-of-river dams with little or no active water storage (National Energy
45 Education Development Project, 2007). Plant elevations also vary. In California multi-purpose

46 dams are usually at lower elevations than plants served by reservoirs operating primarily for
47 hydropower.

48

49 California relies on hydropower for 9 to 30 percent of the electricity used in the state, depending
50 on hydrologic conditions (Aspen Environmental Group and M. Cubed 2005). California's high-
51 elevation hydropower system is composed of more than 150 power plants, above 305 meters
52 (1,000 feet) elevation. This system, which mostly relies on snowpack, supplies roughly 74
53 percent of California's in-state hydropower, although only about 30 percent of in-state usable
54 reservoir capacity is at high elevations, above 305 meters (Aspen Environmental Group and M.
55 Cubed 2005). The high-elevation reservoirs are predominantly single-purpose reservoirs for
56 generating hydropower (Aspen Environmental and M-Cubed, 2005, Vicuna et al., 2008) with
57 some secondary benefits such as flood control. These reservoirs which are mostly privately-
58 owned are regulated by U.S. Federal Energy Regulatory Commission (FERC) and operated for
59 hydropower revenues only. The high-elevation hydropower plants are generally located below
60 small (within-year storage) reservoirs with high turbine heads compared with much larger multi-
61 purpose reservoirs with low-turbine head downstream (lower elevations).

62

63 California's Mediterranean climate has one wet season and a long dry season. On average, 75
64 percent of the annual precipitation occurs between November and March. These single-purpose
65 reservoirs (except for few such as Lake Almanor) are always emptied by the end of the
66 hydrologic year (September) to capture fall and winter precipitation and spring snowmelt. Since
67 electricity prices are high in summer, it is reasonable to generate and sell hydropower instead of
68 risking energy spill in the wet season when energy prices are lower. Therefore, only one major

69 drawdown-refill cycle per year typically occurs for hydropower and water supply operations in
70 California.

71

72 Hydropower generation varies greatly from year to year with varying inflows, as well as
73 competing water uses, such as flood control, water supply, recreation, and in-stream flow
74 requirements (for water rights, navigation, and protection of fish and wildlife) (National Energy
75 Education Development Project, 2007). Given hydropower's economic value and its role in
76 complex water systems, it is reasonable to seek optimal operation of hydropower generation and
77 adaptation to changing conditions. Optimization models are common for studying the
78 performance of hydropower systems under different conditions and for deriving reservoir
79 operating policies. Conventional simulation and optimization methods used for hydropower
80 systems (Grygier and Stedinger, 1985; Arnold et al, 1994; Vicuna et al., 2008) are quite useful
81 but their application to extensive hydropower systems is intensive and costly. For instance, there
82 are 2,388 hydropower plants in the U.S., of which 411 plants are located in California (Hall and
83 Reeves, 2006). Studying climate change effects on hydropower generation in the U.S. or even in
84 California through conventional detailed modeling of each system requires large investments of
85 time and money, especially when basic information such as stream flows, turbine capacities,
86 storage operating capacities, and energy storage capacity are not readily available for each plant.
87 Given the proprietary nature of most existing hydropower models and data, there is value for a
88 less-detailed method of modeling extensive hydropower systems lacking detailed information.
89 The objective of this paper is to introduce a new method for studying optimal operation of high-
90 elevation systems, which operate predominantly for hydropower, with high head and negligible
91 over-year storage, in absence of detailed information about the system,

92

93 Energy-based modeling of single-purpose hydropower systems is presented, along with
94 application to 137 hydropower plants throughout California. We begin with the general model
95 formulation, followed by novel methods for estimating the energy storage capacity of
96 hydropower units and representing hourly-varying prices in reservoir models at larger time
97 scales. A small change in the formulation is introduced for cyclic seasonal operations.
98 Comparison of model generation estimates is made with the historic generation in an average
99 hydrologic year at a particular facility in California (Loon Lake). Discussion of the general
100 estimation of parameters for 156 hydropower plants in California is made. Then the model is
101 applied to estimate optimal monthly energy generation at 137 hydropower plants in California
102 for a 15 year period. The paper concludes with a discussion of potential applications, limitations,
103 and conclusions. The primary advantage of this approach is to develop policy and operational
104 insights for large numbers of hydropower plants where traditional reservoir model development
105 and estimation would be prohibitively costly and time consuming.

106

107 **2. Energy-Based Hydropower Optimization Model (EBHOM)**

108 Unlike conventional models, where calculations are in volumetric units, the Energy-Based
109 Hydropower Optimization Model (EBHOM), introduced here, is a monthly-step model which
110 does all storage, release, and flow calculations in energy units. EBHOM is developed to
111 investigate the performance of the system under different conditions and can contribute to
112 studies in which the active storage capacity data and penstock head information are unavailable.
113 In such studies, energy storage capacity for each unit can be calculated based on differences in

114 seasonal water inflow distribution and energy generation data. EBHOM can then be applied to
 115 explore the optimal operation of the system for different scenarios.

116

117 Most high-elevation hydropower plants operate for net revenue maximization (Jacobs et al.,
 118 1995). Lower elevation plants tend to operate for a greater variety of purposes. Since
 119 hydropower operating costs are essentially fixed (at monthly scale), an operational surrogate for
 120 net revenue maximization is revenue maximization. EBHOM's simple general mathematical
 121 formulation (in energy units) is:

$$122 \quad \text{Maximize } Z = \sum_{i=1}^{12} P_i \times G_i \quad (1)$$

123 Subject to:

$$124 \quad S_1 = 0 \text{ (initial condition)} \quad (2)$$

$$125 \quad S_i \leq Scap \text{ (storage capacity), } \forall i \quad (3)$$

$$126 \quad S_i = e_{i-1} + S_{i-1} - R_{i-1} \text{ (conservation of energy), } \forall i \quad (4)$$

$$127 \quad G_i \leq R_i, \forall i \quad (5)$$

$$128 \quad G_i \leq Gcap \text{ (generation capacity constraint), } \forall i \quad (6)$$

$$129 \quad G_i, S_i, R_i \geq 0 \text{ (non-negativity), } \forall i \quad (7)$$

$$130 \quad (i = 1, 2, 3, \dots, 12)$$

131

132 where Z = revenue; G_i = hydropower generation in month i (MWh/month); P_i = price of
 133 electricity in month i (\$/MWh); S_i = energy storage at the beginning of month i (MWh); $Scap$ =
 134 energy storage capacity (MWh); e_i = energy runoff in month i (MWh); R_i = energy release from
 135 the reservoir in month i (MWh/month) (decision variable); $Gcap$ = generation capacity

136 (MWh/month); and $i = 1$ corresponds to the first month of the refill cycle with energy storage at
137 the beginning of this month set equal to zero (Equation 2).

