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What do economic water storage valuations reveal about optimal vs. historical water management?

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Abstract

What is the economic value of storing water for future droughts, and what are the consequences of this valuation for water management? One way to answer this question is to ask: 'what is the valuation, which if used, would maximize a region's economic use of water?' This prescriptive valuation can be done by linking classical hydro-economic models to global search methods. Another way to answer this question is to ask: 'what do historical water management operations reveal about water's economic value?' Indeed, past reservoir uses reveal the empirical inter-temporal valuations of past water managers. Although they may not have been optimized in a formal sense, in mature water resource systems with economic water demands, reservoir storage rules evolve via a socio-political process to embody societies' valuation of water. This empirical, 'positive', or descriptive valuation is captured by calibrating a hydro-economic model such that carry-over storage functions enable simulated storage to match a historical benchmark. This paper compares both valuations for California's Central Valley revealing that carryover storage values derived from historical operations are typically greater than prescribed values. This leads to a greater reliance on groundwater use in historical operations than would have been achieved with system-wide optimization. More generally, comparing the two approaches to water valuations can provide insights into managers' attitudes as well as the impact of regulatory and institutional constraints they have to deal with – and that are not necessarily included in optimization models.

Keywords: Water storage valuation, Historical water management, descriptive vs. prescriptive approaches, hydro-economic modeling, California Central Valley.

1 Introduction

What can water storage valuation tell us of the difference between optimal and historical water management decisions? Economic valuation of water across space and time informs water allocation and the design of the physical and regulatory infrastructure that supports it; this valuation reflects the hydrological, economic, institutional and ecological situation of a river basin [1, 2]. Modeling-based approaches that derive water values aim to integrate these various aspects within a river basin model. Such approaches can be descriptive or prescriptive, used to examine historical or optimal water management decisions respectively. Descriptive approaches generally integrate the existing allocation rules and benefits from water allocation into a simulation framework to derive a valuation [3]. Prescriptive approaches use optimization to find a "best" system-wide allocation strategy according to a benefit-maximization criterion, and get an economically "efficient" valuation of water as a by-product of optimization [4-6]. Economic valuation of water according to these two types of approaches has different interpretations. Water values in descriptive models come from the actual allocation whereas in prescriptive models, they correspond to value extracted from optimal use. What is more, descriptive valuations are generally set to reflect the rules that direct water management rather than reproduce historical operations – i.e., historical outcomes of this rule system.

This paper contributes a methodology to infer a descriptive valuation directly from historical operations, in a way that makes it comparable to a prescriptive valuation. It uses a recent modeling framework fit for prescriptive valuation of surface water storage in large-scale conjunctive use systems [6], and instead finds the valuation of water storage that calibrates the model against a historical benchmark - making it a descriptive valuation approach. A higher water value in a given reservoir from one approach to another would reflect a premium placed on conservation of water from that reservoir. This enables further investigation of the cause for these discrepancies: is it because managers had a myopic behaviour in historical operations? Or is the prescriptive model missing something? Previous "positive" approaches [7] aimed to calibrate users' benefit functions in hydro-economic models, generally focusing on agriculture [8, 9]. In contrast, this framework aims to investigate the water value implications of already derived benefit functions.

These modeling-based approaches are a type of non-market valuation techniques – such techniques can also be survey-based [10]. In contrast, in market valuation techniques the value of an asset is based on the selling price or the price that consumers are willing to pay for a commodity in the market. Water markets are common in Western US [11-13], Australia [14-17], and the UK [18, 19].

In theory, descriptive and prescriptive market valuations are the same as actual water prices converge towards the socially optimal value. Yet, water markets are far from a universal solution [5] and further, they often fail to achieve their primary objective of economic efficiency unless an adequate regulatory and institutional framework is designed and implemented to sustain them [20-22]. In conjunctive use systems, different prices between local and non-local water, and between surface water and groundwater, may lead to overexploitation of groundwater resources even with a functioning market [23]. Optimization models tend to behave like water markets in the sense that they allocate water to most beneficial uses first, therefore comparing prescribed valuation to a historical benchmark has the potential to unveil some of the mechanisms that separate current operations from those that would result from a water market. Besides, system scale and complexity make water valuation more complicated. Under the phrase "curse of dimensionality", scale by itself is a major obstacle to most optimization methods (e.g., SDP, most recently [24-26]). Even methods that can circumvent this limitation (e.g. SDDP; [27]) are subject to restricting assumptions. In the case of SDDP for instance, it is necessary for future benefits to be convex, which is a problem when studying conjunctive use systems [28]. It is noteworthy that the present work builds on an approach [6] that handles system scale as well as non-linearity and non-convexity. That approach was the first to the link an evolutionary algorithm (EA) to a hydro-economic model [2] for this purpose.

Application of EAs to aid decision-making in economics can be seen in several studies [29-31]. The comparison of optimization results to water valuation from a historical benchmark is applied to the California Central Valley system, a system with 30 reservoirs in an agricultural area that also relies on groundwater, especially in times of drought [32-36]. Results are used to compare the two management practices using the concept of risk aversion. Risk aversion is the behaviour of decision-makers when they are exposed to uncertainty. This is quantified by risk aversion coefficient [37, 38] whose positive (negative) sign reveals risk-taking (risk-averse) attitudes.

The remainder of this paper is structured as follows. Section 2 explains the proposed approach; section 2.5 presents the California Central Valley application; results are shown in section 4, followed by discussion and conclusions in sections 0 and **Error! Reference source not found.**, respectively.

2 Methods

2.1 Water storage valuations

This work looks at the value of water storage for future uses, in a context where benefits from different water uses are already known. Valuation of water storage in reservoir balances current and future uses through the carry-over storage value function (COSVF). The COSVF describes water value as a function of reservoir storage. This work focuses on the end-of-year COSVF that determines the value of water for next years' uses. It compares carryover storage values obtained from a prescriptive optimization framework, to those that enable reservoir operations to most closely fit a historical benchmark. Therefore, there needs to be a common and easily interpretable functional form from which to derive carryover storage values in both cases.

At each point on the end-of-year COSVF, marginal benefits from an additional unit of storage for future uses are a unit value of water. In other words, end-of-year COSVF is the integral of the function known as the demand curve [39], that describes the unit value of water as a function of storage (Figure 1). This unit value can be interpreted as the marginal price that water users are willing to pay, and is therefore noted P. In its most general form, the end-of-year COSVF of a single reservoir is a function of that reservoir's storage S and of the parametrisation vector π chosen for the demand curve:

$$COSVF(S;\pi) = \int_{S_{min}}^{S} P(s;\pi)ds \tag{1}$$

A direct consequence of equation (1) is that a reservoir's COSVF is a growing function of storage, with $COSVF(S_{min};\pi) = 0$. In its simplest form, the demand curve is linear, therefore the parameters π are water values at minimal and maximal storage (p_1 and p_2 respectively):

$$P(S;\pi) = P(S;\, p_1, p_2) = p_1 + (p_2 - p_1)\frac{S - S_{min}}{S_{max} - S_{min}} \tag{2}$$

This means that the integral of equation (2), the end-of-year COSVF, is quadratic; since it is 0 at minimal storage, it is entirely defined by $\pi = (p_1, p_2)$. When storage in reservoirs is close to dead storage S_{min}, water is scarce for future uses, therefore each unit of stored water is close to its maximal value p_1. Conversely, when reservoir levels get close to the maximum allowable storage S_{max}, water is more abundant for future uses, leading to lowering the value of an additional unit of water towards its minimum value p_2 (see Figure 1). In practice, this paper will use the linear demand curve of equation (2), and the associated two-parameter end-of-year COSVF, to compare prescriptive and descriptive valuations.

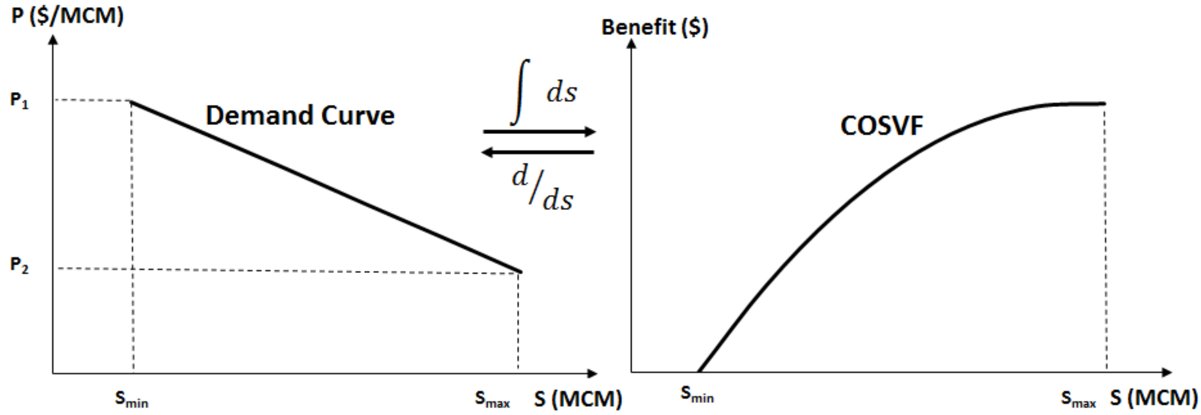


Figure 1. Relation between demand curve and benefit function of a surface reservoir, in the case of a linear demand function.

