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Key Points:
- This paper introduces an approach to estimating the economic value of interannual reservoir storage
- The approach uses an evolutionary search algorithm linked to a hydroeconomic optimization model
- A regional model of the California Central Valley water resource system illustrates the approach

Supporting Information:
- Supporting Information S1

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Estimating the Economic Value of Interannual Reservoir Storage in Water Resource Systems

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Abstract Reservoir operators face pressures on timing releases of water. Releasing too much water immediately can threaten future supplies and costs, but not releasing enough creates immediate economic hardship downstream. This paper examines how the economic valuation of end-of-year carryover storage can lead to optimal amounts of carryover storage in complex large water resource systems. Economic carryover storage value functions (COSVFs) are developed to represent the value of storage in the face of interannual inflow uncertainty and variability within water resource optimization models. The approach divides a perfect foresight optimization problem into year-long (limited foresight) subproblems solved sequentially by a within-year optimization engine to find optimal short-term operations. The final storage state from the previous year provides the initial condition to each annual problem, and end-of-year COSVFs are the final condition. Here the COSVF parameters that maximize the interannual benefits from river basin operations are found by evolutionary search. This generalized approach can handle nonconvexity in large-scale water resources systems. The approach is illustrated with a regional model of the California Central Valley water system including 30 reservoirs, 22 aquifers, and 51 urban and agricultural demand sites. Head-dependent pumping costs make the optimization problem nonconvex. Optimized interannual reservoir operation improves over more cautious operation in the historical approximation, reducing the average annual scarcity volume and costs by 80% and 98%, respectively, with more realistic representation of hydrologic foresight for California's Mediterranean climate. The economic valuation of storage helps inform water storage decisions.

1. Introduction

This work proposes a generalized approach for the valuation of over-year storage in large-scale water resources systems, even when simplifying assumptions such as convexity do not apply. In particular, it proposes a generalizable approach to value interyear water storage for small or large systems with a variety of mathematical characteristics of the associated economic optimization problem. Such approaches are insightful as water engineering shifts from planning and construction of new storage facilities and to managing existing infrastructure. In this context, water is valuable for competing uses, but its value varies across space and time (Harou et al., 2009). Holistic approaches promoting efficient water allocation in water systems are needed (Cai, 2008; Lund et al., 2006). The need for appropriate water valuation is underscored by regulatory frameworks that promote economically efficient water allocation, for example, the Water Framework Directive (European Commission, 2000, 2012) in the European Union or the emergence of water markets in the western United States (Hadjigeorgalis, 2009; Hansen et al., 2014; Wheeler et al., 2017), Australia (Garrick et al., 2018; Lewis & Zheng, 2018; Owens, 2016; Wheeler et al., 2013), or the United Kingdom (Erfani et al., 2015; Parker, 2007).

Most approaches for efficient allocation of reservoir storage are limited by the so-called *curse of dimensionality* where computational time and memory to increase exponentially with the number of storage units (Bellman & Dreyfus, 1966; Giuliani et al., 2016). Examples include dynamic programming (Banihabib et al., 2017; Fontane & Labadie, 1981; Ji et al., 2017; Mansouri et al., 2017; Marino & Mohammadi, 1983; Tauxe et al., 1979; Yakowitz, 1982; Yeh & Becker, 1982), stochastic dynamic programming (Butcher, 1971; Scarcelli et al., 2017; Soleimani et al., 2016; Stedinger et al., 1984; Torabi & Mobasheri, 1973; Zhou et al., 2017), and model predictive control (Anghileri et al., 2016; Galelli et al., 2015; Mayne et al., 2000; Raso & Malaterre, 2017). Other studies (Cai et al., 2002; Shiau, 2011) used nonlinear optimization formulations with constrained carryover storage volumes. Such approaches require a good understanding of the topology and hydrology of the problem, which makes them case dependent and reduces their generalizability. Few solutions strategies are fit for optimizing large-scale systems. An example is stochastic dual dynamic programming (SDDP; Pereira & Pinto, 1991), a method initially created for large hydropower generation systems and since extended to large-scale transboundary issues including hydropower and irrigation (Tilmant & Kelman, 2007) and other uses (Tilmant et al., 2010). Still, SDDP assumes that the benefit-to-go (or future benefits) function is convex. Nonconvexities are found for instance in head-dependent pumping costs (Davidsen et al., 2016) or endogenous hydropower prices (Kristiansen, 2004; Mo et al., 2001). While SDDP has been extended to systems with both groundwater and surface water reservoirs (Macian-Sorribes et al., 2017), these models omit head-dependent pumping costs.

These remarks (on water allocation optimization methods) extend to the economic valuation of stored water, which is usually tied to the dual values of the solutions in the above methods. The analytical valuation of carryover storage (Draper & Lund, 2004; You & Cai, 2008b) is limited to cases with a few reservoirs. Dual values from optimization with SDDP have been used to approximate the economic value of water storage in large-scale systems with hydrological uncertainty (Tilmant et al., 2008, 2014) or for water accounting (Tilmant et al., 2015). Yet this is only applicable in the absence of significant groundwater abstractions that introduce nonconvexities if the head dependence of pumping costs is included.

To avoid both curse of dimensionality and convexity assumptions, the current paper proposes a generic hybrid approach using evolutionary algorithms (EAs) to estimate the value of water. EAs have been used in conjunction with mathematical programming to deal with the irregular topology of highly constrained decision spaces in global-local hybrid search for complex multireservoir systems (Nicklow et al., 2010), where local optimizations help in finding global optima. With a few exceptions (Tospornsampan et al., 2005), the EA has generally been the global nonconvex search tool, often paired with a linear program (Afshar et al., 2010; Ahn & Kang, 2014; Cai et al., 2001; Reis et al., 2006) or other methods, for example, stochastic dynamic programming in mainly parallel multireservoir systems (Huang et al., 2002). There remains an opportunity to build a generic hybrid approach that can handle (1) complex multireservoir systems featuring serial and parallel reservoirs as well as (2) nonconvexity and (3) interannual uncertainty.

The proposed approach divides the multiyear horizon into year-long subhorizons. These year-long optimization problems are solved sequentially, using reservoirs' end-of-year carryover storage value functions (COSVFs; Draper, 2001; Draper & Lund, 2004) as final annual (boundary) states that contain information on the expected value of water for use during the following years. Contrary to previous analytical approaches for systems of a few reservoirs, here the COSVFs parameters are determined through an evolutionary algorithm that finds the valuation of end-of-year storage defined by COSVF parameters, leading to optimal multiyear operations. This hybrid method contributes a generalizable approach with explicit valuation of stored water. This approach avoids convexity assumptions for surface water and groundwater storage.

This is the first application of EAs to explicitly value water in a hydroeconomic model (Harou et al., 2009). In contrast, some hybrid genetic algorithm-linear programming approaches use evolutionary computation to find end-of-year conditions such as storage targets to prevent reservoirs from being emptied by a within-year mathematical program. Yet this end-of-year state either depends on hydrological conditions in the following year (Cai et al., 2001), in which case it implies year-ahead foresight or on linear weights (Reis et al., 2006), which contradicts the economic intuition that the marginal value of storage decreases as reservoirs fill, analytically demonstrated for a single reservoir (Draper & Lund, 2004; You & Cai, 2008b). A nonlinear concave COSVF, as the one used in this study, can maintain this economic intuition.

