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Influence of crop-water production functions on the expected performance of water pricing policies in irrigated agriculture

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ABSTRACT

Agricultural economics Water Programming Models (WPM) has found that irrigators in water scarce areas have a rather inelastic response to water prices, making water pricing cost-ineffective towards water saving. We hypothesize that the predicted water saving performance of pricing is significantly underestimated by issues of model structure, due to the exclusion of deficit irrigation from the set of decision variables available to agents in conventional WPM. To test our hypothesis, we develop a model that integrates a continuous crop-water production function into a positive multi-attribute WPM, which allows us to assess agents' adaptive responses to pricing through deficit irrigation. The model is illustrated with an application to the El Salobral-Los Llanos irrigated area in Spain. Our results show that incorporating deficit irrigation as an adaptation option makes the water demand curve significantly more elastic as compared to an alternative model setting where deficit irrigation is precluded. We conclude that ignoring deficit irrigation can lead to a significant underestimation of the cost-effectiveness of water pricing towards water saving.

1. Introduction

1.1. Rationale

Reconciling growing freshwater demand with finite supply is one of the great policy challenges of our time (WEF, 2020c). Given that agriculture represents 70% of global water withdrawals, which contribute to 6.4% of the world's Gross Domestic Product (FAO, 2021a; World Bank, 2020d), governments are increasingly constrained to adopt agricultural water saving policies to reallocate irrigation water towards higher value-added economic uses, households and the environment. One such policy are water charges, often referred to as pricing, which are defined as an administrative levy imposed on irrigators to recover the costs of water use.[1] Theoretical and conceptual research has long argued that putting the "right price tag" on water can efficiently reallocate irrigation water towards other uses (Dinar and Subramanian, 1997; Tsur and Dinar, 1997). Echoing these results, several governments worldwide have integrated innovative water pricing instruments into their legal bodies to save water (Dinar et al., 2015a). For example, Article 9 of the EU Water Framework Directive states: "[…] water pricing policies provide adequate incentives for users to use water resources efficiently, and thereby contribute to the environmental objectives of this directive" (OJ, 2000).

However, the claim that agricultural water pricing can save water for other uses, including the environment, is not substantiated by empirical evidence. Virtually no water scarce area uses pricing as a water conservation/reallocation tool (the objective being mostly financial, through—partial—cost recovery of capital investments), which means

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[1] From an economic standpoint, charges are levies introduced administratively, while prices refer to the exchange value of any good arising from an interaction between supply and demand in a market environment. In the policy arena, though, many discussions on introducing 'charging' mechanisms for natural resources use the term "price" or "pricing", as is the case in the Water Framework Directive (OJ, 2000). This use of the term "prices" as a synonym of "charges" is also common in the scientific literature (see e.g., Dinar et al., 2015a; Olmstead and Stavins, 2007). For the sake of simplicity, in this paper we use both terms interchangeably throughout.

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Table 1
Type of crop water production functions used in WPM for the representation of farmers' behavior.

Authors	Economic calibration	Crop water production function	Development of the crop water production function	Application
Adamson et al. (2007)	No calibration	Piecewise	Expected yield penalties function of salinity	Basin-wide water reallocation to maximize agricultural income under alternative states of nature
Connor et al. (2009)	non-linear WPM	Continuous	Quadratic yield function of applied water and rain, calibrated with observed yield values.	Capital losses (death of permanent crops) under climate change
Connor et al. (2012)	PMP	Piecewise	Quadratic yield function of water and salinity, PMP calibration	Costs of salinity and climate change in the agricultural sector
Cortignani and Severini (2009)	PMP	Piecewise	Expected yield calculated with FAO's CropWat	Optimal water reallocation through agricultural profit maximization under changing water availability scenarios
Finger and Schmid (2008)	No calibration	Continuous	Yield function of water and nitrogen estimated with robust regression	Costs of climate change and related water availability uncertainty
Frisvold and Konyar (2012)	USARM	Continuous	Nested CES production function, PMP calibration	States-wide adaptation to large reduction in water supplies.
García-Vila and Fereres (2012)	non-linear WPM	Continuous	4 crops yield response to water application	Profit maximization by farmers under climate change
Graveline et al. (2012)	LP	Piecewise	Different expected yield values	Changes in utility through incremental/ decremental provision of profit and risk aversion
Graveline and Mérel (2014)	PMP	Continuous	Yield obtained as function of water with parameter estimated with non-linear least squares method, calibrated with agronomic function	Homogeneous reduction in water availability to all crops.
Howitt et al. (2009)	SWAP	Continuous	CES production function, PMP calibration	Optimal water reallocation through agricultural profit maximization
Kampas et al. (2012)	No calibration	Continuous	Yield function, fixed at optimal water application	Changes in agriculture water demand through water pricing
Loch et al. (2020b)	No calibration	Piecewise	In the different state of nature the yield is different	Basin-wide water reallocation to maximize agricultural income under alternative states of nature
Medellín-Azuara et al. (2010)	PMP	Continuous	Yield CES function with scaling parameter for different scenarios	Farmers response to external shocks or new policy
Medellín-Azuara et al. (2012)	PMP	Continuous	Nested CES function with scaling parameter for different scenarios	Farmers and regional responses to external shocks or new policy
Ortega Álvarez et al. (2004)	No calibration	Piecewise	Yield production function based on FAO's methodology	Basin-wide water reallocation to maximize agricultural income
Peña-Haro et al. (2010)	No calibration	Continuous	Quadratic crop production function, obtained with inputs from GEPIC model	Profit maximization by farmers subject to max. nitrate concentration
Peña-Haro et al. (2014)	No calibration	Continuous	Quadratic crop production function depends on water and nitrogen; depends on GEPIC model agronomic simulation	Profit maximization by farmers subject to max. nitrate concentration
Reca et al. (2001)	No calibration	Piecewise	Yield production function based on FAO's methodology	Basin-wide water reallocation to maximize agricultural income