In a river basin comprising multiple reservoirs, end-of-year carry-over storage values can be summed across all reservoirs, and a total end-of-year carry-over storage value function $COSVF_{all}$ can be written as a function of the vector of system state *x*, usually including storage values at all the reservoirs, and the vector π of end-of-year COSVF parameters π_i at each individual reservoirs:

$$COSVF_{all}(x;\pi) = \sum_{i=1}^{n} COSVF(S_i;\pi_i) \tag{3}$$

where n is the number of reservoirs in the system. For instance with a linear demand function, π_i comprises the values of p_1 and p_2 at each reservoir i.

2.2 Prescriptive water valuation

Prescriptive water valuation corresponds to the storage valuations that are obtained by maximizing operating benefits from water uses in a water resource system over a given time frame [1, T], with discrete time-steps of a month or less. This is expressed by:

$$Z = E\left[\sum_{t=1}^{T} f_t(x_t, u_t, q_t) + v_{T+1}(x_{T+1}, u_{T+1})\right] \tag{4}$$

where *E*[.] is the expectation operator and f_t (.) represents the net benefits from water usage (consumptive uses, hydropower generation, ecological benefits, etc.) at stage *t*. As introduced for equation (3), vector x_t is the state of the system at *t*, typically including storage in the different reservoirs. u_t is the vector of operational decisions taken at that stage t, such as reservoir releases and water allocations to spatially distributed users, including farmers, industries or domestic uses from cities. q_t is the vector of inflows. Finally, v_{T+1} (.) is a final value function that expresses that reservoirs should not be simply emptied at the end of the optimization horizon, because water has value beyond that. In short, v_{T+1} (.) expresses the carry-over value of water within the system. This optimization problem is subject to a number of constraints such as the water balance equation, lower/upper bounds on flows and storage levels, or hydropower generation capacity, to name a few. Solving the stochastic maximization problem of equation (4) requires mapping decisions u_t as a function of system state and expected inflows. Except for situations where specific assumptions such as convexity hold [40], this maximization problem is plagued by the well-known curse of dimensionality, whereby the required computational resources increase exponentially, making the resolution of large-scale problems intractable.

Khadem et al. [6] proposed a general approximate solution methodology to the problem of maximizing (4), based on two key remarks. The first relates the general optimization problem of equation (4) to prescriptive water valuation in reservoirs across the water resource system of interest. Indeed, defining single-year maximization problems involves end-of-year COSVF as a final boundary condition. For year $(k = 1 \dots K)$ spanning $[t_k + 1, t_{k+1}]$, the single-year maximization objective can be written as a function) of current year inflows $Q_k = (q_{t_k+1}, \dots, q_{t_{k+1}})$ and end-of-year COSVF parameter vector π:

$$Z_k(Q_k, \pi) = \sum_{t=t_k+1}^{t_{k+1}} f_t(x_t, u_t, q_t) + COSVF_{all}(x_{t_{k+1}}; \pi) \quad (5)$$

Contrary to the stochastic problem of equation (4), each maximization of the single-year objective Z_k is a deterministic optimization problem that can be handled by state-of-the-art solvers (e.g. the 30-reservoir problem in the application is solved in 15 seconds for each year). Then, the second key remark is that maximizing the objective of equation (4) can be approximated by the following objective function (see [6] for details):

$$Z(\pi) = \sum_{k=1}^{K} \left(\max_{u_t}\{Z_k(Q_k, \pi)\} - COSVF_{all}(x_{t_{k+1}}; \pi) \right) \quad (6)$$

The problem of maximizing equation (6) and that of equation (4) are subject to the same physically-based constraints (water balance, limits on reservoir storage and hydropower production, etc.), but crucially, equation (6) transforms the decision problem of equation (4) (intractable for large systems) into a problem of finding the end-of-year COSVF parameters in the system reservoirs. Evolutionary algorithms are well-suited to searching this large parameter space provided they can associate a value to each parameter vector. This value is:

$$\min_{\pi} F_{pres}(\pi) = \min_{\pi}[-Z(\pi)] \quad (7)$$

It is interpreted as "prescriptive" and noted F_{pres} because the vector π that solves the maximization problem of equation (6) directly gives the functional form of end-of-year COSVF at each of a system's reservoirs. This enables a prescriptive valuation of end-of-year water storage.

2.3 Descriptive valuation

In contrast to the prescriptive valuation, a descriptive valuation seeks end-of-year COSVF parameters that maximize the fit with benchmark time series, reflecting the system's states (e.g., storages) across the study area. The descriptive case seeks to find COSVFs that reflect how water storage has been valued in practice, which is not necessarily equal to marginal benefits from future water uses in the prescriptive case. For a given vector π, we can compute $Z(\pi)$ as in equation (6), by sequentially solving the single-year optimization problem of equation (5). Yet, instead of being interested in maximizing the value of the economic objective $Z(\pi)$ itself, we are now interested in the vector of system states $x(\pi)$ that has been computed to obtain $Z(\pi)$ – recall that those typically include reservoir storage. We explore the parameter space to find the parameter vector that minimizes the mean-squared errors with the benchmark:

$$\min_{\pi} F_{desc}(\pi) = \min_{\pi}\left[\frac{1}{N.T}\sum_{n=1}^{N}\sum_{i=1}^{T}\left(x_{t,i}(\pi) - x_{t,i}^{benchmark}\right)^2\right] \quad (8)$$

where N is the number of state variables used for calibration and F_{desc} is the descriptive objective function to minimize.

2.4 Workflow

For both water storage valuations, parameter values that maximize the respective objectives are found by evolutionary computation. Yet in both cases, many reservoirs will be refilled every year if p_2 is above a threshold value p_2^0. Then, any value of p_2 above this threshold (i.e., in $[p_2^0, +\infty[$) produces the same operations – stored water is valuable enough to warrant the reservoir to be full at the end of any water year. Then, the algorithm could return a marginal water value of $5 million per MCM without affecting the system's operations at all. To ensure the parameter values found by the algorithm make economic sense, a second objective is introduced to limit the value of p_1 and p_2 , similar to what was done in [6]:

$$\min_{p} F_2 = \min_{p}\frac{1}{N}\sum_{n=1}^{N}\frac{p_{\min n} + p_{\max n}}{2} \quad (9)$$

This second objective turns the single objective optimization problem into a multi-objective optimization problem. This type of problem is solved by multi-objective evolutionary algorithms (MOEA) which are broadly similar to genetic algorithms except for the fact that they can optimize two objectives or more at once. As a result, contrary to traditional genetic algorithms that return a single solution, a MOEA generally returns a set of solutions such that one cannot improve any objective without degradation in another objective. These solutions are called non-dominated and are collectively called the Pareto front (see [41] for details on MOEA). In this work, the MOEA is meant to find the set of states such that one cannot find a better solution both in the minimization of the first objective (either F_{norm} or F_{desc}) and in the minimization of the second objective F_2. Each solution associates to these objectives a vector of parameters that fully define the COSVF for all reservoirs.

2.5 Post-Pareto analysis

The output of a multi-objective optimization problem is the Pareto front, a set of non-dominated 'best' solutions. This often contains hundreds of solutions which sometimes complicate the decision-making process: which solution or group of solutions are preferred? This paper answers this using a post-Pareto stage which prunes the non-dominated set of solutions following the concept of knee points [42]. In knee points, small improvement in either of objectives will cause a large degradation in other objective(s) [42]. This essentially means moving in either direction is less desirable. This method is chosen owning to the fact that without any knowledge about users' preferences, the zone around the knee is most likely to be favourable for decision-makers [43].

Here, we measure the level of degradation of objectives by looking at slope (or difference) between any two adjacent solution points from the Pareto trade-off. The judgement on when a severe deterioration happened is made visually. This is where the slope notably changes compared to its next immediate value. This process creates a box within which lies Pareto non-dominated solutions with high optimality quality with respect to all objectives. This box is called "zone of concentration".

2.6 Risk aversion coefficient

Since COSVFs are utility functions, a common way of comparing the two management practices (that is used to derive descriptive and prescriptive valuation) in terms of how cautious they are, is to illustrate it through risk aversion coefficient [37, 38]. This coefficient determines how much satisfaction or utility can be obtained from an experience, a commodity, or money [44]. We use Arrow-Pratt risk aversion coefficient (*AP*), also known as absolute risk aversion coefficient, which is mathematically described as:

$$AP = -\frac{COSVF''\left(x_{t_{k+1}}\right)}{COSVF'\left(x_{t_{k+1}}\right)} \tag{10}$$

Considering the functional form of the quadratic COSVF used in this study (*a* and *b* being the quadratic and linear coefficients of COSVF respectively; see equation 21), the above equation for each reservoir *sr* is:

$$AP^{sr} = -\frac{2a_{t_{k+1}}^{sr}}{2a_{t_{k+1}}^{sr} x_{t_{k+1}} + b_{t_{k+1}}^{sr}} \tag{11}$$

3 Application

3.1 California's Central Valley

California's Central Valley (Figure 2) is one of the world's most productive agricultural regions [45] with over 2.3 million ha of irrigated farmland [46]. More than 250 different crops are grown in the Central Valley with an estimated value of $17 billion per year [47]. About 75 percent of California's irrigated land is in the Central Valley, which depends heavily on surface water diversions and groundwater pumping [45]. Nearly 75 percent of renewable water supply originates in the northern third of the state in the wet winter and early spring while almost 80 percent of agricultural and urban water use is in the southern two-thirds of the state in the dry late spring and summer [48]. In the context of California's Mediterranean climate, perfect within-year foresight is consistent with early spring measurements of the depth and water content of the snowpack which enable predicting discharge months ahead with reasonable accuracy and until the end of the water year [49]. The Central Valley often suffers from droughts such as 1918-20, 1923-26, 1928-35, 1947-50, 1959-62, 1976-77, 1987-92, 2007-09, and 2012-16 [50].