The proposed approach also enables a realistic estimation of interannual reservoir storage that is missing from existing perfect foresight models, for example, which assume a perfect knowledge of hydroclimatic conditions over the period of interest, potentially years in advance. Such models have enabled the integration of significant multisectoral complexity in large-scale systems, but naturally, the perfect forecast assumption is at odds with the uncertain information water managers have to deal with. It can lead to suboptimal reservoir policies if their results are interpreted too prescriptively (Philbrick & Kitanidis, 1999). Yet their ability to formulate and solve complex water resources problems means perfect foresight has remained attractive (Bharati et al., 2008; Fowe et al., 2015; Mendes et al., 2015; Parehkar et al., 2016; Vieira et al., 2011; Yang & Yang, 2013; Zambon et al., 2012; Zarghami et al., 2015). This approach provides a convenient and rigorous method for integrating interannual uncertainty into existing models without having to reformulate them from scratch. One benefit of deterministic perfect foresight models is that they are easier to apply to large real-world systems, so providing an approach that permits reducing hydrologic foresight while estimating the economic value of over-year storage is a valuable contribution. This approach is particularly suitable where most hydrologic uncertainty is between years, as is the case for large-scale water supply in Mediterranean climates (such as California).

A synthetic large-scale and multireservoir water system inspired from California's Central Valley illustrates the approach. It is based on existing models of the region, primarily CALVIN (CALifornia Value Integrated Network; Draper et al., 2003) a large-scale hydroeconomic optimization model with perfect foresight. In the remainder of this work, section 2 describes the proposed method; section 3 presents the California Central Valley application; results are shown in section 4, followed by discussion and conclusions in sections 5 and 6, respectively.

2. Method

2.1. COSVFs

The objective of maximizing benefit (or minimizing cost) from operating infrastructure—reservoirs, demand sites, etc.—in a river basin is classically formulated as a stochastic multistage decision-making problem (Bellman, 1964):

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

where [1,T] is the time frame over which the optimization takes place; E[.] is the expectation operator; f_t (.) is the benefit function at stage t; u_t are the decisions taken at t; x_t is the state of the system, typically including reservoir storage; q_t is the vector of stochastic inflows; and v_{T+1} (.) is a final value function. This final value function is incorporated to avoid emptying storage at the end of the modeled time horizon. This optimization occurs under constraints on water balance, physical flow and storage capacities, and institutional and regulatory operations.

Few strategies can tackle the curse of dimensionality that often makes optimization computationally intractable in large systems. This is especially true for nonconvex objectives. A common strategy has been to eliminate uncertainty by solving for a predetermined sequence of inflows $Q = (q_t)_{t \in [1, T]}$, such as the historical sequence of inflows. The maximization of objective Z is approximated by its perfect foresight counterpart Z_{PF}:

$$Z_{\text{PF}}(Q) = \sum_{t=1}^{T} f_t(x_t, u_t, q_t) + v_{T+1}(x_{T+1}, u_{T+1}). \tag{2}$$

Perfect foresight (or deterministic) optimization assumes that all future inflows are known, which can lead to decisions anticipating wet and dry years in advance. This work proposes dividing the time frame [1,T] into K year-long time frames [$t_k + 1, t_{k+1}$]. For instance with a monthly time step and K years, $t_k = (k - 1) \times 12$ so [$t_1 + 1, t_2$] = [1, 12] and [$t_K + 1, t_{K+1}$] = [$T - 11, T$]. A maximization subproblem can be proposed for each year, with the following objective:

$$Z_k(Q, p) = \sum_{t=t_k+1}^{t_{k+1}} f_t(x_t, u_t, q_t) + COSVF_k\left(p; x_{t_{k+1}}, u_{t_{k+1}}\right), \tag{3}$$

where the final condition $COSVF\left(p; x_{t_{k+1}}, u_{t_{k+1}}\right)$ is the COSVF of reservoirs, which describes the expected value of stored water for use beyond the end of the current water year. Assuming a functional form, reservoirs' COSVF can be described by the parameters p of this function—for example, in this work, two parameters for a quadratic COSVF with zero value at dead storage (see equation (13)).

The K subproblems described by equation (3) are solved sequentially. The initial condition of subproblem $k + 1$ is given by the final state from subproblem k. The sequential optimization of objectives Z_1 to Z_K leads to maximizing a limited foresight objective Z_{LF}:

$$Z_{\mathrm{LF}}(Q,p)=\sum_{k=1}^{K}\left(\max_{u_t}\{Z_k(Q,p)\}-COSVF_k\left(p;x_{t_{k+1}},u_{t_{k+1}}\right)\right), \tag{4}$$

where according to equation (3), the term between brackets corresponds to the sum of operational benefits over year k. The limited foresight objective Z_{LF} still assumes perfect foresight in the short term but is limited to the end of the sub-time frame. After that, future inflows are uncertain. The benefits and associated river basin operations yielded by maximizing Z_{LF} depend on the parameters p describing the COSVF. Z_{LF} computes the sum of operational benefits. Contrary to Z in equation (1), the existence of the COSVF into each Z_k ensures that there will not be any unrealistic behavior (emptying reservoirs) at the end of the time horizon. Therefore, the final boundary condition of equation (1) does not need to feature into equation (4), and maximization of the overall objective Z can be approximated by finding the set of parameters p that maximizes $Z_{\mathrm{LF}}(Q,p)$.

2.2. Solution Strategy

In equation (4), finding $\max_{\pi} Z_{\mathrm{LF}}(Q,p)$ is a double maximization problem, with (i) a series of within-year deterministic optimizations and (ii) an optimization in the parameter space of the COSVF (Draper, 2001). Maximization (i) is carried out for a given set of COSVF parameter values p using deterministic optimization. Evolutionary computation is then used to carry out maximization (ii), taking COSVF parameter space as the evolutionary algorithm's decision space. Maximization (ii) locates economically meaningful carryover storage values.

Yet there can be a problem with COSVF coefficients where some reservoirs within the system fill every year. For these reservoirs the search for the highest performing economic valuation of storage becomes insensitive to COSVF parameterization and so a second objective must be added. The second objective finds the lowest valuation that attains best overall economic performance and allows the proposed approach to achieve a meaningful valuation. Thus, maximization (ii) is carried out as part of the resolution of the following multiobjective problem:

$$\min_{\pi}(F_1,F_2), \tag{5}$$

where the first fitness function is that of finding parameter values that maximize benefits from operations in the limited foresight operations:

$$F_1=-\max_{\pi} Z_{LF}(Q,p) \tag{6}$$

The second fitness function eliminates parameter sets that have unreasonably high marginal values of water and carryover storage—the marginal value of storage is a COSVF's derivative. Therefore, fitness function F_2 accounts for the average marginal water value A_{sr} of each reservoir sr with n_{sr} being the number of reservoirs:

$$F_2=\frac{1}{n_{sr}}\sum_{sr}A_{sr} \tag{7}$$

For a quadratic COSVF, A_{sr} is the arithmetic mean of marginal water value at empty and full storages. F_2 weighs all reservoirs the same regardless of size to avoid undervaluing storage in smaller reservoirs. Figure 1 shows the flowchart of the proposed approach.

