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Key Points:
- A large-scale stochastic optimization algorithm is combined with a stream-aquifer simulation model
- Its optimal decisions consider surface resources and their impact on stream-aquifer interaction
- The proposed algorithm identified optimal joint management strategies in the case study

Supporting Information:
- Supporting Information S1

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Improving operating policies of large-scale surface-groundwater systems through stochastic programming

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Abstract The management of large-scale water resource systems with surface and groundwater resources requires considering stream-aquifer interactions. Optimization models applied to large-scale systems have either employed deterministic optimization (with perfect foreknowledge of future inflows, which hinders their applicability to real-life operations) or stochastic programming (in which stream-aquifer interaction is often neglected due to the computational burden associated with these methods). In this paper, stream-aquifer interaction is integrated in a stochastic programming framework by combining the Stochastic Dual Dynamic Programming (SDDP) optimization algorithm with the Embedded Multireservoir Model (EMM). The resulting extension of the SDDP algorithm, named Combined Surface-Groundwater SDDP (CSG-SDDP), is able to properly represent the stream-aquifer interaction within stochastic optimization models of large-scale surface-groundwater resource systems. The algorithm is applied to build a hydroeconomic model for the Jucar River Basin (Spain), in which stream-aquifer interactions are essential to the characterization of water resources. Besides the uncertainties regarding the economic characterization of the demand functions, the results show that the economic efficiency of the operating policies under the current system can be improved by better management of groundwater and surface resources.

1. Introduction

One of the challenges of Integrated Water Resources Management is to increase the effectiveness and efficiency in the operation of water resource systems [*Labadie*, 2004]. The widely-used public water allocation system, generally based on historical priorities of water rights, often leads to misallocation of water in terms of economic efficiency [*Dinar et al.*, 2007]. Two approaches, deterministic and stochastic programming, have been used to improve the operating rules of large-scale water resource systems through the joint management of surface and groundwater resources, assuming a central and perfectly coordinated system operation. Deterministic optimization models can handle complex conjunctive use optimization problems [e.g., *Reichard*, 1995; *Pulido-Velazquez*, 2003; *Pulido-Velazquez et al.*, 2004, 2006a, 2016; *Jenkins et al.*, 2004; *Marques et al.*, 2010; *Hanson et al.*, 2012]. The primary disadvantage of this approach is that optimal operational policies are unique to the assumed hydrologic time series [*Labadie*, 2004]. This issue becomes highly relevant under extreme operating conditions like floods and droughts [*Rani and Moreira*, 2010], in which the perfect foresight of future inflows becomes a decisive, but unrealistic, advantage. In contrast, stochastic optimization algorithms explicitly consider inflow uncertainty. They can be divided into two main areas: approaches in which uncertainty is handled by taking expectations on the future state of the system (often based on expected inflows), and methods in which uncertainty is treated in a broader perspective. Within the latter one can mention the Info-Gap Decision Theory [*Ben-Haim*, 2006] and the Robust Optimization [*Ben-Tal et al.*, 2009]. The approaches that take expectations on the future system state often treat the problem as a single objective (often, maximization of expected benefits), fitting a probabilistic description to the inflow data that is, embedded in an algorithm with no pre- knowledge of future inflows. Nonetheless, they are computationally challenging compared with deterministic methods and with limitations for their applicability to large-scale water resource systems [*Labadie*, 2004]. This issue, known as the curse of dimensionality, hinders the use of stochastic programming methodologies for the management of complex water resource systems.

In most reported applications of stochastic optimization of large-scale water resource systems, groundwater and stream-aquifer interaction are either not explicitly modeled [*Pereira and Pinto*, 1985, 1991; *Tilmant and Kelman*, 2007; *Tilmant et al.*, 2008; *Goor et al.*, 2010; *Marques and Tilmant*, 2013] or represented as underground reservoirs with no connection to the surface water system [*Marques et al*., 2010; *Zhu et al*., 2015; *Davidsen et al*., 2015a, 2015b]. However, in surface-groundwater systems, both components interact. In fact, groundwater withdrawals can have a significant impact on surface resources with streamflow depletion due to reduced groundwater discharge [e.g., *Barlow and Leake*, 2012].

Stochastic Dual Dynamic Programming (SDDP) [*Pereira and Pinto*, 1985, 1991] is one of the few alternatives [*Rani and Moreira*, 2010] for solving management problems in large-scale water resource systems avoiding the perfect foresight phenomenon. The approach has been used to derive optimal operating rules for multireservoir systems and to assess marginal water values [e.g., *Tilmant and Kelman*, 2007; *Tilmant et al*., 2008; *Goor et al*., 2010; *Marques and Tilmant*, 2013].

This paper presents an extension of the SDDP formulation in which stream-aquifer interactions are explicitly considered, making it possible to define optimal conjunctive operating rules. To achieve this objective, the extended SDDP algorithm integrates the formulation of the Embedded Multireservoir Model (EMM) [*Pulido-Velazquez et al*., 2005]. The EMM is based on the functional form of the analytical solution of the stream-aquifer interaction problem derived from the groundwater flow equations in linear systems [*Sahuquillo*, 1983]. Based on an analogy of that solution with the equation of the linear reservoir model, stream-aquifer flow exchange in any aquifer with linear behavior can be represented as the sum of the discharge of an infinite number of linear reservoir models [*Pulido-Velazquez et al*., 2005]. The model provides a general explicit solution of stream-aquifer interaction [*Pulido-Velazquez et al*., 2006a]. In most real cases, an accurate representation of stream-aquifer interaction can be achieved simply by using a reduced number of linear reservoirs. Therefore, the approach allows the development of parsimonious models with this general formulation, yielding results comparable to those from numerical solutions that depend on a high number of parameters, such as the MODFLOW finite-difference model [*Pulido-Velazquez et al*., 2005]. It is applicable even for aquifers with high heterogeneity, such as karstic units; for example, *Estrela and Sahuquillo* [1997] reported a successful two-linear reservoir model for reproducing stream-aquifer interaction in a complex karstic system in which the parameters of discharge and stress allocation were directly calibrated by automatic methods from springflow data.

The extended algorithm has been named as Combined Surface-Groundwater Stochastic Dual Dynamic Programming (CSG-SDDP). It adds to the SDDP method the EMM's ability to reproduce stream-aquifer interaction and its response to external stresses due to groundwater development (such as groundwater pumping or changes in groundwater recharge). The extended algorithm provides optimal conjunctive operating rules of large-scale water resource systems with a stochastic approach. Consequently, inflow uncertainty can be explicitly considered in the design of conjunctive use management strategies in large systems. It has been applied to the Jucar River Basin system (Spain) to improve the current operating rules by considering the interactions between the surface and groundwater components. This is accomplished by developing a hydroeconomic model of the basin, in which the demands are economically characterized using demand curves or functions [e.g., *Harou et al*., 2009; *Pulido-Velazquez*, 2008]. The system operating costs are also included in the economic objective function. The model maximizes the net economic returns from water allocation in the system over time and space subject to physical, environmental, and institutional constraints.

Section 2 introduces the SDDP method, the EMM procedure and its integration, the case study and the hydroeconomic model. Section 3 describes the results and the proposed changes in the current operating policies for a more efficient management of both reservoirs and aquifers. Finally, section 4 discusses the results obtained and the conclusions.

2. Method

2.1. Stochastic Dual Dynamic Programming

The mathematical formulation of a multistage stochastic programming problem can be expressed in the following way:

$$\max_{r_t}\left\{E\left[\sum_{t=1}^{T}B_t(s_t,r_t,q_t)+v(s_{T+1},q_T)\right]\right\} \tag{1}$$

Where r_t is the vector of management decisions (releases or target storages); T is the planning horizon; $E[]$ is the expectation operator considered; B_t are the benefits in time stage t; s_t is the vector of storages at the beginning of time stage t; q_t is the vector of inflows during time stage t; and v is the terminal value function. This equation is subject to the water mass balance in the system and the limits imposed on the storages and management decisions.

Stochastic dual dynamic programming (SDDP) [*Pereira and Pinto*, 1985, 1991] approximates the expected benefits using hyperplanes whose parameters are estimated in an iterative process. The quality of the estimations is assessed using stochastically generated inflow series. At the end of each iteration, the accuracy of the estimated parameters is evaluated and, if insufficient, it is improved and tested again. The iterations are repeated until the estimation is considered good enough, and thus an adequate representation of the expected benefits is obtained. A comprehensive description of the algorithm is provided in *Pereira and Pinto* [1985, 1991], *Tilmant and Kelman* [2007], and *Tilmant et al*. [2008]. The extension of the algorithm for integrating stream-aquifer interaction is described in the subsections that follow.

2.2. Modeling Stream-Aquifer Interaction

Stream-aquifer interaction was integrated into the SDDP algorithm using the conceptual Embedded Multireservoir Model (EMM) [*Pulido-Velazquez et al*., 2005]. The formulation of the EMM is based on the structure of the analytical solution of the stream-aquifer interaction problem derived from the groundwater flow equation for linear systems (confined aquifers or unconfined ones with negligible variations in head with regard to their thickness, in which a linear partial differential equation applies) and its analogy with the state equation of the linear reservoir model [*Sahuquillo*, 1983]. This conceptual model represents stream-aquifer interaction as the sum of the drainage of one or several virtual reservoirs or units with discharges linearly proportional to the volume stored above the outlet level. Although the EMM is not an aquifer model, since it is unable to obtain spatially-distributed groundwater heads, it can provide an accurate representation of stream-aquifer interaction while maintaining the balance of available groundwater resources. Consequently, combining EMM with SDDP seems promising as the focus is on determining the system's management policies, not the changes in groundwater heads. Further information on analytical and numerical derivations of the EMM and its relation with the eigenvalue method [*Sahuquillo*, 1983] can be found in *Pulido-Velazquez et al*. [2005, 2008, 2006b].