138

139 This formulation is valid when the reservoir is used only for hydropower generation, and
140 primarily for seasonal (as opposed to over-year) storage. The formulation also requires a “high-
141 head” condition where storage does not significantly affect hydropower head.

142

143 **3. Estimating Seasonal Energy Storage Capacity**

144 Normal estimation of a reservoir’s energy storage capacity involves integrating the potential
145 energy content over all reservoir elevations, presuming detailed knowledge of penstocks,
146 reservoir geometries, and bank storage. Obtaining storage capacity data and penstock head
147 information for many individual reservoirs is a big obstacle in large-scale hydropower systems
148 modeling, especially if they belong to private owners with proprietary interests in information.
149 Even if volumetric storage capacities were available, conventional estimation of energy storage
150 capacities (that portion of the capacity storing water for electricity generation) would have been
151 tedious and probably unreliable. To estimate the energy storage capacity of each power plant, it
152 is assumed that the existing storage and release capacities of a high-elevation hydropower
153 reservoir are sufficient to operationally accommodate the historical runoff in an average water
154 year without water spilling from the reservoir.

155

156 The proposed No Spill Method (NSM) estimates seasonal energy storage capacity under the
157 following conditions:

158 1. The reservoir does not spill energy in the average year, and all releases are made through
159 the turbines. Energy spill results from runoff lost from the system because it can be neither
160 stored nor sent through the turbines due to limited storage and turbine capacities. Energy
161 spill is the equivalent energy value of the available runoff which cannot contribute to
162 energy production at a site. For California, this lack of spill in an average year was
163 confirmed in conversations with the private hydropower operators of most high-elevation
164 plants in California. This condition sets a lower bound for storage capacity estimation.
165 Actual reservoir capacity will exceed this lower bound if the reservoir does not fill in an
166 average year. However, for calculation purposes it is assumed that the reservoir fills in an
167 average year. This makes the approach pessimistic.

168 2. The power plant is a high-head facility, where the effect of reservoir storage level on
169 turbine head is small. Generally, turbine head in high-elevation hydropower facilities is
170 mostly from large penstock drops, rather than additional elevation within the reservoir.
171 This allows a linear relationship between the amount of water stored in the reservoir and
172 energy stored, and seems common for many proprietary models for this system.

173 3. The seasonal distribution of inflow is known. Average seasonal flow distributions from
174 nearby gages are used here to reflect seasonal runoff and snowmelt conditions.

175 4. There is only one major drawdown-refill cycle per year. Hydropower reservoirs typically
176 fill once each year in California.

177 High-elevation hydropower facilities usually have a within-year storage pool and mostly have
178 watersheds above 305 meters 1,000 feet. In California, many of these systems rely on snowpack
179 to increase the seasonal storage of the system.

180

181 The NSM estimates seasonal storage capacity in energy units by finding the area between the
182 monthly runoff and monthly generation curves when both are expressed as monthly percentages
183 of the annual average quantity. In month i , the runoff percentage ($runoffPercent_i$) and generation
184 percentage ($genPercent_i$) can be calculated by dividing the average monthly runoff in month i
185 ($average\ runoff_i$) and the average monthly generation in month i ($average\ generation_i$) to the
186 average annual runoff ($average\ annual\ runoff$) and the average annual generation ($average$
187 $annual\ runoff$), respectively.

$$188 \quad runoffPercent_i = \frac{average\ runoff_i}{average\ annual\ runoff} \quad (8)$$

$$189 \quad genPercent(i) = \frac{average\ generation(i)}{average\ annual\ generation} \quad (9)$$

190 In percentage terms, the sum of differences between the two curves for a year (12 months)
191 should be zero.

$$192 \quad \sum_{i=1}^{12} (runoffPercent_i - genPercent_i) = 0 \quad (10)$$

193 In the 12 month period there are months i when the runoff percentage exceeds the generation
194 percentage value (when some runoff is stored in the reservoir) and months j when the generation
195 percentage exceeds the runoff percentage (when some hydropower is generated by releasing
196 stored water).

$$197 \quad \sum_i (runoffPercent_i - genPercent_i) - \sum_j (genPercent_j - runoffPercent_j) = 0 \quad (11)$$

198 So, if there is only one refill-drawdown cycle per year, little over-year storage, and the reservoir
199 is on the verge of spilling at its fullest, the seasonal storage capacity ($StorCapPercent$) as a
200 percent of total inflow is (Figure 1):

201
$$StorCapPercent = \sum_i (runPercent_i - genPercent_i) \quad (12)$$

202 or:

203
$$StorCapPercent = \sum_j (genPercent_j - runoffPercent_j) \quad (13)$$

204 Multiplying the storage capacity percentage (*StorCapPercent*) by the average annual generation
205 gives the active (operational) energy storage capacity (*Scap*).

206
$$Scap = StorCapPercent \times average\ annual\ generation \quad (14)$$

207 Multiplying the storage capacity percentage by the average annual runoff gives the volumetric
208 active (operational) water storage capacity (*WScap*) which is directly used for hydropower
209 generation.

210
$$WScap = StorCapPercent \times average\ annual\ runoff \quad (15)$$

211 Significantly, this method produces a lower bound estimate of energy storage capacity, as many
212 reservoirs will not spill or fill in wetter than average years. The NSM also assumes reservoirs
213 have negligible over-year storage, which is true for high-elevation hydropower reservoirs in
214 California with a few exceptions (such as Lake Almanor in California).

215

216 Figure 1 shows how the active storage capacity of the Buck Island (also known as Rubicon or
217 Loon Lake) Reservoir, with the storage capacity of 96 million cubic meters (mcm) (or 78
218 Thousand Acre-Feet (TAF)), located above Loon Lake Hydropower Plant with generation
219 capacity of 38 GWh per month and Average Annual Generation of 104 GWh in California was
220 estimated using NSM. Monthly generation data was available for the years 1984 to 1998.
221 Monthly runoff (inflow) data was obtained for the same period from U.S. Geological Survey
222 (USGS) gauges. The mean monthly and mean annual runoffs were estimated for the study

223 period. Mean monthly runoff and mean monthly generation values were then normalized into
224 percent of mean annual runoff (Equation 8) and mean annual generation (Equation 9),
225 respectively, as shown in Figure 1. Based on Equation 12 or 13, the shaded area between the
226 two curves (29 percent) represents the storage capacity as a percentage of total generation or
227 flow (*StorCapPercent*). Active storage capacity of this reservoir (the portion of actual energy
228 storage capacity used for storing water for hydropower) was found to be 31 GWh based on
229 Equation 14 and 13.6 mcm (11 TAF) based on Equation 15.