Figure 2. The Central Valley reservoir and river system (Adopted from Khadem et al, 2018).

The illustrative case of this paper is built upon CALifornia Value Integrated Network (CALVIN; [51]). CALVIN OP, a hydro-economic model [2] with perfect foresight, is the 'unconstrained' run of CALVIN used to simulate the Central Valley water system by maximizing the system-wide net economic benefit from water allocation. CALVIN OP applies economic drivers to allocate water rather than existing system of water rights and contracts [49]. Yet, the perfect hydrological foresight of CALVIN limits its applicability. We use an extended version of CALVIN OP for calibration which corrects the perfect foresight by dividing the planning horizon into year-long runs with initial condition of each run being the ending condition of the previous one and an end-of-year COSVF, representing the potential benefit of allocating water for future uses, set as the terminal condition of each run. Another extension to CALVIN comes from improving the groundwater pumping cost scheme. The CALVIN model represents pumping costs by multiplying the unit pumping cost of \$49.42 per MCM/m lift (\$0.20 per *af/ft* lift; *MCM* is a million m^3) by a static estimate of the average pumping head in each aquifer [52]. The extended version of CALVIN includes pumping costs that dynamically vary with head in the aquifer. This head-dependent pumping cost introduces non-convexity into the problem.

The water system is represented as a network of nodes and arcs [53], where nodes include surface and groundwater reservoirs, urban and agricultural demand points, junctions, etc., and arcs (links) include canals, pipes, natural streams, etc.. The water network of the Central Valley comprises 30 surface reservoirs, 22 groundwater sub-basins, 21 agricultural demand sites, 30 urban demand sites, 220 junction and 4 outflows nodes; and over 500 links (river channels, pipelines, canals, diversions, and recharge and recycling facilities). The period-of-analysis is 72 years, 1922-93, and monthly time-steps are chosen for the hydro-economic model run. This accounts for the strong seasonality of water supply and demands, a key feature of many irrigated water systems [54].

3.2 Model formulation

This section describes in detail how the generic equation (7) was implemented for this California Central Valley application. For details, please see [6]. f_t (.), the net benefit function at date t, is composed of the following terms:

$$f_t(x_t, u_t, q_t) = UR_t(x_t) + AG_t(x_t) + HP_t(x_t) - NW_t(x_t) - GW_t(h_t, x_t) - INF_t(x_t) \tag{12}$$

with

$$UR_t(x_t) = \sum_{ur} a_t^{ur} x_t^2 + b_t^{ur} x_t \tag{13}$$

$$AG_t(x_t) = \sum_{ag} a_t^{ag} x_t^2 + b_t^{ag} x_t \tag{14}$$

$$HP_t(x_t) = \sum_{hp} x_t^{hp} PF_t^{hp} p_t \tag{15}$$

$$NW_t(x_t) = \sum_{i,j} c_t^{i,j} x_t^{i,j} \tag{16}$$

$$GW_t(x_t, u_t) = \sum_{gw,j} PC_t^{gw} x_t^{gw,j} \tag{17}$$

$$PC_t^{gw,j} = unitc \cdot \left(elev^{gw} - h_t^{gw}\right) \tag{18}$$

$$h_t^{gw} = h_{t-1}^{gw} + \frac{q_t^{gw} + \sum_j x_t^{j,gw} - \sum_j x_t^{gw,j}}{sc^{gw} \cdot area^{gw}} \tag{19}$$

$$INF_t(x_t) = \sum_{i,j} infx_t^{i,j} \cdot m \tag{20}$$

Here, *UR* is the urban benefit (utility) function with a^{ur} and b^{ur} being the quadratic and linear coefficients of the function respectively and x_t showing the flow to urban node *ur*; Similarly, *AG* is the agricultural benefits form allocating water to farms with a^{ag} and b^{ag} being the quadratic and linear coefficients of the utility function respectively; HP is the linear economic benefit produced from hydropower generation where *PF* is the power factor of hydropower plant *hp* that relates release to hydropower generation and *p* is the monthly-varying hydropower unit price; *NW* shows the network cost, cost incurred due to treatment, conveyance, and conjunctive uses with *c* representing such cost per unit of flow in link between nodes *i* and *j*; *GW* is the groundwater cost from aquifer *gw* which is the product of pumping cost *PC* and discharge rate *x*; PC varies dynamically as the piezometric head *h* in the aquifer changes. The calculation of *PC* follows storage coefficient formulation [55] where a unit pumping cost *unitc* is multiplied by the distance that water needs to be lifted to reach ground level for allocation. *elev* is the mean ground elevation above aquifer *gw*. According to the storage coefficient formulation, *sc* is the mean storage coefficient and *area* is the surface area of an aquifer. INF represents the infeasibility costs. Numerical infeasibilities may appear in the model, making the network problem infeasible. In order to guarantee feasibility, artificial inflows (*infx*) are made available to the model at each node. These flows are included in model's conservation of mass equations to ensure that such flows are accounted for. These artificial flows which are in fact slack/surplus variables in a mathematical programming context, are not desirable therefore in order to deter the model from introducing infeasibility flows, they are penalised by a high cost (*m*) coefficient in the objective function.

In implementing above equations for the case of California Central Valley few points must be considered: (1) A piece-wise linear equivalent of equation (14) was used for farms. This was due to the slope of the benefit function (marginal value of water delivered) at or near full demand being zero which caused farmers to opt not pumping as it would be more economic to not pay for groundwater pumping costs while any additional unit of allocated water produces near zero benefit. (2) In California, the presence of "high-head" facilities where the effect of reservoir storage on turbine head is small allows for a linear relationship between head and hydropower generation [56, 57].

As explained in Section 2, the model is solved sequentially on a year-by-year basis for all the 72 hydrological years considered, using the maximization problem defined by equation (5). In that equation, end-of-year COSVFs are set as boundary conditions at the end of each year-long model run to prevent depletion of reservoirs. This function represents the potential benefit gained from not releasing for immediate uses and preserving water for future droughts. End-of-year COSVFs are quadratic utility function:

$$COSVF_t(\pi; x_t) = \sum_{sr} a_t^{sr} x_t^2 + b_t^{sr} x_t \qquad \forall t = t_{k+1} \tag{21}$$

where a^{sr} and b^{sr} are the quadratic and linear coefficient of the COSVF for reservoir *sr,* deduced from the demand curve parameters π using equations (1) and (2). In this case, the end of year is the end of the water year, that is, September 30 in the U.S.

3.3 Historical benchmark

In order to produce water marginal values that are descriptive of historical operations, storage data from a historical benchmark are required. In the Central Valley, this benchmark is CALVIN BC, a 'base case' or 'constrained' run of the CALVIN model which applies constraints to reproduce historical events [51]. It is used because observed storage data is not available for all reservoirs for the entire period of analysis. CALVIN BC is an effort to integrate surface and groundwater hydrology developed for the two models of the Central Valley's water system, i.e., DWRSIM and CVGSM. It reconciles inconsistent assumptions in these two separate models, as well as agricultural water demand assumptions with water deliveries. More details on CALVIN BC's modeling approach and assumptions can be found in [51]. Khadem et. al., [6] compared observed storage level data of Shasta, the largest reservoir in the Central Valley, with those of CALVIN BC's and demonstrated a close match between them. As such, we refer to CALVIN BC's results as the historical benchmark hereafter [58].

3.4 Getting water values

Borg [59] was used as the multi-objective evolutionary algorithm (MOEA) because Borg's self-adaptive features increase its robustness and effectiveness while minimizing the search parametrization by the user. Borg has been proved to be a top performing MOEA in systems comprising nonlinearities [60] and for multi-objective reservoir management problems [61]. There are 30 surface reservoirs, so there are 60 decision variables for the evolutionary algorithm to find. End-of-year carryover storage values are positive and bounded by the maximal value among the urban and agricultural water demand curves, i.e., \$5,291,378 per *MCM*. For the case study, an initial population size of 100, 100,000 maximum number of function evaluations as the stopping criterion, and epsilon (search resolution) value of 100,000 MCM^2, \$1,000,000, and \$8,107 per MCM (\$10 per *af*) for the objective functions (F_{desc}, F_{pres}, and F_2 respectively) were used. The nonlinear hydro-economic model of the California system was coded in Generalized Algebraic Modeling System (GAMS) and solved using the Minos solver version 5.5 [62]. Minos applies the generalized reduced gradient method, which is suitable for nonlinear programming problems with linear constraints [63].The case presented here was solved using 96 Intel processors working jointly on a Unix-based computing cluster. Results took about 45,000 hours of computation time to produce for the descriptive valuations and 42,000 for the prescriptive valuation (see [6]).