Each external action (stress) applied to the aquifer (reservoir and stream seepages, groundwater pumping, etc.) is divided among a set of n linear reservoirs according to certain stress allocation coefficients (b_j) [*Pulido-Velazquez et al*., 2005, 2006a]. The linear discharge problem is solved for each unit by using the following equations:

$$G_j(t)=G_j(t-1)\cdot e^{-\alpha_j\Delta t}+\frac{b_j\cdot R(t)}{\alpha_j}\left(1-e^{-\alpha_j\Delta t}\right) \tag{2}$$

$$X_j(t)=G_j(t-1)-G_j(t)+b_j\cdot R(t) \tag{3}$$

$$\sum_{j=1}^{n} b_j=1 \tag{4}$$

Where $G_j(t)$ is the groundwater storage at the end of time stage t in unit j; α_j is the unit discharge coefficient; $R(t)$ is the net recharge (recharge minus pumping) of the aquifer; Δt is the time increment between t and $t-1$; $X_t(t)$ is the groundwater discharge (outflow) from unit j during time stage t. When G_j becomes negative (i.e., groundwater levels below the outlet) X_j turns into negative, representing, in that case, groundwater inflow from a losing river. Equation (2) provides the end-of-stage aquifer storage in each unit while equation (3) obtains its discharge by water balance. Once both have been solved for all the linear units or reservoirs, the total aquifer storage $G(t)$ and outflow $X(t)$ is the sum, over the n units, of the $G_j(t)$ and $X_j(t)$ terms. The EMM assumes no connection between groundwater bodies, thus equations (2)–(4) are applied separately to each one of them, not taking into consideration flows between one aquifer to another.

The net groundwater recharge $R(t)$ is calculated as the sum of all the recharge flows into the aquifer minus the groundwater abstractions. If a linear aquifer response is assumed, the principle of superposition can be applied, and the solution corresponds to the summation of the effects caused by each of the different stresses or actions (pumping, rainfall percolation, artificial recharge and so on) applied to the aquifer [*Pulido-Velazquez et al*., 2005]. If this principle is applicable, we do not need to reproduce the natural stream-aquifer exchange for the simulation of the modifications in stream-aquifer interaction. Natural stream-aquifer interaction is already included in the natural regime inflow time series. The calculation of the aquifer response to the natural stresses is cumbersome, since it requires the use of a large amount of hydrological and aquifer hydraulic properties for the desired analysis period (recharge from rainfall/runoff percolation, groundwater heads, and outflow, etc.). Linear behavior can be assumed in confined aquifers or unconfined ones without significant changes in groundwater head with respect to the aquifer thickness [*Pulido-Velazquez et al*., 2005]. If these requirements are not met, assuming a linear behavior of the aquifer might lead to significant errors in the stream-aquifer interaction assessment.

2.3. The Combined Surface-Groundwater Extended SDDP algorithm

Mathematically, the extended SDDP algorithm, named as Combined Surface-Groundwater SDDP extended algorithm (CSG-SDDP) solves the optimization problem in the same way as the regular SDDP, maximizing the summation of immediate and future expected benefits as in equation (1):

$$F_t(s_t, q_{t-1}) = \max_{r_t} \left[B_t(s_t, r_t, q_t) + F_{t+1} \right] \tag{5}$$

Where F_t are the total benefits between time stage t and the end of the planning horizon; and F_{t+1} is the expected benefit-to-go function.

Equation (5) is subject to equations (2)–(4), which are applied to all the aquifers in the system, as well as the limits of each variable and the water balance equation at each node:

$$s_{t+1} = s_t + I_i(t) + q_t + \sum_m X_m(t) - \sum_j D_j(t) - O_i(t) - E_i(t) \tag{6}$$

where s_t is the storage in node i at the start of time stage t; $I_i(t)$ are the inflows from upstream nodes obtained according to the topological network of the system; q_t are the inflows from the hydrological subbasin discharging into node i; $X_m(t)$ is the discharge of any aquifer m with stream-aquifer interaction with node i; $D_j(t)$ are the deliveries to any demand j with intake located in node i during time stage t; $O_i(t)$ are the outflows to downstream nodes; $E_i(t)$ are seepage and evaporation losses. If the node is not a surface reservoir, both s_t and the E_i variables are equal to zero. Seepage losses from the surface system that end up in groundwater bodies are transferred to them by adding the amount of infiltrated resource to the net recharge $R(t)$ appearing in equations (2)–(3).

The synthetically-generated inflows required are obtained using a first-order multisite periodic autoregressive model MPAR(1), which assumes normally-distributed inflows [*Tilmant and Kelman*, 2007]:

$$q_t = \mu_t + \rho_{t-1,t} \frac{\sigma_t}{\sigma_{t-1}} (q_{t-1} - \mu_{t-1}) + \xi_t \sigma_t \sqrt{1 - \rho_{t-1,t}^2} \tag{7}$$

Where μ_t and σ_t are the mean and standard deviation of the inflows in time stage t; $\rho_{t-1,t}$ is the correlation coefficient between time stages $t-1$ and t; ξ_t is random perturbation following a normal distribution with mean zero and standard deviation one. A comprehensive description of the model is given in *Salas et al*. [1980] and *Salas* [1993].

The benefit-to-go function is approximated using hyperplanes (linear functions). Mathematically, they are represented as a set of constraints that bind the F_{t+1} value to l linear approximations that provide the upper bound of the benefit-to-go function, which must be convex [*Pereira and Pinto*, 1985]:

$$F_{t+1} \leq \varphi_{t+1}^l S_{t+1} + \omega_{t+1}^l G_{t+1} + \gamma_{t+1}^l q_t + \beta_{t+1}^l \tag{8}$$

Where φ_{t+1}^l is the vector of slopes with respect to the reservoir storage in the l approximation of F_{t+1}; ω_{t+1}^l is the vector of slopes with respect to the aquifer storage in all the aquifer cells; γ_{t+1}^l is the vector of slopes with respect to the inflows; and β_{t+1}^l is the independent term.

The one-stage optimization problem formed with equations (2)–(6) and (8) is solved in both the backward optimization and the forward simulation phases. In the backward optimization, the problem is solved backwards to calculate the coefficients φ, ω, γ, and β, passing them to the previous time stage. For each time stage $t+1$, given a triplet of sampled vectors of storages, groundwater levels and previous stage inflows (S_{t+1}^l, G_{t+1}^l, q_t^l), the one-stage problem is solved using the sampled values S_{t+1}^l and G_{t+1}^l for K stochastically-generated vectors of inflows $q_{t+1}^{l,k}$ (usually named as openings) calculated using the sampled inflows q_t^l and equation (7). The primal and dual information available after the solution of each one-stage problem is used to estimate the vectors of slopes. The vector of slopes with respect to the reservoirs can be estimated for each SDDP one-stage optimization problem. For the l^{st} cut and k^{th} hydrological scenario, the slope with respect to the storage state in node i is given by:

$$\varphi_{t+1}^{l,k} = \frac{dF_{t+1}^{l,k}}{dS_{t+1}} = \lambda_{t+1}^{l,k,i} \tag{9}$$

Where $F_{t+1}^{l,k}$ is the total value of the system at time $t+1$; and $\lambda_{t+1}^{l,k,i}$ is the dual variable associated to the mass balance of node i. The expected slope φ_{t+1}^{l} can be estimated taking the expectation from among the k openings:

$$\varphi_{t+1}^{l} = \frac{1}{k}\sum_{k} \varphi_{t+1}^{l,k} \tag{10}$$

The vector of slopes with respect to each linear reservoir of each EMM can be derived using:

$$\omega_{t+1}^{l,k} = \frac{dF_{t+1}^{l,k}}{dG_{m,j,t+1}} = \lambda_{g,t+1}^{l,k,m,j} + \alpha_{m,j} \cdot \lambda_{x,t+1}^{l,k,m,j} \cdot e^{-\alpha_{m,j}} \tag{11}$$

Where $\lambda_{g,t+1}^{l,k,m,j}$ is the dual variable associated with the mass balance in every aquifer m and every linear reservoir j (equation (2)); and $\lambda_{x,t+1}^{l,k,m,j}$ is the dual variable associated with the linear reservoir discharge calculation (equation (3)). Each linear reservoir is, therefore, considered as a separate reservoir when computing the vector of slopes. The final vector ω_{t+1}^{l} can be calculated by taking the expectation over all the openings:

$$\omega_{t+1}^{l} = \frac{1}{k}\sum_{k} \omega_{t+1}^{l,k}. \tag{12}$$

Concerning the vector of slopes with respect to the inflows, this can be calculated following the regular SDDP formulation:

$$\gamma_{t+1}^{l,k} = \frac{dF_{t+1}^{l,k}}{dq_t} = \frac{dF_{t+1}^{l,k}}{dq_{t+1}} \cdot \frac{dq_{t+1}}{dq_t} = \left(\lambda_{t+1}^{l,k,i} + \sum_{l'} \lambda_{t+1}^{l,k,l'} \cdot \gamma_{t+2}^{l'}\right) \cdot \left(\rho_{t,t+1} \cdot \frac{\sigma_{t+1}}{\sigma_t}\right) \tag{13}$$

Where $\lambda_{t+1}^{l,k,i}$ is the dual variable associated with the mass balance in the nodes i that receive inflows (equation (9)); l' is the same index as l but referred to time stage $t+2$; $\lambda_{t+1}^{l,k,l'}$ is the dual variable associated to the l' cut that approximates the F_{t+2} function (equation (8)); $\gamma_{t+2}^{l'}$ is the vector of slopes with respect to the inflow obtained at time stage $t+2$. The vector γ_{t+1}^{l} can be estimated by taking the average of the openings:

$$\gamma_{t+1}^{l} = \frac{1}{k}\sum_{k} \gamma_{t+1}^{l,k} \tag{14}$$

Finally, the constant term can be calculated after the estimation of the vectors of slopes using the regular SDDP formulation:

$$\beta_{t+1}^{l} = \frac{1}{k} \cdot \sum_{k} F_{t+1}^{l,k} - \varphi_{t+1}^{l} S_{t+1}^{l} - \omega_{t+1}^{l} G_{t+1}^{l} - \gamma_{t+1}^{l} q_t^{l} \tag{15}$$

Once estimated for all the L samples, the algorithm moves back from $t+1$ to t and the cuts calculated in the stage $t+1$ are used to estimate the benefit-to-go function at time stage t. This process is repeated until time stage $t=1$ is reached. Given that the linear functions provide an upper bound to F_{t+1}, the value function F_1 overestimates the objective function Z_1.

