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Definition of efficient scarcity-based water pricing policies through stochastic programming

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Abstract

Finding ways to improve the efficiency in water usage is one of the most important challenges in integrated water resources management. One of the most promising solutions is the use of scarcity-based pricing policies. This contribution presents a procedure to design efficient pricing policies based on the opportunity cost of water at the basin scale. Time series of the marginal value of water are obtained using a stochastic hydro-economic model. Those series are then post-processed to define step pricing policies, which depend on the state of the system at each time step. The case study of the Mijares river basin system (Spain) is used to illustrate the method. The results show that the application of scarcity-based pricing policies increases the economic efficiency of water use in the basin, allocating water to the highest-value uses and generating an incentive for water conservation during the scarcity periods. The resulting benefits are close to those obtained with the economically optimal decisions.

1 Introduction

One of the main challenges on integrated water resources management (IWRM) is improving the efficiency in water usage while balancing it with equity. Given that the building of new water supply systems has well-passed its zenith, water management strategies are now devoted to achieve better operating policies. Several criteria can be considered when designing a policy for water allocation: flexibility in the allocation, security of tenure for the users, real cost recovery, predictability of its performance, fairness and acceptability (Dinar et al., 2007). Each system has a unique configuration and, in consequence, a unique combination of factors that lead to an adequate management policy.

There are four major water allocation mechanisms: public water allocation, water markets, user-based allocation and marginal cost pricing. Public water allocation provides an adequate treatment of water as a public good, allows the development of large-scale infrastructures often beyond the private investment capacity, and focuses on equity issues and non-economic objectives. However, it usually fails in achieving optimal economic performance, leads to water prices which are below the water value, and provides no incentive to water saving and efficient use (Meinzen-Dick and Mendoza, 1996). Water markets encourage both sellers and buyers to use it efficiently, provide flexible allocation mechanisms and allow considering the real value of the employed resource. On the contrary, unique characteristics of water can turn markets into a bad allocation mechanism if externalities are not adequately considered (Garrick et al., 2009). User-based allocation, in which water users regulate water resources by themselves, is especially suited for local needs in water management, and is likely to be accepted by the users. However, it may be inadequate in inter-sectorial allocation, requiring also a very transparent structure (Dinar et al., 2007).

Finally, marginal cost pricing provides a theoretically adequate way to consider water values in allocation, encourages users to save it and puts water in its most valuable uses, leading to efficient allocations. It also can play a major role in the long run planning and conservation of water supplies, delaying the need of capacity expansions and offering higher economic returns while holding rationing requirements (Gysi and Loucks, 1971). However, marginal cost pricing would require estimating the non-accounting opportunity costs involved in water allocation (Griffin, 2001). Calculating the marginal value of water is challenging as it varies in space and time according to supply-demand imbalances; requires adequate monitoring; and has some difficulties to deal with equity when water prices are beyond what lower-value users can afford (Dinar et al., 2007). Moreover, administrative constraints on price charges can limit their benefits (Dandy et al., 1984). In Europe, the EU Water Framework Directive (European Commission, 2000) calls for the implementation of new pricing policies that assure the contribution of water users to the recovery of the cost of water services (financial instrument) while providing adequate incentives for an efficient use of water (economic instrument). Not only financial costs should be recovered, but also environmental and resource (opportunity) costs. This issue has been addressed through the use of hydro-economic models as tools able to couple physical and economic water resource aspects (Heinz et al., 2007; Pulido-Velazquez et al., 2008, 2013; Riegels et al., 2013; Ward and Pulido-Velazquez, 2008).

A pricing policy is efficient, according to the economic theory, if the prices charged correspond to the marginal cost of water. Therefore, it must take into account supply costs, opportunity costs and externalities (Rogers et al., 2002). Measuring the opportunity costs of scarce water is difficult: since water markets are usually absent or ineffective, scarcity values are not reflected in the water prices. Given that opportunity cost depends on the alternative uses, an integrated basinwide approach is needed to simultaneously account for all major competing water uses in the basin (Rogers et al., 2002; Pulido-Velazquez et al., 2013). The assessment of these opportunity costs requires a systems approach and a proper method to estimate the value of water across the different users (Young, 2005; Pulido-Velazquez et al., 2008). If pricing policies reflect the entire basinwide marginal opportunity costs, then they will act as an economic instrument for efficient water resources management, modifying the demand-supply interaction by acting on the demand side and supporting water allocation to the most valuable users.

The Marginal Resource Opportunity Cost (MROC), or marginal value of water, can be defined as the benefits that would have been obtained at one location and one time if the available resource at that location and time had been increased by one unit (Pulido-Velazquez et al. and 2013; Tilmant et al., 2008, 2014). MROC can be derived from hydro-economic models. Pulido-Velazquez et al. (2013) developed a method to obtain scarcity-based pricing policies using MROC values, in which the time series of MROC obtained after running a hydro-economic model are post-processed to derive step pricing policies whose performance can be simulated using a Decision Support System (DSS) shell. However, in those studies pricing policies were based on either priority-based simulation (which are not representing an optimal policy) or deterministic hydro-economic optimization, with the inherent limitation of the perfect foresight (the optimization algorithm knows future flows in advance and, in consequence, it has an unrealistic advantage that diminish the applicability of the results) (Labadie, 2004).