4 Results

This section uses the solution analysed in-depth in [6] as the prescriptive solution. For this reason, Section 4.1 and 4.2 focus respectively on the obtaining of descriptive valuations and on their fit with the historical benchmark. Then, Section 4.3 compares the two valuations and Section 4.4 investigates what they mean for water management in the Central Valley.

4.1 Trade-off analysis for the descriptive valuation of storage

A five-seed Random Seed (RS) analysis was performed to obtain the Pareto trade-off and to ensure robust algorithm convergence towards the same Pareto-set. By definition, a Pareto front (Figure 3) consists of non-dominated solutions with respect to the two objective functions, where any improvement on the value of either objective function comes at the expense of the other.

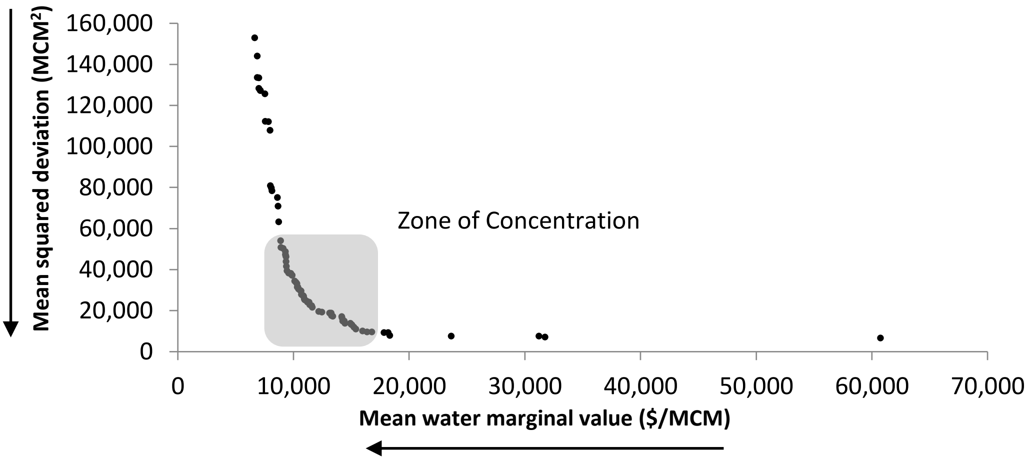


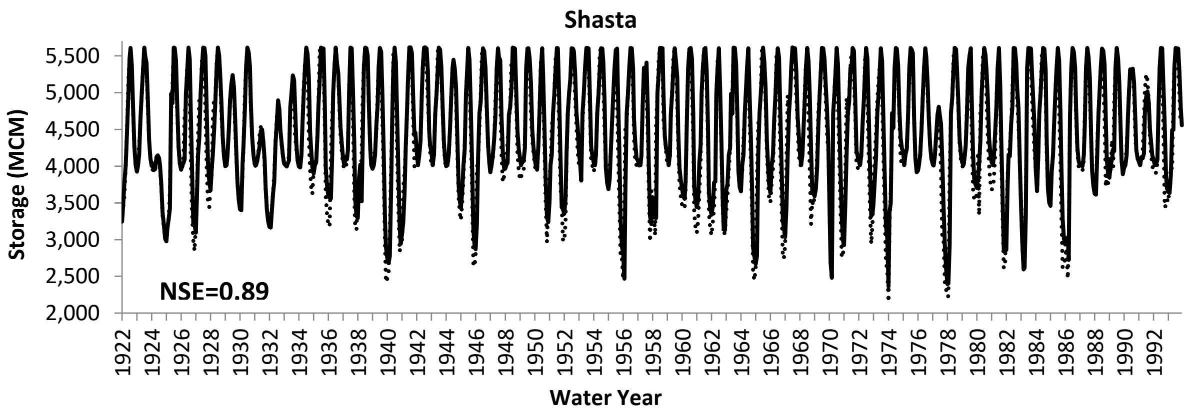
Figure 3. Pareto non-dominated solutions of the two objective functions (arrows show the direction of preference).

This analysis focuses on the zone of concentration (ZC) within the Pareto set (grey box in Figure 3, as outlined in section 2.5). Concentration of solution points in this zone suggest that the estimate for historical water marginal values can be sought there. The analysis will consider both this ensemble of solutions and a “representative solution” obtained by simulating the system using for each reservoir the average p_{min} and p_{max} across all solutions within the zone of concentration.

4.2 Quality of the fit with the historical benchmark

The quality of the fit is evaluated through the classical Nash-Sutcliffe efficiency criterion (NSE; [64]) at individual reservoirs by comparing benchmark historical storage values with storage from the representative solution (Table 1 and Figure 4). NSE is chosen as a goodness-of-fit criterion because it is coherent with the MOEA’s first objective; it determines the relative magnitude of the residual variance compared to the observed data variance [65]. It has a range of (-∞,1], with NSE=1 indicating a complete match between the modeled and observed values. A value between 0 and 1 shows an acceptable calibration performance and a negative NSE means that observed value is a better predictor than the simulated value, which indicates unacceptable performance. In Table 1, NSE values ranging from 0.82 to 1 indicate an excellent fit with the historical benchmark, which becomes close to perfection for some reservoirs (Figure 4). To better understand the quality of different solutions across the Pareto trade-off (Figure 3), solutions with the best and worst quality (those with lowest and highest value of F_{desc} respectively) are compared to the representative solution (average of solutions from zone of concentration) in Table 1. The quality of fit is also expressed by the fact that average relative deviations from the historical benchmark are relatively low.

This quality-of-fit at individual reservoirs holds across the ensemble of solutions within the zone of concentration, because operations are robust to different water valuations within this zone. Supplementary material illustrates this with three of the system’s major reservoirs. This said, it is worth noting that the zone of concentration figures a range of valuations and not a single valuation, be it at dead storage (Figure 5.a) or full storage (Figure 5.b). This means that this range, and not only the representative solution, must be used when comparing descriptive and prescriptive storage valuations.