Note: PMP: Positive Mathematical Programming; SWAP: Statewide Agricultural Production Model; LP: Linear Programming; USARM: U.S. Agricultural Resource Model; CES: Constant Elasticity of Substitution.
Source: Own elaboration with inputs from the papers listed in the first column of the table.

that field data on the water saving performance of pricing is limited and inconclusive (Dinar et al., 2015a; Rey et al., 2018). Moreover, applied research through agricultural economics Water Programming Models (WPM), which we define here as "a system of equations including an objective function and a set of constraints including resource constraints as a minimum" that is used to represent the behavior of individual economic agents such as irrigators (Graveline, 2016), has found that water pricing can only achieve relevant savings in water scarce areas at disproportionate costs due to the inelastic response of irrigators to higher prices (including in the initial stretches of the demand function) (see e.g. Berbel et al., 2007; Cornish et al., 2004; Dinar and Subramanian, 1997; Molden et al., 2010; Montilla-López et al., 2017; Pérez-Blanco et al., 2015; Steenbergen et al., 2007). This has led some to conclude that water pricing is cost-ineffective and even "irrelevant" as a water saving instrument (Berbel et al., 2007).

Our research hypothesis is that the predicted water saving performance of agricultural water pricing policies is significantly underestimated by issues of model structure, and specifically by the exclusion of deficit irrigation from the set of decision variables available to agents (irrigators) in conventional WPM applied to pricing.

In real life, irrigators decide on the crop portfolio, timing, investments (e.g. irrigation system) and water application, so to maximize their expected utility derived from one or a set of utility-relevant attributes (e.g. profit) provisioned through the production of agricultural goods, subject to a series of policy and resource constraints (i.e. feasible region). Conventional WPM reduce this complex choice to a decision on the crop portfolio, where each feasible choice represents a unique combination of crop, timing, investments, and water application. Note that this approach does not include an explicit crop-water production function; instead, water input is applied in fixed proportions to land (Arata et al., 2017; Gómez-Limón et al., 2016; Graveline et al., 2014). While this simplification allows for simulating adaptive responses to water conservation policies at the extensive margin (land reallocations towards less water intensive crops) and super-extensive margin (land reallocations from irrigated to rainfed agriculture), it does not allow for simulating intensive margin adjustments through deficit irrigation, a relevant management option in water stressed areas (Koundouri, 2004). Without water stress, it is reasonable to assume that economic agents will always apply water to the point where the marginal utility equates the marginal cost of water and thus maximize utility (i.e., no intensive margin adjustment will ever take place, only super-extensive and extensive margin adjustments); however, under scarcity conditions where water is a binding constraint, intensive margin adjustments are likely to be observed as agents now aim to determine the point at which each additional unit of water is providing the maximum attainable utility from its application, which needs not match