The main purpose of this paper is to propose a method for the design of scarcity-based water pricing policies based on the MROC derived from a stochastic hydro-economic model. With stochastic programming procedures, uncertainty is taken into account in the optimization process. Therefore, it removes the effect that the "perfect foresight" phenomenon causes in the marginal values, which are flattened across time losing an important part of their short-term variability. The marginal values obtained using stochastic programming are representative of an optimal policy while reflecting the future uncertainties in the system's inflows. After describing the method to obtain the MROC values, we propose a method for the definition of a stochastic-programming-based water pricing policy. Finally, a case study is developed to prove and illustrate the methodology using a hydro-economic simulation model of the Mijares river basin system (Spain). Pricing policies are applied in this paper exclusively as economic instruments whose purpose is achieving an efficient use of water. Financial issues are not addressed.

2 Method and materials

2.1 Assessment of the Marginal Resource Opportunity Cost (MROC)

For a specific water demand, the benefit obtained by the user, B_i, given a change in water delivery level from x_1 to x_2 can be calculated by integrating the demand curve (D_i) (Fig. 1):

$$B_i = \int_{x_1}^{x_2} D_i(q)\mathrm{d}q \tag{1}$$

Similarly, for a given location L and time t, the benefit B_t achieved by a change in its state $s_{L,t}$ (water availability) from x_1 to x_2 can be calculated integrating the marginal water value (or MROC) function:

$$B_t = \int_{x_1}^{x_2} \mathrm{MROC}_{L,t}(s_{L,t})\mathrm{d}s \tag{2}$$

The MROC can be defined as the derivative of the benefit function with respect to the system state. Therefore, if the MROC integration obtains the systemwide benefits, the MROC can be calculated as:

$$\mathrm{MROC}_{L,t} = \frac{\mathrm{d}B_t(s_{L,t})}{\mathrm{d}s} \tag{3}$$

The MROC value for a specific location and time can be estimated: (1) under a simulation approach, as the benefits obtained by an increase of one unit in the available resource at that location and time (Pulido-Velazquez et al., 2008, 2013); and (2) under an optimization approach, as the shadow value, dual variable or Lagrange multiplier associated to the mass-balance equation at the desired place and the specified time (Pulido-Velazquez et al., 2008, 2013; Tilmant et al., 2008).

2.2 MROC assessment through stochastic programming

Stochastic programming (SP) procedures are powerful and useful methodologies to derive optimal management of water systems with uncertain inputs (Tejada-Guibert et al., 1993). Various SP algorithms are available. Among them, Stochastic Dynamic Programming (SDP) has been widely used in water resources management because: (1) it is able to handle non-linearities in the objective function in an efficient way; (2) the inflow uncertainty representation is clear and simple; and (3) it treats the decision-making process sequentially, as done in real-life operation (Labadie, 2004). The SDP algorithm solves the Bellman's recursive equation as follows:

$$F_t(\boldsymbol{S}_t,\boldsymbol{Q}_t) = \max_{D_t}\left[B_t(\boldsymbol{S}_t,\boldsymbol{Q}_t,D_t) + E_{\boldsymbol{Q}_{t+1}|\boldsymbol{Q}_t}\{F_{t+1}(\boldsymbol{S}_{t+1},\boldsymbol{Q}_{t+1})\}\right] \tag{4}$$

where F_t is the total benefit function; $\boldsymbol{S}_t$ the current (time t) system state vector; $\boldsymbol{Q}_t$ current inflow vector; D_t decision made at time step t; B_t immediate benefit function; $E_{\boldsymbol{Q}_{t+1}|\boldsymbol{Q}_t}$ expectation operator between the current and future inflows; and F_{t+1} future benefit function or benefit-to-go function.

In the SDP method, the state variables $\boldsymbol{S}_t$ and $\boldsymbol{Q}_t$ are discretized over all the state space forming a grid, allowing only transitions between grid points. The expectation operator is then defined by using a Markov chain that relates the current hydrological state $\boldsymbol{Q}_t$ with all the possible future states $\boldsymbol{Q}_{t+1}$ through a set of transition probabilities.

