

Reorganization of water demand under changing conditions with possibilistic programming

Mike Spiliotis, Luis Garrote and Adriana Chavez-Jimenez

ABSTRACT

To adapt water resources management to changing conditions, the amount of water allocated to the different demands may be redistributed to satisfy water availability constraints. To achieve this, an interactive possibilistic programming procedure is proposed. The main criterion for the reorganization of water allocation to irrigation demands is net water productivity. To cope with uncertainty in problem formulation, the decision variables (amount of water allocated to each demand) are considered fuzzy triangular numbers. The proposed methodology is a combination of an intensive simulation process that determines the maximum cumulative potential water withdrawal with an interactive flexible possibilistic approach. The use of multicriteria techniques can be easily included within the interactive process in order to face the fuzziness of the water productivity term and to improve the final decision incorporating several dimensionals. The proposed method is applied to a real and complex problem, the Guadalquivir River Basin District in Spain, to identify an adaptive water resources management scheme that can react to the projected climate change scenarios by reorganizing the water allocated to irrigation demands.

Key words | changing conditions in water resources, fuzzy sets, multicriteria methods, possibilistic programming, water availability constraints, water resources management

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INTRODUCTION

The idea of adaptive management has been discussed in ecosystem management for quite some time (Walters 1986; Pahl-Wostl 2007), and it is based on the insight that the ability to predict future key drivers influencing an ecosystem, as well as system behavior and responses, is inherently limited. Hence, management should include the ability to change management practices based on new experience and insight or the ability to cope with or recover from a potentially damaging change in climate conditions (Iglesias *et al.* 2011) and, more generally, to track the changing conditions of the water systems (Goodwin *et al.* 2006). In this framework, the adaptive water resources management approach should incorporate significant non-stationarity of water resources and, more generally, the apparent uncertainties in factors affecting water resources management systems (climate change, extreme hydrological phenomena, prediction of water consumption, etc.).

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A significant change of water availability could take place in the case of long-term management of water resources, which could make the situation worse. This may occur on account of climate change, obsolescence of the existent infrastructure, unexpected population or socio-economic changes, etc. For instance, in Spain, several studies about climate change suggest a significant increase in temperature and a reduction and changed annual distribution of rainfall during the twenty-first century (e.g., Moreno 2005; IPCC 2007). To address the change in water availability, especially in the case of long-term management, one option is to reorganize the water allocation to demands, which in extreme cases may imply significant reductions for certain demands (e.g., Loukas *et al.* 2007). In regions with a high degree of exploitation of water resources (as in several developed countries), the reorganization of the water allocation to demands is one of the primary measures to face

changing conditions. In the Mediterranean region, the major quantitative consumer is the irrigation sector. Owing to the apparent importance of urban demand, the possibility of the reduction of water allocation to irrigation demands is one of the key factors for long-term adaptation to more intense water scarcity conditions.

In this article, we deal with the ability of a water system to achieve its reorganization (here, reduction of the water allocation to irrigation demands) in order to face changing conditions based on a new optimization method incorporating the inherent uncertainties of the long-term predictions in a direct way. The article addresses two questions on the long-term adaption in water resources management systems. The first one is the complexity of the optimization problem in a basin with well-developed hydraulic infrastructure, and the second is the uncertainty of adaptation to long-term climate projections.

In fact, in real water resources management problems, the reorganization of water allocation to demands quite often leads to a non-conventional optimization problem. To address the complexity, there are two basic approaches. The first one is to make several simplifications in order to conclude in a final conventional optimization problem. In most cases, the simplifications are applied in the optimization formulation (e.g., [Psilovikos & Tzimopoulos 2004](#)). Another alternative is to establish a two-phase heuristic approach. In this case, a two-phase method is applied, combining the heuristic optimization searching process with the simulation of the system (e.g., [Bozorg Haddad *et al.* 2008](#); [Shourian *et al.* 2008](#); [Fallah-Mehdipour *et al.* 2013](#)). Although this approach incorporates the complexity of the water resources system, the heuristic approach may lead to local optimum results, and furthermore, it may sometimes require a great amount of time to find a sufficient solution.

In this article, a different approach is followed. An intensive simulation process is carried out before the optimization problem is addressed. The simulation aims to determine the potential water availability at relevant locations of the river network nodes based on considerations regarding water consumption and supply reliability. For this purpose, the concept of maximum cumulative potential water withdrawal (MCPWW) is proposed. Thereafter, a conventional optimization problem is modulated in order to constrain demands in the system to meet water

availability. The theory of fuzzy sets and logic is applied in order to address the variable conditions of the water system.

Many applications of the fuzzy logic are based on the grounds of IF-THEN rule-based systems. In this case, the linguistic variables are expressed as fuzzy sets (e.g., [Wang 1997](#); [Yannopoulos & Spiliotis 2013](#)). However, many other applications based on fuzzy numbers and fuzzy arithmetic have been developed in the fields of multicriteria analysis, optimization procedures, simulation, etc. It should be mentioned that the work of [Dubois & Prade \(1980\)](#) enhanced the mathematical foundation and created a general field of applications of the fuzzy sets and logic. In this article, we use fuzzy triangular numbers in order to express the uncertainty of water availability. The mathematical foundation of fuzzy numbers enables us to use algebraic operations and in general crisp functions within a fuzzy domain. Therefore, by using fuzzy numbers, we can address an optimization problem within an uncertain environment.

The uncertainty is an inherent property of some aspects of water resources systems, and consequently, a large variety of applications of fuzzy sets and logic lies in the field of water resources management aiming to deal with its uncertainty. The majority of the applications are concentrated in the use of fuzzy flexible programming, where the decision variables are crisp numbers while some inequality and equality constraints are relaxed with the assistance of fuzzy sets. The flexible approach can also incorporate uncertainty on the values of the objective functions with the form of fuzzy inequality constraints. Thus, the elasticity of the constraints and the flexibility of the target values in the objective function can be expressed by using the corresponding membership functions ([Sun *et al.* 2014](#)) while fuzzy aggregators must be selected in order to combine both the membership functions of the fuzzy constraints and the fuzzy objectives. Most applications have used the [Zimmermann \(1991\)](#) fuzzy flexible approach in a variety of cases.

In the framework of fuzzy flexible programming, many articles deal with reservoir management with the use of multiple criteria (e.g., [Chang *et al.* 1997](#); [Jairaj & Vedula 2001](#); [Ghosh & Mujumdar 2010](#); [Regulwar & Gurav 2011](#)), conjunctive use of surface and groundwater (e.g., [Tsakiris & Spiliotis 2006](#)), water quality management, etc. In several cases, the uncertainty arises from the conflict of the multiple objective

functions, even if both the decision variables and the value of the objective functions are crisp numbers.

Another formulation of fuzzy programming is possibilistic programming, which in general terms uses fuzzy numbers. Most of the possibilistic programming applications use fuzzy numbers to express the coefficients of the decision variables and the available resources (e.g., Tanaka *et al.* 2000). However, it seems reasonable to adopt fuzzy numbers as decision variables in an uncertain environment (Tsakiris & Spiliotis 2004). By selecting fuzzy numbers for the decision variables, we provide the ability to formulate an adaptive decision in order to face the changing conditions. This is essential since in variable conditions, such as in long-term water management problems, it is rather impossible to predict future water availability with accuracy. Further information about possibilistic programming is provided in the 'Discussion' section.

According to the methods presented in this section, we propose the use of possibilistic programming with fuzzy numbers as decision variables since in our problem here, fuzziness is regarding water availability. The proposed method tackles the problem of water resources adaptation in the case of changing conditions (here in the case of climate change) by suggesting the reorganization of the water allocation to irrigation demands. Climate change projections introduce uncertainty to the water availability constraints that should be satisfied. The suggested reallocation should be expressed as fuzzy rather than crisp numbers, for three main reasons: (1) to acknowledge the uncertainty inherent to the problem; (2) to allow for adaptive management under changing conditions; and (3) to facilitate a further process of discussion with stakeholders to achieve an agreed solution. A possibilistic programming-based approach is used because it fits the above requirements. Based on the simulation procedure, both the water availability values and the decision variables are expressed as fuzzy triangular numbers.

An interesting point of the proposed methodology is that the decision variables are not required to be symmetrical numbers as in many other applications, as we analyze further. That is closer to reality, since in general terms, we cannot support a symmetrical membership function about the expected water availability. In addition, an interactive procedure is established in order to address the uncertainty of the initially examined objective function. Furthermore, within the interactive process, the use of multicriteria

techniques can be easily applied so as to improve the final decision incorporating several dimensionals. To achieve this multicriteria synthesis, we use the element of fuzzy flexible programming.

The proposed method is applied to a real and complex problem in the Guadalquivir River Basin in Spain. The problem addressed can be formulated as follows: given a range of future hydrological predictions linked to climate change, identify the optimal strategy for the reduction of water allocation to irrigation demand in order to adapt it to the expected future water availability, specifying where to concentrate the reorganization of the water supply efforts.