After the backward optimization, the forward simulation solves the one-stage problem using—at each time stage—the cut parameters obtained during the backward optimization, passing the final system state values S_{l+1} and G_{l+1} to the next time stage. This forward-moving loop is run for V inflow series generated using the inflows at time stage $t=0$, q_0, and the autoregressive model shown in equation (7). For each time series, the total benefits obtained, named Z_2^v, are calculated as the sum of the immediate benefits:

$$Z_2^v = \sum_{t} f_t^v \tag{16}$$

As the benefit-to-go functions are estimated by excess, each one-stage subproblem solution tends to favor future benefits over immediate ones. Therefore, all the Z_2^v values are lower bounds of the real benefits obtained for each time series. Once the process is completed, a normal distribution is fitted to the Z_2^v values to obtain the average lower bound Z_2 and its standard deviation σ_Z.

After each iteration (backward-forward cycle) the convergence is checked by determining if the upper bound Z_1 falls inside the 95% confidence interval of the lower bound Z_2, defined by the following equation:

$$\left[Z_2 - 1.96\frac{\sigma_z}{\sqrt{v}}, Z_2 + 1.96\frac{\sigma_z}{\sqrt{v}}\right] \tag{17}$$

If Z_1 falls within this interval, then the accuracy provided by the F_{t+1} piece-wise linear interpolation is adequate and the process ends. Otherwise, a new iteration is started adding a new set of sampled values S^l, G^l, and q^l. The best candidates for a new sample are the S and G values obtained during the forward simulation of the last iteration.

2.4. The ESPAT DSS Tool

A general-purpose Decision Support System (DSS) was developed, the Explicit Stochastic Programming Advanced Tool (ESPAT), for the implementation of the CSG-SDDP extended algorithm. It eases the development of stochastic programming models, avoiding the need to build ad hoc codes for each system. In contrast, ESPAT uses a general-purpose code valid for any water resource system configuration.

The main components of the ESPAT tool are the user interface and the code, developed using the GAMS language [*Brooke et al*., 1998]. The interface allows the user to introduce the required features of the model (related to the topology of the system, the surface hydrology, the capacity and operating constraints of the hydraulic infrastructure, the parameters for modeling the stream-aquifer interaction, and the economic demands). No knowledge of the GAMS language is required to run ESPAT, since the code execution is controlled directly from the interface. The results following the code execution refer to reservoirs (storages, outflows, and marginal economic values), streams or canals (flows and seepage losses), stream-aquifer interaction (exchanged flows), demands (deliveries, deficits, and benefits), and hydropower plants (turbinated flows, energy production, and benefits). The tool also includes additional modules for deterministic optimization and simulation of the system performance under predefined operating rules.

3. Model implementation

3.1. Case Study: The Jucar River Basin, Spain

The Jucar river basin is located in Eastern Spain (Figure 1). The mean annual river discharge is 1548 Mm^3 (1980–2010 period). The intra-annual flow pattern is typical of Southern Mediterranean basins, with peak floods at the start of autumn, high flows during winter and spring, and low flows during summer. Most surface water resources in the basin are regulated by the three main surface reservoirs: Alarcon (1088 Mm^3 of useful storage, in the Jucar river); Contreras (429 Mm^3 of useful storage, in the Cabriel river, its main tributary) located in the upper basin, parallel to Alarcon; and Tous (369 Mm^3 of useful storage), downstream.

Three main aquifers interact with the Jucar river and play a major role in water supply. The largest is the Mancha Oriental aquifer, with an area of 7145 km^2. As it is hydraulically connected to the Jucar river, the intense transformation from dry to irrigated lands that has occurred since the 1970s has led to a significant drop in the groundwater table. This issue has provoked a significant streamflow depletion compared to natural conditions [*Sanz et al*., 2011]. The Plana de Valencia Sur aquifer, located in the lower basin, is mined for agricultural purposes during droughts by pumping from "emergency" drought wells. Finally, the Hoces del Cabriel aquifer receives the seepage losses from the Contreras reservoir, which returns back to the Cabriel river several kilometers downstream. We have assumed that there is not a significant flow exchange among the groundwater bodies, in accordance to *Sanz et al*. [2009, 2011], and so they are treated as independent.

The total annual consumptive demand in the basin is estimated to be 1505 Mm^3 [*CHJ*, 2013], split among agricultural (89%), urban (9%), and industrial (2%) uses. The non-consumptive water demands are the minimum ecological flows allocated in several basin locations and for hydropower production. The current operating rules of the Jucar river system give the priority on water allocation to urban uses over agricultural uses and power generation. The minimum ecological stream flows and the deliveries to the Cofrentes nuclear

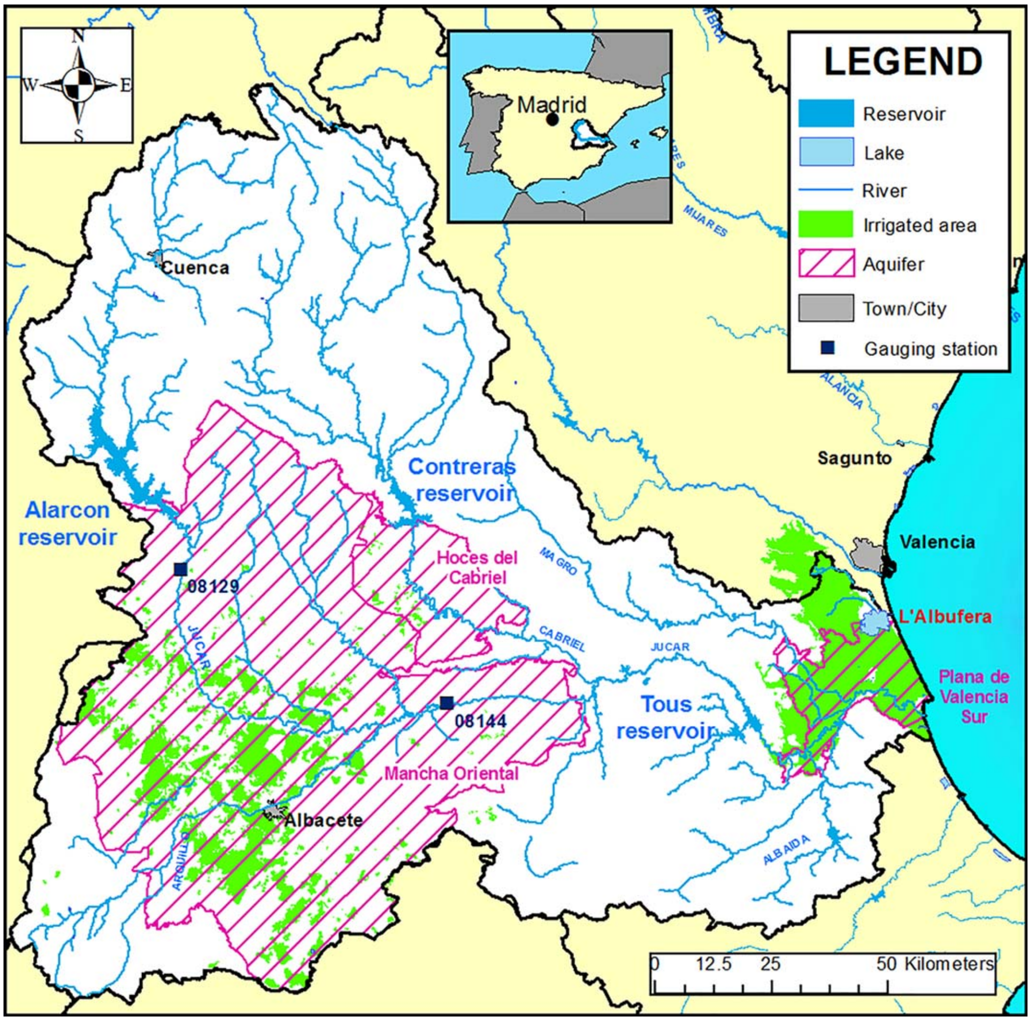

Figure 1. Jucar river basin map.

power plant are always fully met. Among agricultural users, the most senior water rights correspond to the irrigators grouped in the user's union USUJ (Unidad Sindical de Usuarios del Júcar). The USUJ enjoys the highest priority in surface water allocation for agriculture. The remaining agricultural demands use groundwater as the main or complementary resource. Furthermore, surface water supply to agricultural demands other than the USUJ is not allowed if the Alarcon reservoir storage falls below pre-defined limits (defined in a treaty, the Alarcon agreement, see *CHJ* [2013]), forcing them to increase groundwater use. Although the Mancha Oriental irrigated areas are mainly supplied with groundwater, they are also entitled to a small amount of surface water from the Alarcon reservoir (33 Mm^3/yr) when surface deliveries to agriculture demands other than the USUJ are allowed.