With the application of the previously showed equation, the optimal policies $D_t(\boldsymbol{S}_t,\boldsymbol{Q}_t)$, and benefit-to-go function $F_t(\boldsymbol{S}_t,\boldsymbol{Q}_t)$ are calculated at the grid points. Then, interpolation methodologies can be applied to obtain the optimal policies $D_t^*(\boldsymbol{S}_t,\boldsymbol{Q}_t)$ and the optimal benefits $F_t^*(\boldsymbol{S}_t,\boldsymbol{Q}_t)$ over the entire state-space. An alternative is to use a reoptimization approach as in Tejada-Guibert et al. (1993). With this approach, the Bellman function is implemented forward with the SDP-derived benefit-to-go functions as inputs.

$$F_t(\boldsymbol{S}_t,\boldsymbol{Q}_t) = \max_{D_t}\left[B_t(\boldsymbol{S}_t,\boldsymbol{Q}_t,D_t) + \sum_q \{p_{p,q}^t \cdot F_{t+1}^*(\boldsymbol{S}_{t+1},\boldsymbol{Q}_{t+1})\}\right] \tag{5}$$

Where $\boldsymbol{S}_t$ and $\boldsymbol{Q}_t$ are the simulated system state (storage) and inflows at stage t; and $p_{p,q}^t$ is the transition probability (Markov Chain) between inflow class p at time stage t and inflow class q at time stage $t+1$. The $\boldsymbol{S}_{t+1}$ and $\boldsymbol{Q}_t$ values are not subjected to a discrete grid. The reoptimization provides time series of allocation decisions and the corresponding λ values associated to the system's nodes, which correspond to the MROC.

2.3 From MROC values to pricing policies

The time series of MROC values cannot be directly used for the definition of pricing policies: it will be neither operative, nor fair nor secure to implement a pricing scheme in which prices would vary at each time stage. The raw MROC values previously obtained have to be post-processed in order to transform them into scarcity-based pricing policies. Several operations must be carried out to transform the time series of MROC into a step pricing policy depending on the system state variables ($\boldsymbol{S}_t, \boldsymbol{Q}_t$), in which a step function defines the price to be applied each time period. Those operations can be summarized as: MROC values aggregation/disaggregation, MROC statistical analysis, and step pricing policy construction.

Aggregation/disaggregation of the MROC time series previously obtained is required in order to derive pricing functions at a certain spatial and temporal scale. Regarding the spatial dimension of the intended pricing policy, different pricing schedules for raw water in different zones in the system will better capture the MROC spatial variability. However, the complexity of pricing policies will probably imply greater implementation difficulties. With regards to the temporal scale, pricing policies varying at a lower time resolution (seasonal or monthly) are more accurate than annual ones, although they might also face more implementation problems and higher uncertainty in future prices. Defining a general procedure to aggregate/disaggregate MROC values is difficult, since it depends on the desired pricing policy features and each system unique features. An example of aggregation/disaggregation process for the specific features of the desired pricing policy is shown in the case study section.

Once the combined MROC values are obtained, their cumulative probability distribution can be determined. Several characteristic MROC values can then be chosen using different percentiles of the cumulative probability distribution. Those characteristic values can be used to estimate the MROC-state relationship by: sorting the time series of state variables obtained with SDP according to the respective MROC values; selecting the MROC-state pairs in which the MROC value was a characteristic one; and organizing the results in the form of state-MROC steps. To sum up, the method presented in this paper can be divided in the following steps:

1. Definition of the main pricing policy features
2. Development of a hydro-economic stochastic programming model of the system
3. Determination of MROC (marginal water values or λ-values) time series at the reference nodes (e.g. main reservoirs)
4. Aggregation/disaggregation of previous MROC time series to calculate the combined MROC time series
5. Development of a statistical analysis over the final MROC time series to obtain their cumulative probability distribution
6. Building of k steps by:
    (a) Choose k different cumulative probability MROC values (characteristic values)
    (b) Sort according to the MROC values the system state values obtained in the stochastic programming run
    (c) Obtain, for each characteristic MROC value, the system states associated to it
    (d) Summarize all the possible state values associated to each MROC value in the form of steps
7. Definition of several step pricing policies based on the obtained steps

Pricing policies can be simulated to assess their performance and to compare them to SDP-derived policies. In case the pricing policies' performance is found to be inadequate, the process must be restarted: the pricing policies' features are reassessed and the build-up and analysis stages must be redone.

2.4 Case study: Mijares river basin (Spain)

The Mijares river basin is located in eastern Spain (Fig. 2). It is characterized by the existence of several relevant water springs in its headwater (Mas Royo and Babor); the implementation of conjunctive use water strategies to improve water management (Andreu and Sahuquillo, 1987); and the existence of an allocation framework accepted by all the users (SCRM, 1974). Regulated by the Arenós (93 Mm^3) and Sichar (49 Mm^3) reservoirs, surface water is mostly devoted to agricultural purposes (mainly orange trees), with groundwater as complementary or substitutive resource; while urban demands are entirely supplied using groundwater. There are 10.499 ha irrigated exclusively by surface water and 11.622 ha irrigated by surface and groundwater.

The Mijares river simplified flow network is showed in Fig. 3. Although groundwater supply is significant in the lower basin (Plana de Castellon aquifer), it has not been explicitly represented in the optimization model, as there is not hydraulic connection between the river and the aquifer (disconnected aquifer). Upstream, stream-aquifer interaction is implicit in the inflow (discharge) time series. Seepage equations are also added in certain lower reaches of the river. Consequently, the all-groundwater supplied demands have not been considered, and the mixed-supplied demands have been reduced an amount equivalent to its groundwater supply. The characteristics of each element are showed in Table 1.