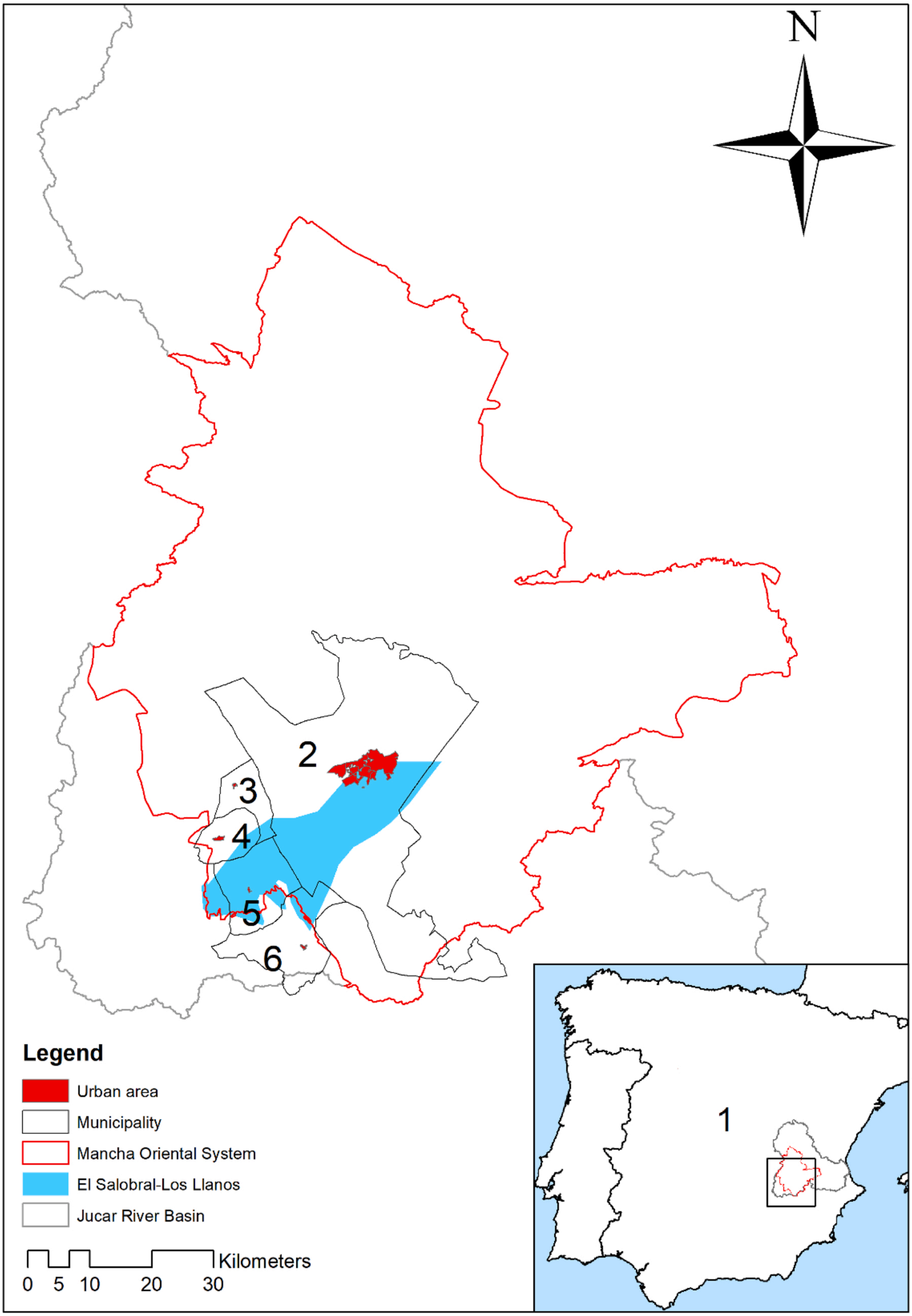

Fig. 1. Case study area. Legend: 1 Spain, 2 Albacete, 3 La Herrera, 4 Balazote, 5 Pozuelo, 6 Peña de San Pedro.
Source: own elaboration.

the point at which marginal utility and costs are equated (which may be unfeasible under the new constraint). Accordingly, ignoring intensive margin adjustments can lead to biased estimates of human responses; biased estimates of the water saving potential and the economic impacts of pricing; and misleading policy recommendations (Frisvold and Konyar, 2012). This calls for the integration of crop-water production functions that reflect the biological processes occurring in the agricultural system into economic models assessing the impacts of pricing.

1.2. Literature review of agricultural economics WPM that integrate crop-water prediction functions

An expanding literature explores the integration of crop-water production functions in WPM to allow for intensive margin adjustments. Table 1 presents the WPM that incorporate a crop-water production function, classified in accordance with i) the calibration of the WPM, ii) the type of crop-water production function (functional form and development), and iii) the relevant policy issues addressed by these models.

Among *non-calibrated WPM*, Reca et al. (2001) develop an expected utility model composed of three sub-models: the first optimizes the water application for every crop through a continuous crop-specific water production function inspired in FAO's CROPWAT (FAO, 1992); the second approximates the crop water production function "to a discrete function considering a series of interval of irrigation depths" (Reca et al., 2001), and maximizes profit over the irrigated area subject to existing constraints (i.e. optimizing a linear objective function defined as crop-specific prices times yield minus per ha costs, multiplied by the crop's area); while the third optimizes water allocation over the entire water system taking into account water availability and maximum and minimum flows. A similar approach is followed by the MOPECO model (Ortega Álvarez et al., 2004), which integrates FAO's production function into an economic optimization model to determine the seasonal net irrigation depths, simulate water distribution and maximize the total profit at farm level. Finger and Schmid (2008) use regression methods to estimate the parameters of a continuous crop water production function for Swiss corn and wheat under different water availability scenarios. Crop production functions are subsequently integrated into the objective function of a linear economic model that maximizes profit, and the optimization problem is solved under alternative climate and water availability scenarios. Authors use this information to estimate the certainty equivalent for each climate and water availability scenario considered and reveal the minimum payoff agents would be willing to make to avoid climate change and related water availability uncertainty. Kampas et al. (2012) build a quadratic and continuous crop production function where yield depends on water and nitrates application. The crop water production function is calibrated for key crops in a case study area in Thessaly (Greece), namely corn and cotton; while water is used in fixed proportions to land for the remaining crops. This results in a model that combines non-linear (corn and cotton) with linear optimization (other crops). García-Vila and Fereres (2012) develop a non-linear programming model that uses FAO's AquaCrop model to simulate yield responses to water application for the four most relevant crops in Santaella, Spain (namely cotton, corn, potato and sunflower), and optimizes farmer profit under alternative price and climate change scenarios. Peña-Haro et al., (2014, 2010) develop an integrated economic-agronomic model featuring a non-linear quadratic production function where yield is a function of water and nitrogen application, which is integrated in a normative economic model that maximizes irrigators profit subject to groundwater quality constraints (maximum nitrate concentration). Loch et al. (2020b) integrate a piecewise crop-water production function into a WPM that aims to optimally reallocate water so to maximize a linear function of profit at a catchment level, under alternative states of nature that represent hypothetical water availability conditions. For permanent crops, the model divides the crop water production function into two components: the minimum amount of input necessary to guarantee crop survival and 'productive watering' that returns effective crop yield.