METHODOLOGY

The main criterion in order to achieve a rational water allocation to irrigation demands is the total profit of water used for irrigation in the basin, based on net productivity of water in the different irrigation districts. The water availability constraints of the optimization problem are established linearly by using the concept of the MCPWW as a way of quantifying water availability. The next section presents the basis for the intensive simulation of the water resources systems required to estimate water availability. The following sections refer to the optimization formulation. To take into account the changing conditions, general principles of the possibilistic programming and the interpretation of the fuzzy inequalities are developed in the section 'Adaptability based on possibilistic programming'. The constraints are interpreted with the use of the h -cuts, while the decision variables were selected to be fuzzy triangular numbers. In the section, The proposed interactive flexible possibilistic approach, a hybrid possibilistic multicriteria approach is presented, in order to address the fuzziness of the objective function. By establishing an interactive process in order to address the fuzziness of the objective function, we may as well incorporate a multicriteria aspect in the final solution.

Maximum cumulative potential water withdrawal and its use

A critical factor in water system analysis is water availability under future climate predictions. Water availability is an

intuitive concept, but there are many different interpretations in the literature (e.g., [Martin-Carrasco et al. 2013](#); [Garrote et al. 2014](#)). This uncertainty arises from both the complex nature of the hydrological cycle and the variety of modes of water consumption (e.g., the existence of several types of water users requiring different supply characteristics). In this paper, we interpret water availability as the maximum water demand that can be supplied at a given point in the river network satisfying certain reliability conditions.

Water availability is proposed to be computed with an algorithm, which estimates the MCPWW at nodes of the river network. The analysis of water availability is performed on a network composed of river reaches. The network consists of nodes and branches (e.g., [Cetinkaya et al. 2008](#)). Each node identifies a sub-basin and each branch a river reach. In the topological model, there is equivalence between sub-basin and river reach. Each sub-basin is associated with the river reach that connects the sub-basin with the next downstream node, and each branch is associated with the upstream sub-basin that

drains to it. All nodes receive the monthly runoff time series that corresponds to the sub-basin. Some nodes include regulation reservoirs with certain storage capacity.

The maximum potential water withdrawal at the node i , ($MPWW_i$), is defined as the maximum water demand value, which could be supplied at node i for a given reliability criterion. $MPWW_i$ is computed using the well-known bisection algorithm ([Garrote et al. 2011](#)), starting from an upper bound of the solution, for instance, a demand value equal to the mean annual flow at that location. The algorithm restricts the upper and lower bounds of the solution until a pre-specified accuracy is reached.

The computation of MCPWW is performed by accumulation of local MPWW along the river network, as illustrated in [Figure 1](#). The figure represents three nodes (0, 1, and 2) and two branches (0-1 and 1-2). Water is flowing downstream, from node 0 to 2, as indicated by the dashed arrows. Starting from the upstream sub-basin, the reservoir located at node 0 is considered. The MCPWW at node 0 ($MCPWW_0$) is the local MPWW ($MPWW_0$) that can be provided to a fictitious demand by the reservoir at node 0. This

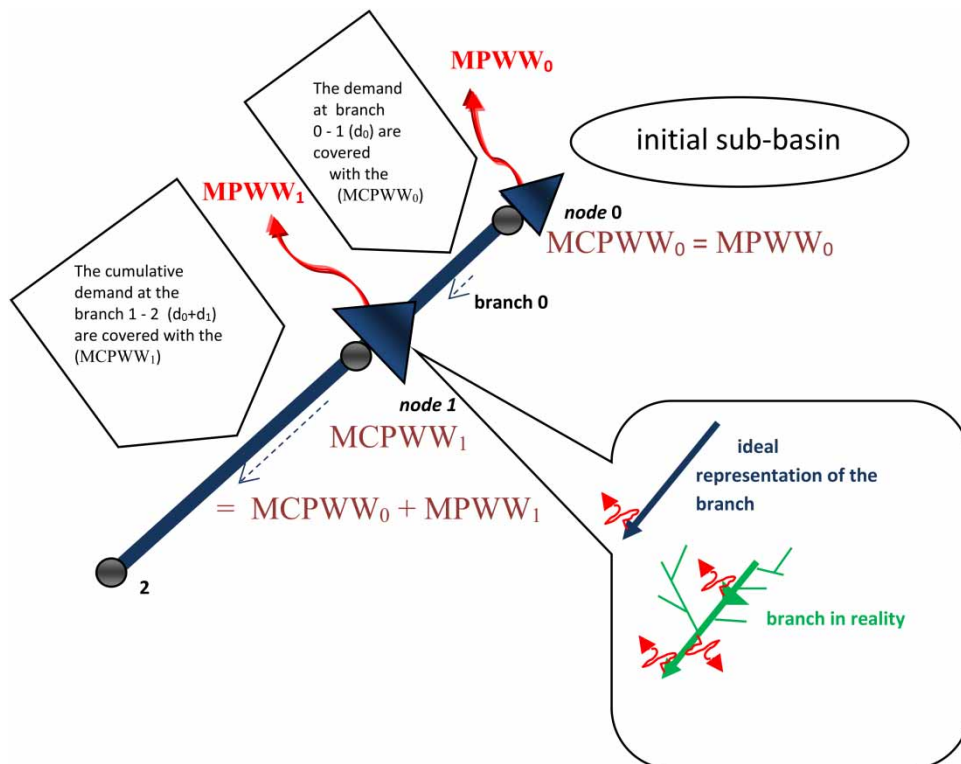


Figure 1 | Calculation of the maximum cumulative potential withdrawal.

quantity, $MCPWW_0$, is the water availability that can be allocated in order to cover the water demands located downstream of node 0, along branch 0–1. Thereafter, for the next node, 1, the reservoir located at node 1 would receive local runoff from sub-basin 1 plus inflows coming from the upstream branches. This reservoir would provide local MPWW to a fictitious demand located in node 1. Thereafter, for the next node, 1, the $MCPWW_1$ is the sum of the local MPWW at node 1 ($MPWW_1$ in Figure 1) with the $MCPWW$ provided by the immediate upstream cumulative water demand, corresponding to the immediate upstream branches ($MCPWW_0$ in Figure 1). This is a simplified representation of the real basin, where actual reservoirs may be distributed over the sub-basins, and actual water abstractions may be distributed along the branches considered in the model topology.

The $MCPWW$ in a node must have the ability to cover the (real) cumulative water demand, namely, the sum of all the upstream water demands plus the local (real) water demand in the current branch. Therefore, the $MCPWW$ may characterize both the corresponding node and the immediate downstream branch. In Figure 1, the above principle can be expressed with the following linear inequalities:

$$\begin{cases} d_0 \leq MCPWW_0 = MPWW_0 \\ d_0 + d_1 \leq MCPWW_1 = MCPWW_0 + MPWW_1 \end{cases} \quad (1)$$

To be more accurate, at the initial upstream branch of the network, we must include at the initial demand, d_0 , any probable demand that corresponds to the initial marginal upstream sub-basin before the initial upstream node.

More generally, let i be the identification number of the branch and d_i be the water allocation to demand in branch i . It must hold

$$\sum_{i \in X(n)} d_i \leq MCPWW_n \quad (2)$$

in which $MCPWW_n$ is referred at node n , $X(n)$ is the set of all the water demands that exist upstream of the node n plus the water demand at the branch downstream of the node n .

To determine the $MCPWW$, we must assume one reliability criterion, regardless of the demand type. This assumption can be easily made if there is a dominant

demand type. For instance, if the irrigation demand is the major consumer, as is the case in several Mediterranean areas, the reliability criterion adopted is that corresponding to irrigation demands. If the other demands present in the system are quantitatively less important, it is usually not difficult to supply them with adequate reliability by applying standard management practice. Here, we consider the simplified hypothesis that there are only ecological, urban, and irrigation demands in the system. Ecological and urban demands are a minor fraction of total demands and are always supplied with adequate reliability.

The total water allocation to demands in future scenarios should be reduced so as to meet the water availability everywhere in the basin. It is assumed that, if a reduction of water allocation is needed in order to meet water availability, the reduction will be taken by irrigation demands. This implies that water allocation to the other demands present in the basin (ecological and urban demands) cannot be further reduced without unacceptable impacts.

An optimization procedure is established in order to achieve a reorganization of the allocation to water demands and to adapt it to the estimated $MCPWW$, so as to effectively meet the existing demands with adequate reliability. This procedure can be applied whenever we maintain the existent water infrastructure. The allocations to water demands in every branch i , d_i , are proposed as decision variables. In this way, the decision variables are located in a continuous space. By adopting the proper objective function f , we lead to the following (crisp) problem of the water demand reorganization:

$$\begin{cases} \max f(\mathbf{d}) \\ \text{s.t.} \\ \sum_{i \in X(n)} d_i \leq MCPWW_n \quad \forall i \in n \quad \forall n \in N \end{cases} \quad (3)$$

where \mathbf{d} is the vector of allocations to water demands at branches and N is the set that contains all the demand nodes. Evidently, by considering constant urban and ecological demands, the decision space is restricted to the irrigation demands.

Water productivity provides an estimation of the contribution of water to the productive process (Playán & Mateos 2006) and is utilized in this paper as a proxy parameter to identify the areas where reduction water allocation to

irrigation demand would have less impact on society. The individual water productivity for each area is usually expressed as the agricultural production (in either economic or mass terms) per unit volume of water. If we consider that the urban and ecological demands remain constant, then the decision is restricted to the water allocated to irrigation demand. Consequently, the following simplified objective function can be adopted as objective function to express the total profit:

$$f(\mathbf{d}) = \sum_{i \in X(M)} p_i d_i, \tag{4}$$

in which p_i is the individual irrigation productivity (usually in €/m³) of the area that corresponds to branch i , d_i is the corresponding water allocation to irrigation demand, and M is the last considered node of the system (downstream outlet).