230

231 At a monthly time scale, several stair-stepped power houses (in series) might benefit from water
232 storage in one upstream reservoir. When one powerplant draws water from several upstream
233 reservoirs (in parallel or series) the energy storage calculated for the powerplant will reflect the
234 total effective energy storage upstream of the plant. For instance for 2 reservoirs in series, the
235 effective storage capacity belonging to the power station located below the second (lower)
236 reservoir is determined based on the difference between the undisturbed (natural) runoff to the
237 first reservoir and the energy outflow from the second powerplant. In that case, the calculated
238 storage capacity is equal to the effective storage capacity of the lower reservoir plus the portion
239 effective storage capacity of the upper reservoir used for regulating the inflow to the lower
240 reservoir. Indeed, in this case the difference between the runoff and generation curves could be
241 smaller if there was no up-stream reservoir. However, when an upstream reservoir exists, energy
242 is stored in the upper reservoir for some period, so the total effective storage capacity is higher
243 than the effective storage capacity of the lower reservoir. This can become a more complicated
244 issue, as inflows for downstream powerplants might be dominated by releases from upstream
245 plants, not the assumed monthly inflow distribution for the powerplant. Ultimately, this is one of

246 the limitations of such coarse less-detailed modeling. Incorporating such effects would require
247 much greater modeling effort, which we needed to avoid here.

248

249 **4. Energy Price Representation**

250 If fixed monthly energy prices are used in Equation 1, EBHOM is linear as done in studies by
251 Vicuna et al. (2008), and Madani and Lund (2007). However, if fixed monthly energy prices are
252 used, while maximizing revenue, the model suggests no generation in months with low energy
253 prices to allow more generation in months with higher average prices, within storage capacity
254 limits (Madani and Lund, 2007). In real electricity markets, prices fluctuate hourly and marginal
255 revenues of generation decrease with increased hours of generation. Linear EBHOM (monthly
256 basis model) does not capture the varying nature of energy prices and the considerable effects of
257 on-peak and off-peak pricing on the revenues. Considering on-peak and off-peak monthly prices
258 in the linear model (Vicuna et al., 2008) captures some effects of non-constant energy prices. It
259 is possible to capture the varying nature of energy prices by linear EBHOM if it is formulated on
260 an hourly basis. However, such a model takes much more time as it requires 730 times more
261 decision variables (with 730 hours in average month). To decrease calculation time and effort,
262 EBHOM can be formulated on a monthly basis as a concave non-linear problem to represent on-
263 peak and off-peak price variability, with a revised objective function (Equation 1) as follows:

$$264 \quad \text{Maximize } Z = \sum_{i=1}^{12} P_i(h_i) \times G_i \quad (16)$$

265 where average monthly energy price $P(h_i)$ is a function of total hours of generation in month i .
266 The variation in price with generation is not a result of price effects from an individual power
267 plant's generation. Instead, this price variation represents the hourly variability in energy prices
268 of the overall energy market responding mostly to on-peak and off-peak variability in energy

269 demands. Price for an individual plant's operation varies with the number of hours it operates.
270 Since these plants are run to maximize power revenues, they are assumed to be operated in hours
271 when the energy market offers higher prices.

272

273 If a plant operation is solely for hydropower, then the frequency distribution of hourly
274 hydropower prices (Figure 2) can be integrated into an average revenue function of turbine
275 release as a percent of monthly turbine capacity (Figure 3). If operating only for hydropower, a
276 utility will release first at high-valued times and only release at lower-valued times as water
277 becomes more abundant. The resulting benefit function allows approximate representation of
278 hourly pricing within a monthly model. Hourly price frequencies from 2005 are used to develop
279 revenue functions for each month (the 2005 prices were used only because of unavailability of
280 price data for earlier years). Figure 2 shows the frequency of real-time market hourly energy
281 prices in October 2005 in California, spanning on-peak and off-peak prices. For optimal
282 hydropower operations, average energy price declines as hours of generation increase, so small
283 releases are targeted for the maximum energy price and lowest average price occurs when release
284 equals generation capacity. Since monthly generation increases by increasing the hours of
285 turbine-run, it is assumed that the revenue from each hydropower plant is a function of the
286 portion of used monthly generation capacity:

$$287 \quad z_i(h_i) = z_i(g_i) \quad (18)$$

288 where: g_i is the portion of monthly generation capacity used.

$$289 \quad g_i = \frac{G_i}{Gcap} \quad (19)$$

290 Integration over the price curve in a given month (Figure 2) gives that month's revenue (z_i) as
291 follows:

292
$$z_i(g_i) = Gcap \cdot \int_0^{g_i} P_i(g_i) dg_i \quad (20)$$

293

294 Using Equation 20, concave revenue curves for each month (October in this example) can be
 295 derived, as shown in Figure 3. In this figure, the horizontal axis shows g_i (October), and the
 296 vertical axis shows the corresponding average revenue per unit of plant generation capacity
 297 $(\frac{z_i(g_i)}{Gcap})$. From Figure 3, if the power plant generates at its full capacity in October, revenue at

298 that power plant is 48 \$/MWh times its generation capacity. Revenue curves for any given
 299 fixed-head Californian hydropower plant in each month can be derived by multiplying both axes
 300 of Figure 3 by generation capacity of that power plant. Such curves can then be piece-wise
 301 linearized or included non-linearly, and summed over the months for the objective function of
 302 EBHOM (Equation 16 as follows):

303
$$\text{Maximize } Z = \sum_{i=1}^{12} z_i(g_i) \quad (21)$$

304 This formulation reflects the on-peak on off-peak pricing. The prices occur for the same hours of
 305 the day, across all plants. The price does not decrease because of the quantity of energy
 306 generated, but because of the hours of the day generated.

307

308 **5. Reformulation for Cyclical Operations**

309 The EBHOM, as defined earlier, can be sensitive to the initial storage condition (Equation 2).
 310 Each reservoir has a specific refill and drawdown cycle. To find the best initial condition (refill
 311 month) for a single reservoir, the EBHOM should be run 12 times for the 12 different possible
 312 refill months, saving the decision values from the best performing refill month.

313

314 Although simple and comprehensible, running the model 12 times for each reservoir requires
315 excessive computation time for large systems. To decrease the calculation time the formulation is
316 revised by replacing the first two constraints (Equations 2 and 3) with the following four
317 constraints:

318
$$S_1 = \text{big} \text{ (initial condition)} \quad (22)$$

319
$$S_{min} \leq S_i, \forall i \quad (23)$$

320
$$S_i \leq S_{max}, \forall i \quad (24)$$

321
$$S_{max} - S_{min} \leq \text{Scap} \text{ (storage capacity constraint)} \quad (25)$$

322

323 where big = an arbitrary large number greater than or equal to Scap ; S_{min} = minimum monthly
324 energy storage during the year (12 months period) (a decision variable); and S_{max} = maximum
325 monthly energy storage during the year (a decision variable).