3. Application

This approach is applied to a model inspired from CALVIN (Draper et al., 2003), an existing optimization model developed for water policy and management in California. CALVIN is a hydroeconomic optimization model with perfect foresight to maximize economic gains from water allocation and management throughout the system over the historical period. CALVIN includes many features of California's water system, such as the integration of surface water and groundwater supplies, the use of optimization over rule-based simulation models, and the use of economic drivers to allocate and operate water rather than water rights and contracts (Draper, 2001). Yet it suffers from the limitations of perfect hydrologic foresight. In the model used here, inspired from CALVIN, hydrological uncertainty is introduced by dividing the monthly 72-year deterministic

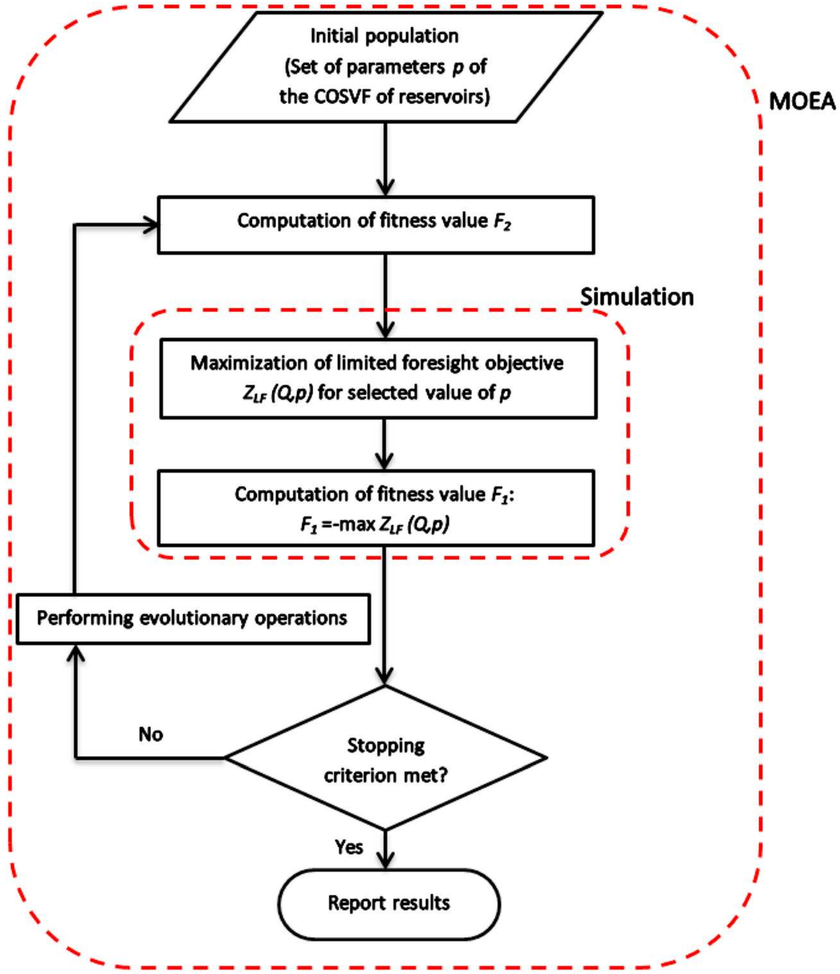

Figure 1. Proposed model workflow. COSVF = carryover storage value function.

model into 72 shorter periods of 1 year each. In the context of California, perfect intraannual foresight is reasonably consistent with the observation that early spring measurements of snow depth and water content enable predicting discharge months ahead with reasonable accuracy and until the end of the water year (Draper, 2001). The impact of perfect within-year forecast on winter operations is limited because the Central Valley inflows are dominated by springtime snowpack melt. For cases where this condition does not hold, one can apply the proposed approach with shorter time frames for which inflow forecasts are sufficiently accurate.

California's Central Valley (see map on Figure 2) covers 20,000 square miles (51,800 square kilometers) and is one of the world's most productive agricultural regions (Faunt, 2009). This area serves over 30 million people and over 2.3 million hectares of irrigated farmland (California Department of Water Resources [CDWR], 2009). More than 250 different crops are grown in the Central Valley with an estimated value of $17 billion per year (Great Valley Center, 2005). About 75% of California's irrigated land is in the Central Valley, which relies heavily on surface water diversions and groundwater pumping (Faunt, 2009). Another major demand is hydropower which is 9% to 15% of the electricity used in the state, depending on hydroclimatic conditions (Aspen Environmental Group & Cubed, 2005). The study area is delimited by mountain ranges on all sides, except around its outlet on the San Francisco Bay to the West (Faunt, 2009). The northernmost reservoirs in the study area are Shasta and Whiskeytown, and the southernmost is Isabella.

The spatial and temporal distributions of water supplies and demands are skewed in California. Nearly 75% of renewable water supply originates in the northern third of the state in the wet winter and early spring. Nearly 80% of agricultural and urban water use is in the southern two thirds of the state in the dry late spring and

Figure 2. The California Central Valley storages and river system. EBMUD = East Bay Municipal Utility District; SF = San Francisco.

summer (California Natural Resources Agency, 2009). California's Central Valley often suffers from droughts. Historic dry periods include 1918–1920, 1923–1926, 1928–1935, 1947–1950, 1959–1962, 1976–1977, 1987–1992, 2007–2009, and 2012–2016 (CDWR, 2015).

An arc-node representation of the water system is used. Nodes include surface and groundwater reservoirs, urban and agricultural demand points, and junctions, and arcs (links) include canals, pipes, and natural streams (Shamir, 1979). This network comprises over 300 nodes, including 30 surface reservoirs, 22 groundwater subbasins, 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).

This model uses the same input data that were originally used in the CALVIN model, including the network, the hydrology, demands, costs, and constraints. In particular, hydrological data is from a 72-year historical inflow data covering 1922 to 1993 and used in CALVIN (Jenkins et al., 2004). Demand data adopted from

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the CALVIN model are projected at 2020 levels according to the CDWR data on per capita urban water use by county and population by detailed analysis unit assembled for Bulletin 160-98. However, the current model excludes CALVIN's region 5 and replaces CALVIN's fixed-rate groundwater pumping cost with a head-dependent scheme. One should keep in mind that this is a distinct model centered around the Central Valley and not of the whole California system.

3.1. Annual Optimization Model

For year $k \in [1; 72]$, benefits are computed over a monthly time step, and the benefit maximization objective from equation (3) translates into

$$Z_k(Q,\pi) = \sum_{t=12\times(k-1)+1}^{t=12k} \left(\sum_{ur} UB_t^{ur} + \sum_{ag} AB_t^{ag} + \sum_{hp} HB_t^{hp} - \Sigma_{i,j} NC_t^{i,j} - \Sigma_{gw} PC_t^{gw} - \Sigma_i IC_t^i \right) + \Sigma_{sr} COSVF_{t=12k}^{sr}. \tag{8}$$

The sums of monthly benefits (between brackets) are in order of urban benefits summed over urban demand sites *ur*, agricultural benefits summed over agricultural demand sites *ag*, hydropower benefits summed over hydropower plants *hp*, network costs summed over all links between any pair of nodes (*i,j*), pumping costs summed over all exploited aquifers *gw*, and infeasibility penalties summed over all nodes *i*. The end-of-year COSVF condition over all surface reservoirs *sr* is the same as in equation (3). For each month, the model is subject to the water balance constraint; lower/upper bounds on flows and storage levels; and hydropower generation capacity. In addition, a major aspect of California's hydrology is return flows from agricultural and urban activities (Jenkins et al., 2001). Return flows of applied water from agricultural and urban water use to surface and groundwater deep percolation are included in the proposed model. They are expressed as a percentage of water used at each demand site.

Economic benefits come from water use by urban and agricultural demand sites and from hydropower generation. Benefit functions used convey the economic intuition that allocating an additional unit of water increases benefits as long as demand is not fully met (positive first derivative) but that marginal returns are decreasing (negative second derivative). Piecewise linear benefit functions (*AB*) for agricultural demand sites are identical to those of CALVIN. Quadratic urban benefit functions (*UB*) use data from Jenkins et al. (2001) with water retail prices (Black & Veatch, 1995) to represent urban willingness-to-pay at target demand.