Adaptability based on possibilistic programming

In this section, we extend the method presented above in order to attain a reorganization of the allocation to water demands to achieve adaptability in changing and uncertain conditions (e.g., climate change scenarios) in a robust way. The methodological tool, which is introduced to accomplish the above purpose, is the use of fuzzy sets and logic.

In general, the methodology of fuzzy sets comprises a mapping from a general set X to the closed interval $[0, 1]$ which is described by its membership function, $\mu: X \rightarrow [0, 1]$.

The fuzzy numbers are a special case of fuzzy sets (Papadopoulos & Sirpi 1999). A fuzzy triangular number can be described by the following membership function (e.g., Simonovic & Nirupama 2005):

$$\mu_A(x) = \begin{cases} 0 & \text{if } x < \alpha_1 \\ \frac{x - \alpha_1}{\alpha_2 - \alpha_1} & \text{if } \alpha_1 \leq x < \alpha_2 \\ \frac{\alpha_3 - x}{\alpha_3 - \alpha_2} & \text{if } \alpha_2 \leq x \leq \alpha_3 \\ 0 & \text{if } x > \alpha_3 \end{cases} \tag{5}$$

where $\alpha_2 - \alpha_1 = w^-$, $\alpha_3 - \alpha_2 = w^+$ are the semi-widths of the lower and the upper part of the fuzzy number correspondingly. As can be seen in Figure 2(a), the lower

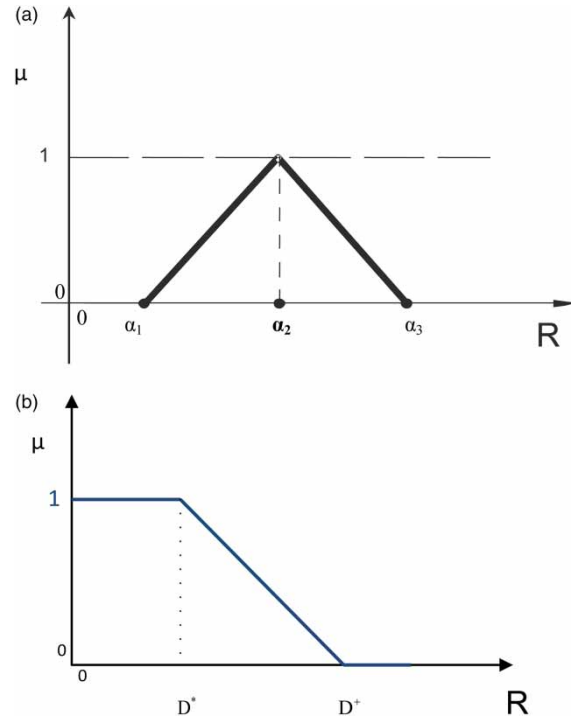


Figure 2 | (a) Fuzzy triangular number and (b) semi-triangular fuzzy number, here the diagrammatic representation of fuzzy linear membership function in the case of the distance minimization.

boundary of the left part ($\alpha_2 - \alpha_1$) of the fuzzy set A is α_1 while the upper boundary of the right part ($\alpha_3 - \alpha_2$) of the fuzzy set A is α_3 . The general definition of the fuzzy numbers can be found in Klir & Yuan (1995) as well as in Kechagias & Papadopoulos (2007). The use of several simulations, where each simulation corresponds to one sub-scenario, is needed in order to modulate the membership function of MCPWW for each branch.

According to the proposed methodology, fuzzy triangular numbers are selected to be both decision variables, namely, the allocation to water demand at each branch and the maximum cumulative potential withdrawal (MCPWW). As can be seen from Equation (5), because of linearity, in order to describe the fuzzy triangular number that represents the MCPWW, it is enough to know the central value, let $(MCPWW)_2 = \alpha_2$, the upper boundary (with respect to the 0-cut), let $(MCPWW)_3 = \alpha_3$ and the lower boundary, let $(MCPWW)_1 = \alpha_1$ (with respect to the 0-cut). In the case of (MCPWW), the mean value of each node $(MCPWW)_2$ is produced by the mean value for all climate

change scenarios. The lower and the upper boundary of the 0-cut ($\overline{(\text{MCPWW})}_1$, $\overline{(\text{MCPWW})}_3$, respectively) can be produced based on the minimum and the maximum values of all the tested scenarios. Therefore, the central and both the upper and the lower boundaries of the water allocation to the irrigation demand are produced by the simulation procedure.

An interesting point of the proposed methodology is that the decision variables are not required to be symmetrical numbers as in many other applications. Owing to the fact that the membership functions of the water availability (through the concept of $\overline{(\text{MCPWW})}$) are modulated based on the simulation process, those membership functions have a significant non-symmetrical shape. Indeed, since the $\overline{(\text{MCPWW})}$ has non-symmetrical shapes, it is irrational to force the decision variables to follow the symmetrical shape.

Finally, the new water allocation to irrigation demand, \tilde{d}_i , at each branch i , and the $\overline{(\text{MCPWW})}_n$, at each node n , are selected to be fuzzy triangular numbers while the urban and ecological demands are considered as crisp numbers. Therefore, the crisp optimization problem presented above is transformed into the following fuzzy optimization problem:

$$\left. \begin{aligned} \max f(\tilde{\mathbf{d}}) &= \sum_{i \in X(M)} p_i \tilde{d}_i, \\ \text{s.t.} & \\ \sum_{i \in X(n)} \tilde{d}_i + \sum_{i \in X(n)} (d_{\text{urban demand}}) & \\ & + d_{\text{ecological demand},i} \leq \left(\overline{(\text{MCPWW})}_n \right) \quad \forall n \in N \quad (6) \\ \tilde{d}_i &\leq d_i^* \quad \forall i \in N_1, \\ \tilde{d}_i &\geq 0 \quad \forall i \in N_1, \\ &\text{other crisp constraints} \end{aligned} \right\}$$

in which, d_i^* is the existent water demand at the branch i . In this section, we focus on the interpretation of the fuzzy inequalities, which is a critical decision. In the next section, the interpretation of the fuzziness in the objective function will also be presented.

There are several available interpretations of the fuzzy inequalities, which are dependent on the nature of the problem, the available data, and the preference of the decision-

maker. For this reason, the possibilistic programming is an ill-constructed problem. The interpretation of the fuzzy inequalities is dependent on the physical problem. In our case, we can suppose that ‘the less the water availability is, the worse the water supply becomes’. The interpretation of the constraints of fuzzy availability is done based on this assumption. The interpretation of the fuzzy inequalities is based on the h -cut concept, as is shown in Appendix A, available online at www.iwaponline.com/jh/017/008.pdf. In brief, each fuzzy set can be represented by a set of crisp sets while the lower and the upper boundaries of this crisp set (h -cut) are used for further calculations. Based on the interpretation of the fuzzy inequalities as it is presented at Equation (A3) (Appendix A), the fuzzy inequalities hold if the inequalities hold for every h -cut of the corresponding fuzzy numbers (Rommelfanger 1989). By following this definition, in the case of fuzzy triangular numbers, the problem is reduced to a binary comparison between the central values of both the cumulative demand at each branch i , the lower boundaries of both the cumulative demand and the $\overline{(\text{MCPWW})}$ (with respect to the 0-cut), and, finally, the binary comparison of both the upper boundaries of the cumulative demand and the $\overline{(\text{MCPWW})}$ (with respect to the 0-cut) (see Equation (A4)).

Since in the left part of the inequalities there are simple sums of fuzzy numbers, $\sum_{i \in X(n)} \tilde{d}_i$, the membership function of the fuzzy sum can be easily determined by applying the ‘extension principle’. Elements of the ‘extension principle’ for determining the operations among fuzzy numbers are presented briefly in Appendix B, available online at www.iwaponline.com/jh/017/008.pdf. The membership function of the sum among fuzzy triangular numbers will have also a linear shape. The linearity remains as well in the case of the objective function since we have multiplication between crisp number, p_i , and fuzzy triangular numbers, $p_i \cdot \tilde{d}_i$, and, finally, a corresponding sum, $\sum_{i \in X(M)} p_i \cdot \tilde{d}_i$.