326

327 This formulation sets initial storage equal to a large nominal level (*big*). Storage changes are
328 then made conventionally around this nominal level, with storage constrained to return to this
329 initial level. The storage capacity constraint is enforced by defining the minimum and maximum
330 storages from all months (Equations 23 and 24), and then constraining the difference (Equation
331 25), which is the amplitude of the annual drawdown-refill cycle. This limits real storage within
332 the real storage capacity. Since the nominal initial storage exceeds the reservoir's capacity,
333 nominal storage cannot be negative in any month.

334

335

336 **6. Comparison for Loon Lake Power Plant**

337 Figure 4 compares the average historic (recorded) hydropower generation (period 1982-2002)
338 and the EBHOM's estimation of optimal monthly hydropower generation in an average
339 hydrologic year of the same period at Loon Lake Hydropower Plant, which belongs to the
340 Sacramento Municipal Utility District (SMUD) reservoir system. Assuming a fixed energy head,
341 un-regulated water runoff is linearly related to available energy runoff. Based on the No-Spill
342 assumption, total annual energy generation for a given hydropower plant (from observed energy
343 generation data) in a given year equals the annual available energy runoff at its location in that
344 year, and only the seasonal distributions differ. Accordingly, monthly distribution of energy
345 runoff in each year of the study period was assumed to be exactly the same as the distribution of
346 mean monthly runoff for the period 1928 to 1949. Monthly energy runoff was computed (for use
347 in Equation 4) based on the monthly runoff distribution given by the hydrologic record where
348 annual energy runoff equals the annual hydropower generation. Monthly revenue curves were
349 based on information from California Independent System Operator Open Access Same-Time
350 Information System Web Site for the year 2005 (California ISO OASIS, 2007). The non-linear
351 optimization problem was solved by linear programming through piecewise linearization of the
352 concave revenue function.

353

354 Generally, the difference of historic and modeled values is due to the mismatching runoff,
355 hydropower generation, and price data sets used, and non-energy hydropower operations such as
356 maintaining spinning reserves. The summer generation peak found by the model (in September)
357 is due to the high price of energy in September in the data set, which might not be true for the
358 period 1982 to 2002. Often hydropower generators pre-sell their power through long-term

359 contracts with fixed prices and control only that portion of hydropower generation not already
360 sold. A more extensive comparison of the EBHOM with a traditional hydropower optimization
361 model of the Sacramento Municipal Utility District (SMUD) reservoir system produced similar
362 results and showed good reliability of EBHOM predictions (Madani et al., 2008).

363

364 **8. Estimation for 137 Plants in California**

365 EBHOM was applied for modeling the high-elevation hydropower system in California. One
366 hundred fifty-six (156) high-elevation (above 305 meters or 1,000 feet) hydropower plants in
367 California were identified. Monthly hydropower energy generation information from U.S.
368 Energy Information Administration Databases for the period 1982 to 2002 was used to estimate
369 the average monthly hydropower energy generation and the generation capacity of each power
370 plant. Instead of using the name-plant capacity of each hydropower plant in this study, the
371 maximum actual monthly generation over the 1982-2002 period was used as the monthly
372 generation capacity. For estimating energy storage capacity available for each hydropower unit,
373 mean monthly generation and mean annual generation were estimated. Mean monthly values
374 were then normalized into percent of mean annual generation (Equation 9) to characterize the
375 average seasonal distribution of energy generation at each unit. Since runoff patterns vary by
376 elevation, three elevation ranges are considered (305-710 meters or 1,000-2000 feet, 710-915
377 meters or 2000-3000 feet, and above 915 meters or 3000 feet). Monthly runoff data for the study
378 period were obtained for several USGS gauges representing these elevation ranges, selected in
379 consultation with the former California Department of Water Resources (DWR) chief
380 hydrologist. For each elevation range, mean monthly and mean annual runoffs were estimated.
381 Mean monthly values were then normalized into percent of mean annual runoff (Equation 8) to

382 characterize the average seasonal distribution of available water runoff for each elevation range.
383 Energy storage capacity of each unit was then estimated using the NSM. Real time hourly
384 hydroelectricity prices were obtained from the California ISO OASIS for the year 2005
385 (California ISO OASIS, 2007) and used to derive convex monthly revenue curves.

386

387 EBHOM was used to estimate the optimal historic monthly generation. The EBHOM for each
388 plant was solved in Microsoft Excel (through piecewise linearization) with “What’sBest”, a
389 commercial solver package for Microsoft Excel. With the cyclic EBHOM formulation, each run
390 for one reservoir for each year under a given hydrology takes 3 to 4 seconds. Historical
391 generation data was complete for 137 high-elevation plants for the period of 1984-1998. The
392 piecewise-linear optimization model was run for each year to find revenue-maximizing monthly
393 reservoir storage and energy generation for these 137 power plants. The model was run with the
394 historical hydrology. Assuming no over-year storage, release decisions in each year are
395 independent. Figure 5 shows the range of the estimated energy storage and generation capacities
396 of the studied high-elevation hydropower plants. The annual energy storage capacities of most of
397 the studied power plants are at least 1.3 times larger than their monthly generation capacity,
398 which provides some flexibility in operations. For most power plants, energy storage capacity
399 exceeds one month of generation capacity.

400

401 Figure 6 shows the historical and modeled average energy generation of 137 hydropower plants
402 for the period 1984 to 1998. (The analysis has not been done for an average year but for 15 years
403 of hydrologic (energy inflow) annual variability, spanning dry, wet, and average years. The

404 results are reported as average over the 15 year period for which 15 model runs were required).
405 The optimized generation for the historic climate differs from historic observations (the dashed
406 curve in Figure 6). Differences arise from a variety of factors, including non-hydropower
407 operating factors, differences in hydropower prices from the recorded years, non-energy
408 hydropower operations such as spinning reserves, and the foresight of the model regarding
409 incoming flows during the year. Another reason for divergence between the EBHOM's results
410 and the observed generation is application of a representative annual hydrograph for each
411 elevation band rather than locally measured inflows for each year. The generation results are
412 highly price driven and follow the California ISO energy price trends in 2005.

413

414 Figure 7 shows the average end-of-month energy storage in all reservoirs combined in the study
415 period for operations optimized for hydropower. EBHOM suggests that reservoirs reach their
416 minimum storage level by the end of January in preparation to capture inflow from winter
417 precipitation and spring snowmelt. On average, reservoirs are full by June and gradually empty
418 for energy generation over summer when energy prices are higher and there is little natural
419 inflow. Under historical conditions, refill starts in February and drawdown starts in July.