In California, it is assumed that 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 (Madani & Lund, 2007; Vicuna et al., 2008):

$$HB_t^{hp} = R_t^{hp} PF^{hp} p_t, \tag{9}$$

where *R* is the release from the reservoir for the power plant *hp*, *PF* is the power factor that relates release to hydropower generation, and *p* is the monthly varying hydropower unit price.

Costs in the objective function include network costs (*NC*) for conveyance, treatment, and conjunctive use operations; costs for infeasibilities (*IC*); and energy costs for groundwater pumping (*PC*). Network costs are linear with respect to flows through a link, that is, a constant unit cost for each link. To guarantee algorithmic feasibility, artificial inflows can be made available at each node, similar to Draper et al. (2003) for CALVIN. These flows only exist to allow for constraints being met, so they are penalized by a penalty (cost) several orders of magnitude above other costs. These are particularly valuable for identifying and debugging infeasibilities.

The CALVIN model represents pumping costs by multiplying the unit pumping cost of \$49.42 per MCM/m lift (\$0.20 per af-per-ft lift; MCM is a million cubic meters) by a static estimate of the average pumping head in each groundwater subbasin (Hansen, 2007)), the current model has pumping costs that dynamically vary with head in the aquifer, following the equations proposed by Harou and Lund (2008). Systemwide groundwater pumping costs are represented as follows:

$$PC_t^{gw} = uc_t^{gw} \sum_{gw,j|gw,j \in CO} Q_t^{gw,j}, \tag{10}$$

$$uc_t^{gw} = c^{gw} L_t^{gw}, \tag{11}$$

In above equations, uc is pumping unit cost; CO is the connectivity matrix, which defines how nodes are linked; c is the unit cost per lift; and L is the height water being lifted to reach the ground elevation. Harou and Lund (2008) suggest that the storage coefficient formulation is a parsimonious method to model both lumped groundwater volume and head functions. The storage coefficient relates the volume of water released or absorbed into or from storage (net stress) per unit surface area of the confined aquifer per unit change in piezometric head. Piezometric head in each groundwater subbasin is calculated as follows (lift is set equal to the difference between ground elevation and the piezometric head level):

$$L_t^{gw} = L_{t-1}^{gw} - \frac{i_t^{gw} + \sum_{i,gw|i,gw \in CO} l^{i,gw} Q_t^{i,gw} - \sum_{gw,j|gw,j \in CO} Q_t^{gw,j}}{s^{gw} a^{gw}}, \tag{12}$$

where i is the net recharge from precipitation, l is the loss coefficient in links (due to evaporation and/or seepage), s is the mean storage coefficient, and a is the aquifer's area. Finally, end-of-year COSVF are quadratic functions of storage in each surface reservoir, depending on two parameters $\left(p_1^{sr}, p_2^{sr}\right)$ defined by

$$\begin{cases} COSVF^{sr}\left(p_1^{sr}, p_2^{sr}; s_{\min}^{sr}\right) = 0, \\ \left.\dfrac{\mathrm{d}COSVF^{sr}}{\mathrm{d}s}\right|_{s=s_{\min}^{sr}} = p_1^{sr}, \\ \left.\dfrac{\mathrm{d}COSVF^{sr}}{\mathrm{d}s}\right|_{s=s_{\max}^{sr}} = p_2^{sr}. \end{cases} \tag{13}$$

The nonlinear model of the California system is coded in GAMS and solved using the Minos solver version 5.5 (Murtagh & Saunders, 1998). Minos applies the generalized reduced gradient method, which is suitable for nonlinear programming problems with linear constraints (Labadie, 2004).

3.2. Multiobjective Problem and Resolution

The multiobjective problem formulation is as described in the method section, equations (5) to (7). Using the parametrization of end-of-year COSVFs, the fitness of the carryover storage objective is given by

$$F_2 = \frac{1}{n_{sr}} \sum_{sr} \frac{p_1^{sr} + p_2^{sr}}{2}. \tag{14}$$

Borg (Hadka & Reed, 2013) was used as the multiobjective evolutionary algorithm (MOEA) because Borg's self-adaptive features increase its robustness and effectiveness while minimizing the search parametrization by the user. There are 30 surface reservoirs, so there are 60 decision variables for solution by the evolutionary algorithm. Carryover storage value can only have positive values and are bounded by the maximal value of the urban and agricultural water demand curves. 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 \$1,000,000 and \$8,107 per MCM (\$10 per af) for the fitness functions (equations (6) and (7), respectively) were used. The case presented here was solved using 96 Intel processors working jointly on a Unix-based computing cluster.

Results are presented as a set of *nondominated* solutions, or Pareto front, where any improvement to one objective is at the expense of the other objective. Evolutionary algorithms are heuristic search methods that approximate the Pareto front without ever reaching it in an absolute mathematical sense. Formally therefore, the trade-offs are *Pareto-approximate* although they are subsequently being referred to as *Pareto-optimal* to simplify the discussion (Hurford et al., 2014).

Finally, to assess the sensitivity of the resulting COSVFs to different streamflow conditions within the range of plausible historical behavior, basin management is simulated with those COSVFs and an ensemble of synthetic scenarios generated by bootstrap. A hundred time series are generated.

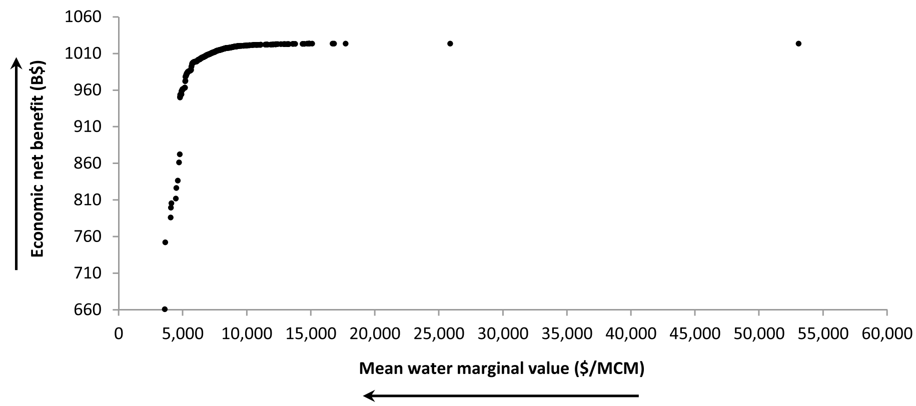

Figure 3. Nondominated solution points showing the Pareto-optimal trade-off between the two objective functions: economic benefits and mean water marginal values (arrows show the direction of preference).

4. Results

4.1. Marginal Water Values

To capture the trade-off between the two fitness functions, a random seed analysis with five seeds was performed. Figure 3 shows the Pareto optimal solution points. The Pareto front quickly becomes nearly flat regarding the main (economic) fitness function F_1, suggesting that the economic optimization problem possesses multiple near-optimal solutions. As detailed in the supporting information S1, the COSVF parameters leading to each of these near-optimal solutions are very similar, with differences mainly for small reservoirs. The remainder of this results section uses averages of the COSVF parameters across these simulations, displayed in Table 1; this is also justified by the supporting information S1.