Consequently, in the case of fuzzy triangular numbers, the water availability constraints (Equation (2) in the case of crisp data) lead to the following set of inequalities (based on Equation (A4)):

$$\left. \begin{aligned} (\text{Cumulative demand})_1 &\leq (\text{MCPWW})_1 \\ (\text{Cumulative demand})_2 &\leq (\text{MCPWW})_2 \\ (\text{Cumulative demand})_3 &\leq (\text{MCPWW})_3 \end{aligned} \right\} \quad (7)$$

In our case, as can be seen from Equation (B5) for $h = 1$ and $h = 0$, the following terms

the branch, d_i^* . In the case of the used formulation of the possibilistic programming, it is sufficient to examine

$$\begin{aligned}
 & ((\text{Cumulative demand})_1, (\text{Cumulative demand})_2, (\text{Cumulative demand})_3) \\
 & = \left(\begin{array}{l} \sum_{i \in X(n)} (d_i - w_{d_i}^-) + \sum_{i \in X(n)} (d_{\text{urban demand}}) + d_{\text{ecological demand},i} \\ \sum_{i \in X(n)} d_i + \sum_{i \in X(n)} (d_{\text{urban demand}}) + d_{\text{ecological demand},i} \\ \sum_{i \in X(n)} (d_i + w_{d_i}^+) + \sum_{i \in X(n)} (d_{\text{urban demand}}) + d_{\text{ecological demand},i} \end{array} \right)
 \end{aligned}$$

are the lower boundary (with respect to the 0-cut), the central value, and the upper boundary (with respect to the 0-cut), of the cumulative demand at the corresponding nodes. In the same way,

$$\tilde{B} = (MCPWW_n)_1, (MCPWW_n)_2, (MCPWW_n)_3$$

are the lower boundary (with respect to the 0-cut), the central value, and the upper boundary (with respect to the 0-cut) of the MCPWW. Therefore, Equation (7) becomes

only the upper boundary $((d_i + w_{d_i}^+) \leq d_i^*)$. Finally, negative water allocations to demands are not permitted in any case, since this has no physical meaning $((d_i - w_{d_i}^-) \geq 0)$.

Apart from the strict possibilistic formulation, additional constraints should be added to obtain a more balanced solution. For instance, a common level of satisfaction of the existent demand for the central value can be established, ensuring a balanced and stable optimal solution.

$$\left. \begin{array}{l} \sum_{i \in X(n)} (d_i - w_{d_i}^-) + \sum_{i \in X(n)} (d_{\text{urban demand}}) + d_{\text{ecological demand},i} \leq (MCPWW_n)_1 \\ \sum_{i \in X(n)} d_i + \sum_{i \in X(n)} (d_{\text{urban demand}}) + d_{\text{ecological demand},i} \leq (MCPWW_n)_2 \\ \sum_{i \in X(n)} (d_i + w_{d_i}^+) + \sum_{i \in X(n)} (d_{\text{urban demand}}) + d_{\text{ecological demand},i} \leq (MCPWW_n)_3 \end{array} \right\} \quad (8)$$

in which n is the examined branch, $X(n)$ is the set of all the upstream demands at node n plus the water demand at the branch downstream of the node n .

As mentioned in the previous section, the water allocations to urban and ecological demands are meant to be crisp numbers, because they are less dependent on policy decisions. Those demands also have a high priority, and consequently, it is required that their allocations should be maintained without any uncertainties.

Evidently, the widths of the fuzzy decision variables, $w_{d_i}^+, w_{d_i}^-$ for the lower and the upper part of the fuzzy number with respect to the 0-cut correspondingly, can take only positive or zero values ($w_{d_i}^+, w_{d_i}^- \geq 0$). In addition, the model should ensure that there is no overflow of the existent water allocation to demand at

$$d_i \geq \kappa\% \cdot d_i^* \quad \forall i \in N \quad (9)$$

where κ is the common level of existent water demand satisfactions.

As an objective function, we primarily select the total profit as mentioned before. At this point, we must consider two difficulties. First, since fuzzy numbers are selected as the decision variables, the total profit will also be a fuzzy number. Second, instead of the widely used fuzzy mathematical formulations (e.g., Zimmermann 1991), in most real problems, we have no a priori information about the objective function. Coping with the fuzziness of the objective function cannot be achieved by following only one consideration. A rational simplification approach is to use a weighted sum of the lower and upper boundaries and the central value (e.g.,

Gurav & Regulwar 2012). This might be interpreted as a defuzzification procedure. However, if we used a defuzzification procedure with emphasis on the central values, we would achieve a solution which would work well (optimum) in the case the MCPWW at nodes was near to the central value, but it would not work if the MCPWW at nodes was near the extreme sub-scenarios of A2. Therefore, we propose a more sophisticated interactive approach, which could take into account the maximum profit with respect to the central value, the lower, and the upper boundaries of the productivity. The context of this work is decision-making on adaptation to climate change. The implemented solution would have to be discussed with stakeholders through public participation. The model output produces a framework for such discussion, and in this case, fuzzy numbers are more flexible and produce a better description of reality than crisp numbers.

Within the interactive procedure, we can enhance the decision by adding a multicriteria aspect. In this article, we proposed the consideration of the weighted dimensionless distance measure between the existent irrigation demand and the proposed reorganized water allocation to irrigation demand, $D_2(d)$. These two objective functions are not in full competition. To give more emphasis on the total profit objective function, we select the second objective function, $D_2(d)$, to be a function with respect to the central values of the water allocation to irrigation demand at branches, that is, without including the right and the left widths of the fuzzy number. Finally, we conclude on the following multicriteria problem:

$$\left. \begin{aligned}
 &\max f(\tilde{\mathbf{d}}) = \sum_{i \in X(M)} p_i \tilde{d}_i \\
 &\min D_2(d) \\
 &s.t. \\
 &\sum_{i \in X(n)} \tilde{\mathbf{d}}_i + \sum_{i \in X(n)} (d_{\text{urban demand}}) \\
 &\quad + d_{\text{ecological demand},i} \leq (\overline{\text{MCPWW}})_n \quad \forall n \in N \\
 &\tilde{d}_i \leq d_i^* \quad \forall i \in N_1, \\
 &\tilde{d}_i \geq 0 \quad \forall i \in N_1, \\
 &\text{other crisp constraints}
 \end{aligned} \right\} \quad (10)$$

The goal of the maximum profit is faced based on an interactive procedure. Finally, a crisp function $D_1(d, w_d^-, w_d^+)$ is established, which expresses a common distance measure between the achieved profit and the

ideal central value, the ideal lower, and the ideal upper boundaries of profit. At the last step of the procedure, the fuzzy flexible approach is used (see Appendix C, online at www.iwaponline.com/jh/017/008.pdf) in order to achieve a compromise solution between $D_1(d, w_d^-, w_d^+)$ and $D_2(d)$ within the possibilistic inequality constraints.

$$\sum_{i \in X(n)} \tilde{d}_i + \sum_{i \in X(n)} (d_{\text{urban demand}}) + d_{\text{ecological demand},i} \leq (\overline{\text{MCPWW}})_n \quad \forall n \in N$$

The proposed interactive flexible possibilistic approach

As mentioned before, we primarily propose an interactive approach in order to face the fuzziness of the total profit, which is considered the objective function. The proposed procedure is based on a multicriteria interactive fuzzy algorithm. At first, as multiple objectives, the central, lower, and upper boundaries (further, we mean with respect to the 0-cut) of the objective function are selected.

Furthermore, this interactive procedure can easily incorporate a multicriteria aspect in the decision. This can be achieved by considering multiple objective functions and finally by establishing additional steps in the interactive approach. In a later stage, the aim is to achieve a common satisfaction of the maximum profit (in fuzzy terms) and other selected objective functions.

Therefore, an interactive process is established in two stages. During the first stage, we address the profit's fuzziness (Equation (6)), aiming at a solution, which could achieve the simultaneous minimum distance between the ideal central value, the ideal lower, and the ideal upper boundaries of profit (from steps 2 to 5). Those ideal values are approached based on the individual corresponding maximization problems of the central value, the ideal lower boundary, and the ideal upper boundary of the water profit. The central value, the ideal lower, and the ideal upper boundaries of the water profit can be determined based on Equation (B4) for $h = 1$ and $h = 0$, respectively. Second, we establish a second cycle of the interactive multicriteria approach, aiming at the incorporation of the multidimensions of the problem. The multicriteria approach should be based on the schematization of the membership functions based on the previous interactive process and the use of the min-intersection (steps 6 and 7).

The proposed methodology can be summarized using the following steps:

- (1) We determine the MCPWW for each climate change prediction. Based on the mean values and the minimum and maximum values, we modulate accordingly the $(\overline{\text{MCPWW}})$ in the form of triangular numbers (Equation (5)).
- (2) We solve the problem of the maximum profit with regard to the central values solely (namely, the widths have no influence) as follows:

$$\left\{ \begin{array}{l} \max \sum_{i \in X(M)} p_i d_i \\ \text{s.t.} \\ \sum_{i \in X(n)} d_i + \sum_{i \in X(n)} (d_{\text{urban demand}}) + d_{\text{ecological demand},i} \\ \leq (\text{MCPWW}_n)_2 \quad \forall n \in N \\ d_i \leq d_i^* \quad \forall i \in N_1, \\ d_i \geq 0 \quad \forall i \in N_1, \\ d_i \geq \kappa\% \cdot d_i^* \quad \forall i \in N_1 \end{array} \right\} \quad (11)$$