420

421 Figure 8 indicates the average shadow prices of energy storage and generation capacities (the
422 average increase in annual revenue per unit of capacity expansion) for all 137 reservoirs for the
423 study period. This figure shows the average increase in annual revenue (y-axis) per MWh
424 energy storage/generation capacity expansion for corresponding number of power plants (x-
425 axis). For instance, increase in annual revenue is less than \$10 revenue per MWh energy storage

426 capacity expansion for 50 of the studied power plants. Generally, storage capacity expansion is
427 more beneficial than generation capacity expansion. Water can be stored in the reservoir in low-
428 value months to be released in summer when energy prices are higher. Thus, shadow price of
429 energy storage capacity always exceeds the shadow price of generation capacity for all the
430 reservoirs. Generation capacity expansion does not increase average revenue of about 90
431 hydropower plants while energy storage capacity expansion always increases annual revenues.
432 Although expansion of storage and generation capacities can increase average annual revenues,
433 expansions might not be justified due to expansion costs. In some cases, where hydropower
434 plants are in series and draw on the same upstream reservoir, the value of expanding that
435 reservoir would be the sum of storage expansion values for all downstream plants. Since the
436 NSM (No-Spill Method) tends to underestimate energy storage capacities, the values for storage
437 capacity expansion are probably high estimates.

438

439 **9. EBHOM Applications**

440 Generally, an EBHOM can be applied in any hydropower system operation study where there is
441 relatively little effect of storage on head and there is an interest in the big picture of the system
442 and details are of lesser importance (e.g. large-scale policy, preliminary planning, and adaptation
443 studies). Some potential applications are discussed below.

444

445 Climate warming is a hydropower concern in regions with significant snowmelt runoff, such as
446 California. High-elevation hydropower systems in California rely on snowpack for seasonal
447 storage of precipitation, which makes those systems more vulnerable to climate warming
448 (Vicuna et al., 2008; Madani and Lund, 2007). EBHOM is convenient for studying climate

449 change effects on large-scale hydropower systems. Monthly runoff (energy inflow) can be
450 perturbed for various climate change scenarios. The effects of several climate scenarios can be
451 calculated quickly to allow quick, broad system-scale studies to accompany narrower
452 conventional hydropower optimization studies (Vicuna et al., 2008).

453

454 Effects of energy demand/pricing changes on hydropower generation and resulting downstream
455 flows also can be studied using EBHOM. Greater energy demand increases energy prices.
456 Currently, electricity is more expensive in summer and winter months from cooling and heating.
457 Energy demand can change for various climatic, economic, technologic, policy, or market
458 reasons. Climate warming also can reduce winter energy demand and prices (for heating) and
459 increase demand and prices in summer (for cooling). Energy prices also might change from
460 changes in supply. For instance, more energy generation in early spring from earlier snowmelt
461 might reduce energy prices in that period. Energy prices also can change with long-term changes
462 in energy-use technologies (e.g. for heating and cooling), economic growth, energy market
463 conditions (availability of non-hydropower energy supplies), energy conservation, or energy
464 regulatory policies. The effects of changes in energy prices on hydropower generation can be
465 studied conveniently by developing representative revenue curves (similar to Figure 3) for
466 conditions of interest.

467

468 In some parts of the world, large-scale expansions of hydropower storage and generation are
469 being contemplated. EBHOM formulations can be used to preliminary explore and identify

470 promising types and locations of power plant expansions, employing the Lagrange multiplier
471 (shadow price) results for energy storage and generation capacity constraints.

472

473 A final application of this type of coarse model might be for seasonal energy production and
474 market studies and forecasts. A coarse EBHOM can quickly give seasonal energy planners and
475 schedulers insights into when and how much hydropower is likely to be produced over a coarse
476 seasonal horizon, although operators are likely to have access to more detailed proprietary
477 models.

478

479 **5. Limitations**

480 The No-Spill Method (NSM) for estimating energy storage capacity should be applied to the
481 systems where there is little or no spill in many years and there is little over-year storage.
482 Nevertheless, the NSM will tend to under-estimate storage capacities and therefore also
483 underestimate the adaptability of the hydropower system to hydrologic and economic conditions.
484 More detailed studies could provide better estimates of energy storage capacities.

485

486 For this application to California, we assume that inflow distributions adhere to a fixed seasonal
487 pattern, which seem reasonable for California's Mediterranean climate. This EBHOM is
488 formulated without considering environmental flows. Environmental constraints sometimes
489 restrict the flexibility of operations and introduce trade-offs between hydropower generation
490 revenues and ecosystem conservation benefits. These tend to be less for high-elevation
491 reservoirs, but will probably increase with time. Environmental constraints could be

492 incorporated in the model as minimum releases or as changes in the objective function or the
493 frequency distribution of prices.

494

495 EBHOM is a deterministic model and optimizes generation based on perfect foresight for
496 seasonal inflows and the frequency distribution of prices. Such management is impossible in
497 practice, because of imperfectability of forecasts of hydrologic and price conditions. Long-term
498 generation contracts also will affect operations.

499

500 **6. Conclusions**

501 This study introduced an innovative approach for exploring the performance of high-elevation
502 hydropower systems without detailed information on volumetric storage capacity, inflow, or
503 geometric configuration. Estimation of energy storage capacity is made based on seasonal shifts
504 of energy inflows to generation, energy inflows are based on seasonal inflow distributions, and
505 generation capacity is estimated from maximum observed generation rates.

506

507 The goal of this study was to explore an approach for studying extensive multi-facility high-head
508 hydropower systems with minimal available information and efficient. This approach is used to
509 represent 137 high-elevation (high-head) units in California. The method required some
510 simplifying assumptions. EBHOM can be applied in high-elevation hydropower operation
511 studies examining climate change effects and adaptations for hydropower generation, the effects
512 of electricity demand and pricing changes on hydropower generation, early planning for
513 extensive capacity expansions, and seasonal energy forecast and scheduling studies.

514

515 The contributions of this work are:

- 516 1. An energy-unit based model (Energy-Based Hydropower Optimization Model or
517 EBHOM) of single-purpose hydropower generation systems, requiring little model
518 development effort for low-detailed modeling.
- 519 2. The No-Spill Method (NSM) for estimating energy storage capacity.
- 520 3. A price-frequency method of better representing hourly energy prices in models with
521 larger time steps.
- 522 4. A cyclic storage formulation to decrease the calculation time and cost.
- 523 5. A simple approach for developing a good representation of an extensive system with little
524 time or resources for policy and adaptation studies for various purposes.