3.2. Modeling Mancha Oriental—Jucar River Stream-Aquifer Interaction

The most relevant stream-aquifer interaction in the basin takes place between the Jucar river and the Mancha Oriental (MO) aquifer. An EMM with two linear reservoirs was developed to reproduce that interaction. The model calibration was based on the Jucar river streamflow records across the MO aquifer boundaries (station codes 08129 and 08144 in *CEDEX* [2010]; depicted in Figure 1), the pumping rates were estimated for the MO aquifer using remote sensing [*Castaño et al.*, 2010; *Sanz et al.*, 2009, 2011] and the simulated time series of natural net groundwater discharge, obtained in previous studies of the River Basin Authority by calibrating a groundwater flow simulation model to the historical records and then removing the anthropic actions [*UPV*, 2002; *CHJ*, 2013]. Given that the natural discharge of the aquifer was already available, there was no need to obtain the aquifer response to the natural stresses, since the principle of superposition (section 2.2) could be applied. The Mancha Oriental aquifer complies with the requirements of a linear behavior assumption to use this principle, as the changes in groundwater head assumed during the analysis period (up to 10 m), are not significant in comparison with the aquifer thickness (200 m at least). The EMM was exclusively built to represent the effects of the anthropic stresses on the stream-aquifer interaction in the river basin model, since the natural discharge was already implicit in the natural inflow time series included in the model.

The anthropic impacts on that interaction (*X(t)* in equation (3)) can be calculated as the historical stream-aquifer interaction minus the natural component. The real stream-aquifer interaction can be assessed as the difference between the downstream and the upstream Jucar river discharge records, since surface runoff entering the reach is almost negligible (except after exceptional rainfall events, see *Sanz et al*. [2011]). The anthropic-induced net recharge corresponds to the agricultural percolation minus groundwater abstractions. The EMM (equations (2)–(4)) was fitted to reproduce the time series of stream-aquifer interaction due to anthropic actions (least-squared fitting). The two discharge parameters α_i were determined as 3.94 and 0.0055 months^{-1}, with external stress allocation factors b_i of 0.18 and 0.82, respectively (i.e., 18% of net recharge goes to the linear reservoir with rapid discharge and 82% to the one with the slowest response).

Figure 2 shows the times series of stream-aquifer interaction and the resulting river discharge at the downstream station (08144 in Figure 2). The negative values of stream-aquifer interaction indicate a decrease in

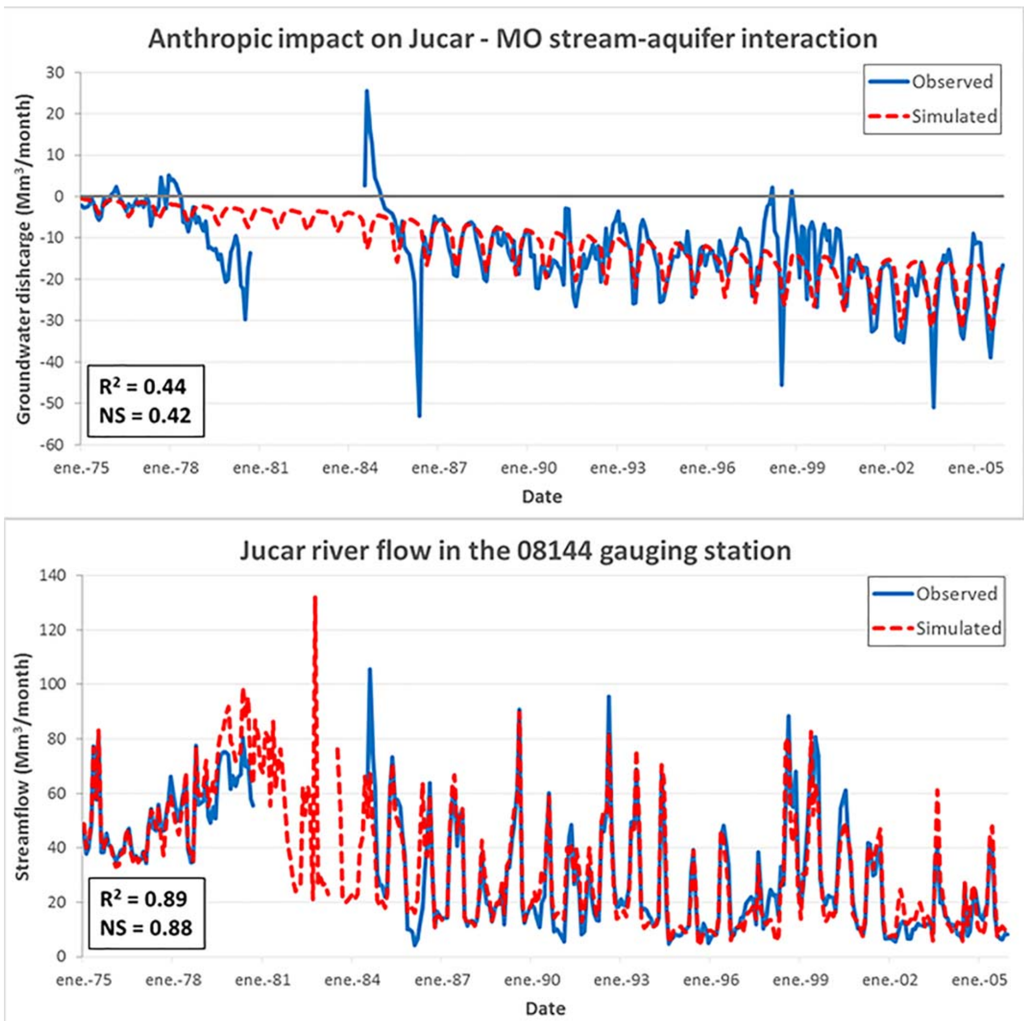

Figure 2. EMM of Jucar—(top) MO stream-aquifer interaction due to anthropic actions and (bottom) Jucar river discharge at 08144 gauging station.

groundwater outflow to the Jucar river caused by groundwater pumping. The fitted EMM is able to capture both the over-year trend and the seasonal variation of the historical values. However, there are periods when the model departs from the historical records, especially between 1977 and 1980 and 1997 and 2000. This is mainly caused by events of high surface runoff, with a low impact in downstream Jucar river flows (Figure 2, lower figure). Nevertheless, the Jucar river discharge downstream of the region in which the stream-aquifer interaction takes place is adequately reproduced (as shown by the R^2 and Nash-Sutcliffe indicators shown in Figure 2), validating the two-reservoir EMM.

3.3. Stochastic Hydroeconomic Optimization Model

The hydroeconomic model of the Jucar river considers the physical, hydrological, economic, and environmental features of the system. It comprises 27 nodes, 8 surface reservoirs, 5 aquifer elements, 7 subbasins, 18 consumptive demands, 9 hydropower plants, and 6 environmental flows (Figure 3). The number of state variables (reservoirs and aquifers) is 13, well beyond the dimensionality limit of SDP. Its physical features were obtained from *CHJ* [2013]. The model was run on a monthly timescale. The goal of the stochastic optimization model built using CSG-SDDP is to maximize the net total benefits (current plus expected) obtained from water allocation over space and time. A simulation model was also developed to compare the impacts of the current operating policies with the optimal decisions (explained in the next section).

The reservoirs considered were Alarcon (whose main role is water regulation for consumptive uses), Molinar (mainly for hydropower production), Contreras (consumptive uses), Cortes II (hydropower), Naranjero (hydropower), Tous (consumptive/flood protection), Forata (consumptive uses), and Bellus (consumptive/flood) (features shown in the supporting information).

The main stream-aquifer interactions in the basin are included in the model. The Hoces del Cabriel aquifer returns the seepage losses from the Contreras reservoir to the Cabriel river. The Plana de Valencia Sur aquifer receives irrigation percolation and returns part of it to the Jucar and Albaida rivers. The overexploitation of the Mancha Oriental aquifer has significantly reduced groundwater discharge to the Jucar river. The EMM of the Jucar-Mancha Oriental stream-aquifer interaction, the most significant in the basin, was presented in the previous section. The rest of the stream-aquifer interactions included in the model could not be calibrated as in Mancha Oriental, due to the lack of data. For that reason, we just used the EMMs set up by the Jucar River Basin Authority for the last Jucar River Basin Management Plan [*CHJ*, 2013].

The consumptive demands were characterized through monthly targets [*CHJ*, 2013] and economic demand functions [*Pulido-Velazquez et al*., 2006b]. The latter are described in the supporting information [*Howitt*, 1995; *Sumpsi et al*., 1998; *Jenkins et al*., 2003; *MMA*, 2004; *Pulido-Velazquez et al*., 2006b; *Harou et al*., 2009]. The pumping costs for the demands that can use wells were estimated based on the equations in *Pulido-Velazquez et al*. [2006b]. The demand function of the Cofrentes nuclear power plant was obtained from *Pulido-Velazquez et al*. [2006b], modified using the energy market prices appearing in *CHJ* [2013]. The physical and economic features of the hydropower plants (installed capacity, turbine capacity, efficiency, and so on) were obtained from *CHJ* [2013]. The urban economic demand functions were characterized using the point expansion method [*Jenkins et al*., 2003], based on current water prices and consumption and demand price-elasticity estimates from an econometric model based on panel data for the Valencia region [*Garcia Valiñas*, 2004]. The demand curves for agricultural uses, estimated by *Pulido-Velazquez et al*. [2006b], were obtained using Positive Mathematical Programming (PMP) [*Howitt*, 1995] for the different agricultural demand units.