Table 1 shows that marginal water values are low for surface reservoirs with very low annual net inflow (e.g., Los Vaqueros, Del Valle, Turlock, San Francisco aggregate, and San Luis), suggesting that the Central Valley economy usually does not rely on them (at the margin) for water supply. Surface reservoirs in the northern regions (upstream) and those on the eastern range of the Central Valley have higher marginal values for stored water (e.g., Shasta, Whiskeytown, Folsom, Oroville, New Bullards Bar, and New Melones). Reservoirs producing hydropower normally show higher marginal values. These reservoirs are also on the eastern range (Figure 2). This is consistent with taller mountains and higher volumes of inflow. Table 1 demonstrates how valuable water is at different points in the basin, a proxy for economic water scarcity (Pulido-Velazquez et al., 2013). This suggests to decision makers where of focus for new policy decisions—regulations, investments, etc. Figure 4 shows a map of surface reservoirs' mean marginal water value in California Central Valley. This figure depicts that geographical distribution of reservoirs is the main reason for variation in the valuation.

4.2. Basinwide Interannual Operation

Interannual reservoir operation results compare the approach proposed here with perfect foresight results for the same model and with historical conditions as estimated by the CALVIN model (Jenkins et al., 2004) using a highly constrained model calibrated to represent operation policies in 1998. All models use identical starting storages. The perfect foresight model also has a final boundary condition to avoid emptying surface reservoir and groundwater aquifers in the final years of the record.

Total surface storage time series is shown in Figure 5. The perfect foresight model uses more of the available storage because it hedges ideally against future droughts and knows when these droughts are going to end. COSVF in the limited foresight model encourages saving water for subsequent potentially dry years, and thus this model leads to a more cautious water allocation to hedge against droughts. Historical operations (as estimated by CALVIN) are still more conservative than the limited foresight model, due to (1) historical demand being less than the projected 2020 demand levels used, (2) greater groundwater use than predicted by the limited foresight model (Figure 6), and (3) a more cautious approach by real-world reservoir operators who lack perfect intraannual foresight.

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Table 1
Marginal Economic Value of Stored Surface Water in September at Major California Central Valley Reservoirs, Evaluated by the Limited Foresight Hydroeconomic Model

Reservoir	End-of-year active storage (MCM)	Annual average net inflow (MCM)	Marginal benefits from hydropower generation ($ per MCM)	Marginal value at dead storage ($ per MCM)	Marginal value at full storage ($ per MCM)
Shasta	3,344	6,816	7,475	51,659	7,493
Whiskeytown	138	1,144	9,258	70,557	9,288
Black Butte	122	488	0	785	0
Oroville	2,682	4,966	11,180	22,263	22,263
New Bullards Bar	560	1,496	21,719	55,829	21,720
Camp Far West	126	458	0	190	25
Indian Valley	731	529	0	21,636	13
Folsom	701	3,271	5,245	64,711	5,246
Berryessa	1,926	438	0	21,311	0
Pardee	235	840	0	26,668	0
New Hogan	263	184	0	30,807	25
New Melones	1,507	1,285	9,015	29,984	9,015
EBMUD aggregate	63	0	0	95	0
Los Vaqueros	41	0	0	16	0
Lloyd-Eleanor	333	542	27,953	27,953	27,953
Hetch Hetchy	399	936	0	1,403	1,402
Del Valle	23	0	0	552	0
Don Pedro	1,727	792	7,815	39,475	7,957
Turlock	69	0	0	363	0
McClure	907	1,128	5,221	35,396	5,231
SF aggregate	277	0	0	0	0
Eastman	99	82	0	490	37
Santa Clara	209	156	0	154	23
Hensley	79	101	0	61,784	0
San Luis	1,958	0	0	2	0
Millerton	495	2,082	0	74	0
Pine Flat	1,177	2,041	2,910	8,563	2,971
Kaweah	101	581	0	1,825	0
Success	81	170	0	10,773	0
Isabella	453	876	0	900	151

Note. Reservoirs are from north to south. Maximum capacity varies per month due to flood control rules. Net inflow includes deductions for evaporative and seepage losses. EBMUD = East Bay Municipal Utility District; SF = San Francisco.

Regarding total groundwater storage, the main feature is the dynamic pumping cost (equations (10)–(12)), which incentivizes conserving and replenishing groundwater (Figure 6) to reduce subsequent pumping costs. Groundwater abstraction is also bounded by a minimum aquifer storage limit. The more liberal use of surface reservoirs in the perfect foresight model avoids pumping costs by maintaining storage levels in groundwater subbasins close to full capacity (Figure 5). The conservative operation of surface reservoirs in the historical case means the state relies more on groundwater sources as reflected with its more intensive use in Figure 6. The perfect foresight model hedges against future droughts using groundwater resources. This is why aquifer storages reach near full capacity over the few years prior to every drought. It is worth noting the difference between refill cycle in surface reservoirs and groundwater subbasins. While surface reservoirs refill every year (or every few years in case of drought), aquifers are drawn down and refilled in longer periods, for example, a decade. This is specifically apparent for the perfect foresight model (Figure 6), which knows of upcoming droughts many years in advance.

Difference in the operation of storage leads to different allocation results. The simulated allocation is seen in water scarcity among demand sectors (Figure 7). The perfect foresight model anticipates droughts to store additional water and hedge lower value uses, which leads to a small but constant water scarcity—there is no shortage of urban demand and negligible 0.024% agricultural shortage. Scarcity costs are shared across time in an economically efficient way. The proposed hybrid optimization approach is geared to avoiding large costs from severe droughts, at the expense of recurrent shortage for the least valuable water uses—