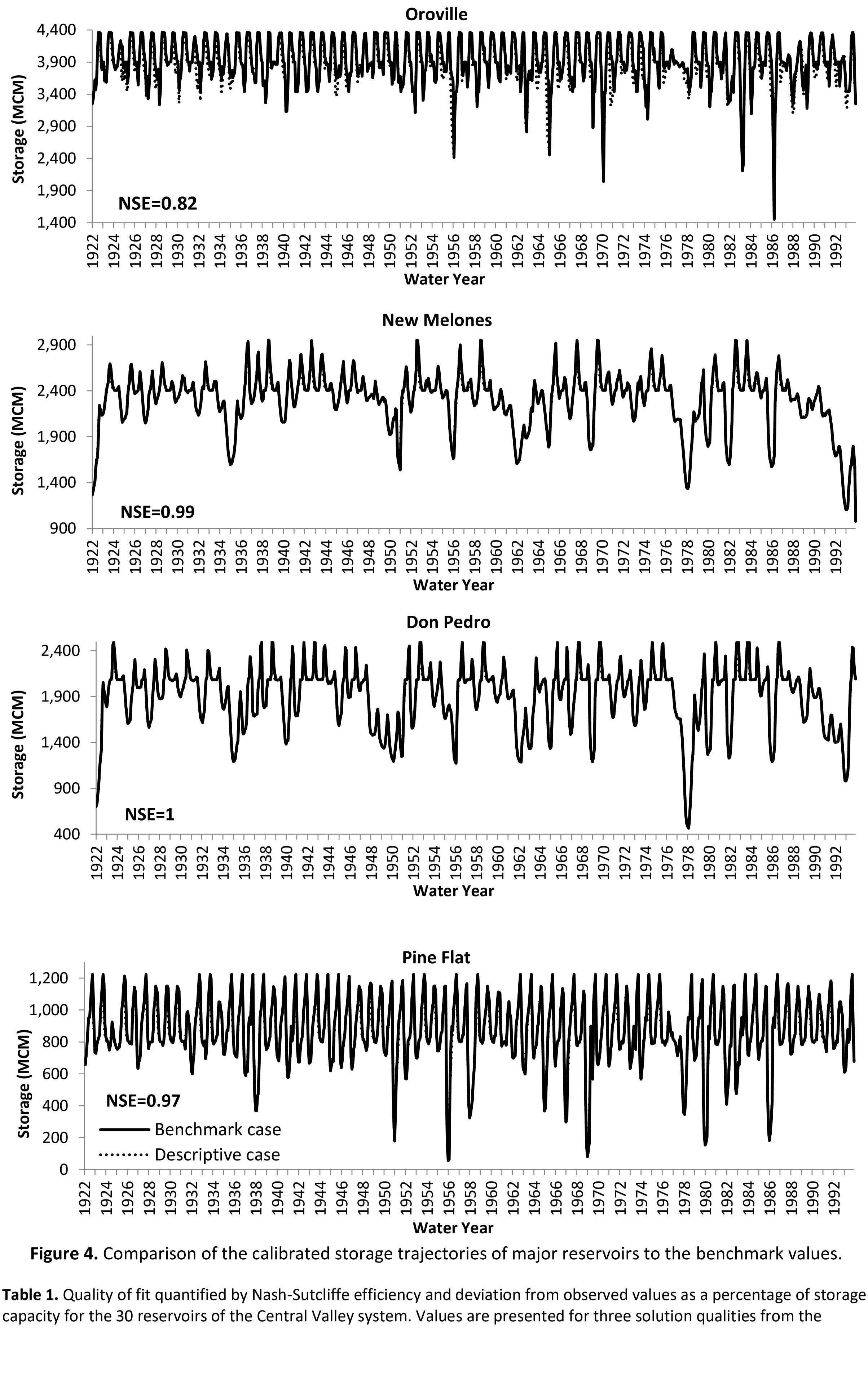


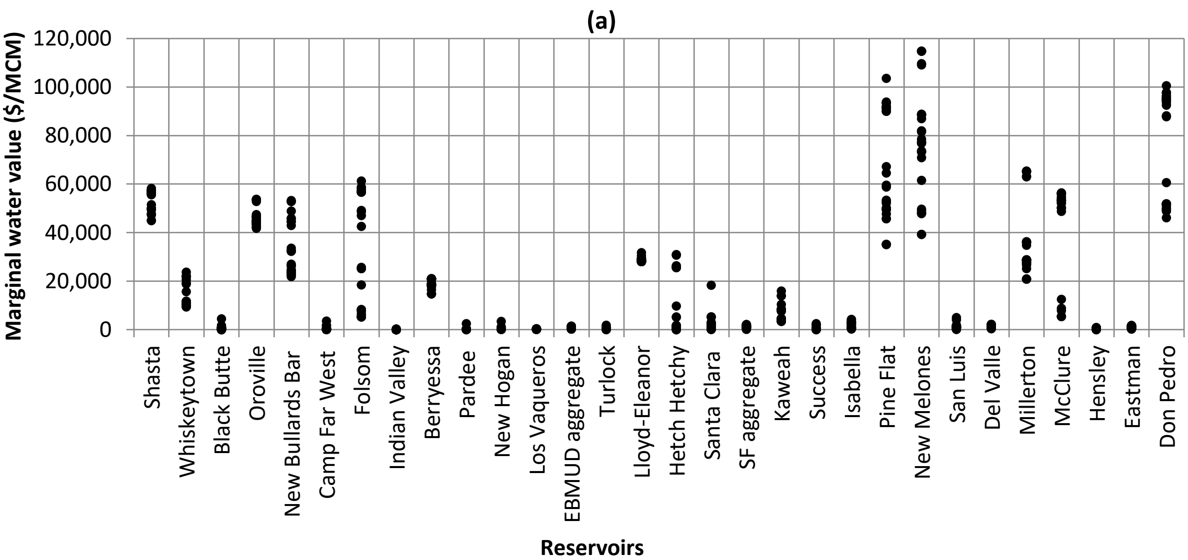
Figure 4. Comparison of the calibrated storage trajectories of major reservoirs to the benchmark values.

Table 1. Quality of fit quantified by Nash-Sutcliffe efficiency and deviation from observed values as a percentage of storage capacity for the 30 reservoirs of the Central Valley system. Values are presented for three solution qualities from the

Pareto trade-off (Figure 3): Worst NSE with the lowest value of Y axis, Average NSE with the values from the average of zone of concentration (ZC)-this is also called representative solution, and Best NSE with the highest value of Y axis.

Reservoirs	Worst NSE		Average of ZC NSE		Best NSE	
	NSE	Deviation (%)	NSE	Deviation (%)	NSE	Deviation (%)
Shasta	0.87	3.29	0.89	3.12	0.95	2.31
Whiskeytown	0.60	10.11	0.92	3.05	0.97	2.13
Black Butte	0.82	9.42	0.97	3.53	0.98	2.50
Oroville	0.78	2.85	0.82	1.51	0.98	0.47
New Bullards Bar	0.94	4.19	0.95	3.27	0.95	3.17
Camp Far West	0.87	7.46	0.99	2.04	0.99	1.15
Folsom	0.91	5.09	0.94	3.96	0.96	3.22
Indian Valley	0.99	1.78	1.00	0.12	1.00	0.12
Berryessa	0.99	1.40	0.99	1.23	0.99	1.20
Pardee	0.93	5.13	0.99	1.72	1.00	0.12
New Hogan	0.95	4.50	0.98	2.26	0.98	2.05
Los Vaqueros	0.65	5.32	0.97	1.00	1.00	0.21
EBMUD	0.66	4.53	0.94	1.63	0.98	0.67
New Melones	0.98	1.02	0.99	0.61	0.99	0.49
Turlock	0.55	9.16	0.82	4.97	0.87	3.43
Lloyd-Eleanor	0.96	4.09	0.98	2.38	0.99	1.68
Don Pedro	0.99	1.02	1.00	0.19	1.00	0.12
Hetch Hetchy	0.93	5.86	0.96	3.46	0.96	2.73
Del Valle	0.59	10.37	0.80	2.35	1.00	0.14
San Luis	0.97	1.12	1.00	0.15	1.00	0.03
Santa Clara	0.57	12.92	0.91	5.05	0.96	2.98
SF aggregate	0.22	8.74	0.79	4.03	0.93	1.87
McClure	0.98	2.10	0.99	1.32	0.99	1.14
Eastman	0.89	4.45	0.96	2.45	0.96	1.83
Hensley	0.57	11.50	0.91	5.22	0.94	3.73
Kaweah	0.75	8.62	0.96	5.51	0.97	3.07
Success	0.78	11.27	0.95	5.12	0.97	3.95
Isabella	0.98	2.00	0.99	1.21	0.99	1.09
Pine Flat	0.95	3.04	0.97	1.69	0.97	1.51
Millerton	0.96	3.43	0.99	0.95	0.99	0.65

Note: EBMUD stands for East Bay Municipal Utility District and SF is San Francisco.



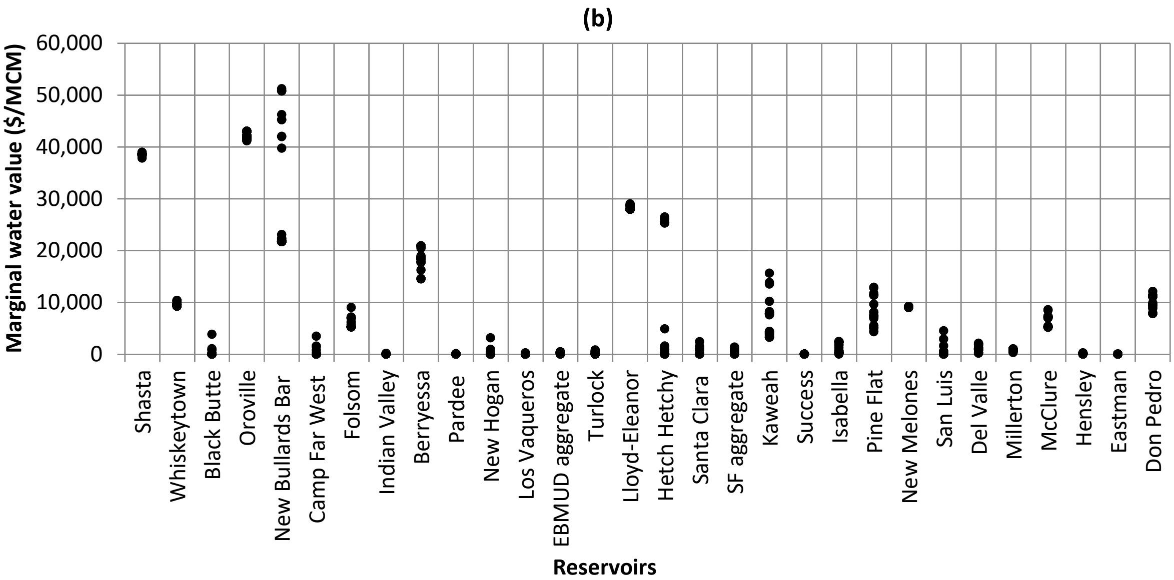


Figure 5. Dispersion of descriptive marginal water value solutions from zone of concentration at: a) dead storage, and b) full storage.

4.3 Comparison of reservoir storage valuations

Having verified that the descriptive valuation of water storage led to a good fit between the benchmark historical operations and simulated operations, we compare the descriptive and prescriptive storage valuations, using both the ensemble of descriptive solutions (Figure 6), and the representative solution (Table 2). Column (1) of Table 2 contains active storage (full storage – dead storage) of surface reservoirs in the last month of the water year, i.e. September. Note that maximum capacity varies per month due to flood control requirements. The second column shows the annual net inflow calculated as annual surface runoff minus any loss (e.g. seepage and evaporation). Columns (3) and (4) include the descriptive marginal water values for the representative solution. Values in column (5) are the average of values in columns (3) and (4), which corresponds to the average marginal value of water from the representative solution – total water value (Figure 6) is then the product of that figure and the active storage. Column (5) of Table 2 can be used as an economic proxy for comparing reservoirs valuation, and to contrast descriptive valuation against its prescriptive counterpart (column 6).

