



# Multipurpose Reservoir Operation: a Multi-Scale Tradeoff Analysis between Hydropower Generation and Irrigated Agriculture

Jose M. Gonzalez<sup>1,2,3</sup> · Marcelo A. Olivares<sup>1,2</sup>  · Josué Medellín-Azuara<sup>4</sup> · Rodrigo Moreno<sup>5,6,7</sup>

Received: 10 May 2018 / Accepted: 27 May 2020 / Published online: 08 June 2020  
© Springer Nature B.V. 2020

## Abstract

Reservoir operations often require balancing among several water uses. Despite the non-consumptive nature of hydropower, conflicts exist between irrigation and hydropower due to a demand seasonality mismatch. Hydropower operations are scheduled as part of a large-scale power grid, whereas irrigation decisions takes place at a smaller scale, most often the river basin. Balancing these water uses should involve a co-optimization at the power grid level, integrating all basins contributing hydropower to the grid. However, grid-wide co-optimization is not always possible due, for instance, to separate regulatory settings between water uses. For those cases, we propose a basin-wide co-optimization approach that integrates two decision scales—power grid and river basin—into a hydro-economic model. Water for irrigation is usually allocated by water rights or binding contracts, represented as constraints on grid-wide power operation models. We propose a water allocation scheme that integrates monthly marginal benefits of water for irrigation and hydropower at the basin level. Monthly water demand functions for irrigation are developed using an agricultural economic model, and marginal benefits of hydropower production are derived from a cost-minimization, grid-wide power scheduling model. Results for 50 inflow scenarios show that the proposed basin-wide co-optimization provides an economically sound operation. Total benefits from water use in the basin are on average 2.5% higher than those obtained under mandatory irrigation. Moreover, expected benefits under co-optimization are 5.4% and 1.8% higher for irrigated agriculture and hydropower, respectively, alleviating the conflicts between water uses in the basin.

**Keywords** Sampling stochastic dynamic programming (SSDP) · Irrigation and hydropower water demand conflicts

---

✉ Marcelo A. Olivares  
maroliva@uchile.cl

## 1 Introduction

The conflict between hydropower and irrigation has been addressed in the last decade under the paradigm of water-food-energy (WFE) nexus (Cai et al. 2018). This concept requires integrated modelling tools (Bazilian et al. 2011) and adequate governance (Pahl-Wostl 2019) to be properly implemented. The operation of multipurpose reservoirs for hydropower and irrigation is subject to complex multi-scale forcings, posing a challenge on both tools development and governance. Hydropower operations are commonly prescribed as part of a power grid-wide scheduling process by an Independent System Operator (ISO). This process can be based either on a market clearing bidding scheme or grid-wide cost minimization (Scott and Read 1996; Steeger et al. 2014). Under the cost minimization scheme, particularly for power systems dominated by thermal and hydropower, a key step is to determine the long-term value of water stored in reservoirs, expressed as a future value function (FVF), which represents avoided future thermal costs. Estimation of the FVF for multi-purpose reservoirs is challenging, particularly when water allocation decisions occur at different spatial scales. Indeed, hydropower operations are forced by the entire power grid scheduling, which typically includes several river basins. On the other hand, in absence of water transfers, irrigated agriculture planning takes place at basin scale. Despite hydropower is a non-consumptive water use, it can interfere with irrigation due to mismatched seasonality within the year, especially when power demands are highest in winter and irrigation water demand peaks during summer (Castelletti et al. 2008). Water used for power generation during winter will not be stored in the reservoir for the irrigation season.

In large-scale reservoir systems such tradeoffs have been studied using stochastic dual dynamic programming (SDDP) by Tilmant and Kelman (2007), and Tilmant et al. (2008), representing the water use for irrigated agriculture through operational constraints—annual irrigation requirements— or co-optimizing by including its economic value in the objective function, respectively. This latter approach was used by Tilmant et al. (2009) to study water transfers from agriculture to hydropower within the Euphrates river basin. Regardless the strategy, optimal water allocation among uses calls for proper economic representation of the effects of alternative allocations using hydro-economic models, which can be the basis for water decision making at various levels (Medellín-Azuara 2006; Pulido-Velazquez et al. 2008; Tilmant et al. 2008, 2009; Harou et al. 2009; Medellín-Azuara et al. 2010; Arjoon et al. 2014).

Unfortunately, sometimes an economic representation of water use for irrigation cannot be directly included into a grid-wide power scheduling model and therefore explicit co-optimization at the grid level is not possible. This is, for instance, the case in Chile, where the law establishes that only direct power-related costs can be considered by the ISO, leaving aside all other economic effects of scheduling (Law N° 4/20018 2007). To overcome this limitation, we propose a novel alternative strategy to identify promising operational schemes in multi-purpose reservoirs contributing hydropower to a power grid and water for basin-wide irrigation. The proposed strategy relies on integrating two decision scales -power grid and river basin- to represent the benefits for both water uses within a basin-wide co-optimization hydro-economic model. The value of water for irrigated agriculture is obtained from an agricultural economic model at the river basin level, whereas the marginal benefit of water used for hydropower production is derived from a grid-wide power scheduling model. This modeling framework is compared with the alternative approach of imposing mandatory irrigation requirements, represented as constraints on reservoir releases.