Among *calibrated WPM*, Graveline et al. (2012) integrate a piecewise crop water production function into a Linear Programming (LP) model to simulate stepwise changes in utility through the incremental/decremental provision of the two utility-relevant attributes considered, namely profit and risk aversion. Connor et al. (2009) develop a model for profit maximization with a quadratic crop water production function that distinguishes between annual and perennial crops, so to account for future penalization if the trees die or are damaged. The yield function is calibrated with observed values of water application and yield in the Murray-Darling Basin in Australia. Cortignani and Severini (2009) integrate a piecewise crop water production function into the objective function of a Positive Mathematical Programming (PMP) model; yield responses to water application are obtained from FAO's CropWat. Connor et al. (2012) introduce a piecewise quadratic crop water production function in a PMP model to evaluate the impact of salinity and climate change in the agricultural sector. The model is calibrated following the method proposed by Röhm and Dabbert (2003), which follows the classical PMP approach of adding quadratic components in the cost function from dual values' constraints while allowing for higher elasticity of substitution between groups of similar crops. The objective function distinguishes between annual and perennial crops to account for a future penalization in case of not reaching the minimum water supply that guarantees perennial crop survival. Frisvold and Konyar (2012) and Medellín-Azuara et al., (2012, 2010) integrate a continuous CES production function that assess crop yield responses to different inputs, including water, in a classical PMP and in the USARM[2] models, so to account for the elasticity of substitution between inputs. Frisvold and Konyar (2012) nest the crop production function in two steps: in the first they include land and water, and in the second chemicals, fertilizers, labor, capital and energy input. Medellín-Azuara et al. (2010) consider five inputs (land, applied water, supplies, a water capital bundle, and a composite input called effective water) and calibrate the parameters of a CES objective function for land, supplies, and effective water. Medellín-Azuara et al. (2012), add a new step to the calibration procedure of the CES production function above to consider the "substitution relationship between water and capital irrigation investment". In the SWAP model, Howitt et al. (2009) use a PMP model that adopts a CES objective function to maximize profit along 4 inputs (land, water, labor and supplies). The model has a multistage calibration process to specify the CES and exponential cost function parameters. Finally, Graveline and Mérel (2014) build on previous works by Mérel et al., (2014, 2011) to shift the non-linear components of the PMP objective function away from the cost function and into the production function. While conventional PMP models add a quadratic component to the cost function, so to introduce a non-linear component in the objective function that bounds the solution of the utility maximizing problem to observed decisions, Graveline and Mérel (2014) calibrate non-linear CES crop-water production functions to explicitly specify the "elasticities of substitution between land and water and calibrate them to replicate a set of exogenous agronomic crop yield responses to water application". Following this approach, the non-linearity in the objective function now comes from "decreasing return to scale at the crop level, rather than increasing marginal cost" (Graveline and Mérel, 2014). Applying this approach authors identify the shadow value of water, while the shadow value of land is set exogenously from the observed agricultural land value.

Three key commonalities emerge from our literature review of agricultural economics WPM that integrate a crop-water production function. The first commonality is that there are no applications of

[2] A PMP based model developed to simulate market and policy shocks in the US agricultural sector; it considers effects in land reallocation, water use, yield and production, labor and net farm income.

integrated WPM and crop-water production functions that assess the impacts of water pricing. Most applications research the impacts of water availability constraints and optimal basin-wade reallocations.

The second commonality is that, although most applications of agricultural economics WPM that integrate crop-water production functions rely on calibrated models (Graveline, 2016), non-calibrated models account for almost half of the papers in our review on integrated WPM and crop-water production functions.

The third commonality is that all the crop-water production functions in our literature review on agricultural economics WPM that integrate crop-water production functions study the relationship between crop yield and *water applied*, instead of the (more stable) relationship between crop yield and crop evapotranspiration that is typically reported in agronomic models (Steduto et al., 2007). This is because while irrigators can control water application, they cannot control crop evapotranspiration (which is a function of water applied and technology, but also of variables out of control of the irrigator such as wind or solar radiation). Thus, agricultural economics models that explore intensive margin adjustments use water applied as the argument of the objective function (together with land allocation) (Graveline, 2016).

Crop-water production functions relating water applied to yield are site specific and depend on several local factors (soil type, topography, irrigation method, farm management practices, precipitation regime, percentage of crop water requirements satisfied by rainfall). Fereres and Soriano (2007) and Trout and DeJonge (2017) show how small amounts of applied water increase yield linearly until a threshold is reached, from which the relationship becomes curvilinear because part of the water applied does not contribute to crop evapotranspiration due to increased deep percolation, runoff or evaporation, and less effective use of precipitation that reduces the efficiency of water application. Thus, when studying the relationship between crop yield and water applied, the use of a nonlinear concave crop-water production function is more realistic. In our literature review, the relationship between crop yield and water applied is approximated using either piecewise functions obtained from process-based crop simulation models or continuous functions parameterized using statistical methods (typically quadratic). Independently of the form used (piecewise or continuous), all crop-water production functions in the review are deterministic. Use of deterministic crop-water production functions is instrumental to integrate agronomic modeling and data into the structure of WPM, where all variables in the objective function (including yields, but also e.g. revenues and costs) are defined as a deterministic function of the decision variables (crop portfolio, water application).