Current water management agreements give priority to the supply to the Traditional Irrigation District (ID), which has been using water since the 13th century, over the remaining IDs (established in mid 20th century). In year 1970, before the construction of the Arenós dam (with public funding), an agreement was signed between users to regulate the use of the Sichar reservoir (funded by the Traditional ID) (SCRM, 1974). That agreement established a monthly storage limit for the Sichar reservoir below which only the Traditional ID can be supplied (see Fig. 4). That agreement has continued to be applied after the construction of the Arenós reservoir, but referred to the total system storage (Arenós and Sichar).

2.5 SDP hydro-economic model of the Mijares river

The SDP hydro-economic model comprises all the elements previously described and depicted in Fig. 4. The hydrologic variables $\{q_t, t = 1, \ldots, 12\}$ were discretized into 4 equally-likely intervals per sub-basin, each one represented by a characteristic value. Water demand curves are derived from Alvarez-Mendiola (2012). The minimum flow requirement has been considered as a constraint. A lag-1 Markov chain captures the temporal persistence found in the inflow data. The discrete storage classes adopted were 13 (Arenós) and 7 (Sichar). Minimum flows, demand curves, evaporation and infiltration losses, stream capacities and benefits (obtained as the sum of integrations under all the demand curves) are also taken into account in the model. The model was built using a generalized SDP algorithm developed using GAMS software (Macian-Sorribes and Pulido-Velazquez, 2014). This model was optimized, for an infinite horizon, taking target storages as decision variables.

3 Results

3.1 SDP-obtained benefits, policies and MROC values

The policies and benefits obtained depend on a vector consisting of four variables: Arenós storage, Sichar storage, Upper Basin inflow and Middle Basin inflow. The optimal decisions obtained with the algorithm followed the classic "rule of thumb" of reservoirs in series devoted to water supply: fill the upper reservoirs first, and empty the lower reservoirs first (Lund and Guzman, 1999); as the results empty first Sichar (the lower reservoir) and fill first Arenós (the upper reservoir). In addition, Traditional ID users are subject to greater water deficits compared to the other ones, inverting the current criteria, caused by the river seepage in the lower Mijares streams.

A reoptimization procedure was applied to obtain the time series of MROC values at Arenós and Sichar reservoirs, depicted compared with the sum of storages in Fig. 5.

The plots show the same values during most of the historical time series. The slight differences between them found in certain time stages correspond to the opportunity cost of the CC220 ID delivery. Water values increase between 1977 and 1986, period that corresponds to the largest drought suffered by the Mijares river basin. The average MROC value is equal to EUR 0.15 m^{-3}, ranging from 0 to EUR 0.68 m^{-3}.

3.2 Pricing policies in the Mijares river basin

Regarding the aggregation/disaggregation of the MROC time series at Arenós and Sichar reservoirs, the pricing policy used was defined at basinwide scale. This decision has been made considering the proximity of the intakes for the demands and the possibility of releasing water from the two reservoirs to satisfy almost all of them. The chosen temporal scale for the pricing policy was annual, with the same pricing policy for all the months. For simplicity, the state variable for defining the pricing schedule was the sum of the storage in Arenós and Sichar reservoirs, without considering the corresponding monthly inflow. That departs from the SDP formulation, but it is consistent with the current management policies, based exclusively on storages. The aggregation operation driven by these features was simply a non-weighted average of the MROC values at Arenós and Sichar reservoirs, as the MROC values are almost coincident for both reservoirs.

Figure 6 shows the MROC cumulative probability distribution. To establish pricing policies, we sampled the 5 (EUR 0 m^{-3}), 25 (EUR 0.06 m^{-3}), 50 (EUR 0.13 m^{-3}), 75 (EUR 0.24 m^{-3}) and 95 (EUR 0.51 m^{-3}) percentiles. The MROC-storage pairs were then organized in intervals (as depicted in Fig. 7). Each interval or step represents the range of storage values associated to that MROC.

Those steps were used to define the pricing policies. Firstly, the storage space was divided into intervals of 25 Mm^3. A price was then defined for each interval as either the minimum or the maximum or the average over the MROC values associated to the steps found within the interval. As a result, a set of 15 pricing policies was obtained. Figure 7 shows some of them, corresponding to policies regarding maximum between steps (Pricing Policy 1), average (Pricing Policy 2) and minimum (Pricing Policy 3). The remaining pricing policies were based on different combinations between prices obtained in the first three.

3.3 Pricing policy performance by hydro-economic modelling

Each pricing policy was simulated for the 1940–2009 period with a hydro-economic simulation model using MatLab. This model implements the network showed in Fig. 3 with the corresponding element features (storage capacity, historical monthly inflows, seepage losses equations, etc.), the current demand priority scheme (first the Traditional ID, then the rest), and the current system operation scheme (first fill Arenós, first empty Sichar and avoid as much as possible the streams subjected to seepage losses). More details can be found in Macian-Sorribes (2012). This simulation model calculates at each month the price that corresponds to the available storage, redefines water demands using the demand curves, and then allocates resources using the system's river network and infrastructure. Simulation results are then analysed and compared to the performances obtained with both current and SDP-derived policies (Table 2). Figure 8a shows the time series of benefits resulting from SDP, current management rules and the best pricing policies for the 1940–2009 period.