Specifically, the water value for irrigated agriculture is quantified from irrigation water demand functions, which represent the marginal benefit of water used for this purpose (Young 2005). Seasonal demand functions are obtained by solving the farmer’s decision problem, which consists in allocating land and water to each crop, maximizing the net benefit (Johansson 2005; Medellín-Azuara et al. 2010). This agricultural economic model was solved using Positive Mathematical Programming (PMP) (Howitt 1995a, b), with observed cropping patterns from a base year. These seasonal demand functions are then disaggregated monthly. On the other hand, the grid-wide power scheduling model was solved using Stochastic Dual Dynamic Programming (SDDP) (Pereira and Pinto 1985, 1991). This is one of the most common methods to solve the medium- and long-term power scheduling problem at the power-grid level in hydrothermal systems, especially those dominated by hydropower (dos Santos and Diniz 2009; Shapiro 2011; Matos and Finardi 2012).

This paper is organized as follows. The modelling framework is described in section 2. Operational and economic results are presented in section 3. Finally, section 4 includes the main conclusions in terms of tradeoffs and policy implications.

## 2 Modeling Framework

### 2.1 Conceptual Framework

As a proof of concept, the proposed approach is applied on the hypothetical system depicted in Fig. 1. The system includes a power grid composed by one reservoir hydropower plant and one thermal plant which represents an aggregation of several thermal generators connected to the grid. Energy demand is assumed to be known, represented by a single demand profile. The reservoir serves irrigation demands by releasing water through the turbines. This conceptual system resembles Chile’s largest hydropower reservoir, with a storage capacity of 5850 Hm<sup>3</sup>.

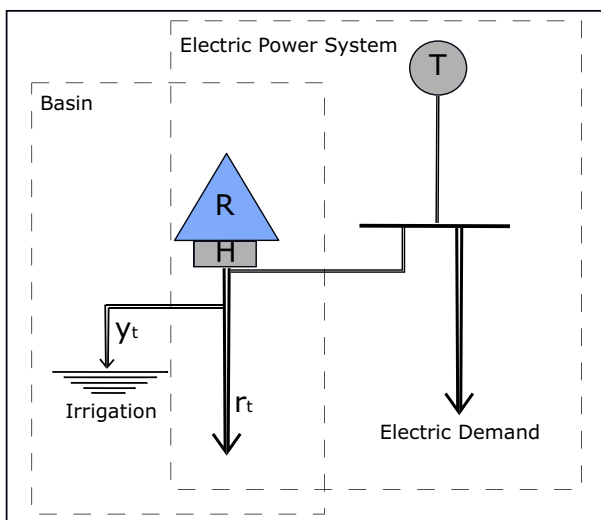


Fig. 1 Hypothetical system schematic showing basin and power system scales

The basin-wide problem for the system in Fig. 1 consists of finding the release decisions sequence ( $y_t$ ,  $r_t$  for irrigated agriculture and hydropower, respectively) from the reservoir so that the joint benefit for the two uses is maximized over a planning horizon. Given the system configuration, hydropower and irrigated agriculture are not instantaneously rival, since all releases through the turbines ( $r_t$ ) are available for downstream irrigation ( $y_t$ ).

The nature of the seasonal conflict between hydropower and irrigation for the system in Fig. 1 is illustrated in Fig. 2. Irrigation demands are highest during the September–April period, including the entire spring and summer, thus defining an irrigation season. In contrast, energy demand peaks during April–September. Water availability, expressed as inflows to the reservoir, exhibits a mixed regime with the highest flows associated to spring snowmelt (September–December) and a smaller peak during the rainy winter season (May–August). A more complete description of the Laja river basin can be found in (Muñoz et al. 2019).

## 2.2 Building Blocks: Grid-Wide Power Scheduling and Basin-Wide Agricultural-Economic Model

The proposed approach considers a situation where irrigation and hydropower cannot be explicitly co-optimized at the power grid level, as it is the case in Chile. This calls for an indirect strategy, based on the marginal value of water for each water use. These marginal values are obtained from two building blocks: a grid-wide power scheduling model and a basin-wide agricultural-economic model.

### 2.2.1 Grid-Wide Power Scheduling Model

The marginal value of water for hydropower production is obtained from a grid-wide power scheduling model. We assume an ISO schedules electric power production within a planning horizon  $T$ , satisfying a known demand profile at minimum cost. The marginal value of water corresponds to the dual value of the water balance constraint in the optimal solution of the grid-wide power scheduling model (Steeger et al. 2014).

The above problem is challenging due to the common large-scale nature of power systems. We used Stochastic Dual Dynamic Programming (SDDP) (Pereira and Pinto 1985, 1991), the most widely used method to solve the medium- and long-term power scheduling problem at grid level in dominated hydrothermal systems (dos Santos and Diniz 2009; Shapiro 2011; Matos and Finardi 2012). Inflow uncertainty is incorporated into the model through a 50-