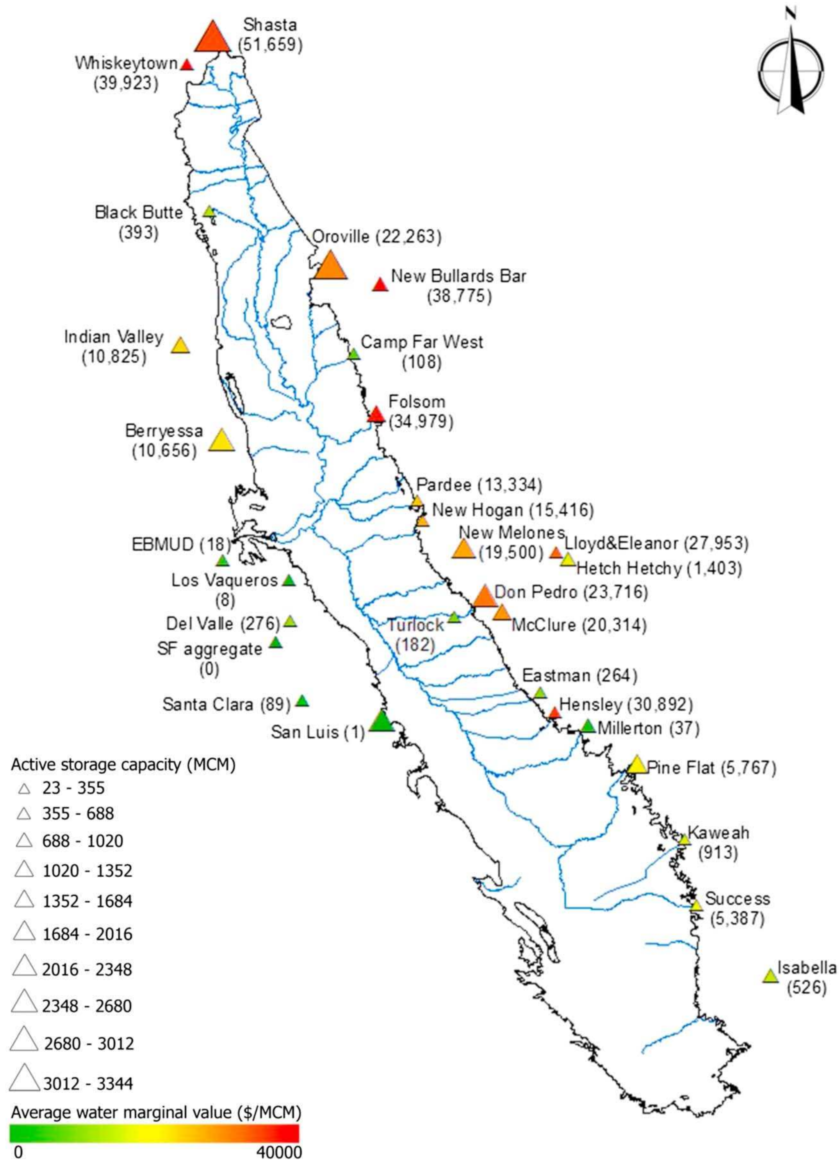

Figure 4. Distribution of average stored water marginal value in the Central Valley. Values in parenthesis are average marginal value. EBMUD = East Bay Municipal Utility District; SF = San Francisco.

in agriculture, with scarcity up to 1.4% in 1977. It still avoids almost any water scarcity to cities, with peaks at 1.2% shortage in the severe 1977 drought. Yet average scarcity remains quite small in the model (0.3% of target demands per year). Cautious operation obtained by the run constrained to near-historical operations incurs higher scarcity of deliveries (1.5% of target demands per year), perhaps reflecting some real historical water scarcity and historical demand levels smaller than those modeled here. The reduction in the average annual scarcity volume from the historical operation to the limited foresight model was equal 80%. Comparison of annual scarcity costs indicates that more efficient hedging in the limited foresight model decreased average annual scarcity cost by 98% (Figure 7b). The reduction in average annual scarcity volume and cost was respectively 95% and 100% from the proposed limited foresight model to the perfect foresight counterpart.

4.3. Sensitivity Analysis

This section investigates the robustness of the COSVF coefficients from the optimization results to different streamflow conditions within the historical range, that is, with climatic conditions similar to those of the

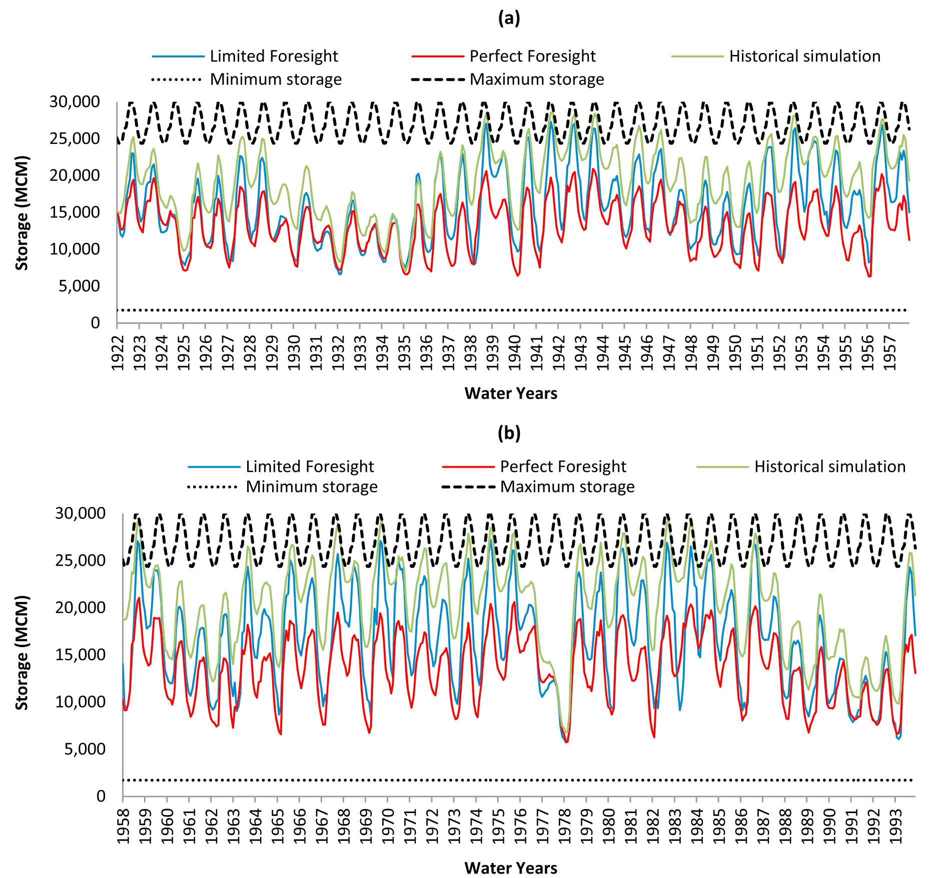

Figure 5. Annual aggregated surface reservoirs' storage level comparison during: (a) 1922–1957 and (b) 1958–1993.

72-year time series used for the limited foresight model run. An ensemble of synthetic scenarios was created by bootstrapping from the historical time series. We generated a set of 100 monthly time series of 72-year length by bootstrap resampling of the historical streamflow time series (Anghileri et al., 2016; Harou et al., 2007, 2010; Knight et al., 2018). These scenarios are built by randomly reordering annual blocks of inflow from historical data (Salas, 1992; You & Cai, 2008a). This preserves monthly autocorrelation but not interannual correlation. However, it is noteworthy that for system-wide annual runoff, interannual autocorrelation is not statistically significant even at the 90% level (0.109 vs. 0.194). Therefore, rather than

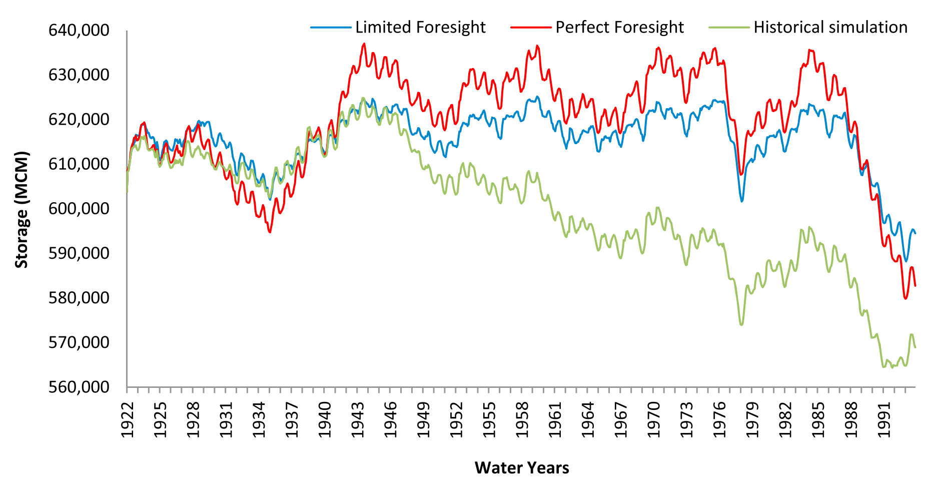

Figure 6. Annual aggregated groundwater storage level.