1.3. Contribution of this research

The contribution of this paper to the scientific literature is twofold. *First*, we integrate a continuous crop-water production function into a positive WPM with a multi-attribute utility function as objective of the optimization process – known as Positive Multi-Attribute Utility Programming (PMAUP) (Gómez-Limón et al., 2016; Gutiérrez-Martín and Gómez, 2011). To the best of our knowledge, this is the first time a crop-water production function is integrated into a multi-attribute WPM. Adding new modeling approaches to the literature on integrated WPM and crop-water production functions can improve our understanding of irrigators' adaptive responses; and is instrumental towards the development of ensemble experiments that sample parameter and structural uncertainties arising from model choice. Ensemble experiments can be used to compare simulation results of the proposed integrated model against those of other integrated models in Table 1, under alternative model settings (i.e., exploring alternative functional forms and parameterization of the crop-water production functions and utility functions) and scenarios. The result is a large database of simulations in which each simulation represents the performance under one plausible future. This information can be used to identify futures where proposed policies meet or miss their objectives, explore potential tipping points, and inform the development of robust policies that show a satisfactory performance under most conceivable futures (Saltelli and Funtowicz, 2014; Sapino et al., 2020).

Second, we use our newly developed model to assess the water saving and economic performance of water pricing considering all three possible adaptive responses: extensive, super-extensive and intensive margin adjustments. The net effect of considering the option to adapt through the intensive margin is revealed through a comparison with a classic PMAUP model where the continuous agronomic production function is substituted by point values that represent expected yield under irrigated and/or rainfed agriculture, thus allowing only for extensive and super-extensive margin adjustments. Methods are illustrated with an application to the agricultural area of El Salobral-Los Llanos domain (SLD) located on the overallocated Mancha Oriental System (MOS), a major aquifer within the Júcar River Basin (southeastern Spain).

2. Background to the case study: El Salobral-Los Llanos domain in the mancha oriental aquifer (Spain)

2.1. Water use and pressures

The SLD comprises part or the totality of the municipalities of Albacete, Balazote, La Herrera, Peña de San Pedro and Pozuelo (Fig. 1). The SLD has an extension of 420 km^2, of which 337 km^2 are devoted to agriculture (80%) and 100 km^2 are irrigated. Most relevant irrigated crops in the area include wheat, barley, corn, onion, garlic and almond, which have an average water allotment available of 1500 m^3/ha. About 90% of water withdrawals in the SLD come from irrigated agriculture, most of which are met through groundwater extractions from the MOS. On top of agricultural water demand, water bodies within the SLD supply water to a population of circa 5000 inhabitants (about 10% of the total demand) (Peña-Haro et al., 2014).

The MOS in the Júcar River Basin is one of the largest groundwater bodies in Spain (7260 km^2), encompassing parts of the provinces (NUTS3[3]) of Albacete, Cuenca, and Valencia. In the last three decades, a significant increase in agricultural water demand and withdrawals has been observed in the MOS through the development of an intensive irrigated agriculture that represents a significant share of the employment and value added of the region. At present, over 80,000 ha of land equipped with modern technologies are irrigated in the MOS, mostly with groundwater. Because of irrigation expansion, the aquifer has been subject to an intensive groundwater overexploitation since the 1980 s, which has resulted in a continued reduction in the piezometric levels, especially in the southern area where the SLD is located. Stream–aquifer interaction with the Júcar River has been substantially affected as a result of aquifer overdraft: previously, the MOS discharged water into the Júcar River and enhanced its streamflow, while today these dynamics have been reversed and the Júcar River recharges the MOS (Sanz et al., 2011). Groundwater overdraft has led to a significant streamflow reduction in the Júcar River with non-trivial environmental consequences, such as the drying of a significant reach of the Júcar River in the summers of 1994 and 1995, which in turn has caused significant conflicts with downstream uses (Apperl et al., 2015). This situation is expected to be exacerbated by future climate and land use change scenarios (Pulido-Velazquez et al., 2015). Some measures have been recently proposed to reduce agricultural water use and restore the balance in the overexploited MOS Aquifer, notably water pricing (Peña-Haro et al., 2014).

[3] The Nomenclature of Territorial Units for Statistics (in French: Nomenclature des unités territoriales statistiques, or NUTS) is "a geocode standard for referencing the subdivisions of countries for statistical purposes" used by the EU (Eurostat, 2020a). NUTS3 is equivalent in Spain to provinces.

2.2. Water pricing

In Spain, irrigators relying on surface water bodies pay river basin authorities a Water Use Fee (in Spanish: *Tarifa de Utilización del Agua*) and a Regulation Fee (*Canon de Regulación*) designed to recover the investment and maintenance costs of conveyance and water storage infrastructure operated by the public administration (e.g. reservoirs, large canals, water transfers), for which cost recovery levels range from low to moderate (EEA, 2013). Water Use Associations (WUA) can also price water through an additional fee to recover the investment and maintenance costs of storage and distribution infrastructures operated by the WUA (e.g. canals within the WUA). Most irrigators across the MOS rely on groundwater bodies and do not use water storage and distribution infrastructure, and typically do not belong to any WUA, which makes them exempt from the payment of all the above-mentioned fees (Water Use, Regulation and WUA fees). On the other hand, the falling piezometric levels of aquifers are increasing the energy costs of groundwater pumping, which now are 0.1 EUR/m^3 in average (up to 0.2 EUR/m^3 for the deepest extractions) in the SLD and other irrigated areas in the MOS (ITAP, 2020; JCRMO, 2009; JRBA, 2016).