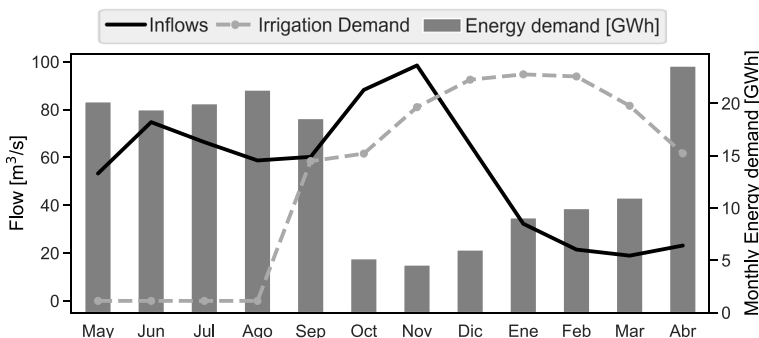


Fig. 2 Seasonal pattern of irrigation demand, energy demand and inflows in the system

scenarios tree based on historical records, with a 3-year long planning horizon (T) with monthly stages. The model is run for 5 years to avoid ending conditions affecting the reservoir storage at the end of the horizon, as suggested by Kelman et al. (2001).

### 2.2.2 Basin-Wide Agricultural-Economic Model

The agricultural-economic model is based on Positive Mathematical Programming, PMP (Howitt 1995a, b), a deductive approach to simulating the effects of policy changes on cropping patterns at the extensive and intensive margins (Medellín-Azuara et al. 2010; Howitt et al. 2012). This method calibrates the parameters of production and cost functions within an optimization model by matching empirical observations, in this case, observed cropping patterns from a base year. Details of the model can be found in Medellín-Azuara et al. (2007) and Howitt et al. (2012).

The model was implemented with data from the Laja river basin, located in the Biobío region in Chile. This river basin holds the largest reservoir in the country, which satisfies water demands for hydropower and more than 100,000 ha of irrigated agriculture. For illustrative purposes, all irrigation areas in the basin were aggregated into a single, representative sector. This system is characterized by an 8-month (September–April) irrigation season. From this model, we obtain the marginal value of water for multiple water availability levels, i.e. water demand functions for irrigation, for the entire irrigation season. These functions, which represent the farmers willingness to pay for varying quantities of water for their crops (Harou et al. 2009), are then disaggregated into monthly water demand functions for irrigation. Table 1 shows the data used to calibrate the agricultural-economic model.

### 2.3 Basin-Wide Hydro-Economic Model

The basin-wide hydro-economic model derives stationary monthly FVF's integrating the value of both hydropower and irrigation. The proposed hydro-economic model at the river basin level is represented by Eqs. (1) to (1e).

$$\text{Max}_{R_t, y_t} Z = \frac{E}{q_t} \left[ \sum_{t=1}^T B_t(S_t, R_t, y_t) + \nu(S_{T+1}) \right] \tag{1}$$

$$S.t. \quad S_{t+1} = S_t + q_t - R_t - Sp_t - ev_t(S_t) \quad \forall t = 1, \dots, T \tag{1a}$$

**Table 1** Input data to calibrate the Agricultural-economic model

Crops	Crop Area (ha)	Total production (t)	Production per area (kg/ha)	Land Cost \$USD/ha	Water Cost \$USD/ha	Crop price \$USD/kg	Water Requirement m <sup>3</sup> /s-ha
Corn	22,028	330,426	15,000	2113	833	0.20	0.005
Oats	37,520	180,097	4800	434	339	0.21	0.005
Potato	10,487	314,606	30,000	3175	2041	0.29	0.002
Bean	5400	6966	1300	2318	812	2.61	0.004
Wheat	102,391	614,346	6000	522	266	0.28	0.005

$$g_t^h \leq g_{max}^h \quad \forall t = 1, \dots, T \quad (1b)$$

$$g_t^h = \gamma R_t \quad \forall t = 1, \dots, T \quad (1c)$$

$$y_t \leq R_t + Sp_t \quad \forall t = 1, \dots, T \quad (1d)$$

$$B_t(S_t, R_t, y_t) = p'_t g_t(S_t, R_t) + B_{ir_t}(y_t) + \xi'_t Sp_t \quad \forall t = 1, \dots, T \quad (1e)$$

Equation (1) represents the objective function which maximizes the expected value of total benefit  $B_t(\cdot)$  from water uses over the time horizon  $T$ , plus the value  $v(\cdot)$  of ending storage. Equation (1a) represents the water balance in the reservoir, where  $S_t$  is the storage at the beginning of stage  $t$ ,  $q_t$  [ $m^3/s$ ] is the natural inflow during the stage  $t$  and  $R_t$  [ $m^3/s$ ] is the release through the turbines decided at the beginning of stage  $t$ .  $Sp_t$  [ $m^3/s$ ] and  $ev_t(\cdot)$  [ $mm/month$ ] are spills and evaporation during stage  $t$ , respectively. Equation (1b) is the capacity constraint of the hydropower plant. Equation (1c) is the approximate linear dependence of hydro generation ( $g_t^h$ ) [MWh] with releases through the turbines. Equation (1d) limits water allocation to irrigation to the sum of turbined flows and spills. Equation (1e) defines the total benefit as the sum of hydropower and irrigation benefits, where  $p'_t$  is the marginal value of energy obtained from the grid-wide power scheduling model,  $B_{ir_t}(\cdot)$  is the monthly irrigation benefit function, and  $\xi'_t$  a vector of penalty coefficients on spills.