Regarding Table 2 and Fig. 8a, only slight differences can be found between policies. All pricing policies increase the economic results of current management policies by around EUR 0.70 million per year, being close to the ones obtained with the direct use of the SDP policies. This situation is caused by the natural robustness of the Mijares river water system and by the homogeneity of the cropping pattern (mainly citrus crops, mostly oranges) found in the basin. The benefit improvement caused by pricing policies is due to temporal relocations: the prices hedge the immediate supplies to allow greater deliveries in the next months. In that way, the deficits and their induced scarcity costs are distributed over several months of slight delivery reductions rather than a single large deficit. As the income losses are non-linear with respect to the deliveries, that deficit distribution improves the total economic return for the system.

Focusing on the most severe historical drought faced by the Mijares basin, from year 1977 to 1986 (Table 2 and Fig. 8b), the differences on benefits between the current management and the SDP results are higher (around EUR 1.10 million per year), indicating that SDP-derived policies better hedge available resources against the drought events. To sum up, pricing policy application resulted in greater benefits. Especially in drought situations, the adoption of these strategies would lead to greater economic performances and to a more efficient water use.

4 Discussion and conclusions

This paper presents a method to design an efficient scarcity-based pricing policy based on marginal water values (MROC) derived from stochastic programming. The method is applied to a case study, the Mijares river basin, in Spain. The results show that the benefits from the application of the resulting pricing policies are close to those obtained by the optimal SDP policy for both the entire historical hydrological data series and the drought conditions. By pricing marginal water opportunity costs, water would be reallocated to the highest-valued uses, significantly increasing the total net benefit of water use in the basin (by EUR 0.75 million per year).

The differences between this method and the one proposed in Pulido-Velazquez et al. (2013) consist basically of: (1) using a stochastic programming approach instead a deterministic programming or a simulation one; and (2) obtaining pricing policies via statistical analysis and system state sorting according to the MROC values. The use of stochastic programming methodologies implies that the MROC-state relationship obtained reflects an optimal but realistic situation, instead of a non-optimal situation (simulation) or an unrealistic optimal one (deterministic optimization). In addition, the method proposed in this paper to obtain pricing policies avoids trial-and-error procedures, whose time requirements are hard to estimate.

The MROC values measure the opportunity cost associated to water use. Therefore, in order to determine the final prices charged to the users, the cost recovery component of the supply costs (O and M and capital charges) and the environmental externalities have to be added (Rogers et al., 2002). Final pricing policies require estimating all those components and combining them with the results obtained with this methodology.

To gain social acceptability and policy equity, mechanisms of financial compensation can be implemented (e.g., Tilmant et al., 2009). Additional financial resources generated could be them be employed to compensate the users, or to develop adequate infrastructure to increase water security (for example, by financing desalination plant that reduce water scarcity). The main objective in the design of the pricing policies discussed here focuses on the use of water prices as economic instrument for an efficient management of the interaction between supply and demand. The role of pricing for cost-recovery of water services (pricing as financial instruments) will require a complementary analysis.

Regarding the established methodology and the case study, several conclusions can be drawn:

1. Stochastic programming is a useful tool for estimating optimal policies and MROC time series under hydrological uncertainty. These time series capture and summarize the overall performance of the optimization policies, and can be therefore used to assess pricing policies able to be applied at the basin scale.

2. Pricing policies defined using MROC data series, after statistical analysis and step building, are adequate to enhance system's global economic efficiency. They establish a univocal relationship between the system state (storages and inflows), and a water price based on the marginal value of water in a reservoir, linking the price concept to the MROC one.

3. It can be used to define pricing policies either under general conditions or drought events.

4. Participatory framework processes are needed to define the features and characteristics that the desired pricing policies should have, as they condition the MROC

aggregation/disaggregation mechanism. These procedures are key milestones for the pricing policy implementation.

5. The proposed methodology aims at designing efficient pricing policies. Other issues should be incorporated in the design of a final pricing policy, such as cost recovery of financial costs related to water services and of environmental cost (externalities), as well as equity issues and other social objectives (eg. rural development, environmental protection, etc.).

6. Pricing policy is one of the economic policy instruments that can be implemented to adapt individual decisions to collective goals. We can also apply a mix of them (water markets, pollution taxes, etc.) in order to better reach the social and environmental targets in the management of water resource systems.

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Table 1. Characteristic values of elements of the Mijares river network.

Element	Characteristic value
Arenós reservoir	93 $\mathrm{Mm^3}$ capacity
Sichar reservoir	49 $\mathrm{Mm^3}$ capacity
Upper Basin inflow	138 $\mathrm{Mm^3}$ annual discharge
Middle Basin inflow	55 $\mathrm{Mm^3}$ annual discharge
Traditional Irrigation District	83.5 $\mathrm{Mm^3}$ annual demand
MC Canal Irrigation District	7.6 $\mathrm{Mm^3}$ annual demand
CC100 Canal Irrigation District	16.3 $\mathrm{Mm^3}$ annual demand
CC220 Canal Irrigation District	11.9 $\mathrm{Mm^3}$ annual demand
Minimum flow downstream Sichar	0.2 $\mathrm{Mm^3}$ annual requirement

Table 2. Benefits for the 1940–2009 and 1977–1986 periods with stochastic optimization (SDP), current management rules and pricing policies.