- (3) We solve the possibilistic problem aiming at the maximization of the upper boundary of the profit as follows:

$$\left\{ \begin{array}{l} \max \sum_{i \in X(M)} p_i (d_i + w_{d_i}^+) \\ \text{s.t.} \\ \mathbf{d}, \mathbf{w}_d^-, \mathbf{w}_d^+ \in A \end{array} \right. \quad (12)$$

where $d, w_s^-, w_s^+ \in A$ corresponds to the satisfaction of the following constraints:

$$\left. \begin{array}{l} \sum_{i \in X(n)} (d_i - w_{d_i}^-) + \sum_{i \in X(n)} (d_{\text{urban demand}}) + d_{\text{ecological demand},i} \leq (\text{MCPWW}_n)_1 \quad \forall n \in N \\ \sum_{i \in X(n)} d_i + \sum_{i \in X(n)} (d_{\text{urban demand}}) + d_{\text{ecological demand},i} \leq (\text{MCPWW}_n)_2 \quad \forall n \in N \\ \sum_{i \in X(n)} (d_i + w_{d_i}^+) + \sum_{i \in X(n)} (d_{\text{urban demand}}) + d_{\text{ecological demand},i} \leq (\text{MCPWW}_n)_3 \quad \forall n \in N \\ w_{d_i}^-, w_{d_i}^+ \geq 0 \quad \forall i \in N_1, \\ (d_i + w_{d_i}^+) \leq d_i^* \quad \forall i \in N_1, \\ (d_i - w_{d_i}^-) \geq 0 \quad \forall i \in N_1, \\ d_i \geq \kappa\% \cdot d_i^* \quad \forall i \in N_1 \end{array} \right\} \quad (13)$$

- (4) We solve the possibilistic problem aiming at the maximization of the lower boundary of the profit as follows:

$$\left\{ \begin{array}{l} \max \sum_{i \in X(M)} p_i (d_i - w_{d_i}^-) \\ \text{s.t.} \\ \mathbf{d}, \mathbf{w}_d^-, \mathbf{w}_d^+ \in A \end{array} \right. \quad (14)$$

- (5) Let P_1^*, P_2^*, P_3^* be the ideal solutions of the individual optimization procedure of the mean, the upper, and the lower boundaries of the objective function correspondingly. Subsequently, the following optimization problem is formulated, which is based on the simultaneous minimization of the distance between the achieved optimal solution and the corresponding ideal lower, upper, or central values based on the Euclidean distances (widely used multicriteria approach):

$$\left\{ \begin{array}{l} \min D_1(\mathbf{d}, \mathbf{w}_d^-, \mathbf{w}_d^+) \\ \text{s.t.} \\ \mathbf{d}, \mathbf{w}_d^-, \mathbf{w}_d^+ \in A \end{array} \right. , \quad (15.1)$$

where

$$D_1(d, w_d^-, w_d^+) = \left[k_3 \left(\sum_{i \in X(M)} p_i (d_i - w_{d_i}^-) - P_3^* \right)^2 + k_1 \left(\sum_{i \in X(M)} p_i (d_i + w_{d_i}^+) - P_1^* \right)^2 + k_2 \left(\sum_{i \in X(M)} p_i (d_i) - P_2^* \right)^2 \right]^{1/2}$$

where k_1, k_2 , and k_3 are the corresponding weights,

$$k_1 + k_2 + k_3 = 1, \quad k_1, k_2, k_3 \geq 0 \tag{15.2}$$

Plainly, another way to express the simultaneous consideration of the central value, and the lower and upper boundaries of the total water profit can be considered. With the application of step 5, the first cycle of the interactive process is finished. By following the next steps, a multicriteria approach is established to enhance the decision. It should be also noticed that the selected simple multicriteria approach to face the fuzziness of the objective function (steps 2–5) enables us to use the following fuzzy flexible approach.

- (6) Other objective functions are established in order to describe other criteria. For instance, the weighted dimensionless distance measure between the existent allocation to irrigation demand and the proposed reorganized allocation can be established in order to distribute the allocation reduction in a more balanced way, as mentioned before.

$$D_2(\mathbf{d}) = \left\{ \left[\sum_{i \in X(M)} \left(\beta_i \cdot \left(\frac{d_i^* - d_i}{d_i^*} \right)^2 \right)^{1/2} \right] \right\} \tag{16}$$

where β_i is the relative importance of the irrigation activity for each branch. Here, we propose considering that the importance of the irrigation activity for each branch is equal to the water productivity at branch ($\beta_i = p_i$). This choice directs the solution, based mainly on the total profit while the multicriteria process expands the decision aspect. Therefore, the following mono-criterion problem is resolved in the following form:

$$\begin{cases} \min D_2(\mathbf{d}) \\ \text{s.t.} \\ \mathbf{d}, \mathbf{w}_d^-, \mathbf{w}_d^+ \in A \end{cases} \tag{17}$$

- (7) Finally, a multicriteria approach in order to achieve the combination of all the criteria was selected. For this purpose, the fuzzy flexible programming is used to combine the two objective functions. Primarily, the membership function of two (or more) distance measures expresses either the distance of the total

profit from its fuzzy ideal or the distance formulated from the existent allocation (Figure 2(b)). The membership function in this step represents only the fuzziness from the conflict of those two goals as occurs in fuzzy flexible programming approach.

In most practical applications, the lowest acceptable level D^+ and the aspired level D^* can be determined by the individual solutions of the corresponding optimization of the objective function and by supposing linear membership functions (Appendix C) (steps 5 and 6). Therefore, each membership function ($\mu_{D_1}(d, w_d^-, w_d^+), \mu_{D_2}(d)$) (Figure 2(b)) expresses the information that each distance function is fuzzily less than a quantity (Spiliotis & Tsakiris 2007), while the quantification of the term ‘fuzzily less than a quantity’ was determined from the previous interactive procedure.

In this study, the min-intersection is implemented to aggregate the two final objectives as it secures a common satisfaction of all the selected membership functions (Tsakiris & Spiliotis 2006; Ghosh & Mujumdar 2010). As the decision-maker should conclude in a crisp decision proposal, it seems more appropriate that they should suggest the dividend with the highest degree of membership function in the fuzzy set decision. Therefore, the problem can be modulated as follows:

$$\max_{\mathbf{d}, \mathbf{w}_d^-, \mathbf{w}_d^+ \in A} \min[\mu_{D_1}(\mathbf{d}, \mathbf{w}_d^-, \mathbf{w}_d^+), \mu_{D_2}(d)] \tag{18}$$

Or equivalently by introducing the auxiliary variable λ , which can be seen as a common degree of acceptability (Ghosh & Mujumdar 2010) considering the two objective functions as follows:

$$\begin{cases} \max \lambda \\ \text{s.t.} \\ \begin{cases} \mu_{D_1}(\mathbf{d}, \mathbf{w}_d^-, \mathbf{w}_d^+) \geq \lambda, \\ \mu_{D_2}(d) \geq \lambda, \\ \lambda \in [0, 1] \end{cases} \\ \text{s.t.} \\ \mathbf{d}, \mathbf{w}_d^-, \mathbf{w}_d^+ \in A \end{cases} \tag{19}$$

The achieved multi-objective solution based on Equation (19) is a compromise solution. We may at least repeat steps 6 and 7 if the achieved solution is not appropriate, by modifying the ideal and the anti-ideal point of the membership functions of the distances (see Figure 2(b)).

CASE STUDY

The methodology described above has been applied to the analysis of water scarcity problems in the Guadalquivir River Basin under climate change projections. The Guadalquivir River Basin is located in the south of the Iberian peninsula and has an area of 57,527 km². The main river runs along a deep valley surrounded by mountain ranges with heights between 1,000 and 3,500 m. The climate is Mediterranean, with mild temperatures (annual average of 16.8 °C) and irregular precipitation (mean annual value of 573 mm/yr, with a coefficient of variation of 0.23). Precipitation is frequently of torrential nature and the basin is recurrently affected by periods of drought and high temperatures. Mean annual runoff in the basin is estimated at 124 mm/yr, which corresponds to 7,000 hm³/yr of mean annual flow in the main river. Regulation infrastructure

has been intensively built across the basin, with around 60 large dams, totaling over 8,000 hm³ of storage volume. Water resources in the Guadalquivir Basin provide a water supply for over 4 million, while agriculture is a strategic pillar of the regional economy and the main water supply, with over 800,000 ha irrigated. About 25% of the total irrigation consumption is obtained from groundwater. Industrial uses correspond to less than 1% of total water consumption in the basin. Considering the urban demand, the cumulative urban water demand is about 11% of the total demand while the irrigation demand is 89% of the total demand.

The schematization of the water resources system of the Guadalquivir Basin is presented in Figure 3. The river network is represented by 26 branches. The topology of the model of the water resources system was based on the characteristics of the water body, water infrastructure, water productivity, and water consumption (Chavez-Jimenez