The main water-dependent ecosystem in the Jucar river basin is the Albufera wetland, whose main inflows are the surface returns from the demands of rice agricultural. To preserve this ecosystem in the model, the supply to the rice demands was considered a constraint (demands labeled as rice in Figure 3). The CHJ also establishes minimum environmental flows in several river streams (wide green lines in Figure 3) treated as constraints by the model. Another quantitative measurement of the environmental status of the system, not taken as a constraint by the model, is the discharge of the overexploited Mancha Oriental aquifer.

3.4. Priority-Based Simulation Model

The simulation model allocates water resources based on the current operating rules of the system, trying to mimic the historical modus operandi of the aquifer and the reservoirs. The flow network is the same as that presented in Figure 3, using the same input data. However, in this case, economics does not drive

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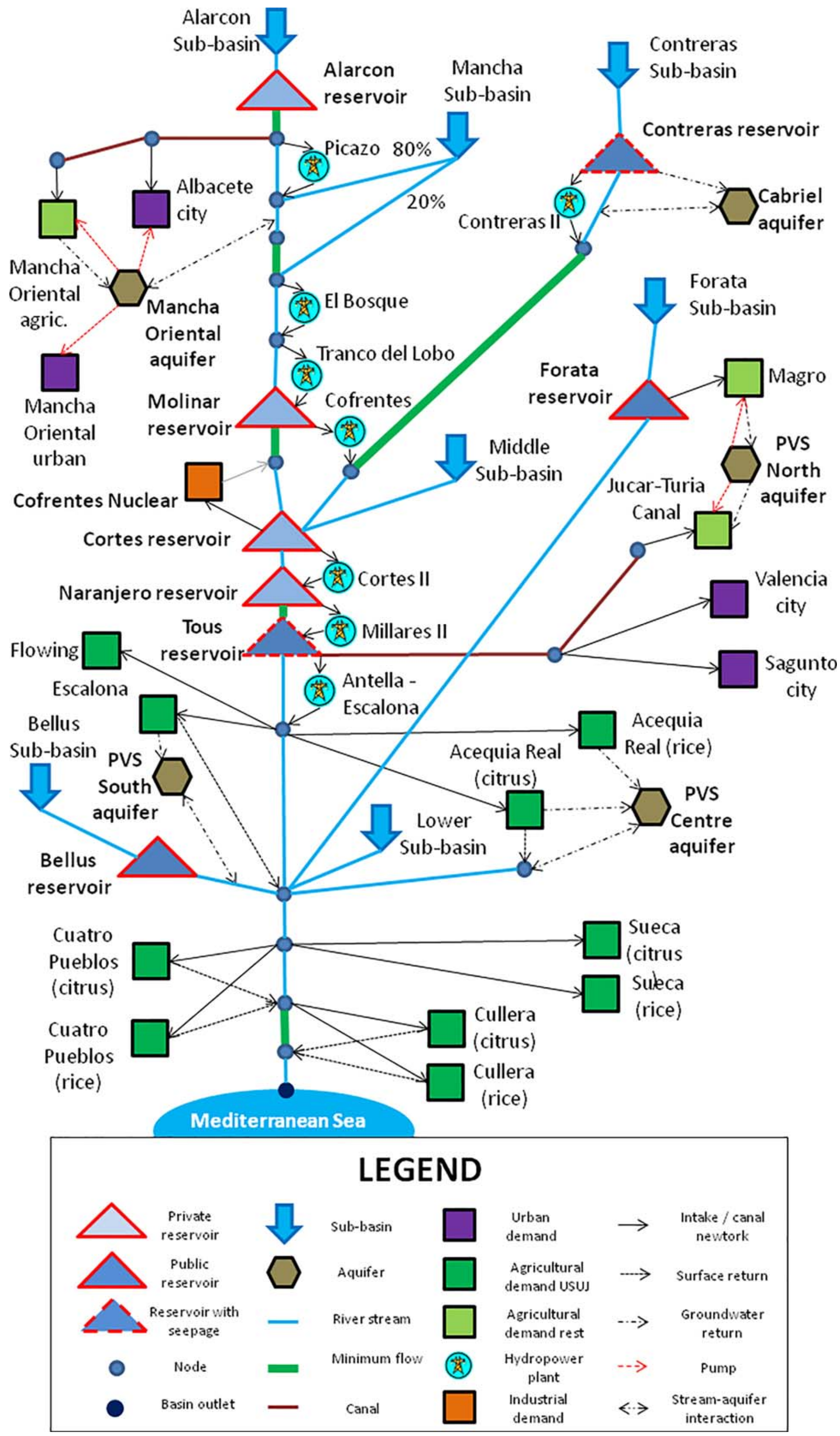

Figure 3. Jucar river network schematics.

water allocation; instead, water is allocated based on the relative priorities for the different demands and environmental flows. This is introduced in a monthly objective function that minimizes the weighted gaps to the targets on deliveries to demands, environmental flows, hydropower production, and reservoir storages, using unit penalties previously calibrated to reproduce the priorities on the operation of the system [*Andreu et al*., 1996; *Israel and Lund*, 1999]. After the simulation has been run, the economic demand functions are used for post-processing the resulting deliveries into economic benefits or scarcity costs of water use. The simulation model was trained against the historical records obtained from *CEDEX* [2010] and *CHJ* [2013]. Details about the comparison between the model and the data records available for training are presented in the supporting information.

4. Results

The stochastic optimization model was solved using the CSG-SDDP. The results include water allocation over space and time and its consequences (storages, flows, deliveries, deficits in demands, groundwater pumping, hydropower production, and economic benefits from water use). The system performance under the current operating rules was also obtained using the simulation approach.

4.1. System Performance

The model results offered include surface and groundwater allocations, turbined flows, energy produced, economic benefits, and MO aquifer discharge for both the current policies and the optimal management of the system (Table 1). In the majority of the variables listed, both alternatives show similar performances. This is due to the current rules, which are the result of a long management experience and intense negotiation between users. Consequently, the optimal operating rules found by stochastic programming do not strongly oppose the current system operation, but focus on the management options that can enhance the economic benefits and the environmental status of the system.

The stochastic programming diminishes groundwater abstractions by agriculture in Mancha Oriental by almost 80 Mm^3/yr, although the net economic benefits in Mancha Oriental are only reduced by €0.55 M/yr on average (0.7% reduction in benefits). The pumping reduction increases the streamflows downstream via stream-aquifer interaction by 33 Mm^3. This additional streamflow represents a substantial contribution towards preserving ecological flow in the basin downstream of the Alarcon reservoir during droughts. This scenario also provides additional resources for the downstream agricultural demands affected by restrictions in drought conditions under the current policies. Economic benefits in the lower Jucar grow by around €3 M/yr, six times greater than the loss of net profit experienced in Mancha Oriental. Part of the success in this trade-off is explained by the recovery of the aquifer level, which reduces the pumping costs in Mancha Oriental, and increases groundwater outflow. The greater surface water availability also permits an increase in surface water deliveries to Mancha Oriental. Furthermore, it has an intrinsic environmental benefit due to the maintenance of the ecological streamflow.

Table 1. Average Hydrological, Energy Production, Environmental, and Economic Results for Both Alternatives During the Whole Period (1998–2013)

	Category	Consumptive Uses					Hydropower	Environment	Basinwide Level	
		Urban		Agricultural[a]						
	Type / Variable	Mancha	Valencia	Mancha	USUJ	CJT + Magro	Totals	MO Discharge[b]	Urban	Agricultural[a]
Current policies	Surface deliveries (Mm^3/yr)	14.33	114.51	16.96	540.60	29.49			128.84	587.05
	Groundwater deliveries (Mm^3/yr)	16.10	0.00	315.45	0.00	73.10			16.10	388.55
	Energy produced (GWh)						372.20			
	Economic net benefits (€M/yr)	60.26	228.78	78.89	63.37	51.65	22.26		289.04	193.91
	Net groundwater discharge (Mm^3/yr)							−63.31		
Optimal management	Surface allocation (Mm^3/yr)	13.64	114.51	29.13	556.73	37.31			128.15	623.17
	Groundwater allocation (Mm^3/yr)	16.79	0.00	238.30	0.00	64.81			16.79	303.11
	Energy produced (GWh)						414.03			
	Economic net benefits (€M/yr)	60.36	228.78	78.34	65.83	52.21	25.00		289.14	196.38
	Net groundwater discharge (Mm^3/yr)							−29.91		

[a]Economic net benefits of rice not included.
[b]A negative value of the aquifer discharge implies net aquifer recharge by river seepage.

Table 2. Average Hydrological, Energy Production, Environmental, and Economic Results for Both Alternatives During a Drought Period (2005–2008)

	Category	Consumptive Uses					Hydropower	Environment	Basinwide Level	
	Type	Urban		Agricultural[a]						
	Variable	Mancha	Valencia	Mancha	USUJ	CJT + Magro	Totals	MO Discharge[b]	Urban	Agricultural[a]
Current policies	Surface deliveries (Mm^3/yr)	6.94	114.51	0.00	439.72	5.71			121.45	445.43
	Groundwater deliveries (Mm^3/yr)	23.49	0.00	332.41	0.00	96.88			23.49	429.29
	Energy produced (GWh)						278.04			
	Economic net benefits (€M/yr)	59.84	228.78	77.89	53.24	50.54	16.59		288.62	181.67
	Net groundwater discharge (Mm^3/yr)							−92.43		
Optimal management	Surface allocation (Mm^3/yr)	10.67	114.51	17.47	509.62	26.27			125.18	553.36
	Groundwater allocation (Mm^3/yr)	19.78	0.00	213.78	0.00	75.82			19.76	289.60
	Energy produced (GWh)						326.30			
	Economic net benefits (€M/yr)	60.15	228.78	71.03	64.13	51.68	19.64		288.93	186.84
	Net groundwater discharge (Mm^3/yr)							−45.33		

[a]Economic net benefits of rice not included.
[b]A negative value of the aquifer discharge implies net aquifer recharge by river seepage.