Simulation	Traditional M EUR	MC M EUR	CC100 M EUR	CC220 M EUR	Total M EUR
1940–2009 Benefits per demand and total					
SDP	44.49	4.14	8.56	6.56	63.75
Current policies	46.31	3.60	7.42	5.73	63.06
Pricing policy 10	44.99	4.06	8.29	6.47	63.81
Pricing policy 11	45.00	4.05	8.29	6.46	63.81
Pricing policy 12	45.05	4.04	8.27	6.44	63.81
1977–1986 Benefits per demand and total					
SDP	35.97	3.22	6.80	5.07	51.05
Current policies	42.05	1.69	3.52	2.68	49.93
Pricing policy 4	37.11	3.06	6.09	4.86	51.12
Pricing policy 5	37.11	3.06	6.09	4.86	51.12

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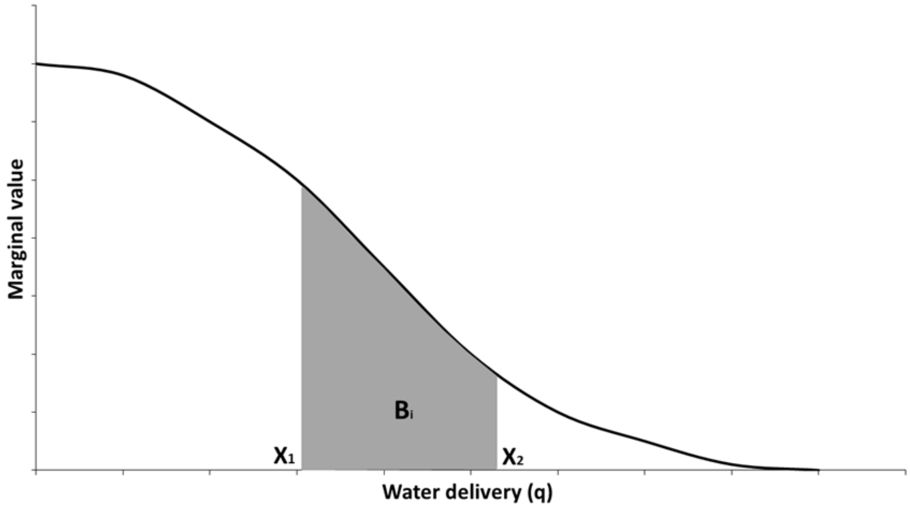

Figure 1. Benefits from an increase of water delivery from x_1 to x_2.

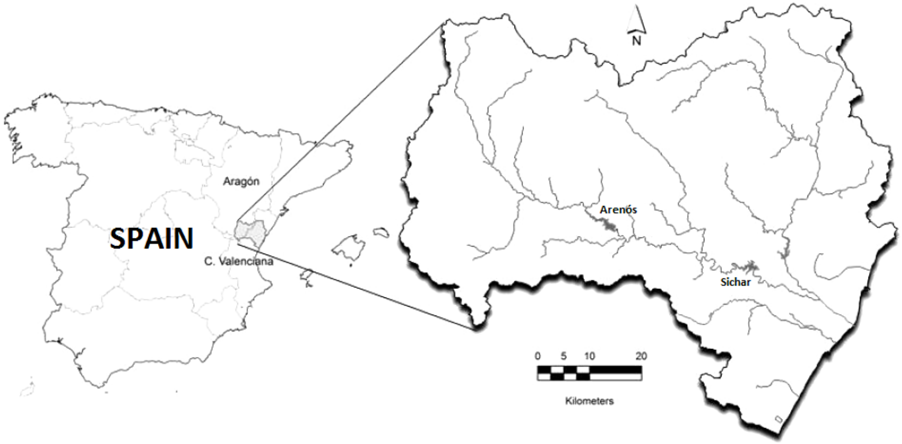

Figure 2. Mijares river basin location (Eastern Spain).