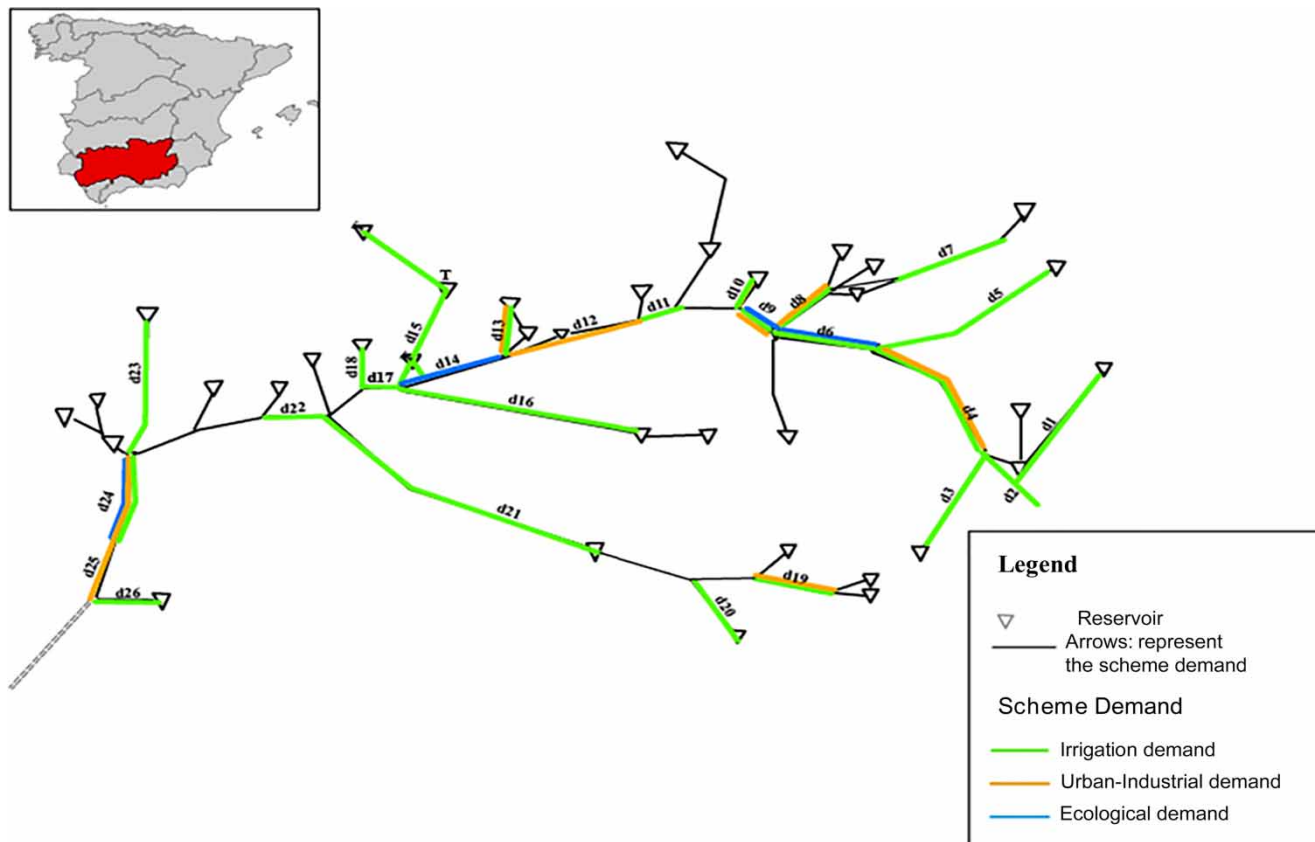


Figure 3 | Scheme of the considered model of the Guadalquivir water decision system.

2010). The reservoir storage volume and water demand considered correspond to the control time horizon (1960–1990) and are based mainly on MIMAM (2000).

The SIMPA model (Estrela & Quintas 1996) was calibrated for the whole Spanish territory, and allows us to obtain naturalized streamflow series on a monthly time scale (Gonzalez-Zeas et al. 2012). The streamflow series obtained with the SIMPA model were used for the simulation of the water resources system of the Guadalquivir Basin.

The effects of climate change will entail variations in temperature, shifts in rainfall patterns, and increased drought frequency that will, accordingly, influence water availability to varying extents according to the respective location (IPCC 2007). Several studies have examined variations in streamflow in the Guadalquivir Basin, such as the work carried out in Spain by the Center for Public Works Studies and Experimentation (CEDEX 2011). The CEDEX work provided results for two emission scenarios, B2 and A2, in four periods, 1960–1990 (control), 2011–2040, 2041–2070, and 2071–2100, with changes in mean annual values. The methodology proposed in this work is suitable to account for uncertainty within a given emission scenario, and therefore, the six long-term (2071–2100) projections under emission scenario A2 were selected for this study (Table 1). Percentage changes in average annual runoff, as projected in CEDEX sub-scenarios, were applied to the monthly inflow series in every point of the flow network.

The values of (\overline{MCPWW}) were estimated at each node in the flow network for the reliability criterion corresponding to irrigation demand under Spanish legislation. The reliability

criterion is based on the maximum cumulative deficit over three periods of time: 1 year, 2 consecutive years, and 10 consecutive years. To satisfy the reliability criterion, the following restrictions should be satisfied: maximum deficit in 1 year should not be greater than 50% of annual demand, maximum deficit in 2 consecutive years should not be greater than 75% of annual demand, and maximum deficit in 10 consecutive years should not be greater than 100% of annual demand. Finally, fuzzy numbers were selected for the (\overline{MCPWW}) as mentioned in Figure 4.

The productivity for each area was taken from Rodríguez et al. (2008). In this study, apparent net productivity values were determined for the years 1996 and 2002, and the productivity for each irrigation demand in the basin model was determined by relating the productivity for year 2002 for each area under analysis (Rodríguez et al. 2008) with the corresponding irrigation demands in the water resources model. Productivity values are shown in Table 2. An interesting perspective is that there are many branches with the same water irrigation productivity ($p = 0.25 \text{ €/m}^3$), especially near the main river, while other regions have significantly larger productivities (e.g., Cacán, Guadajoz, etc.).

The dotted lines in Figure 3 indicate the branches with minimum ecological discharge requirement. Branches 12, 14, and 25 have no irrigation water demand, but were included because the corresponding upstream irrigation demand influences the balance between water availability and supply in those locations. Those branches have no decision variables. In addition, to ensure a minimum level of equitable reduction for socioeconomic reasons, we considered a maximum acceptable reduction of allocation to irrigation demand at each branch. The adopted value was equal to 80% of the existent water allocation (Equation (9)). The existent water demands at each branch are shown in Table 2 based mainly on the MIMAM (2000) data. Since the analysis is based on surface water resources, Table 2 presents the water demand, which is covered by surface water resources.

According to the proposed method, initially, the objective function is to maximize total profit. During later stages of the optimization, a multicriteria approach is established. The LINGO program Version 13.0 was used in order to solve the optimization problems. Alternatively, instead of

Table 1 | Alteration for the mean ($\Delta\mu$) of annual stream flow, period 2071–2100

Projections of hydrological inflows	Emission scenario A2 $\Delta\mu$
CA	–48
EA	–49
HA	–20
SA	–45
UA	–44
PA	–29

Source: CEDEX (2011).

C, global model CGCM2 and regionalization FIC; E, global model ECHAM4 and regionalization FIC; H, global model HadAM3 and regionalization FIC; S, global model HadAM3 and regionalization SDSM; U, global model HadCM3 and regionalization PROMES (PRUDENCE-UCM); and P, global model ECHAM4 and regionalization RAO (PRUDENCE-SMHI).