As a benchmark, we implemented and solved the problem using mandatory irrigation requirements. This approximates the current practice for some reservoirs in Chile's grid, where water allocation is enforced by binding irrigation agreements between hydropower operators and farmers. Modeling of this case requires redefining the objective function through the introduction of a new variable representing irrigation deficit as shown in Eqs. (2) and (3).

$$Ir_t \leq R_t + Sp_t + DIr_t \quad \forall t = 1, \dots, T \quad (2)$$

$$B_t(S_t, R_t, DIr_t) = p'_t g_t(S_t, R_t) + \xi'_t Sp_t + \xi'_t DIr_t \quad (3)$$

Equation (2) represents the modified irrigation constraint, where  $Ir_t$  [ $m^3/s$ ] is the fixed irrigation requirement at stage  $t$  and  $DIr_t$  [ $m^3/s$ ] is the irrigation deficit, which occurs when releases cannot meet the irrigation requirement. Equation (3) is the modified objective function where the deficits ( $DIr_t$ ) are strongly penalized, becoming a soft constraint.

The basin-wide hydro-economic model was solved using Sampling Stochastic Dynamic Programming (SSDP) (Kelman et al. 1990), with scenarios defined by historical records of inflows to the reservoir. Dynamic programming decomposes the multi-stage problem in Eq. 1 into single-stage subproblems solved recursively.

A polynomial interpolation (Miranda and Fackler 2004) is used in order to alleviate the computational effort and to allow for a continuous approximation of the FVF for each stage (Johnson et al. 1993). The polynomial, stationary monthly FVFs are then used to simulate the

system operation through a re-optimization process (Tejada-Guibert et al. 1993). The SSDP formulation of the basin-wide hydro-economic model is as follows:

$$\max_{R_t^*, y_t^*} \left[ \frac{1}{L} \sum_{l=1}^L [B_t(S_t^j, R_t, q_t^l, y_t) + \alpha f_{t+1}^i(S_{t+1}, l)] \right] \quad \forall S_t^j, \text{ and } t = 1, \quad (4)$$

$$S_{t+1} = S_t + q_t - e_t(S_t, S_{t+1}) - R_t - Sp_t \quad \forall t = 1, \dots, T \quad (4a)$$

$$g_t^h \leq g_{max}^h \quad \forall t = 1, \dots, T \quad (4b)$$

$$g_t^h = \gamma R_t \quad \forall t = 1, \dots, T \quad (4c)$$

$$y_t \leq R_t + Sp_t \quad \forall t = 1, \dots, T \quad (4d)$$

Equation (4) is the objective function at stage  $t$  that maximizes the expected value of present and future benefits, where  $q_t^l$  [m<sup>3</sup>/s] is the reservoir inflow in the stage  $t$  under the  $l$ -th inflow scenario;  $S_t^j$  is the  $j$ -th discrete reservoir storage value at the beginning of stage  $t$ , with  $S_t^1 = S_{min}$  and  $S_t^J = S_{max}$ , and  $i$  is the iteration number. The model optimizes over 50 annual historical inflow scenarios ( $L=50$ ) with monthly stages for an annual planning horizon ( $T=12$  months).

The optimization model in Eqs. 4 through 4d is solved for a set of discrete values of the state variable  $j$  and for each stage  $t$ . The solution for each stage defines a target release for each water use  $R_t^*$  and  $y_t^*$ . These target releases for irrigation and hydropower production are then adjusted for feasibility under each hydrologic scenario  $l$  through Eqs. 4e and 4g, respectively. The adjusted releases ( $R_t^l, y_t^l$ ) are then used to update the FVFs  $f_t^i(\cdot)$  (Eq. 4h), which reflects the total –present plus future– value of the release decision at each stage  $t$ , under each inflow scenario  $l$ . This procedure is repeated for each stage  $t$ , and for each discretization of the state, until the functions  $f_t^i(\cdot)$  converge. In the first iteration, all FVFs are set to zero ( $f_{T+1}^1(\cdot) = 0$ ).

$$R_t^l = \min \left\{ \begin{array}{l} \max [R_t^*, S_t + q_t^l - R_t - Sp_t - e_{v_t}(S_t) - S_{max}] \\ S_t + q_t^l - R_t - Sp_t - e_{v_t}(S_t) - S_{min} \end{array} \right\} \quad (4e)$$

$$g_t^{h,l} = \gamma R_t^l \quad (4f)$$

$$y_t^l = \left\{ \begin{array}{ll} R_t^l & \text{if } R_t^l \leq Ir_t, \\ Ir_t & \text{if } R_t^l > Ir_t \end{array} \right\} \quad (4g)$$

$$f_t^i(S_t^j, l) = B_t(S_t^j, g_t^{h,l}, q_t^l, y_t) + \alpha f_{t+1}^i(S_{t+1}^j, l) \quad \forall j, l \text{ and } t = 1, \dots, T \quad (4h)$$

Once convergence of the FVFs is attained for each inflow scenario  $l$ , these functions are used in a forward re-optimization process using the same 50-scenarios and the same planning

horizon ( $T = 3$ -years) used in the grid-wide power scheduling model. The simulation process is run with 25% of initial storage, with the aim to evaluate the system performance under unfavorable initial storage conditions. The model with mandatory irrigation requirements is solved through a modified version of the model, including Eqs. (2) and (3).