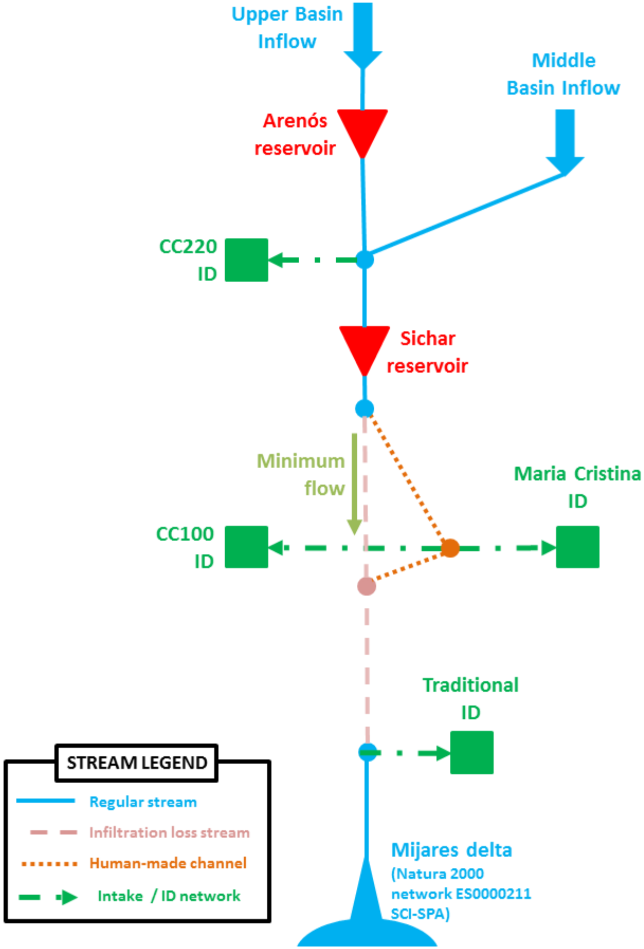

Figure 3. Mijares river network schematic.

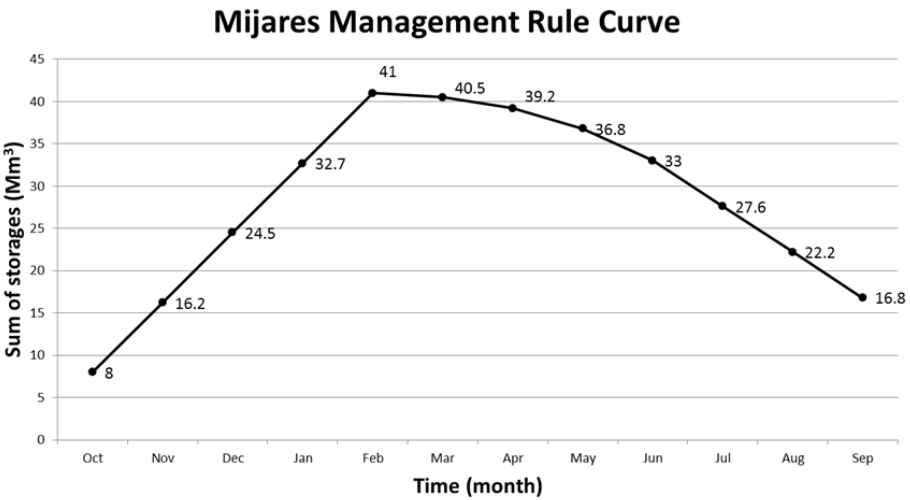

Figure 4. Current management rule curve established in the Mijares river basin.

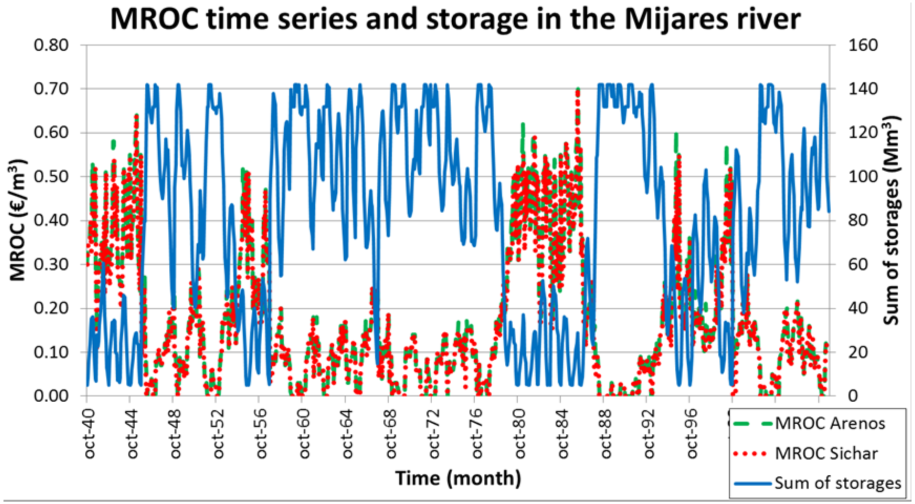

Figure 5. MROC time series and storages in the Mijares river.