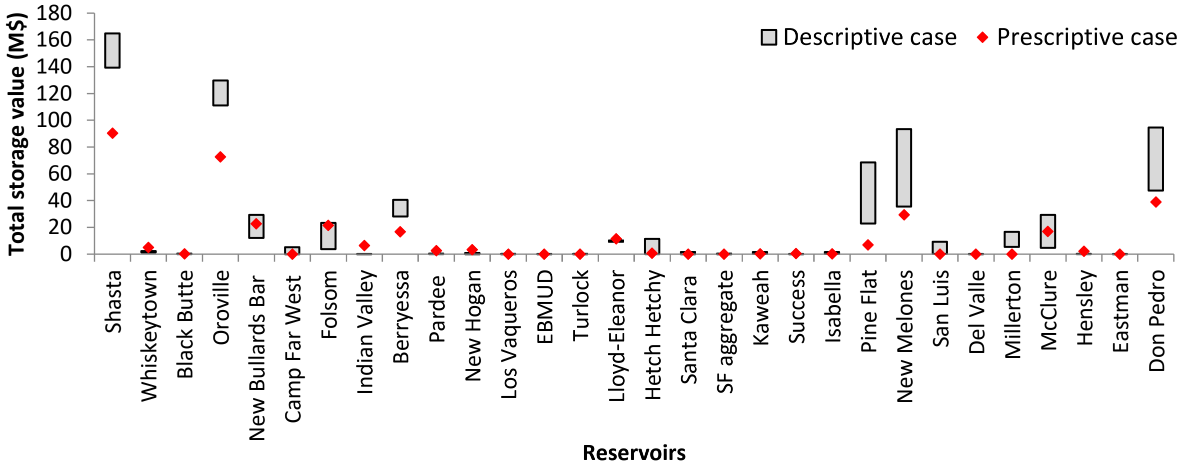


Figure 6. Distribution of the total storage value from the solution points of the zone of concentration. Red points show the maximum COSVF of the prescriptive solution.

Table 2. Descriptive marginal water values of end-of-year surface reservoirs' storage in the Central Valley, listed from north to south compared with prescriptive values.

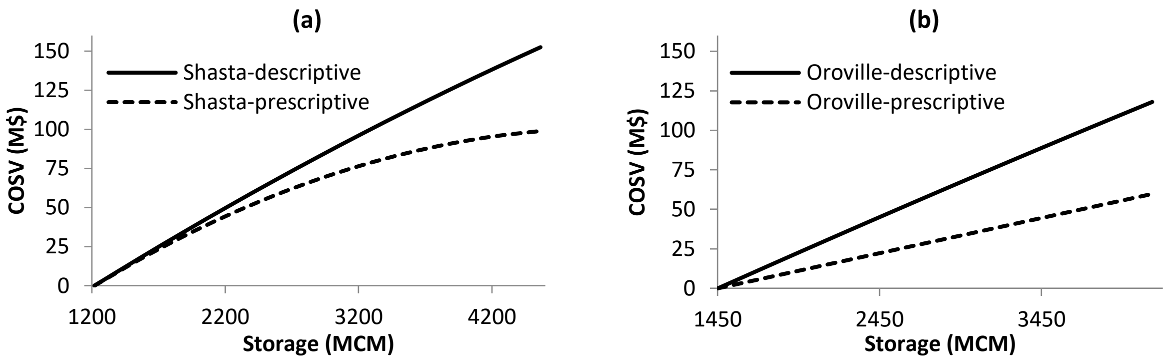
Reservoir	End-of-year active storage (MCM) (1)	Annual average net inflow (MCM) (2)	Descriptive marginal value at dead storage ($/MCM) (3)	Descriptive marginal value at full storage ($/MCM) (4)	Descriptive average marginal value ($/MCM) (5)	Prescriptive average marginal value ($/MCM) (6)
Shasta	3,344	6,816	52,666	38,549	45,608	29,576
Whiskeytown	138	1,144	12,484	9,542	11,013	39,923
Black Butte	122	488	480	189	334	393
Oroville	2,682	4,966	45,830	42,139	43,985	22,263
New Bullards Bar	560	1,496	32,382	28,429	30,406	38,775
Camp Far West	126	458	1,872	1,817	1,844	108
Indian Valley	731	529	15	13	14	10,825
Folsom	701	3,271	27,638	5,830	16,734	34,979
Berryessa	1,926	438	18,915	18,865	18,890	10,656
Pardee	235	840	107	14	60	13,334
New Hogan	263	184	347	120	234	15,416
New Melones	1,507	1,285	74,067	9,108	41,588	19,500
EBMUD	63	0	516	286	401	48
Los Vaqueros	41	0	145	27	86	8
Lloyd-Eleanor	333	542	28,437	28,129	28,283	27,953
Hetch Hetchy	399	936	7,911	7,104	7,507	1,403
Del Valle	23	0	1,273	1,181	1,227	276
Don Pedro	1,727	792	69,837	10,213	40,025	23,716
Turlock	69	0	369	94	232	182
McClure	907	1,128	42,123	5,940	24,032	20,314
SF aggregate	277	0	1,071	650	860	0
Eastman	99	82	959	10	485	264
Santa Clara	209	156	1,766	727	1,246	89
Hensley	79	101	329	135	232	30,892

San Luis	1,958	0	1,275	467	871	1
Millerton	495	2,082	35,190	747	17,969	37
Pine Flat	1,177	2,041	63,661	7,752	35,706	5,767
Kaweah	101	581	5,884	5,747	5,816	913
Success	81	170	281	8	144	5,387
Isabella	453	876	1,670	1,011	1,340	526

Note: EBMUD stands for East Bay Municipal Utility District and SF is San Francisco.

Compared with the prescriptive valuation, the descriptive one is higher for most major reservoirs. Examples are Shasta, Oroville, Berryessa, New Melones, Don Pedro, San Luis, and Pine Flat; and those located in the Sierra Nevada on the eastern range of the Central Valley (e.g. Oroville, New Bullards Bar, Folsom, New Melones, Lloyd & Eleanor, Don Pedro, McClure, and Pine Flat – note how some reservoirs make both groups). These results hold for both Figure 6 and Table 2. This higher valuation in the descriptive solution means that operations conserve surface water in large reservoir by implicitly valuing it more than in smaller surface reservoirs and groundwater reservoirs alike. This has two consequences: (1) groundwater resources are first to supply water; and (2) when it comes to surface reservoirs, smaller reservoirs are prioritised for release. End-of-year COSVF for each reservoir can be derived from values in columns (3) and (4) of Table 2.

COSVF of four large Central Valley reservoirs are compared (Figure 7). To better interpret this result, one can look at the average volumetric water value of these four reservoirs at their full storage i.e. maximum of COSV divided by maximum storage capacity. For the descriptive case, the average volumetric water values at full storage are 33419, 28527, 31605, and 34086 $/*MCM* for Shasta, Oroville, Don Pedro, and Pine Flat respectively. This suggests that attitudes to water conservation in the historical benchmark are similar across these large reservoirs, regardless of their situation within the basins. For the prescriptive case however, the same figures drop to 21672, 14439, 18727, and 5505 $/*MCM* respectively. This suggests different water storage values depending on location within the basin: reservoirs situated upstream can redirect water for use in larger portions of the basin and this makes them more valuable than reservoir situated downstream. More generally, the comparison of these valuations confirms that the descriptive case values stored water more than the prescriptive case, regardless of location.