### 3 Results and Discussion

Results focus on reservoir releases and benefits obtained by each user under both optimized and mandatory irrigation. Figures 3 and 4 show the monthly water demand functions for the agricultural sector and the marginal value of hydropower, respectively. These intermediate results, obtained from the agricultural-economic model and the grid-wide power system optimization, are used as an input for the basin-wide hydro-economic and the fixed-irrigation models.

Figure 3 shows the marginal value of water for irrigation for each month in the irrigation season. As expected, the highest marginal values for water are observed from December through February, when irrigation requirements are highest. Figure 4 shows how the marginal value of hydropower obtained from the grid-wide model represents correctly the intra-annual seasonality of the energy price, with higher prices in winter. Marginal values during the first months in the horizon are quite high, reflecting the unfavorable initial storage in the reservoir.

The main model output is reservoir releases. Cumulative frequency curves of irrigation releases as a percentage of monthly requirements under both co-optimization and mandatory irrigation releases are shown in Fig. 5. These curves include all hydrologic scenarios, with drier scenarios corresponding in general to smaller irrigation releases. Two distinctive situations are observed within the irrigation season. During the first half (Sep-Dec, Fig. 5a), the model with mandatory irrigation prescribes higher releases than the hydro-economic co-optimization model. Under mandatory irrigation, demand is fully met about 55% of the time, while the co-optimization model prescribes releases up to about 80% of the demand. This can be explained because mandatory irrigation forces the system to cover the irrigation requirements at all times, which results in releases meeting the requirement unless infeasible. In the second half of the irrigation season (Jan-Apr, Fig. 5b) this behavior changes, the co-

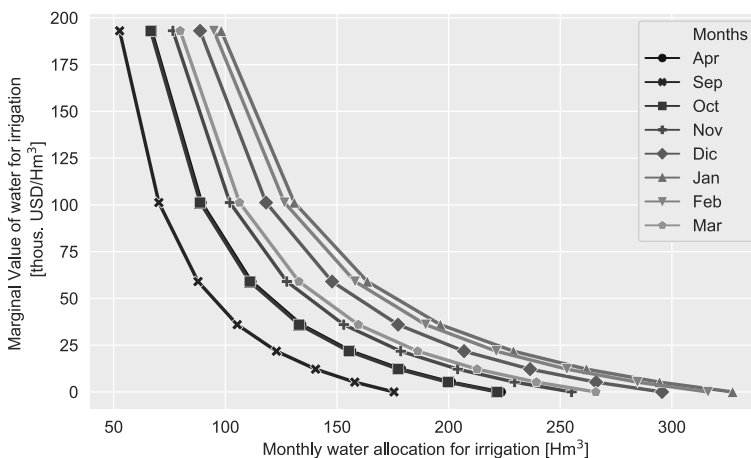
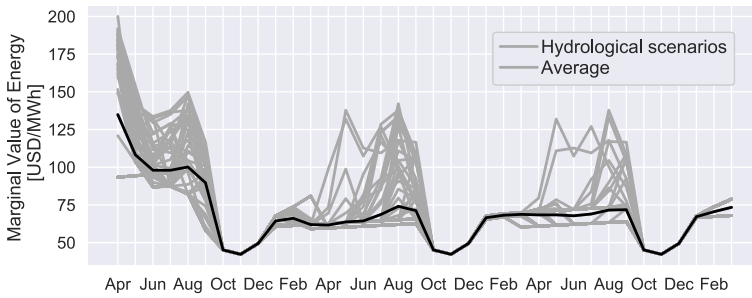