525

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536

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579

580

581

582

583 **Figure Captions**

584 Figure 1- Calculation of operational storage capacity of Loon Lake Reservoir based on NSM.

585 The shaded area between the two curves stands for the storage capacity of the reservoir in
586 percentage terms.

587 Figure 2. Frequency of California's hourly hydroelectricity price in October 2005 (California
588 ISO OASIS, 2007)

589 Figure 3. Revenue-generation correlation in October 2005 (California ISO OASIS, 2007)

590 Figure 4- Comparison of average historic monthly electricity generation and optimal monthly
591 electricity generation (found by EBHOM) at Loon Lake Hydropower Plant in California

592 Figure 5. Comparison of historic average monthly electricity generation and optimal average
593 monthly electricity generation (found by EBHOM) of 137 hydropower units in California in
594 the 1984-1998 period

595 Figure 6. Comparison of historic average monthly electricity generation and optimal average
596 monthly electricity generation (found by EBHOM) of 137 hydropower units in California in
597 the 1984-1998 period

598 Figure 7. Average modeled total end-of-month energy storage (found by EBHOM) of 137
599 hydropower units in California in the 1984-1998 period

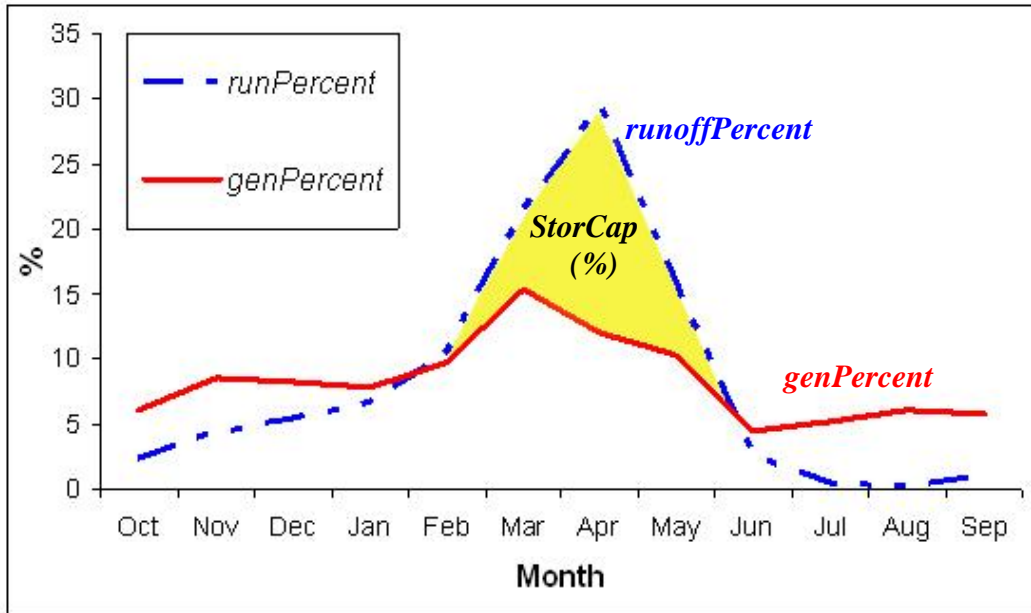
600 Figure 8. Average shadow prices of monthly energy generation and energy storage capacities
601 (found by EBHOM) of 137 hydropower units for California in the 1984-1998 period

602

603

604

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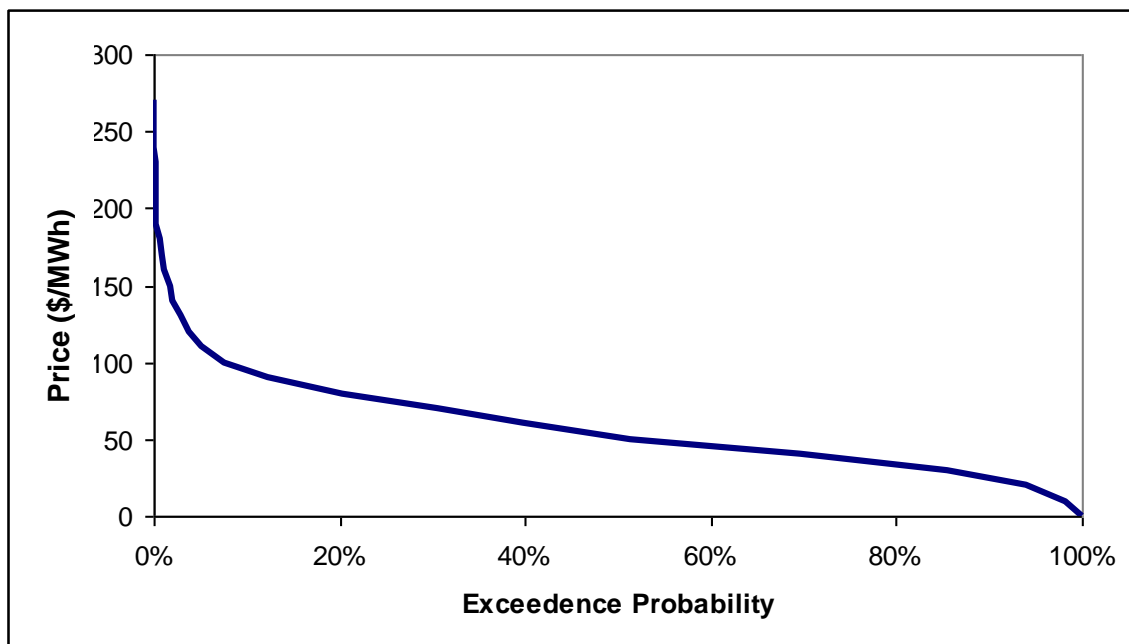


606

607 Figure 1- Calculation of operational storage capacity of Loon Lake Reservoir based on NSM.

608 The shaded area between the two curves stands for the storage capacity of the reservoir in

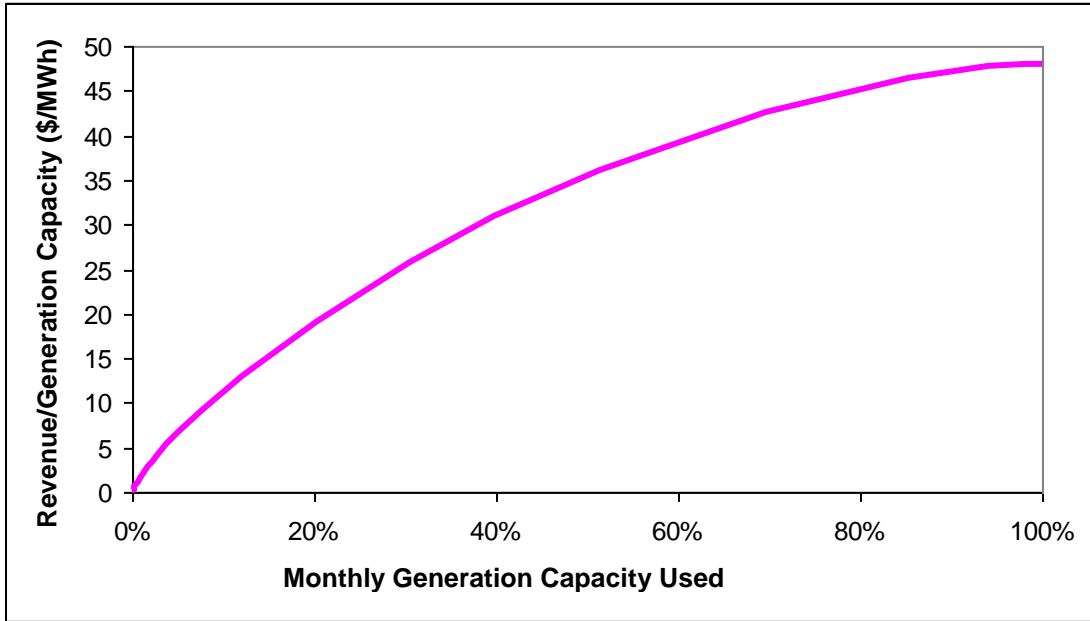
609 percentage terms.