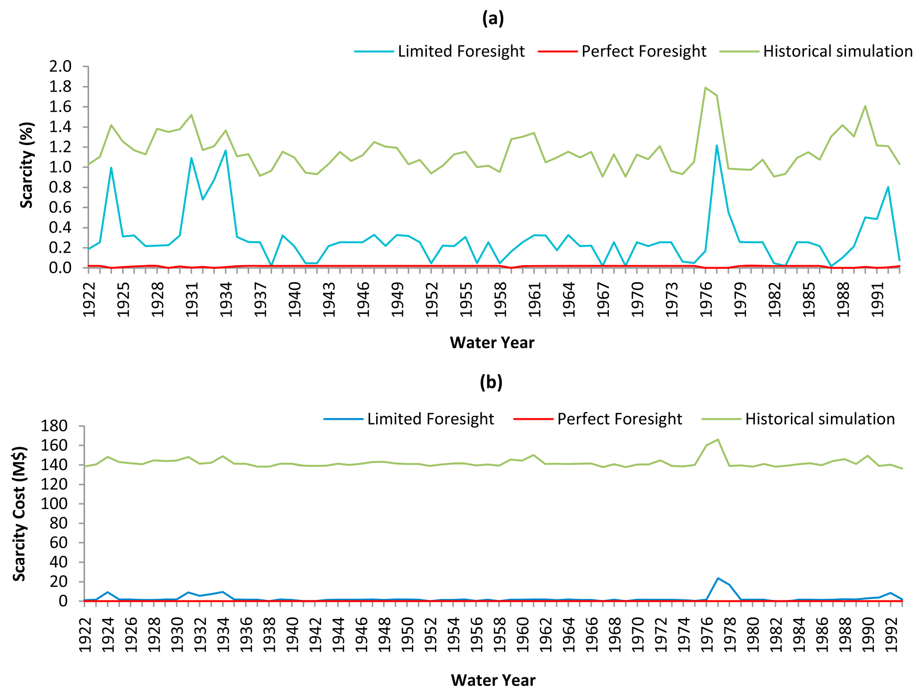

Figure 7. Comparison of (a) water scarcity as the percentage of target delivery and (b) the corresponding scarcity cost in demand sectors (combined agricultural and urban demands).

picking interannual correlation as an indicator of drought persistence, we assessed it based on the runoff for the worst 3-year period for each time series. We found that resampling actually reinforced the likelihood of persistent drought, as evidenced by the fact that the 3-year period with least runoff is more severe in 97 of the 100 synthetic time series than in the historical time series. Below, we show the shortage and drought indicators generated by operating these systems while using the same COSVF coefficients as in Table 1—and sections 4.1 and 4.2. Figure 8 depicts the range of monthly inflows in the synthetic ensemble and compares it to the historical trend.

We used the aggregate 72-year water shortage volume and the volume of the worst 3-year shortage (that is the duration of the worst drought in the historical event) as an indicator to compare the performance of the synthetic ensemble to those of the proposed limited foresight model and the historical simulation. The performance is illustrated as an exceedance probability chart (Figure 9). Each point from this chart shows the percentage of times that scenarios produced a value equal to or greater than the one of that point.

The aggregate water shortage in all synthetic hydrology simulations was lower than the historical simulation's, with 91% of synthetic time series producing less than half the historical 72-year shortage volume. This indicates that the valuation of surface water via COSVFs found using historical inflows can robustly improve the management of water resources under a range of plausible future conditions.

The worst 3-year shortage of each synthetic scenario was also compared with the worst historical 3-year drought. Thirty-seven percent of synthetic scenarios showed higher total water shortage volume than the historical simulation. This is due to their being several worse-than-historical 3-year droughts in the synthetically generated ensemble and to the fact that in some scenarios, conditions were already dry before the selected droughts. The combination of the two is expressed as available water—the total runoff during the 3-year period plus the initial surface water storage, which contrary to groundwater is available without pumping costs—in Figure 10. Recall that 97 out of 100 of these worst 3-year drought periods on this figure feature less available water than in the historical case.

5. Discussion

This paper presents an approach to evaluate interannual reservoir storage in nonconvex and nonlinear large-scale optimization models of water resources systems. It uses optimized end-of-year COSVFs for surface water

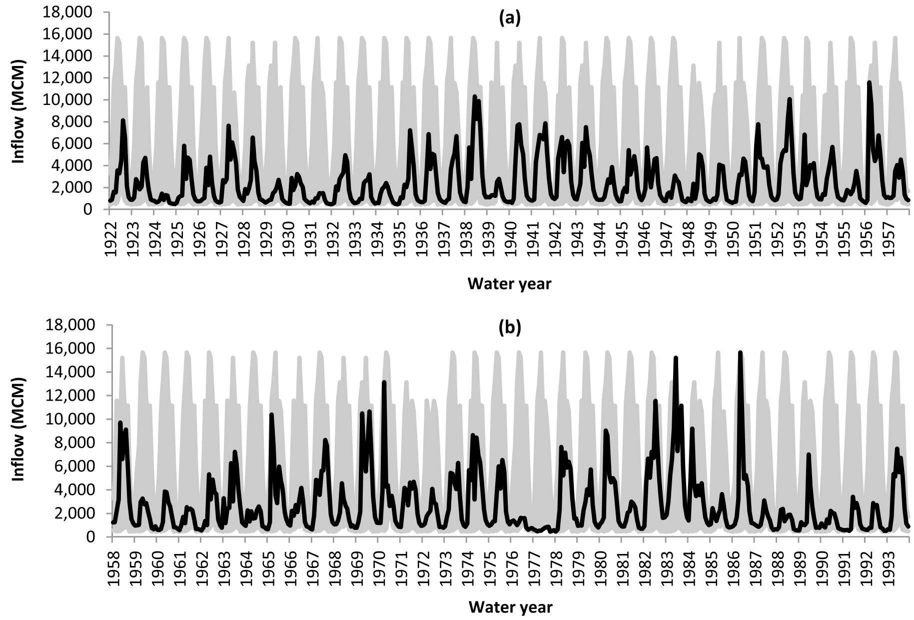

Figure 8. Envelope showing the distribution of river inflows in the synthetic ensemble (in gray) and the historical inflow data (black line) during: (a) 1922–1957 and (b) 1958–1993.

reservoirs to account for the expected value of water availability beyond the current water year. These COSVFs are quadratic to reflect the decreasing marginal value of stored water. Multiyear perfect foresight problems can be reformulated as a suite of multiperiod mathematical programing problems solved sequentially with (a) storage calculated at the end of each subproblem serving as the initial storage condition for the next one and (b) COSVFs representing the imperfect information of system operators