Fig. 3 Monthly water demand functions



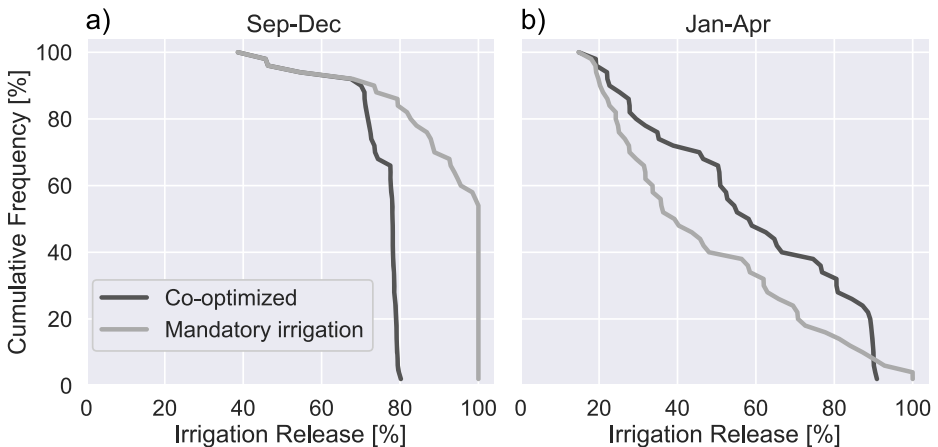


**Fig. 4** Marginal value of hydropower over the 3-year horizon

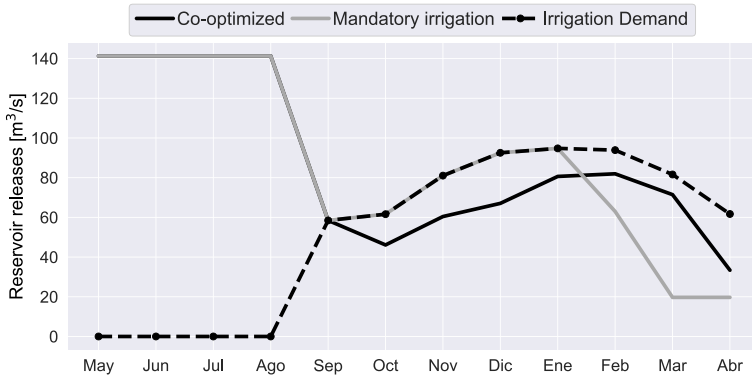
optimization model prescribes higher releases than the mandatory irrigation about 90% of the time. Demand is never fully met in the second half of the irrigation season under co-optimization, whereas it is fully met less than 5% of the time under mandatory irrigation.

For illustrative purposes, Fig. 6 shows monthly reservoir releases for a normal hydrologic scenario. As described above, irrigation releases tend to follow the demand pattern under mandatory irrigation whenever feasible, whereas the co-optimization model distributes the deficits more evenly during the irrigation season. Under the co-optimization model, the reservoir never fully meets the irrigation requirements. However, the worst monthly deficits observed during the second half of the irrigation season are milder than those observed under mandatory irrigation. Reservoir releases in the non-irrigation season, which correspond to the months with higher energy demands, are the same under both schemes and equal to the maximum capacity of the hydropower plant. The severe deficits incurred under mandatory irrigation during the second half of irrigation season, make a big difference in terms of agricultural benefits in the basin. For example, the economic benefit of irrigation in March is 150% greater under co-optimization. In contrast, the worst deficit observed for that scheme—in December—results in benefits 18% lower than those under mandatory irrigation. Annual benefits in the basin for this normal scenario are 3% higher under co-optimization.

Extending the previous analysis to all scenarios, Fig. 7 presents the cumulative frequency distribution of benefits for both users. Benefits for each user were normalized with respect to their maximum attainable benefits. For almost all frequencies, hydropower benefits under co-



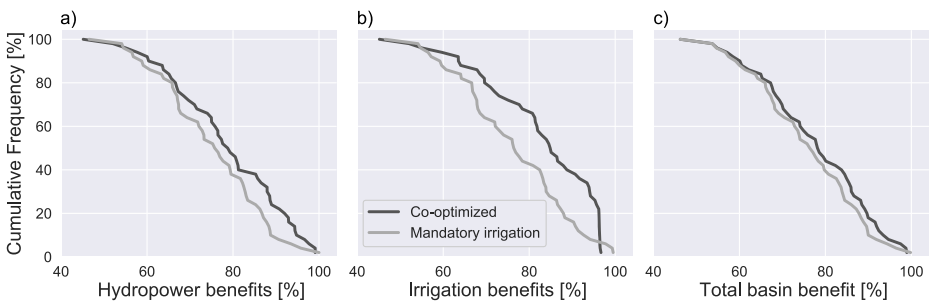
**Fig. 5** Cumulative frequency distribution of irrigation releases. **a)** Sep-Dec. **b)** Jan-Apr



**Fig. 6** Reservoir releases under co-optimization and mandatory irrigation for a normal hydrologic scenario

optimization are higher than those under mandatory irrigation (Fig. 6a). However, the difference in benefits is more significant in the agricultural sector (Fig. 6b), where co-optimization outperforms mandatory irrigation releases except for about 5% of the hydrological scenarios. Total benefits (hydropower plus irrigation) are shown in Fig. 7c. Co-optimized operation results in greater benefits than those under mandatory irrigation for all except the one scenario with highest total benefits.

Since the cumulative frequency curves in Fig. 7 do not necessarily preserve the scenario between co-optimized operations and mandatory irrigation for each percentile, we calculated the relative improvement in benefits of co-optimized operations for each scenario and then performed a frequency analysis. Average and 10%, 50%, and 90% percentile improvements for hydropower, irrigation and total benefits are presented in Table 2. Total (hydropower plus irrigation) benefits under co-optimization are on average 2.5% higher than under mandatory irrigation. A relative improvement of at least 4.1% is obtained with 10% probability. Per sector, benefits are 5.4% and 1.8% higher on average for irrigated agriculture and hydropower, respectively. Notably, with 90% probability, irrigation benefits are better under co-optimized operations. Thus, the proposed approach not only achieves a better aggregated system performance, but also on average every user is better off separately. This is explained mainly by a better water temporal distribution of releases during the irrigation season under co-optimized operations.