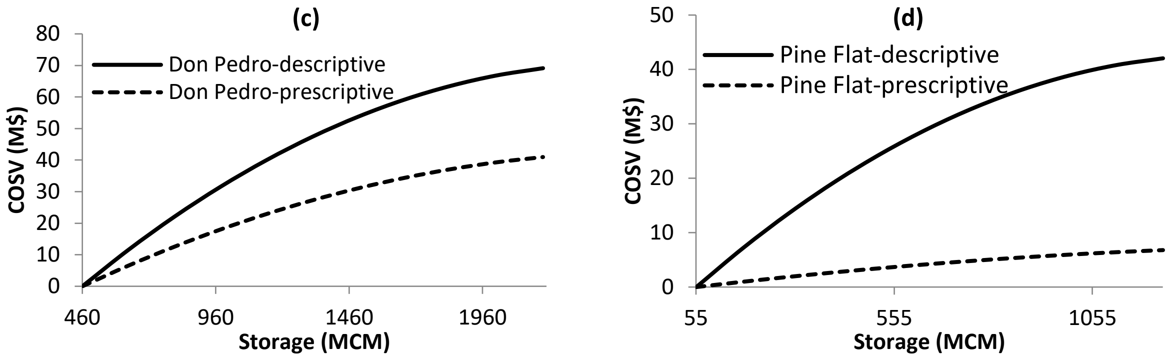
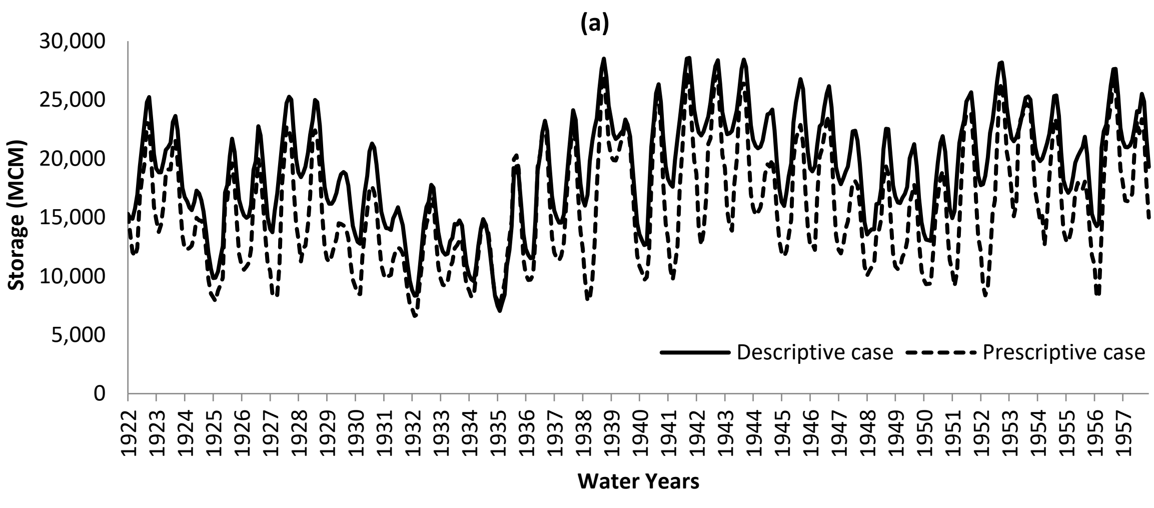
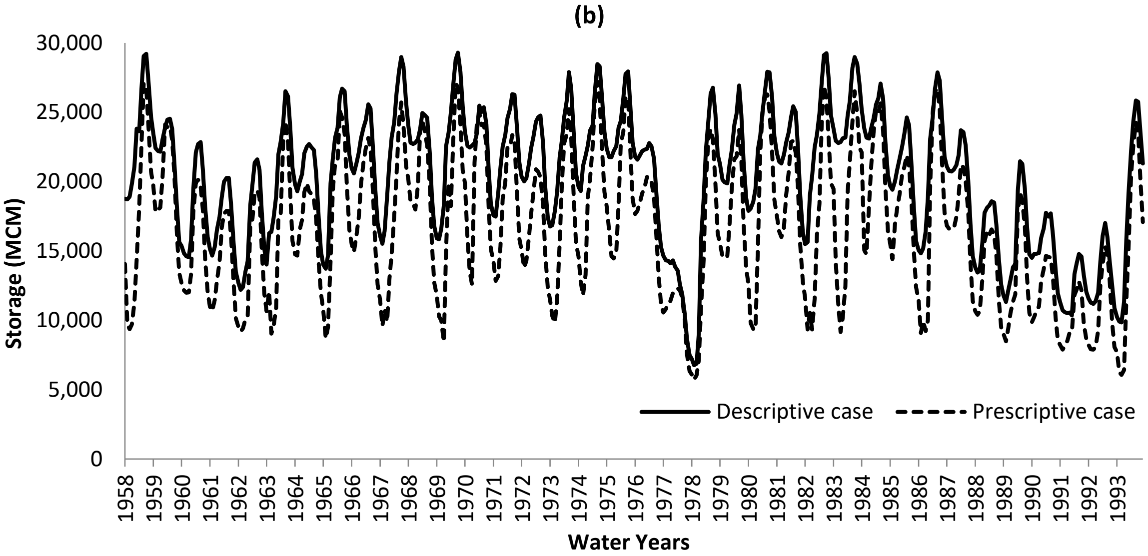


Figure 7. Comparison of the representative solution in descriptive and normative valuation, COSVF of reservoirs in (a) Shasta, (b) Oroville, (c) Don Pedro, and (d) Pine Flat.

4.4 Consequences for water management in California

The system-wide consequences of the difference between the two valuations of water storage are clear through comparison of aggregated surface and groundwater storage during 1922-93 (Figure 8). Implicit overvaluation of surface reservoirs with operations based on a descriptive valuation resulted in a comparative overexploitation of aquifers. At the level of individual reservoirs, columns (1) and (5) of Table 2 show that the historical operation favoured smaller reservoirs when it comes to surface reservoir releases. This can become problematic when a small reservoir is the sole supplier to a demand site (e.g. New Hogan supplying for Stockton). This overcautious operation has led to 80% increase in the annual average scarcity volume [6] compared with operations derived from an "optimal", prescriptive valuation, and to a 5% increase in the average unit pumping cost across the Central Valley.





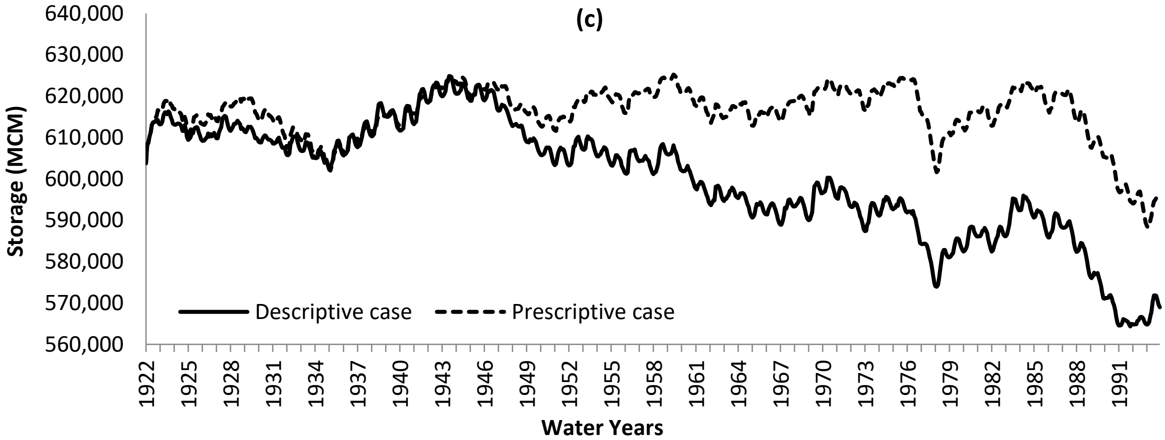


Figure 8. Comparison of the historical simulation and the optimized model for: a) surface reservoirs over 1922-57; b) surface reservoirs over 1958-93; and c) groundwater over 1922-93.

To better demonstrate how risk averse the two reservoir operations are, the absolute risk aversion coefficient for each reservoir is computed and illustrated in Table 3. COSVFs derived from (equation 1) the obtained marginal water values of Table 2 for the descriptive model and [6] for the prescriptive model, are used to calculate the risk aversion (*AP*).

Table 3. Absolute risk aversion coefficient for each reservoir of the descriptive and the prescriptive model. Note that wherever no *AP* is reported, the first derivative of the COSVF i.e. marginal water value is zero.

Reservoirs	September storage (*MCM*)			*AP* of the descriptive model (1/*MCM*)			*AP* of the prescriptive model (1/*MCM*)		
	Dead storage	Mean storage	Full storage	at dead storage	at mean storage	at full storage	at dead storage	at mean storage	at full storage
Shasta	1,220	2,892	4,564	0	0	0	0	0	0.002
Whiskeytown	152	221	290	0.002	0.002	0.002	0.00`6	0.011	0.048
Black Butte	12	73	134	0.005	0.007	0.013	0.008	0.016	-
Oroville	1,453	2,794	4,135	0	0	0	0	0	0.000
New Bullards Bar	310	590	870	0	0	0	0.001	0.002	0.003
Camp Far West	1	64	127	0	0	0	0.007	0.012	0.052
Folsom	102	453	803	0.001	0.002	0.005	0.001	0.002	0.016

Indian Valley	0	366	731	0	0	0	0.001	0.003	2.274
Berryessa	13	976	1,939	0	0	0	0.001	0.001	-
Pardee	15	133	250	0.004	0.007	0.028	0.004	0.008	-
New Hogan	22	153	285	0.002	0.004	0.007	0.004	0.008	4.675
Los Vaqueros	89	109	130	0.020	0.034	0.107	0.025	0.049	-
EBMUD	102	134	165	0.007	0.009	0.013	0.016	0.032	-
Turlock	14	48	83	0.011	0.017	0.042	0.014	0.029	-
Lloyd-Eleanor	38	205	371	0	0	0	0	0	0
Hetch Hetchy	45	245	444	0	0	0	0	0	0
Santa Clara	46	128	210	0.004	0.005	0.009	0.005	0.009	0.035
SF aggregate	38	158	278	0.002	0.002	0.003	-	-	-
Kaweah	1	51	101	0	0	0	0.010	0.020	-
Success	1	41	81	0.012	0.023	0.444	0.012	0.025	-
Isabella	0	226	453	0.001	0.001	0.001	0.002	0.003	0.011
Pine Flat	56	645	1,233	0.001	0.001	0.006	0.001	0.001	0.002
New Melones	978	1,732	2,485	0.001	0.001	0.005	0	0.001	0.002
San Luis	99	1,078	2,057	0	0	0.001	0.001	0.001	-
Del Valle	12	23	35	0.003	0.003	0.003	0.045	0.089	-
Millerton	148	395	643	0.002	0.004	0.093	0.002	0.004	-
McClure	143	596	1,050	0.001	0.002	0.007	0.001	0.002	0.006
Hensley	5	44	84	0.007	0.011	0.018	0.013	0.025	-
Eastman	12	62	111	0.010	0.020	0.948	0.009	0.017	0.124
Don Pedro	460	1,324	2,187	0	0.001	0.003	0	0.001	0.002
Aggregate storage	5,586	15,957	26,329	0.097	0.157	1.761	0.190	0.372	7.252

Table 3 reveals that the prescriptive model is in fact more risk averse in the face of uncertain hydrology. This is consistent with the fact that prescriptive operations minimize shortage. Less intuitively, it shows that even though they value surface water storage more, operations observed in the historical benchmark are not necessarily less risk averse. In fact, this higher valuation is linked with excessive water conservation for future uses in a way that sometimes penalises current uses. This behaviour could be explained by regulatory constraints that water managers have to deal with, but that the model does not account for, such as stream temperature requirements that necessitate cold water released from deep reservoirs lakes to favour salmon habitats.