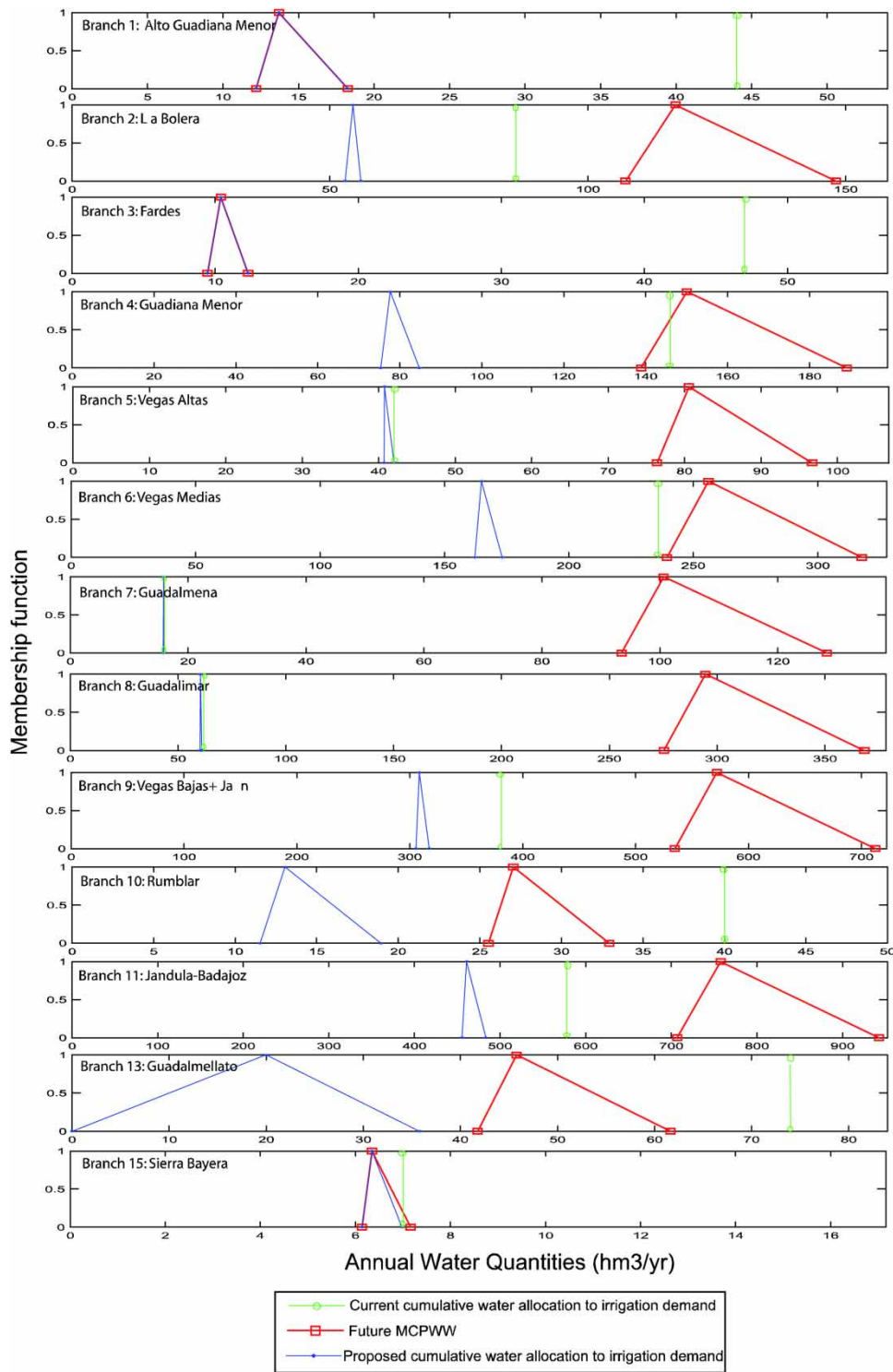


Figure 4 | Model results for selected (all branches with irrigation demand) branches: lines with empty circles show current cumulative water allocation to irrigation demands in branch. Lines with empty squares represent fuzzy numbers indicating future MCPWW in climate change scenarios. Simple lines represent fuzzy numbers indicating proposed water allocation to irrigation demands.

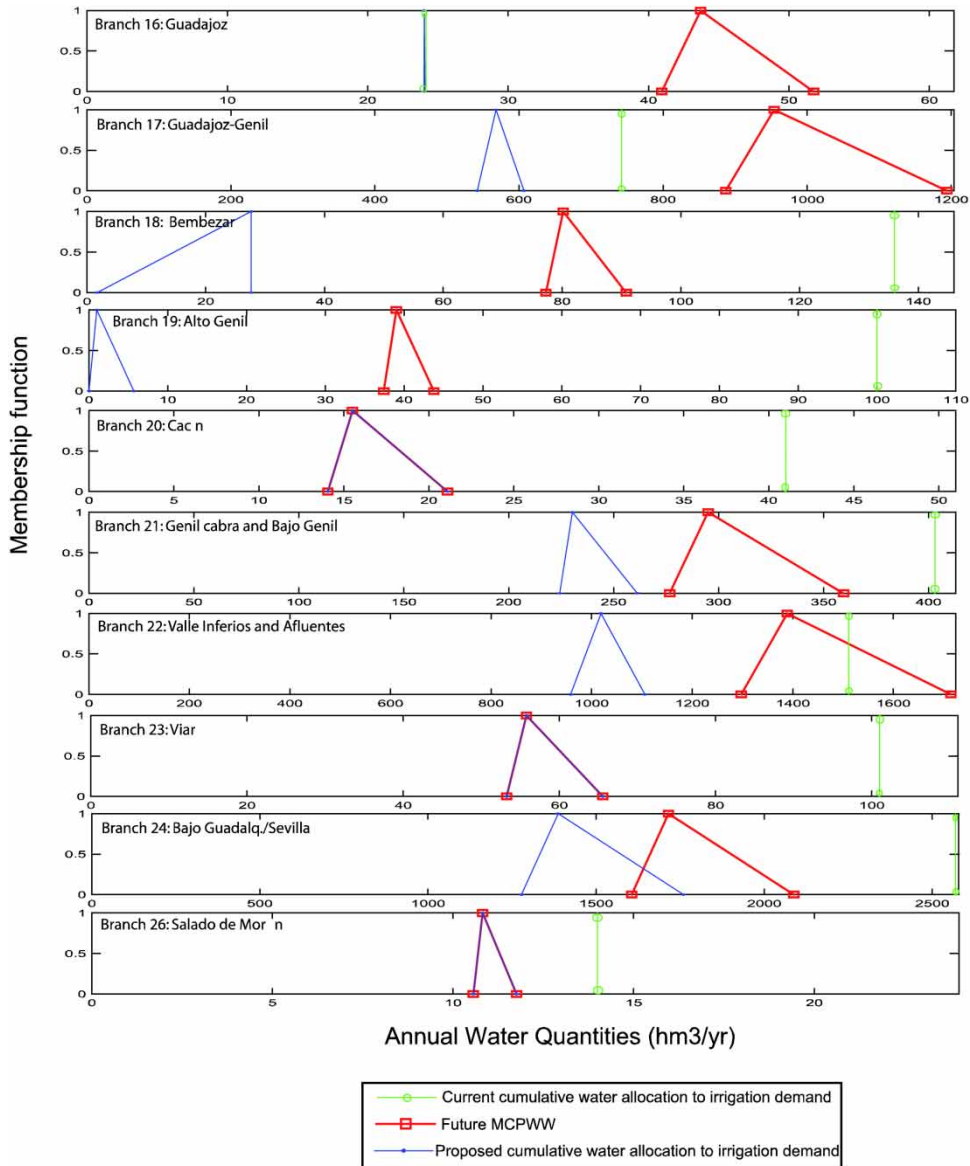


Figure 4 | continued

Lingo toolbox, an interactive procedure can also be programmed in order to achieve an easy modulation of the distance-based membership functions in Matlab environment within an interactive procedure and by using the 'linprog' command.

To address the problem, the seven steps presented in the section 'The proposed interactive flexible possibilistic approach' were followed. A satisfactory common degree of satisfaction of the membership function was found ($\lambda = 0.97$).

RESULTS AND DISCUSSION

The highest degree of the common degree of satisfaction of the membership functions, even if the min-intersection is selected to combine the two objective functions, can be interpreted by the fact that the two objective functions are not in full competition. In addition, there are several branches with the same productivity; more specifically, there are multiple potential alternatives to reorganize the water allocation

Table 2 | Existent urban, ecological, and irrigation demand with the corresponding productivity at branches

Branch	Region	Existent irrigation demand, d_i (hm ³ /yr)	Water irrigation productivity (€/m ³)	Cumulative irrigation demand (hm ³ /yr)	Urban demand (hm ³ /yr)	Cumulative urban demand (hm ³ /yr)	Ecological demand (hm ³ /yr)
1	Alto Guadiana Menor	44	0.31	44	1	1	–
2	La Bolera	42	0.25	86	–	1	–
3	Fardes	47	0.26	47	–	–	–
4	Guadiana Menor	13	0.25	146	–	1	–
5	Vegas Altas	42	0.25	42	–	–	–
6	Vegas Medias	48	0.25	236	–	1	4.15
7	Guadalmena	16	0.25	16	–	–	–
8	Guadalimar	46	0.25	62	8.79	9.79	–
9	Vegas Bajas + Jaén	83	0.42	381	22	31.79	11.40
10	Rumblar	40	0.29	40	14	14	–
11	Jandula – Badajoz	157	0.25	578	–	45.79	–
13	Guadalmellato	74	0.23	74	43 a%	43 a%	–
14	Guadalq. after Cord.	–	–	652	–	88.79	18.70
15	Sierra Boyera	7	0.25	7	–	–	–
16	Guadajoz	24	0.49	24	–	–	–
17	Guadajoz-Genil	59	0.25	742	–	89.79	–
18	Bembezar	136	0.09	136	–	–	–
19	Alto Genil	100	0.48	100	38	38	–
20	Cacín	41	0.48	41	–	–	–
21	Genil-Cabra and Bajo Genil	262	0.25	403	–	38	–
22	Valle Inferior and Afluentes	230	0.25	1511	–	126.79	–
23	Viar	101	0.26	101	–	–	–
24	Bajo Guad./Sevilla	957	0.25	2569	170	296.79	31.4
25	Resto Guadalquivir	–	–	2569	36	332.79	–
26	Salado de Morón	14	0.37	14	–	–	–

to irrigation demand. Thus, in our case of multi-objective programming with non-full competition, we can achieve a successful solution. Otherwise, either the establishment of a new interactive process or the construction of the Pareto curve, which is another methodological direction (e.g., Reed *et al.* 2001), should be followed.

The final results are presented in Figure 4. Model results are shown for all branches with irrigation demand. Lines with empty circles show current cumulative water allocation to irrigation demands in branch. Lines with empty squares represent fuzzy numbers indicating future (MCPWW) in climate change predictions. Simple lines represent fuzzy

numbers indicating proposed cumulative water allocation to irrigation demands.

Based on Figure 4, we can observe that the new total allocation to irrigation demand ($\tilde{d}_1 + \tilde{d}_2 + \dots + \tilde{d}_{24}$) overlaps with the water availability minus the total allocation to urban demand and minus the allocation to ecological demand at that point. Since branch 24 is practically the final branch with irrigation demand in the main river, the model leads to a full allocation of the (MCPWW₂₄), which seems very reasonable.

The allocation to irrigation water demand in branch 16 (Guadajoz) is equal to the existent irrigation water demand

(branch 16, \tilde{d}_{16}), without any uncertainty. This outcome seems reasonable since the water productivity in the area of Guadajoz has the highest value compared to all the other areas.