**Fig. 7** Frequency distribution of benefits for a) Hydropower, b) Irrigation and c) Total

**Table 2** Relative improvement of co-optimized operations w/r to mandatory irrigation (%)

Percentile	Hydropower	Irrigation	Total
10%	4.2%	9.1%	4.1%
50%	1.1%	6.4%	2.6%
90%	0.1%	0.0%	0.5%
Average	1.8%	5.4%	2.5%

## 4 Conclusions

A hydro-economic, co-optimization approach to evaluate the multi-scale tradeoffs between hydropower and irrigated agriculture under seasonal conflicting demands at the river basin level is presented. The method is useful when co-optimization at the power grid level is not possible due to regulatory or institutional conditions. The proposed approach is built upon information of the monthly marginal value of water for each conflicting use. The marginal value of water for hydropower production was derived from a grid-wide power scheduling model. The marginal value of water for irrigation was obtained from a basin-wide agricultural economic model which replicates the farmer's decision process. The method is illustrated using a hypothetical system composed of a single multi-purpose reservoir which contributes with hydropower to a power grid and serves irrigation demands in the basin. System performance is compared with a scheme where the agricultural sector is represented through mandatory irrigation requirements. As expected, results under the mandatory irrigation show that reservoir releases for irrigation tend to follow the demand pattern. However, the system fails to meet those demands in the second half of irrigation season. In the co-optimization model, the reservoir fails to fully meet the requirements during the entire irrigation season, but the worst deficits are milder than those observed for the fixed-irrigation model. Such better water distribution in the irrigation season produces on average an increase of 2.5% in the benefits in the basin, 5.4% for agriculture and 1.8% for hydropower. On all except one scenario, total benefits are higher under co-optimized operations. As expected, hydropower benefits are higher under co-optimized operations for all scenarios. Interestingly, mandatory irrigation gives lower irrigation benefits for all expect 4 scenarios. These results show the potential of the proposed approach to alleviate the conflicts between water users in the basin, in cases where co-optimization at the power grid level cannot be explicitly carried out. This approach can be applied in general to multipurpose reservoirs contributing to grid-wide and basin-wide benefits, whenever the economic value of water for each use can be obtained. This study could be extended in the future to introduce a more disaggregated representation of the power grid, which would allow identifying more flexible schemes to account for heterogeneous conditions in the basin, like water availability and cropping patterns.

**Availability of Data and Material** Not applicable.

**Code Availability** Not applicable.

**Authors' Contributions** Jose M. Gonzalez: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Visualizations. Marcelo A. Olivares: Conceptualization, Methodology, Supervision, Writing – original draft, writing revised version. Josué Medellín-Azuara: Conceptualization, Software. R. Moreno: Conceptualization, Supervision.

## Compliance with Ethical Standards

**Conflict of Interest** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## References

- Arjoon D, Mohamed Y, Goor Q, Tilmant A (2014) Hydro-economic risk assessment in the eastern Nile River basin. *Water Resour Econ* 8:16–31. <https://doi.org/10.1016/j.wre.2014.10.004>
- Bazilian M, Rogner H, Howells M, Hermann S, Arent D, Gielen D, Steduto P, Mueller A, Komor P, Tol R SJ, Yumkella KK (2011) Considering the energy, water and food nexus: towards an integrated modelling approach. *Energy Policy* 39:7896–7906. <https://doi.org/10.1016/j.enpol.2011.09.039>
- Cai X, Wallington K, Shafice-Jood M, Marston L (2018) Understanding and managing the food-energy-water nexus – opportunities for water resources research. *Adv Water Resour* 111:259–273. <https://doi.org/10.1016/j.advwatres.2017.11.014>
- Castelletti A, Pianosi F, Soncini-Sessa R (2008) Water reservoir control under economic, social and environmental constraints. *Automatica* 44:1595–1607. <https://doi.org/10.1016/j.automatica.2008.03.003>
- dos Santos TN, Diniz AL (2009) A new multiperiod stage definition for the multistage benders decomposition approach applied to hydrothermal scheduling. *IEEE Trans Power Syst* 24:1383–1392. <https://doi.org/10.1109/TPWRS.2009.2023265>
- Harou JJ, Pulido-Velazquez M, Rosenberg DE, Medellín-Azuara J, Lund JR, Howitt RE (2009) Hydro-economic models: concepts, design, applications, and future prospects. *J Hydrol* 375:627–643. <https://doi.org/10.1016/j.jhydrol.2009.06.037>
- Howitt RE (1995a) A calibration method for agricultural economic production models. *J Agric Econ* 46:147–159. <https://doi.org/10.1111/j.1477-9552.1995.tb00762.x>
- Howitt RE (1995b) Positive mathematical programming. *Am J Agric Econ* 77:329–342. <https://doi.org/10.2307/1243543>
- Howitt RE, Medellín-Azuara J, MacEwan D, Lund JR (2012) Calibrating disaggregate economic models of agricultural production and water management. *Environ Model Softw* 38:244–258. <https://doi.org/10.1016/j.envsoft.2012.06.013>
- Johansson RC (2005) Micro and macro-level approaches for assessing the value of irrigation water. World Bank policy research working paper 3778
- Johnson SA, Stedinger JR, Shoemaker CA et al (1993) Numerical solution of continuous-state dynamic programs using linear and spline interpolation. *Oper Res* 41:484–500. <https://doi.org/10.1287/opre.41.3.484>
- Kelman J, Stedinger JR, Cooper LA, Hsu E, Yuan SQ (1990) Sampling stochastic dynamic programming applied to reservoir operation. *Water Resour Res* 26:447–454. <https://doi.org/10.1029/WR026i003p00447>
- Kelman R, Barroso LAN, Pereira MVF (2001) Market power assessment and mitigation in hydrothermal systems. *Power Syst IEEE Trans* 16:354–359. <https://doi.org/10.1109/59.932268>
- Law N° 4/20018 (2007) General law of electrical services. Library of the national congress of Chile, Santiago de Chile
- de Matos VL, Finardi EC (2012) A computational study of a stochastic optimization model for long term hydrothermal scheduling. *Int J Electr Power Energy Syst* 43:1443–1452. <https://doi.org/10.1016/j.ijepes.2012.06.021>
- Medellín-Azuara J (2006) Economic-engineering analysis of water management for restoring the Colorado River Delta. Doctoral dissertation, University of California, Davis
- Medellín-Azuara J, Harou JJ, Howitt RE (2010) Estimating economic value of agricultural water under changing conditions and the effects of spatial aggregation. *Sci Total Environ* 408:5639–5648. <https://doi.org/10.1016/j.scitotenv.2009.08.013>
- Medellín-Azuara J, Lund JR, Howitt RE (2007) Water supply analysis for restoring the Colorado River Delta, Mexico. *J Water Resour Plan Manag* 133:462–471. [https://doi.org/10.1061/\(ASCE\)0733-9496\(2007\)133:5\(462\)](https://doi.org/10.1061/(ASCE)0733-9496(2007)133:5(462))
- Miranda MJ, Fackler PL (2004) Applied computational economics and finance
- Muñoz E, Guzmán C, Medina Y, Boll J, Parra V, Arumi JL (2019) An adaptive basin management rule to improve water allocation resilience under climate variability and change—a case study in the Laja Lake basin in southern Chile. *Water (Switzerland)*. <https://doi.org/10.3390/w11081733>
- Pahl-Wostl C (2019) Governance of the water-energy-food security nexus: a multi-level coordination challenge. *Environ Sci Pol* 92:356–367. <https://doi.org/10.1016/j.envsci.2017.07.017>