610

611 Figure 2. Frequency of California's hourly hydroelectricity price in October 2005 (California

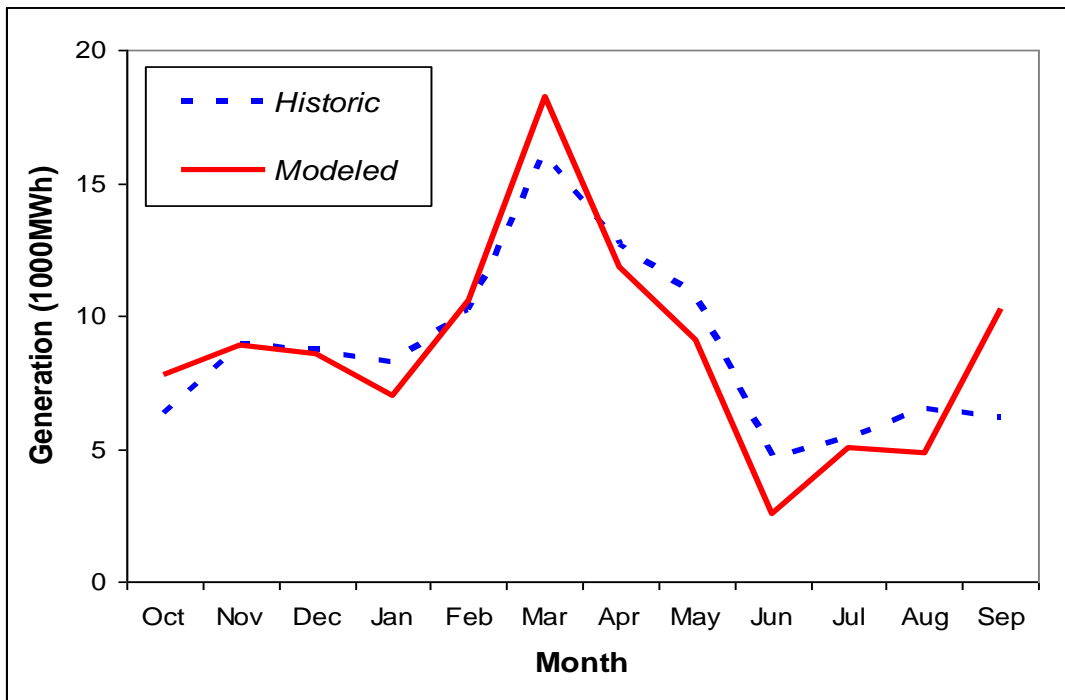
612 ISO OASIS, 2007)



613

614 Figure 3. Revenue-generation correlation in October 2005 (California ISO OASIS, 2007).

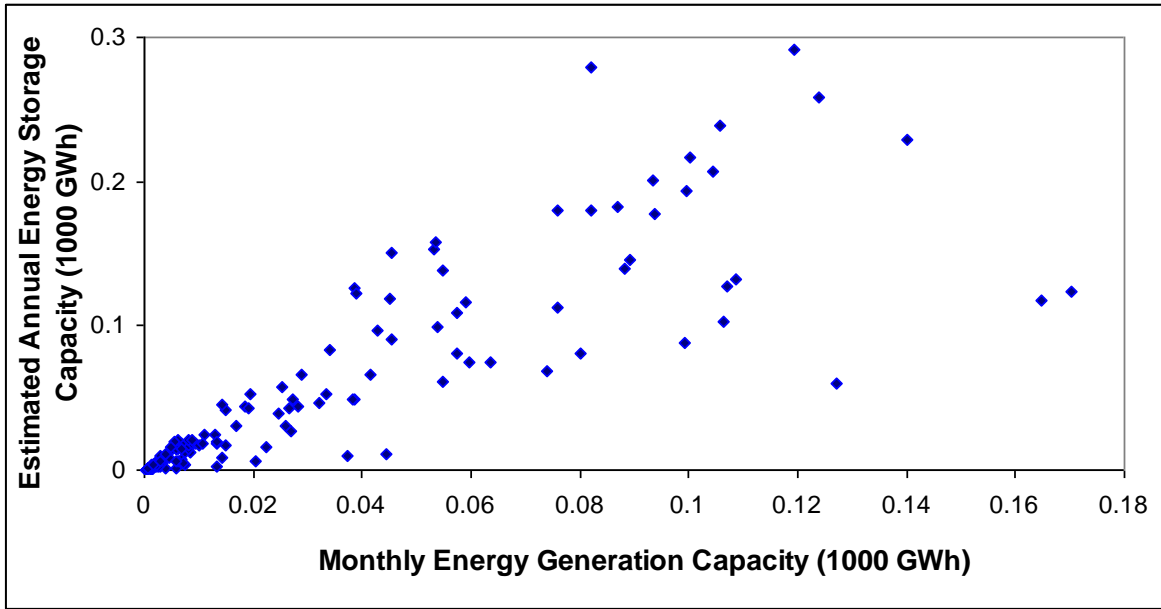
615 Vertical axis shows the average revenue (in \$) per unit of plant generation capacity (in MWh).