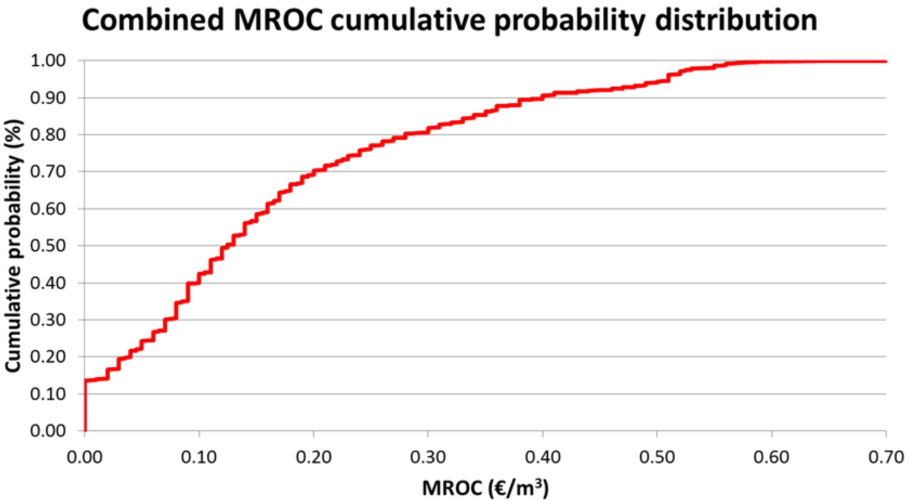

Figure 6. Combined MROC cumulative probability distribution.

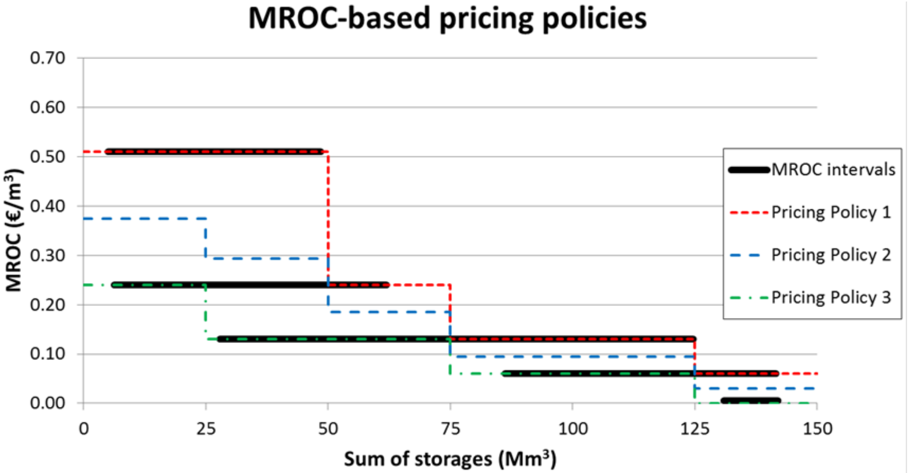

Figure 7. MROC-based pricing policies.

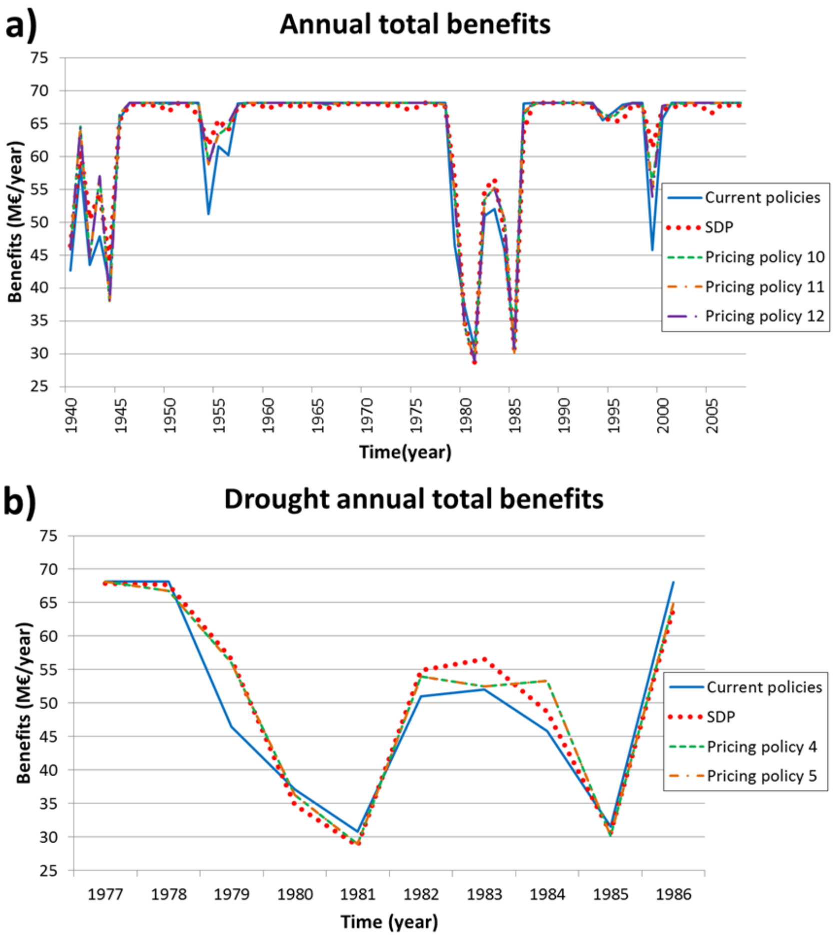

Figure 8. Annual total benefits comparison for the 1940–2009 period **(a)** and for the 1977–1986 drought **(b)**.