The optimal policies derived from stochastic programming also improve hydropower production by 42 GWh/yr (Table 1), 11% of the total. The additional river flow from the increasing Mancha Oriental groundwater outflow enables an increase in the generation of power at the downstream hydropower plants (see Figure 3). The Tous reservoir acts as the tail reservoir of the hydropower system instead of the current one, Naranjero. Consequently, the economic benefits from hydropower production increase by €2.75 M/yr; 12% higher than now. The slight differences between the percentage of increase in energy production and in benefits is caused by a better scheduling of hydropower according to the monthly energy demand and prices. The optimal policies obtained by the extended algorithm increase the net economic benefits in the Jucar river system by €5.25 M/yr, about 1% of the total net returns experienced by the system (around €500 M/yr). However, the increase in groundwater tables adds robustness and resiliency against droughts to the system. Table 2 presents the system performance for the 2005–2008 drought for both alternatives.

The comparison between Tables 1 and 2 shows a different management strategy against droughts for the algorithm's policies. Treating the surface system and the groundwater bodies in isolation, the main policy applied by the current system operation consists in replacing the scarce surface water with groundwater. For example, the Mancha urban and agricultural demands abstract 24 Mm^3/yr more than the average for the whole period, losing 29 Mm^3/yr of streamflow through stream-aquifer interaction. On the other hand, the optimal operation by stochastic programming makes a joint management of both the surface and the groundwater systems. Groundwater management is altered to take advantage of stream-aquifer interaction, reducing groundwater pumping by 22 Mm^3/yr in order to increase the downstream flows. This reduction in pumping raises the downstream flows through stream-aquifer interaction by 47 Mm^3/yr. These higher flows, combined with the adoption of better operating policies in the surface reservoirs, lead to higher surface allocations and thus, lower impact from droughts without increasing groundwater overexploitation. This feature is shown in the surface allocations to agricultural demands: the current policies reduce them by 140 Mm^3/yr while a 71 Mm^3/yr reduction is obtained in the optimal policies. In economic terms, the Mancha Oriental agricultural demand suffers the worst impact from pumping curtailment, changing from a €1 M/yr loss under the current policies to a €7 M/yr loss estimated by the optimal management. However, this is compensated by increased allocations in the downstream demands, with reduced economic losses from €11 M/yr under the current policies to €2.5 M/yr under the optimal policies. The economic impact of drought in urban uses is negligible, and the hydropower sector suffers similar impacts under both alternatives, losing €6 M/yr. It can be concluded that the policies applied by stochastic programming are able to enhance the system performance during droughts, leading to greater surface deliveries caused mainly by a more efficient joint management of surface and groundwater bodies. In addition, these policies recover the groundwater levels of the Mancha Oriental aquifer even during droughts, increasing groundwater outflow into the middle of the Jucar river precisely when it is most necessary.

4.2. Reservoir Operation

The results on monthly storage at the main reservoirs (Alarcon, Contreras, and Tous) were analyzed in order to compare the operating policies implicit in the stochastic optimization results with the current operation

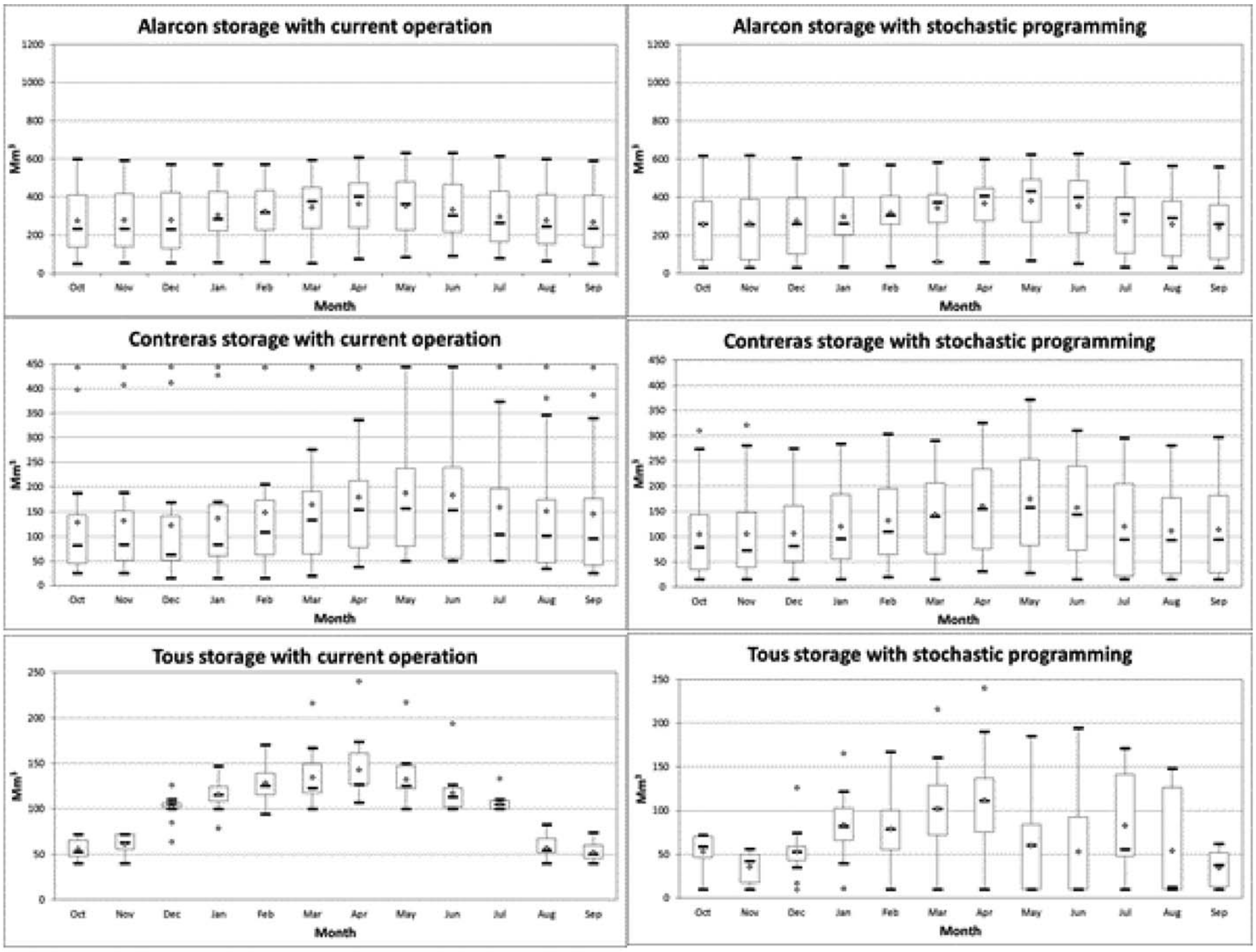

Figure 4. Box-whisker plots of monthly storage in the main reservoirs of the Jucar river system.

of the system (Figure 4). The Alarcon reservoir, with the greatest useful capacity, shows almost the same management patterns under both alternatives. Its operating policy mainly consists in providing carryover storage to move water from wet to dry years. This can be observed by the absence of outliers and the smooth refill-drawdown pattern, although the stochastic optimization shows a clearer intra-annual pattern, as can be seen by looking at the graphs obtained between February and June.

In the Contreras reservoir, located parallel to Alarcon, the stochastic optimization results show both carryover and seasonal storage. This can be seen in the wideness of the box-whisker plots, the smooth refill-drawdown cycle and the lack of summer outliers. On the other hand, its seasonal operation is more relevant under the current policies, especially between October and April, in which the box-whisker plots are narrower than in the stochastic optimization. Nonetheless, there is no significant difference in the average values, so operational changes introduced by stochastic optimization are limited. Finally, the results for the Tous reservoir, located downstream and with a smaller capacity, offer remarkable differences between the alternative management options. The current policies produce a steady refill-drawdown cycle, as can be seen by the narrow box-whisker plots. This cycle is in line with the irrigation season (refill until April, when there is little irrigation, and drawdown from May to October, where the downstream crops are irrigated). On the contrary, the stochastic optimization presents a management with higher flexibility and more aggressive drawdown operations. This can be seen in the wider box-whisker plots and the distinctly lower average storages between April and September. The drawdown pattern lowers the reservoir between April and

June, increasing the storage a little in July and then emptying it again until the end of the season. This is consistent with the use of Tous as the tail reservoir of the system, since energy prices in July are higher than in both June and August.

Taking a broader view, the stochastic programming operates the system in a flexible way compared with the current policies, as can be seen in the range covered by the whiskers of all the plots. The current operation implements similar refill-drawdown patterns regardless of the future hydrology, as seen in Tous. On the contrary, the stochastic optimization makes certain probabilistic projections on future hydrological variables and prospected system states. This is consistent with the algorithm construction, which embeds the stochastic inflow forecasts within its structure. Furthermore, the algorithm seeks to maximize the economic benefits, while the current policies aim exclusively at maximizing the agricultural deliveries to the USUJ. The fact that hydropower generation is not an objective of the current policies is shown in the steady refill-drawdown cycle at Tous. However, the stochastic optimization takes into account hydropower when maximizing the systemwide economic benefits. Due to this, it manages Tous as the tail reservoir of the hydropower system, thus improving the turbinated flows and the benefits associated with higher power generation (see Tables 1 and 2). The use of Tous as a tail reservoir for hydropower, the increase of carryover storage in Contreras and the use of dynamic inflow forecasts are the main differences between both alternative operations.