Branch 10 (Rumblar \tilde{d}_{10}) is an area with medium-high productivity (0.29 €/m^3) upstream of the main river Guadalquivir. If the current allocation to urban demand is added to determine the total water allocation ($14 \times 10^4 \text{ m}^3/\text{yr}$), then the total water allocation to demands is identical with the $\overline{(\text{MCPWW})}_{10}$. In the region of Salado de Moron, the productivity of the area is high, while the determined allocation to irrigation water demand (\tilde{d}_{26}) is identical to the $\overline{(\text{MCPWW})}_{26}$. The same results were concluded in the case of Cacin (\tilde{d}_{20}).

At branch 18 (Bembezar) (\tilde{d}_{18}) with a low productivity of 0.09 €/m^3 , we may observe that all the corresponding availability $\overline{(\text{MCPWW})}_{18}$ is not allocated. Furthermore, in the case of the lower boundary, the allocation to water irrigation demand reaches zero value since there is no restriction. If we apply only steps 1–5, namely, without the multicriteria process, the central value of the allocation to irrigation demand at Bembezar will be equal to 20% of the corresponding current irrigation consumption, while, by following the multicriteria approach, the allocation to irrigation demand at branch 18 is just a little above this value. Although the Bembezar region has the lowest productivity, it keeps a central value of irrigation demand equal to 20% because of Equation (9), which is a crisp constraint. The crisp constraints must be verified. If they are not verified, simply there is no solution to the problem. However, in general, the fuzzy constraints either can hold to some degree, or they can hold with a proper organization of the fuzzy decision variables (e.g., high uncertainty).

A positive outcome of the proposed methodology is that the allocation in upstream branches with high productivity is close to the corresponding maximum cumulative potential withdrawal, while the fuzziness in this case is determined from the fuzziness of the current $\overline{(\text{MCPWW})}$. The proposed multicriteria interactive process expands the decision, which is mainly based on the partial productivity of the branches.

Another interesting point of view is that the selection of the weights (k_1 , k_2 , and k_3) at step 5 (Equation (15.2)) within a rational range does not seem to have a significant

influence on the results in the developed case study. Therefore, all weights in Equation (15) are selected to be equal to 1.

Although they were initially defined as fuzzy triangular numbers, the decision variables sometimes are crisp or semi-triangular numbers (the central value is identical with either the lower or the upper boundary). As mentioned before, this behavior can be interpreted by taking into consideration the values of the water productivity for each branch and the water availability. The shape of the fuzzy number is modulated by the central value and the fuzziness. The decision variables are restricted to the fuzzy non-symmetrical shapes of $\overline{(\text{MCPWW})}$. In addition, the productivity at branches has a determinant influence. For instance, at the branch with highest productivity, branch 16, since the water availability is above the existent demand, the new allocation to the demand is identical with the existent demand, and consequently is a crisp number. Otherwise, the new irrigation demand would follow the central value and the fuzziness current $\overline{(\text{MCPWW})}$, or in other terms, the new irrigation demand would have a non-symmetrical membership function (the same with the current $\overline{(\text{MCPWW})}$). Since from all the parameters of the optimization, $\overline{(\text{MCPWW})}$ are fuzzy numbers, the fuzziness of the decision variables is dependent on the fuzziness of $\overline{(\text{MCPWW})}$.

An interesting point is the possible uncertainty of the ecological and the urban demands. For the Guadalquivir Basin, both demands are to a large extent dependent on water and environmental policies. Since population is not expected to change much in the future, urban demand will be determined by per capita consumption. Ecological demand will be explicitly defined by environmental policies, like the European Water Framework Directive. A clear trend of reduction of per capita consumption in urban demand has been observed in the past in the Guadalquivir Basin. Likewise, a trend of increase of ecological demand is currently taking place in the region. Garrote et al. (2014) evaluated the sensitivity of MCPWW for irrigation to changes in urban or ecological demand in many basins of Mediterranean Europe. They found moderate impacts in the Guadalquivir Basin, since the majority of water demand corresponds to irrigation. For this reason, urban and ecological demands have been assumed constant in this model.

Accounting for the uncertainty on urban and ecological demands can be done implicitly or explicitly. Implicitly, it can be addressed in a Monte Carlo approach, generating combinations of climate and demand (urban and ecological) scenarios and running the model to obtain the corresponding MCPWW. To account for uncertainty on urban and ecological demands explicitly, the extension principle could be applied. However, this approach would require additional constraints on future demands, since this consideration might create a problem at the interpretation of the fuzzy inequalities. As mentioned in Appendix A, the interpretation of the fuzzy inequalities is based on the assumption that 'the worse the water availability is (MCPWW), the greater reduction for water demand'. There are policies targeted at reducing the urban demand, but the dependency of urban demand on population dynamics and its low price elasticity may prevent the success of these policies. As a result, we cannot guarantee that the reduction of water availability will imply a reduction of urban demand. The case for environmental demand is even stronger, since a reduction of water availability will imply a deterioration of aquatic ecosystems that may require an increase of ecological flows. Therefore, only in the case that the previous assumption holds can we apply the proposed methodology to urban and ecological demands.

Compared with other possibilistic programming methodologies, the proposed method has the advantage that it uses triangular numbers instead of semi-triangular ones (e.g., proposed method of Rommelfanger (2004)). Consequently, by following the proposed method, we can exploit the information of the mean value in order to construct the membership function.

The study of the objective function is better to incorporate not only the central values or a weighted sum based on the central, the lower, and the upper boundaries (e.g., as in Rommelfanger (2004) and Regulwar & Gurav (2011)). This is required in our method, as the uncertainty in the objective function arises from the decision variables and not from a fuzzy estimation of the coefficients of the decision variables. Therefore, according to the proposed method, we can robustly incorporate in the decision phase, simultaneously the case of the pessimistic, optimistic, and the 'central' events. This was achieved by following an interactive process and by using the Euclidean distance.

By comparing also the proposed method with the method proposed by Long Liu & Sahinidis (1997), it could be said that it seems unreasonable for our problem to extend the decision into the fuzzy inequalities. Particularly, the strength of the fuzzy inequalities cannot be verified to any degree in agreement with the objective functions. From a methodological point of view, many authors also proposed the concept of fuzzy robust programming in which, according to Inuiguchi & Ramik (2000), 'in case of fuzzy robust programming, the vague decision-maker's preference is represented by a fuzzy satisfactory region, and a fuzzy function value is required to be included in the given fuzzy satisfactory region'. In other words, an assumption must be adopted considering to what degree, according to a possibility measure, a fuzzy inequality holds. On the contrary, in our method, the fuzzy inequalities, namely, the constraints of water availability, should hold for any h -cut while the pessimistic (or optimistic) event is combined with the pessimistic (or optimistic) demand. This can be achieved by using fuzzy numbers as decision variables. On the other hand, in the case that we want to achieve at least a degree of satisfaction for the constraints, this consideration is not applicable.

Recently, several hybrid methodologies have been developed according to which the constraints are fuzzy while the coefficients are described as interval numbers. Stochastic approaches can also be used within this framework. For instance, Liu et al. (2013) proposed the mathematical modeling of water quality management under interval and fuzzy uncertainties within an optimization environment. Li et al. (2013a, 2013b) extended the methodology by using also stochastic constraints. However, in our case, we have evidence about the distribution of the fuzzy coefficient, and therefore, we avoid using interval numbers as we discuss later. In addition, since there are no historical data for the future scenarios, we do not have the evidence to support a probabilistic distribution.

An interesting point for further development of the proposed methodology is the incorporation of non-triangular membership function for either the decision variables or the (MCPWW). In this case, the fuzzy inequalities cannot be treated with only two h -cuts (Equation (8)). A laborious interactive process for several h -cuts (e.g., Lu et al. 2007a) should be established. On the other hand, the construction

of a more sophisticated membership function should be based on real information and not on arbitrary assumptions.

CONCLUSION

The paper addresses the problem of water resources adaptation in the case of changing conditions by suggesting the reorganization of the water allocation to irrigation demand. To achieve a simplification of the optimization procedure, the concept of MCPWW was proposed. MCPWW can be applied in several applications for long-term strategic management with one dominant water user. Based on this approach, we may achieve the linearization of the constraints. Furthermore, an interactive possibilistic programming method is proposed. One of the main suggestions of this article is the selection of fuzzy, non-symmetrical numbers as decision variables in order to face the changing environment of the decision with respect to the water availability constraints. Although there are several ways to approach the fuzzy inequalities, a successful interpretation of the fuzzy inequalities was achieved based on the nature of the examined problem.

Initially, the total irrigation profit can be defined as an objective function. Owing to the fact that the total irrigation profit is also a fuzzy number, the problem is ill-defined, thus an interactive approach is proposed based on the Euclidean distance. This approach together with the simultaneous consideration of fuzzy numbers as decision variables leads to adaptive and successful results. The incorporation of other criteria through the proper objective function can significantly improve the decision and sometimes without significant reduction of the total profit.

The decision variables are restricted to the fuzzy non-symmetrical shapes of (\overline{MCPWW}) . In addition, the productivity at branches has a determinant influence. Since from all the parameters of the optimization the (\overline{MCPWW}) are fuzzy numbers, the fuzziness of the decision variables is dependent on the fuzziness of (\overline{MCPWW}) and from the value of the productivity at each branch as well.

The method can be extended to address any problem of water resources adaptation where the decision variables are in continuous space, while the water conditions are changed (e.g., long-term water resources management) with one main

water user in this area, and, finally, if we assume a scenario with stable water infrastructures.

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