5 Discussion and Conclusion

This paper proposes a methodology to derive comparable descriptive and prescriptive valuations of water storage. In both approaches, values are deduced from a hybrid setup where an EA is linked to a hydro-economic model. While EA searches for the value of stored water, the role of the hydro-economic model is to link water allocation decisions with the space and time distribution of the value of stored water for future uses. In the prescriptive approach, the EA aims at optimizing long-term benefits from water use, whereas in the descriptive approach, the objective is to provide a valuation that calibrates a historical benchmark. To avoid unrealistic storage valuations in small reservoirs, an auxiliary objective is introduced, meaning that both problems are formulated as being multi-objective, and solved using an MOEA. The resulting modeling approach is generalizable because 1) its applicability is not plagued by the curse of dimensionality linked with system size, and

2) it is assumption free, e.g., it does not require non-convexity assumptions that do not apply in conjunctive use systems. The proposed approach is illustrated through valuation of 30 surface reservoirs in California's Central Valley water system.

The descriptive approach is descriptive insofar as it matches a historical benchmark whose outcome – storage levels across time and space – reflects the regulatory and institutional setting that resulted in the operations that led to this outcome. Yet, the approach itself is not based on simulation but on hybrid optimization, in that it uses an intra-annual optimization model coupled with an EA. The EA calibrates water marginal values to find those that replicate real-world observations. This is done by first taking water marginal values as EA's decision variables (calibration parameters). EA randomly assigns values to these parameters and the water resources system is simulated using these values and a hydro-economic model. Note that this optimization-based descriptive approach, though counter-intuitive, is necessary to adequately compare descriptive and prescriptive valuations. This approach is generalizable and can readily be used when market valuation is absent or inefficient and when non-market methods are plagued with non-convexity and/or curse of dimensionality. Yet, the necessity to assume intra-annual foresight means that this approach may be difficult to apply to tropical and temperate areas where runoff is not snow-dominated.

Results are also interesting in several respects. First, they vindicate the choice to represent intra-annual operations with a perfect foresight optimization models. This indicates that this complex system could be simulated with this simple assumption. In particular, it shows that regardless of the uncertainty concerning snowpack, monthly operations are robust to the consequences of that uncertainty. This robustness may break down on a finer, e.g. daily, timescale, but it is worth noting that most state-of-the-art global hydrological models representing complex multi-reservoir systems use a monthly time step [66], and that their results are not yet accurate enough [67] to justify a finer time resolution.

Beyond, the comparison of descriptive and prescriptive operations is a two-way street. On one hand, it provides insights into the differences between the historical benchmark and optimized operations, by providing comparable valuations of surface water storage. In the case of California, this translates into showing how surface water valuation leads to using groundwater instead. On the other hand, interpreting this finding beyond the confines afforded by the models' formulation provides insights into possible causes of historical management decisions. For instance, the quality of the calibration given constant storage valuations, constant groundwater pumping costs, and constant crop prices, shows a remarkable stability of their relative values throughout most of the twentieth century. But both groundwater pumping costs and crop retail prices have changed through time: the storage valuation could suggest that cheap energy may have favoured mining groundwater – a resource for which no strong management institutions exist in California – whereas surface water rights ensured a greater conservation of surface water. This would link cheap energy prices with unsustainable water management practices, a speculative insight that deserves further investigation. More generally, the difference in surface water valuation from the two approaches reflects the role of institutions providing incentives for surface water conservation, and that are traditionally difficult to represent in an optimization model of that size. This was evidenced by further analysis involving risk aversion coefficients. The exercise revealed that the prescriptive valuation showed a more risk-averse approach to managing water resources. The overcautious operation observed in the historical benchmark was perhaps due to other constraints not seen in the model.

Finally, it is worth elaborating on the fact that different storage valuations could lead to a similar fit of the descriptive model with the historical benchmark it is meant to reproduce. The existence of different parametrisations leading to similar goodness-of-fit is well-known in hydrology as equifinality [68, 69]. Equifinality had also been found in water resources systems models, but only in the fact of producing very different reservoir operations leading to similar value of an economic objective [70, 71]. In the descriptive approach proposed here, the opposite occurs as, similar to hydrological modeling; different parametrisations lead to similar operations. This finding runs contrary to the idea that there exists a unique water price that water markets can organically find to arrive to a near-optimal solution.

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Supplementary Material: Impact of different water valuation clusters on major reservoirs' operation

Here we investigate how the diversity in reservoir storage valuation of Don Pedro, New Melones, and Pine Flat manifests in the operation of these reservoirs. The storage trajectory of these three reservoirs is simulated using valuation solutions that created average, minimum, and maximum values in Figure 6. These three valuations of storage are used in three separate runs of the model, with all other parameters unchanged (including COSVF from other reservoirs). This is depicted in Figure S 1. Resulting end-of-year storage levels of the above three reservoirs prove to be identical regardless of which marginal value of water is chosen (Figure S 1). Therefore, it is the "average" valuation that is reported in Table 2 and forms the 'representative solution'.

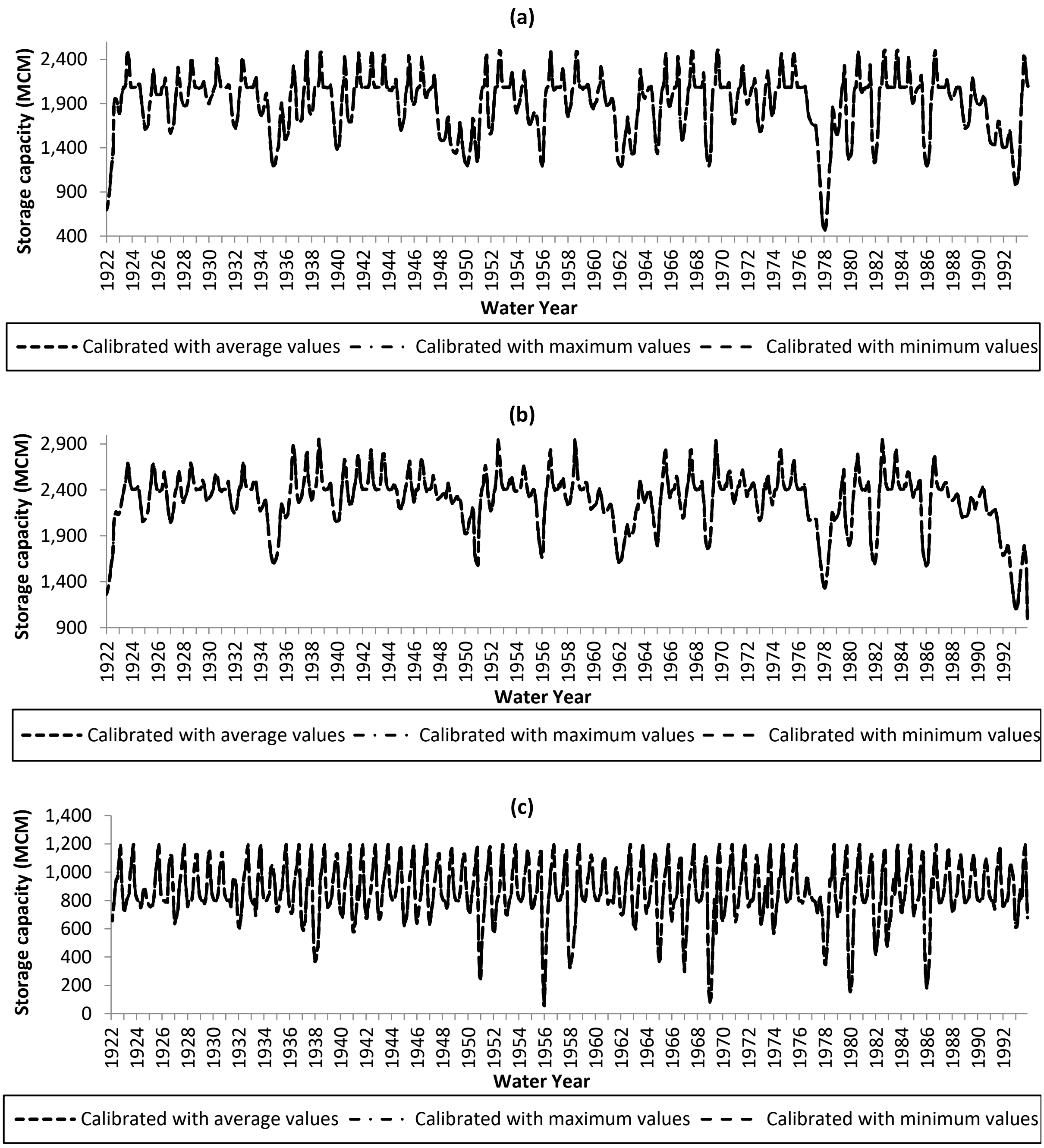

Figure S 1. Calibrated storage trajectories with average, minimum and maximum valuations in: a) Don Pedro, b) New Melones, and c) Pine Flat.