4.3. Conjunctive Use Operation

Monthly allocations to the demands whose major source is groundwater (Mancha Oriental agricultural demand, MOAD; and canal Jucar-Turia, CJT) are contrasted to analyze how the alternatives differ in their conjunctive operation (Figure 5). Differences between alternatives are larger during summer due to the irrigation demands concentration in this season. As is shown in the MOAD scatterplots, the stochastic optimization decreases groundwater abstractions, especially during summer. This is due to the stream-aquifer interaction between the Jucar river and the Mancha Oriental aquifer. The stochastic optimization balances the marginal benefits of the MOAD with the marginal supply costs plus the opportunity costs of increasing downstream flows via stream-aquifer interaction. In contrast, the current operating rules do not account for the opportunity cost of the effect on the stream-aquifer interaction, leading to higher (and less efficient at the basinwide scale) pumping rates.

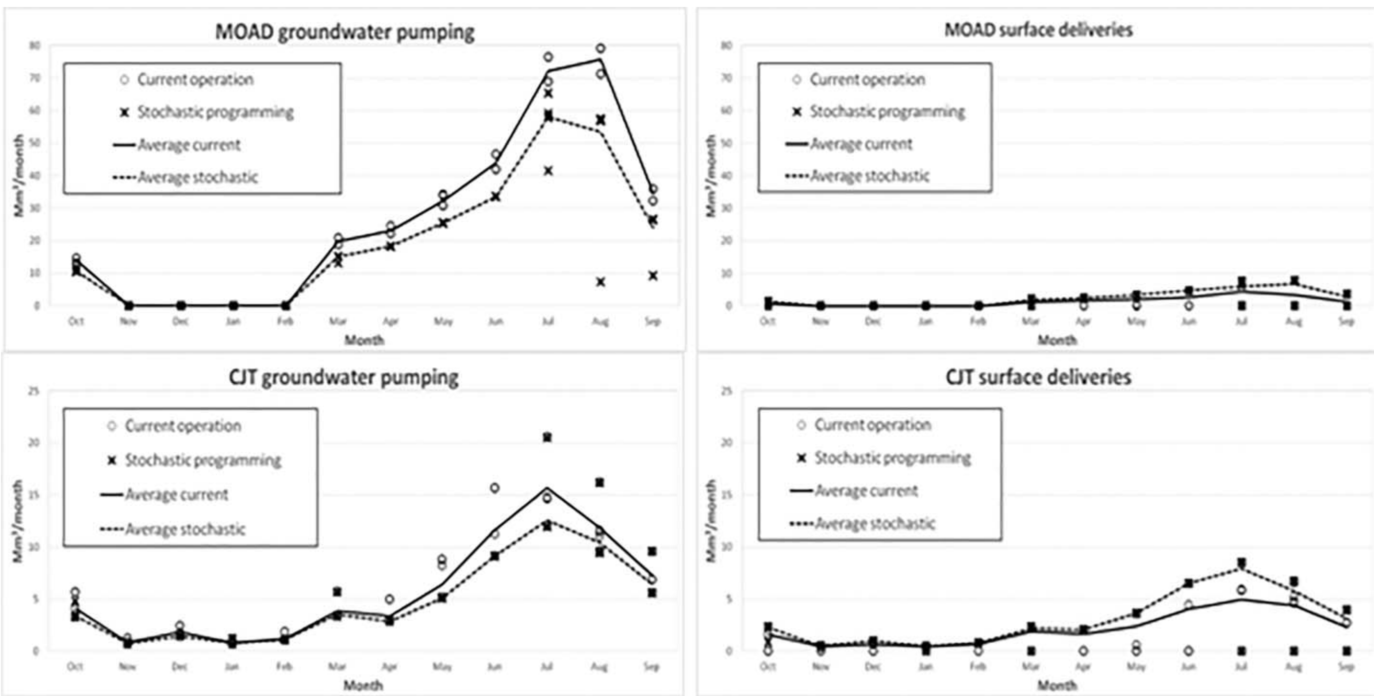

Figure 5. Monthly deliveries to the MOAD and CJT agricultural demands.

The scatterplots for the deliveries to the CJT demand show that the stochastic programming slightly reduces groundwater pumping, allocating more surface resources. The sum of both sources of supply is similar in both runs (see Table 1), which is consistent with the absence of stream-aquifer interaction in the PVS north aquifer. The marginal benefits of supply are balanced against the marginal costs of pumping in both situations. Thus, the only difference corresponds to the higher surface deliveries that, thanks to an improved system management, are allotted through the stochastic programming.

5. Discussion and Conclusions

This paper presents an extension of the SDDP algorithm for the stochastic optimization of large-scale water resource systems with surface and groundwater resources, taking into account stream-aquifer interaction. To achieve this, the SDDP algorithm is combined with the embedded multireservoir model (EMM) for representing stream-aquifer flow exchange. The resulting extended algorithm, named as Combined Surface-Groundwater SDDP (CSG-SDDP), was applied to the Jucar river basin (Eastern Spain). The operating policies derived from the stochastic optimization were compared with the current ones. The stochastic optimization successfully identified promising changes in the operation of both reservoirs and conjunctive use patterns to improve the basinwide economic efficiency of the system management. The following conclusions regarding the method can be drawn:

- The Stochastic Dual Dynamic Programming (SDDP) and the stream-aquifer Embedded Multireservoir Model (EMM) can be combined for stochastic optimization in large-scale water resources systems. The resulting extended algorithm is able to account for stream-aquifer interactions in the definition of optimal operating rules at the basinwide scale.
- Its application to the Jucar river system successfully identified changes in both the reservoir and groundwater management, benefiting from a joint operation of both components of the system. The proposed method opens up the possibility of defining optimal conjunctive-use operations in large-scale water resource systems using stochastic programming.

The main changes in the operation of the Jucar river outlined by the extended algorithm are: the reduced groundwater abstractions in the Mancha Oriental aquifer in about 80 Mm^3/yr, the increased carryover storage in Contreras, using Tous as a tail reservoir for the hydropower plants and employing dynamic inflow forecasts in the operation processes. These changes would not only increase the economic benefits of the system operation around €5 M/yr, but also its robustness and resilience against drought events and the environmental status of the system (especially due to a reduced streamflow depletion by the Mancha Oriental aquifer.

Although the method presented was successfully developed and its application to the Jucar case study defined optimal conjunctive use strategies, the CSG-SDDP algorithm could be employed due to the existence of adequate data to fit the EMMs. The development of an EMM would require assessing the natural stream-aquifer interaction as well the current one in order to take advantage of the principle of superposition. The estimation of both needs adequate streamflow, recharge and pumping measurements, as well as groundwater modeling for isolating the natural component of groundwater discharge; something that is not usually available. This issue limits the applicability of the CSG-SDDP to systems in which an EMM could be adequately fit and the natural regime could be safely estimated.

Moreover, the system representation is subject to several uncertainties. The demand functions and the economic characterization of energy production are the most important among them, since they establish the benefits obtained from allocation decisions. Further research should be carried out in the Jucar river system to improve its economic characterization while maintaining an adequate representation of the global picture, which is crucial for models focusing on the basinwide scale. With regard to other sources of uncertainty, the parameters and mathematical representations assumed by the model are the same as those used by the *CHJ* [2013], whose river basin models are the product of a development, testing, and updating process of many years.

In addition, although the EMM is able to reproduce complex stream-aquifer relationships even in the case of karstic aquifers [e.g., *Estrela and Sahuquillo*, 1997], it does not reproduce groundwater heads. Consequently, the policy implications obtained by it (as pumping reduction in certain demands) need to be further assessed applying detailed groundwater models such as finite-difference ones. Although implementing complex methods for groundwater modeling with techniques such as the eigenvalue method [*Sahuquillo*, 1983] is compatible with basinwide water management optimization [*Andreu et al*., 1996; *Pulido-Velazquez et al*., 2006b], this has been so far applied only with deterministic approaches, and its extension to stochastic dynamic optimization is out of the scope of the paper.

Furthermore, the optimization of system operation is done under the common social-planner paradigm, seeking the operation that maximizes the net total benefit for the system (maximizes economic efficiency). However, the resulting operation might involve benefits asymmetrically distributed among the stakeholders in the basin, creating equity issues. Benefit-sharing mechanisms could be implemented to compensate for equity issues [*Arjoon et al*., 2016].

Although the increase in economic benefits achieved by the CSG-SDDP extended algorithm in the Jucar River basin was not significant in comparison with the current revenues, the main novelty of the paper (the development of an extension of the SDDP method able to perform stochastic optimizations in large surface-groundwater systems) has been successfully applied. The extended algorithm was able to identify changes in the operating rules that further increase the basinwide benefits through a joint operation of reservoirs and aquifers. The results show that the current operating rules of the Jucar River basin are quite economic efficient. It is likely that applying the method to other basins would lead to more significant revenue increases.

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References

Andreu, J., J. Capilla, and E. Sanchís (1996), AQUATOOL, a generalized decision-support system for water-resources planning and operational management, *J. Hydrol.*, *177*(3–4), 269–291, doi:10.1016/0022-1694(95)02963-X.

Arjoon, D., A. Tilmant, and M. Herrmann (2016), Sharing water and benefits in transboundary river basins, *Hydrol. Earth Syst. Sci.*, *20*, 2135–2150.

Barlow, P. M., and S. A. Leake (2012), Streamflow depletion by wells – Understanding and managing the effects of groundwater pumping on streamflow, *U.S. Geol. Surv. Circ.*, *1376*, 84.

Ben-Haim, T. (2006), *Info-Gap Decision Theory*, 368 pp., Elsevier, Amsterdam.

Ben-Tal, A., L. El Ghaoui, and A. Nemirovski (2009), *Robust Optimization*, 576 pp., Princeton Univ. Press, Princeton, N. J.