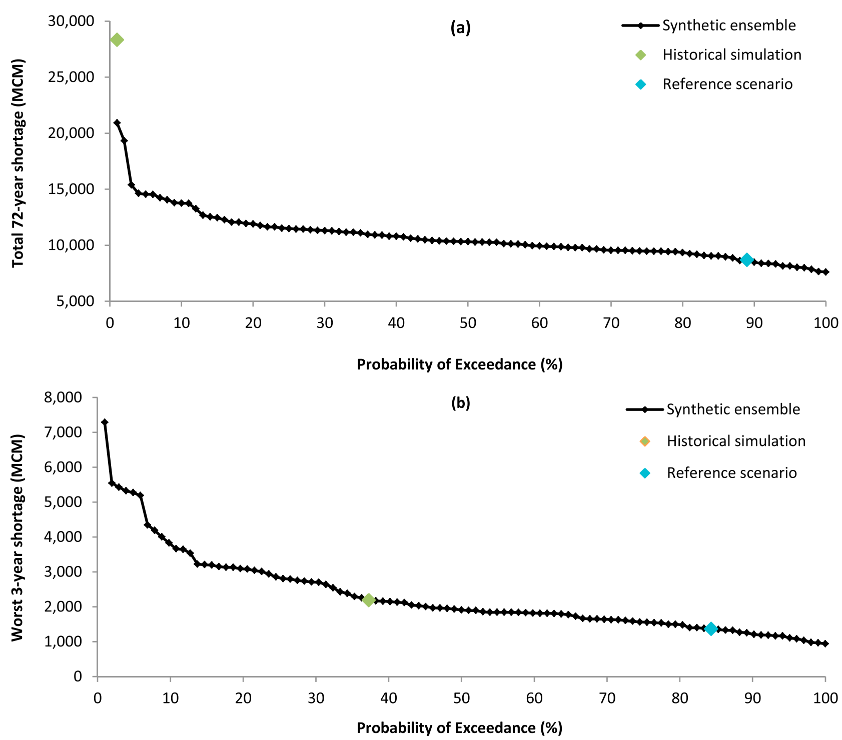

Figure 9. Probability of exceedance of (a) aggregated 72-year shortage volumes and (b) worst 3-year shortage volume. The reference scenario is the one obtained with historical inflow, and with COSVF, that is, the limited foresight model.

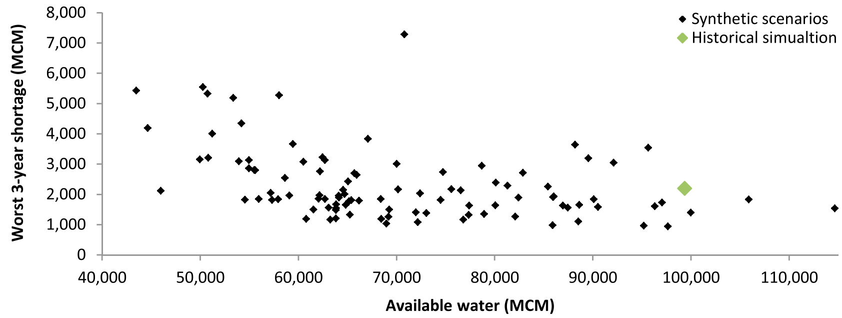

Figure 10. Comparison of water shortage and water availability during the worst 3-year drought.

about future inflows (in this application a water year). COSVFs are represented by quadratic functions whose parameter values are found by evolutionary search methods. To our knowledge, this is the first instance of coupling an evolutionary algorithm with a hydroeconomic model, and the first approach to economically value storage in large-scale systems where the associated optimization problem is nonconvex.

Values obtained for only the economic objective function (F_1) of the MOEA suggest an upper threshold for COSVF parameters rather than a direct estimate. Introducing the second objective (F_2) to optimize these parameter values helps find the lowest possible marginal water values that keep reservoirs from being over depleted at the end of each year. Thanks to the use of MOEA, other management objectives could be integrated into the valuation of carryover storage; this is left to future work.

An application of the proposed limited foresight model to California's Central Valley is compared to results obtained by its perfect foresight counterpart and another model run representing operations constrained to resemble historical ones. These provided useful information on the consequences of management with hyperopia and myopia, respectively. The perfect foresight (hyperopia) model, with full knowledge of future inflows, relies heavily on surface reservoirs rather than groundwater aquifers. Simulated historical results, used to represent real-life operation over the period of study, show that its myopic behavior can lead to poor outcomes: Conservative use of surface water resources implies more intensive use of groundwater and greater groundwater overdraft (Harou & Lund, 2008; Nelson et al., 2016). The historical operating case also shows substantial water scarcity, shorting an average of 1.5% of target demands per year. The proposed limited foresight model showed that its operation is cautious enough to manage future droughts, even though without information about the long-term future hydroclimatic conditions as in the perfect foresight models.

The proposed limited foresight model reported values of end-of-year storage. This can inform operators and water managers about the economic value of keeping water in storage for subsequent potential dry years and be used as a proxy to highlight areas for expansion. Implementing nonconvex head-dependent pumping costs in the model would not be possible with methods that depend on convex (linear) behavior of the model such as SDDP. In addition, simulating the case considered in this study reduced run time from nearly 30 hr for the perfect foresight model to 5 min on the same machine for the limited foresight model and enabling the link to a heuristic search algorithm. The search for optimal COSVFs required 87 hr per random seed per core, using 96 CPU cores on a Unix computing cluster.

Some limitations exist for this work. High nonlinearity and long run times of the proposed approach linking the model to many-objective heuristic search restricts its extendibility. For example, considering the common nonlinear relation for hydropower generation for similar cases of the same scale could make the approach computationally impracticable due to increase in the number of variables (height of water in reservoirs) and model nonlinearity. However, even with the current model, this issue could potentially be addressed by choosing an efficient algorithm for the annual optimization phase of the hydroeconomic model. Also, in the current work on carryover storage, only the value of surface water reservoirs is considered; dynamic pumping costs are considered a proxy for groundwater value to make the problem more tractable (with fewer storage units to optimize COSVF parameters).

Surface and groundwater storages have asymmetric roles in water valuations. Without value functions for surface reservoirs, their use would be free in a hydroeconomic model, leading to their more aggressive depletion. So surface water storage valuation is crucial to represent the uncertainty value of stored surface water.

Besides, surface water storage is filled and depleted every year or every few years at most. This short timescale compared with the study period makes interpretation of COSVFs unambiguous. This is not the case for groundwater. We tested the incorporation of COSVF for groundwater and found that (1) the cost of using groundwater *seen* by the hydroeconomic model is "pumping cost + carryover storage value." In most aquifers, pumping costs are large enough that the COSVF is near zero; (2) as a consequence of (1), integration (or not) of COSVF has little effect on management outcomes; and (3) large, multidecadal variations in the aquifer storage make their COSVF (when it exists) difficult to interpret.

6. Conclusion

Interannual reservoir operation in large water resource systems has long been a challenge. Approaches using models with hyperopia (perfect foresight optimization) assume full knowledge of future supply and demand, which is unavailable to water managers. In contrast, a model with myopia, such as the one used to approximate historical operating policies, manage reservoirs overcautiously, imposing greater economic scarcity during major droughts, and overhedging here in nondrought years. In this paper we present an approach to address this modeling problem by limiting hydrological foresight (to represent the annual forecasting afforded by California snow storage estimation), which requires determining the economic value of end-of-year carryover storage. The proposed approach discretizes the full planning horizon to shorter periods (one water year in this application) and performs sequential optimization runs. The COSVF acts as a boundary condition representing the value of water stored for future use (beyond each 1-year optimized period) and is optimally determined using an external many-objective search algorithm. This approach enables determining the interannual release decisions, and it introduces a method for valuation of carryover storage in large-scale water resources systems with nonconvexity.

The method was applied to a large-scale water resources system: California's Central Valley. Borg, an autoadaptive evolutionary algorithm, was used to search for the optimized economic values of storage in surface reservoirs through repeated use of an optimization-driven hydroeconomic simulation formulated as a series of nonlinear mathematical programs. Results showed an improvement in scarcity management evidenced by a reduction of scarcity (80% in scarcity volume and 98% in scarcity costs) compared to a historical simulation. Groundwater results show how considering nonlinear groundwater pumping costs in management models leads to reduced recommended overdrafting of aquifers. A sensitivity analysis showed that the proposed approach is robust and the obtained solution performs well against a wide range of hydroclimatic scenarios. Using a many-objective search algorithm offers the flexibility to consider more objectives.

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