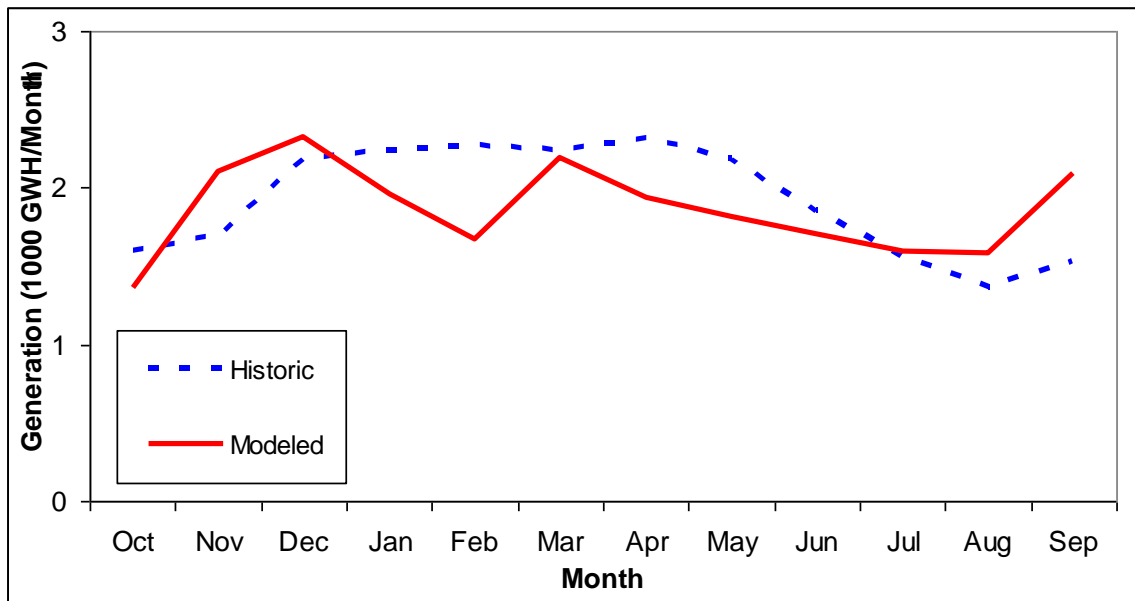
616

617 Figure 4 - Comparison of average historic monthly electricity generation and optimal monthly

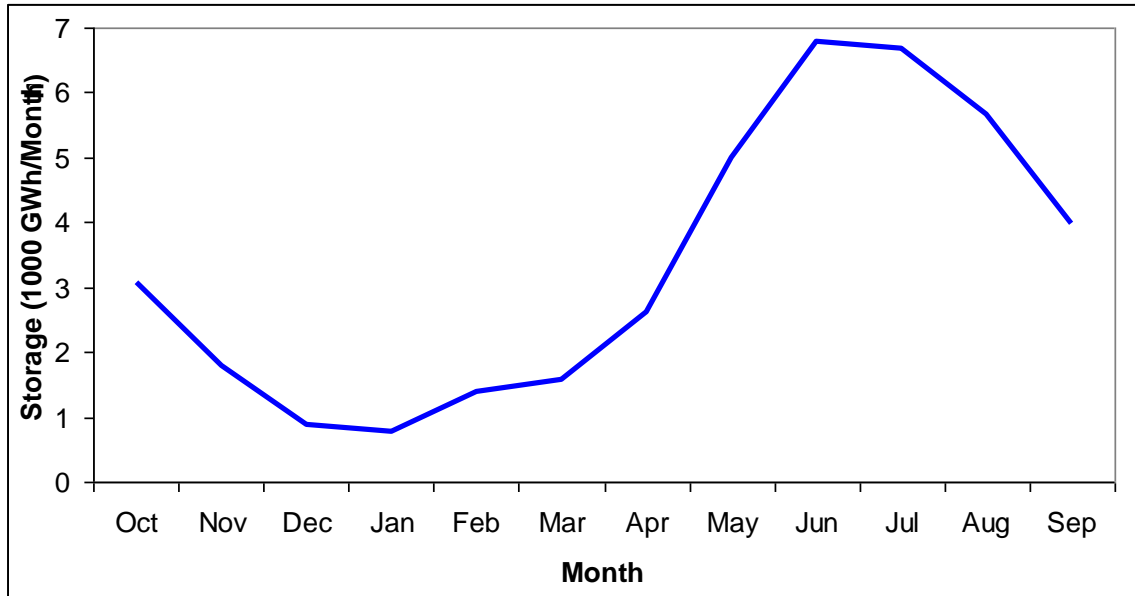
618 electricity generation (found by EBHOM) at Loon Lake Hydropower Plant in California



619
 620 Figure 5. Range of the estimated energy storage and generation capacities of the 137 studied
 621 high-elevation hydropower plants in California



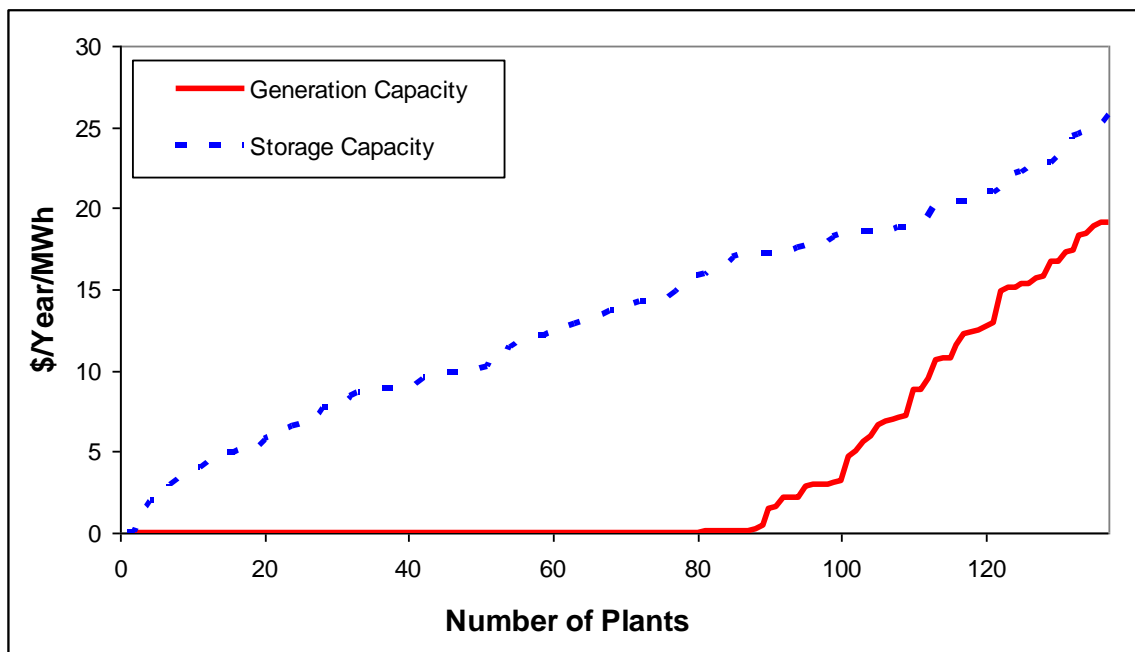
622
 623 Figure 6. Comparison of historic average monthly electricity generation and optimal average
 624 monthly electricity generation (found by EBHOM) of 137 hydropower units in California in the
 625 1984-1998 period



626

627 Figure 7. Average modeled total end-of-month energy storage (found by EBHOM) of 137

628 hydropower units in California in the 1984-1998 period



629

630 Figure 8. Average shadow prices of monthly energy generation and energy storage capacities

631 (found by EBHOM) of 137 hydropower units for California in the 1984-1998 period