Brooke, A., D. Kendrik, and A. Wilson (1998), *GAMS: A User's Guide*, Scientific, Redwood City, Calif.

Castaño, S., D. Sanz, and J. J. Gómez-Alday (2010), Methodology for quantifying groundwater abstractions for agriculture via remote sensing and GIS, *Water Resour. Manage.*, *24*(4), 795–814.

CEDEX (2010), *Anuario de aforos* [in Spanish], Public Site Works Study and Exp. Cent., Minist. of Agric., Food and Enviro., Span. Gov., Madrid, Spain. [Available at http://ceh-flumen64.cedex.es/anuarioaforos/default.asp.]

CHJ (2013), *Proyecto del Plan Hidrológico. Demarcación Hidrográfica del Júcar* [in Spanish], Confederación Hidrográfica del Júcar, Ministerio de Agricultura, Alimentación y Medio Ambiente, Gobierno de España, Valencia, Spain.

Davidsen, C., S. J. Pereira-Cardenal, S. Liu, X. Mo, D. Rosbjerg, and P. Bauer-Gottwein (2015a), Using stochastic dynamic programming to support water resources management in the Ziya River Basin, China, *J. Water Resour. Plann. Manage.*, *141*, 04014086-1.

Davidsen, C., S. Liu, X. Mo, D. Rosbjerg, and P. Bauer-Gottwein (2015b), The cost of ending groundwater overdraft on the North China Plain, *Hydrol. Earth Syst. Sci. Discuss.*, *12*, 5931–5966.

Dinar, A., M. W. Rosegrant, and R. Meinzen-Dick (2007), *Water Allocation Mechanisms – Principles and Examples*, Agric. Nat. Resour. Dept., World Bank.

Estrela, T., and A. Sahuquillo (1997), Modeling the response of a Karstic Spring at Arteta Aquifer in Spain, *Groundwater*, *35*(1), 18–24.

Garcia Valiñas, M. A. (2004). La demanda de agua en las ciudades: estimación comparada para tres municipios españoles [in Spanish], in *III Congreso Ibérico sobre Gestión y Planificación del Agua – La Directiva Marco del Agua, realidades y futuros*, edited by L. Del Moral, pp. 232–253. Univ. de Sevilla, Spain

Goor, Q., C. Halleux, Y. Mohamed, and A. Tilmant (2010), Optimal operation of a multipurpose multireservoir system in the Eastern Nile River Basin, *Hydrol. Earth Syst. Sci.*, *14*, 1895–1908.

Hanson, R. T., L. E. Flint, A. L. Flint, M. D. Dettinger, C. C. Faunt, D. Cayan, and W. Schmid (2012), A method for physically based model analysis of conjunctive use in response to potential climate changes, *Water Resour. Res.*, *48*, W00L08, doi:10.1029/2011WR010774.

Harou, J. J., M. Pulido-Velazquez, D. E. Rosenberg, J. Medellin-Azuara, J. R. Lund, and R. E. Howitt (2009), Hydro-economic models: Concepts, design, applications, and future prospects, *J. Hydrol.*, *375*(3-4), 627–643.

Howitt, R. E. (1995), Positive mathematical programming, *Am. J. Agric. Econ.*, *77*(2), 329–342.

Israel, M. S., and J. R. Lund (1999), Priority preserving unit penalties in network flow modelling, *J. Water Resour. Plann. Manage.*, *125*(4), 205–214.

Jenkins, M. W., J. R. Lund, and R. E. Howitt (2003), Using economic loss functions to value urban water scarcity in California, *J. Am. Water Works Assoc.*, *95*(2), 58–70.

Jenkins, M. W., J. R. Lund, R. E. Howitt, A. J. Draper, S. M. Msangi, S. K. Tanaka, R. S. Ritzema, and G. F. Marques (2004), Optimization of California's water supply system: Results and insights, *J. Water Resour. Plann. Manage.*, *130*, 271–280.

Labadie, J. W. (2004), Optimal operation of multireservoir systems: State-of-the-art review, *J. Water Resour. Plann. Manage.*, *130*(2), 93–111.

MMA (2004), *Caracterización económica del uso del agua en el sector energético y análisis de los factores determinantes de las presiones y escenarios de evolución del 2015 al 2015* [in Spanish], Madrid.

Marques, G. F, and A. Tilmant (2013), The economic value of coordination in large-scale multireservoir systems: The Parana River case, *Water Resour. Res.*, *49*, 7546–7557, doi:10.1002/2013WR013679.

Marques, G. F, J. R. Lund, and R. E. Howitt (2010), Modeling conjunctive use operations and farm decisions with two-stage stochastic quadratic programming, *J. Water Resour. Plann. Manage.*, *136*, 386–394.

Pereira, M. V. F., and L. M. V. G. Pinto (1985), Stochastic optimization of a multireservoir hydroelectric system: A decomposition approach, *Water Resour. Res.*, *21*(6), 779–792.

Pereira, M. V. F., and L. M. V. G. Pinto (1991), Multi-stage stochastic optimization applied to energy planning, *Math. Program.*, *52*, 359–375.

Pulido-Velazquez, M. (2003), Conjunctive use opportunities in southern California, MSc. thesis, Univ. of Calif., Davis.

Pulido-Velazquez, M., M. Jenkins, and J. R. Lund, (2004), Economic values for conjunctive use and water banking in southern California, *Water Resour. Res.*, *40*, W03401, doi:10.1029/2003WR002626.

Pulido-Velazquez, M., A. Sahuquillo-Herraiz, J. C. Ochoa-Rivera, and D. Pulido-Velazquez (2005), Modeling of stream-aquifer interaction: The embedded multireservoir model, *J. Hydrol.*, *313*, 166–181.

Pulido-Velazquez, M., J. Andreu, and A. Sahuquillo (2006a), Economic optimization of conjunctive use of surface water and groundwater at the basin scale, *J. Water Resour. Plann. Manage.*, *132*(6) 454–467.

Pulido-Velazquez, M., M. A. Perez-Martin, A. Solera, G. Collazos, D. Deidda, E. Alvarez-Mendiola, A. Benitez, and J. Andreu (2006b), Desarrollo y aplicación de metodologías y herramientas en la cuenca piloto del río Júcar para los análisis económicos requeridos en la Directiva Marco Europea del Agua [in Spanish], Final research report, Univ. Politècnica de València, Valencia, Spain.

Pulido-Velazquez, M., J. Andreu, A. Sahuquillo, and D. Pulido-Velazquez (2008), Hydro-economic river basin modelling: The application of a holistic surface-groundwater model to assess opportunity costs of water use in Spain, *Ecol. Econ.*, *66*(1), 51–65, doi:10.1016/j.ecolecon.2007.12.016.

Pulido-Velazquez, M., G. Marques, J. J. Harou, and J. R. Lund (2016), Hydro-economic models as decision support tools for conjunctive management of surface and groundwater, in *Integrated Groundwater Management. Concepts, Approaches and Challenges*, edited by A. J. Jakeman et al., Springer, Cham, Switzerland.

Rani, D., and M. M. Moreira (2010), Simulation-optimization modeling: A survey and potential application in reservoir systems operation, *Water Resour. Manage.*, *24*, 1107–1138.

Reichard, E. G. (1995), Groundwater-surface water management with stochastic surface water supplies: A simulation optimization approach, *Water Resour. Res.*, *31*(11), 2845–2865.

Sahuquillo, A. (1983), An eigenvalue numerical technique for solving unsteady groundwater continuously in time, *Water Resour. Res.*, *19*(1), 87–93.

Salas, J. D. (1993), Analysis and modeling of hydrologic time series, in *The McGraw Hill Handbook of Hydrology*, edited by D. R. Maidment, Chapter 19, 72 pp., New York.

Salas, J. D., J. W. Delleur, V. M. Yevjevich, and W. L. Lane (1980), *Applied Modeling of Hydrologic Time Series*, Water Resour. Publ., Littleton, Colo.

Sanz, D., J. J. Gómez-Alday, S. Castaño, A. Moratalla, L. De las Heras, and P. P. Martínez Alfaro (2009), Hydrostratigraphic framework and hydrogeological behaviour of the Mancha Oriental System (SE Spain), *Hydrogeol. J.*, *17*, 1375–1391.

Sanz, D., S. Castaño, E. Cassiraga, A. Sahuquillo, J. J. Gómez-Alday, S. Peña, and A. Calera (2011), Modeling aquifer-river interactions under the influence of groundwater abstraction in the Mancha Oriental System (SE Spain), *Hydrogeol. J.*, *19*, 475–487.

Sumpsi, J. M., A. Garrido, M. Blanco, C. Varela-Ortega, and A. Iglesias (1998), *Economia y política de gestión del agua en la agricultura* [in Spanish], Mundi-Prensa, Madrid.

Tilmant, A., and J. Kelman (2007), A stochastic approach to analyze trade-offs and risks associated with large-scale water resources systems, *Water Resour. Res.*, *43*, W06425, doi:10.1029/2006WR005094.

Tilmant, A., D. Pinte, and Q. Goor (2008), Assessing marginal water values in multipurpose multireservoir systems via stochastic programming, *Water Resour. Res.*, *44*, W12431, doi:10.1029/2008WR007024.

UPV (2002), *Estudio de utlización conjunta de los recursos hídricos superficiales y subterráneos en las cuencas media y baja de los ríos Júcar y Turia* [in Spanish], technical report, Univ. Politècnica de València, Valencia, Spain.

Zhu, T., G. F. Marques, and J. R. Lund (2015) Hydroeconomic optimization of integrated water management and transfers under stochastic surface water supply, *Water Resour. Res.*, *51*, 3568–3587, doi:10.1002/2014WR016519.