Aside from the fees to recover the investments in water storage and distribution infrastructures, and the variable costs of pumping groundwater and operating irrigation systems, no additional levies on agricultural water use exist in the irrigated areas of the MOS. This fails to comply with Article 9 of the EU Water Framework Directive, which calls for the implementation of pricing policies with a double role: cost recovery (financial instrument) and demand management (economic instrument to favor economic efficiency in water use). Those water prices should recover the "environmental and resource costs" of the resource on top of the financial costs from the construction and operation of irrigation system (OJ, 2000). Environmental costs are defined as the damage that water uses impose on ecosystems, which can be measured e.g., as the welfare loss experienced by those who enjoy those ecosystems[4]; while resource costs are defined as the opportunity cost (foregone economic benefits) of water allocation over space and time (Heinz et al., 2007; Pulido-Velazquez et al., 2008; WATECO, 2003). Both of these costs are present and significant in the overallocated and overexploited MOS, but are not recovered (Peña-Haro et al., 2014). As a result, the water charge applied is significantly lower than the theoretical water charge that would allow for full cost recovery, and insufficient to effectively curb down demand (Olmstead and Stavins, 2007; Pulido-Velazquez et al., 2013). In our application of the model to our case study area, we simulate a pricing instrument that applies incremental water charges to recover the resource and environmental costs of water use.

3. Methods and data

3.1. PMAUP model setting

This paper integrates, for the first time to the best of our knowledge, a continuous crop-water agronomic production function into a PMAUP model. PMAUP modeling builds on the Theory of Planned Behavior (Ajzen, 1991), which argues that agent's responses stem from a "summary of psychological evaluations based on farmers' beliefs on the goodness or badness of an object", which "can be associated to multiple attributes that are often conflicting" (e.g. expected profit v. risk) (Gómez-Limón et al., 2016). Accordingly, PMAUP models feature a characteristic multi-attribute utility function that typically includes measures of profit, risk and management complexity, albeit other attributes can be explored (Bartolini et al., 2007; Gómez-Limón et al., 2016; Pérez-Blanco and Standardi, 2019; Rausser and Yassour, 1981). Agents in our PMAUP model decide on the allocation of land and water (i.e. the decision variables) so to maximize utility through the provision of the above-mentioned utility-relevant attributes within a feasible region conformed by a series of constraints (e.g. water availability, land availability):

$$\operatorname*{Max}_{x,w} U = U(\boldsymbol{Z}(\boldsymbol{X},\boldsymbol{W})) = \prod_{p=1}^{m} z_{\mathrm{p}}^{a_{\mathrm{p}}}(\boldsymbol{X},\boldsymbol{W}) \tag{1}$$

s.t.

$$\sum_{i=1}^{n} x_i = 1.0 \leq x_i \leq 1 \tag{2}$$

$$\sum_{i=1}^{n} w_i x_i \leq \mathrm{WA} \tag{3}$$

$$\boldsymbol{X},\boldsymbol{W} \in F \in R^n \tag{4}$$

$$\boldsymbol{Z}(\boldsymbol{X},\boldsymbol{W}) \in R^{\mathrm{m}} \tag{5}$$

Where U is the utility or objective function, which in our case adopts a Cobb-Douglas specification, as it is common practice in the PMAUP literature[5] (see e.g. Sapino et al., 2020); **X** is the crop portfolio vector, which contains information on the fraction of land allocated to each crop i, x_i; **W** is the water application vector, which contains information on the water applied to each crop per hectare, w_i; WA represents the average water availability per hectare; $\boldsymbol{Z}(\boldsymbol{X},\boldsymbol{W})$ is the vector of attributes, a function of the decision variables in vectors $\boldsymbol{X}, \boldsymbol{W}$, which contains information on the provision of each utility-relevant attribute z_p (all attributes are defined so that "more-is-better", i.e. all else equal increasing the provision of a given attribute yields a utility gain); m is the number of individual attributes z_p and parameters a_p considered; and F is the feasible region, which includes the following constraints:

- *Land availability* (see Eq. (2) above). Available agricultural land is assumed constant in all simulations considered.
- *Water availability* (see Eq. (3)). In all simulations, water application has a maximum bound to the observed water allotment per hectare in the case study area.
- *Climate, soil, know-how.* Due to the specific climatic and soil characteristics, and irrigator's know-how, the crop portfolio is restricted to those crops that are already present in the area and observable in the database (which are also the only crops for which historical data is available and ad-hoc continuous crop-water production function can be calibrated) (Essenfelder et al., 2018).

$$\sum_{i=1}^{n} y_i x_i = 0 \,\middle|\, y_i \in \left\{0,1\right\} \tag{6}$$

where $y_i = 0$ means the crop is observable and $y_i = 1$ means the crop is not observable in the area.

[4] An alternative way of setting water charges is to define safe minimum standards for the quantitative status of water bodies, and then impose a set of prices sufficient to achieve these standards. While not Pareto-efficient, such approach can achieve safe minimum standards at a minimum cost for the economy (Baumol and Oates, 1971).

[5] Multiplicative functions such as the Cobb-Douglas are regarded as a superior alternative to additive forms in multi-attribute modeling (Sampson, 1999). Cobb-Douglas functions comply with the Inada (1963) conditions and guarantee the existence of a global optimum, provided the efficiency frontier is convex. Since attributes' parameters (a_j) are all lower than one, Cobb-Douglas functions are also consistent with the neoclassical postulate of decreasing marginal utility. Attributes' parameters can be also interpreted as a weight or indicator of the relative importance of each attribute in driving agents' behavior (for an early discussion on this see e.g. Bronfenbrenner, 1944; Brown, 1957).