- Pereira MVF, Pinto LMVG (1985) Stochastic optimization of a multireservoir hydroelectric system: a decomposition approach. *Water Resour Res* 21:779–792. <https://doi.org/10.1029/WR021i006p00779>
- Pereira MVF, Pinto LMVG (1991) Multi-stage stochastic optimization applied to energy planning. *Math Program* 52:359–375. <https://doi.org/10.1007/BF01582895>
- Pulido-Velazquez M, Andreu J, Sahuquillo A, Pulido-Velazquez D (2008) Hydro-economic river basin modeling: the application of a holistic surface-groundwater model to assess opportunity costs of water use in Spain. *Ecol Econ* 66:51–65. <https://doi.org/10.1016/j.ecolecon.2007.12.016>
- Scott TJ, Read EG (1996) Modelling hydro reservoir operation in a deregulated electricity market. *Int Trans Oper Res* 3:243–253. <https://doi.org/10.1111/j.1475-3995.1996.tb00050.x>
- Shapiro A (2011) Analysis of stochastic dual dynamic programming method. *Eur J Oper Res* 209:63–72. <https://doi.org/10.1016/j.ejor.2010.08.007>
- Steeger G, Barroso LA, Rebenmack S (2014) Optimal bidding strategies for hydro-electric producers: a literature survey. *IEEE Trans Power Syst* 29:1758–1766. <https://doi.org/10.1109/TPWRS.2013.2296400>
- Tejada-Guibert JA, Johnson SA, Stedinger JR (1993) Comparison of two approaches for implementing multireservoir operating policies derived using stochastic dynamic programming. *Water Resour Res* 29:3969–3980. <https://doi.org/10.1029/93WR02277>
- Tilmant A, Goor Q, Pinte D (2009) Agricultural-to-hydropower water transfers: sharing water and benefits in hydropower-irrigation systems. *Hydrol Earth Syst Sci Discuss* 6:2041–2073
- Tilmant A, Kelman R (2007) A stochastic approach to analyze trade-offs and risks associated with large-scale water resources systems. *Water Resour Res*. <https://doi.org/10.1029/2006WR005094>
- Tilmant A, Pinte D, Goor Q (2008) Assessing marginal water values in multipurpose multireservoir systems via stochastic programming. *Water Resour Res*. <https://doi.org/10.1029/2008WR007024>
- Young RA (2005) Determining the economic value of water : concepts and methods. Resources for the Future, Washington, D.C.

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

## Affiliations

Jose M. Gonzalez<sup>1,2,3</sup> · Marcelo A. Olivares<sup>1,2</sup> · Josué Medellín-Azuara<sup>4</sup> · Rodrigo Moreno<sup>5,6,7</sup>

<sup>1</sup> Department of Civil Engineering, Faculty of Physical and Mathematical Sciences, University of Chile, Blanco Encalada 2002, Santiago, Chile

<sup>2</sup> Energy Center, Faculty of Physical and Mathematical Sciences, University of Chile, Plaza Ercilla 847, Santiago, Chile

<sup>3</sup> Department of Mechanical, Aerospace and Civil Engineering, The University of Manchester, Manchester M13 9PL, UK

<sup>4</sup> Civil and Environmental Engineering, University of California Merced, Merced, CA 95343, USA

<sup>5</sup> Department of Electrical Engineering, Faculty of Physical and Mathematical Sciences, University of Chile, Tupper 2007, Santiago, Chile

<sup>6</sup> Instituto Sistemas Complejos de Ingeniería (ISCI), Beauchef 851, Santiago, Chile

<sup>7</sup> Department of Electrical and Electronic Engineering, Imperial College London, South Kensington Campus, London SW7 2AZ, UK