- *Crop-specific constraints*. Some crops in the portfolio have an upper and/or lower area bound. In our application to the SLD, this restriction is used to set a minimum/maximum threshold for Almond trees of ± 5%. Although the pricing policy instrument is designed to work in the long run and it could result in more than ± 5% crop portfolio changes, this may lead to significant (dis)investments with impacts not accounted for in our models, which rely on yearly market variables (notably profit) (Essenfelder et al., 2018). For example, perennials add value outside the agricultural business itself through carbon sequestration and amenities (e.g., landscape value) that would be lost if perennials are substituted by annuals. On the other hand, perennials involve non-trivial investment costs that are not captured by yearly market variables such as profit and would not be recovered and remain as sunk costs if the perennial is replaced by an annual crop (Loch et al., 2020a) .[6] Accurately representing long run changes in the surface of permanent crops would demand the inclusion of other relevant variables (e.g., carbon prices, Payment for Ecosystem Services) and is beyond the scope of this paper. Alternatively, a minimum (maximum) bound for ligneous trees is common practice in the literature (e.g. Gutiérrez-Martín and Gómez, 2011; Parrado et al., 2019).

Note that the optimization problem above is resolved for a representative hectare, and all output variables are expressed in units per hectare.

3.2. PMAUP model calibration

In order to elicit the parameters of the utility function (α), we adapt the PMAUP calibration method originally developed by Gutiérrez-Martín and Gómez (2011) for the case of a single decision variable $\boldsymbol{X}$, to the case of a PMAUP with a crop-water production function and two decision variables $\boldsymbol{X}, \boldsymbol{W}$.

Following standard economic theory, the parameters of the objective function are elicited by means of equalizing the opportunity cost of trading one unit of attribute z_k off for one unit of attribute z_p, i.e. the slope of the efficient frontier or Marginal Rate of Transformation (MRT_{kp}), to the willingness to give up one unit of attribute z_k in exchange for a unit of attribute z_p, i.e. the slope of the indifference curve of the utility function or Marginal Rate of Substitution (MRS_{kp}). Repeating this process for every possible combination of two individual attributes z_k, z_p within the finite set of attributes in the vector $\boldsymbol{Z}$, yields a system of equations that, after being solved, provides the parameter values.

The MRS_{kp} is conditional on the specification used for the objective function. Under a Cobb-Douglas specification as the one used in this paper, the MRS_{kp} can be obtained as follows:

$$MRS_{kp} = -\frac{\partial U/\partial z_p}{\partial U/\partial z_k} = -\frac{\alpha_p}{\alpha_k}\frac{z_k}{z_p} \tag{7}$$

The main challenge in the calibration of PMAUP models concerns the elicitation of the efficient frontier to calculate the MRT_{kp}. The efficient frontier is defined as the maximum value of attribute z_p that can be achieved for a given value of attribute z_k given a series of restrictions, and vice versa. Marginal displacements along the efficient frontier give information on the opportunity cost between attributes, i.e. the cost of increasing the provision of attribute z_k in terms of attribute z_p, also known as the MRT_{kp}. Note that the term 'opportunity cost' implies convexity; if an efficient frontier is not found to be convex, there is no tradeoff between attributes and one of them should be removed from the attribute set. Since efficient frontiers "cannot be analytically defined using a closed function" (Gutiérrez-Martín and Gómez, 2011), numerical methods are typically used to estimate them. PMAUP literature reports several alternative methods to approximate the efficient frontier, among which the projection method developed by Gutiérrez-Martín and Gómez (2011) is the most commonly used (see e.g. Essenfelder et al., 2018; Gutiérrez-Martín et al., 2014; Parrado et al., 2019).

In fact, it is not necessary to know every point of the efficient frontier, but only those landing points between the efficient frontier and the utility function, where the MRT_{kp} will be equaled to the MRS_{kp}, as well as the slope of the efficient frontier (MRT_{kp}) in these points. The projection method starts by resolving two optimization problems in the two-dimensional space kp that calculate the maximum value that attribute z_k can achieve when z_p equals its observed value (i.e. z_p^o), and vice versa, for every $p \neq k$:

$$\underset{x,w}{Max}\; z_p(\boldsymbol{X}, \boldsymbol{W}) \tag{8}$$

s.t.:

$$z_k(\boldsymbol{X}, \boldsymbol{W}) = z_k^o(\boldsymbol{X}, \boldsymbol{W})\ \forall k \neq p \tag{9}$$

And

$$\underset{x,w}{Max}\; z_k(\boldsymbol{X}, \boldsymbol{W}) \tag{10}$$

s.t.:

$$z_p(\boldsymbol{X}, \boldsymbol{W}) = z_p^o(\boldsymbol{X}, \boldsymbol{W})\ \forall p \neq k \tag{11}$$

By solving the two optimization problems above we project the observed attribute values to the efficient frontier, thus obtaining two points (τ) within the efficient set: τ_{z_k, z_p^o} and $\tau_{z_k^o, z_p}$ (see Fig. 2).

These two points are subsequently connected through a hyperplane to approximate the MRT_{kp} through the slope β_{kp}^{τ} as follows:

$$MRT_{kp} = \beta_{kp}^{\tau} = \frac{z_p - z_p^o}{z_k - z_k^o} \tag{12}$$

Next the MRS_{kp} and the approximated MRT_{kp} are equalized for every combination of two attributes z_k and z_p to elicit the parameters of the objective function, as follows:

$$MRS_{kp} = -\frac{\partial U/\partial z_p}{\partial U/z_k} = -\frac{\alpha_p}{\alpha_k}\frac{z_k}{z_p} = \beta_{kp}^{\tau} = MRT_{kp}.\forall p \neq k \tag{13}$$

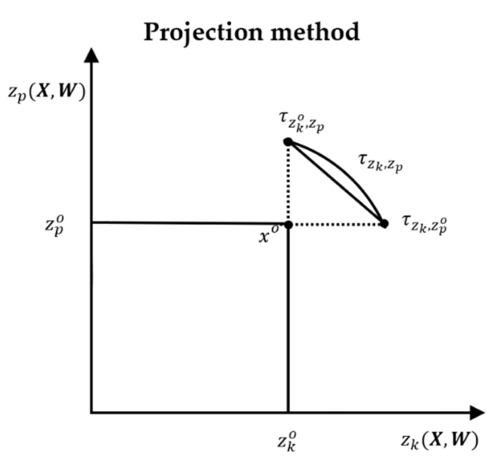

Fig. 2. Graphical representation of the approximation of the efficient frontier in the two-dimensional space pk using the projection method.
Source: own elaboration.

[6] Note that in Spanish Drought Management Plans, perennials are allotted a high priority: perennials are guaranteed the minimum amount of water needed for their survival (not the amount of water towards achieving a positive yield, though), and only after this amount of water is satisfied, annuals can receive any water.

$$\sum_{p=1}^{m} \alpha_p = 1 \tag{14}$$

The system of equations above is resolved for every possible attribute set (i.e. for alternative vectors $\boldsymbol{Z}$) considered, to elicit the corresponding objective function parameters. Next, for each set of attributes considered and related objective function parameters, we resolve the optimization problem in Eqs. (1)–(5) and obtain the simulated land (X^*) and water application (W^*) vectors, and the corresponding provision of attributes (z_p^*; p = 1,…,m). We next assess the performance of each set of attributes considered to represent observed behavior using three calibration residual metrics: i) e_x, the distance between the observed (x^o) and simulated land allocation (x^*), ii) e_w, the distance between the observed (w^o) and simulated water application (w^*), and iii) e_τ, the distance between the observed (z_p^o) and simulated attributes provision (z_p^*), which are then aggregated to calculate the average calibration residual e_m.

$$e_x = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i^o - x_i^*}{x_i^o}\right)^2} \tag{15}$$

$$e_w = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{w_i^o - w_i^*}{w_i^o}\right)^2} \tag{16}$$

$$e_\tau = \sqrt{\frac{1}{m}\sum_{p=1}^{m}\left(\frac{z_p^o - z_p^*}{z_p^0}\right)^2} \tag{17}$$

$$e_m = \frac{\sqrt{e_x^2 + e_w^2 + e_\tau^2}}{3} \tag{18}$$

Of all the attribute sets explored and their related set of parameters and objective functions, the relevant attribute set and objective function that is used in the simulation exercises is the one that minimizes the average calibration residual e_m.

3.3. PMAUP model attributes

The attributes explored are selected based on a literature review on the Multi-Attribute Utility Theory (Bartolini et al., 2007; Gómez-Limón et al., 2016; Pérez-Blanco and Standardi, 2019; Rausser and Yassour, 1981), and include expected profit, risk avoidance and hired labor avoidance, a proxy of management complexity. Expected profit is the only attribute considered in single-attribute WPM, and critical towards explaining agents' choices. Risk avoidance reflects on the fact that agents are willing to sacrifice a fraction of expected profit so to reduce its variability. Finally, hired labor avoidance is a proxy of management complexity avoidance, which reflects on the fact that economic agents are willing to sacrifice a fraction of expected profit so to reduce the management complexity involved in their choices. The relevance of risk avoidance and management complexity avoidance attributes is visible in agents' choices, who rarely select a single profit maximizing crop, but rather a crop portfolio that balances the provision of utility-relevant attributes. All attributes are defined so that "more-is-better", i.e. all else equal increasing the provision of a given attribute yields a utility gain. Below we formally describe each of the attributes explored.

Expected profit (z_1) is obtained as the summation of the expected per hectare gross margin (π_i) of each crop i times the fraction of land allocated to that crop (x_i). The expected gross margin per hectare π_i is obtained as price (p_i, in EUR/kg) times yield (y_i, in kg/ha) plus coupled farm subsidies (s_i) minus variable costs (c_i, in EUR/ha). In the classical PMAUP model, p_i, y_i, s_i and c_i are obtained as the average values of longitudinal data on prices, yields, subsidies and variable costs, respectively. The innovation presented in this work is the integration of continuous crop-water production functions into the PMAUP model, transforming the expected profit attribute as follows:

$$z_1(\boldsymbol{X},\boldsymbol{W}) = \sum_i x_i\pi_i(w_i) = \sum_i x_i(p_i y_i(w_i) + s_i - c_i(y_i(w_i))) \tag{19}$$

where $\boldsymbol{X}$ represents the *crop portfolio* vector, the first-choice variable in the model that allows for extensive and super-extensive margin adjustments; $\boldsymbol{W}$ is the *water application* vector, the second choice variable in the model that allows for intensive margin adjustments; and $y_i(w_i)$ and $c_i(y_i(w_i))$ are the crop-water production function and the variable costs function, respectively, which now are variable and depend on the decision of how much water to apply. Consistent with the majority of papers in our review, we approximate the crop-water production function through a quadratic function that adopts the following form:

$$y_i(w_i) = a_i w_i^2 + b_i w_i + d_i \tag{20}$$

Where $y_i(w_i)$ is the yield in kg per hectare, and a_i, b_i and d_i are the parameters of a quadratic function determining yield responses to alternative water application levels w_i (in m^3/ha), for a given crop i. If the crop can be cultivated under rainfed agriculture, d_i is positive and equals expected yield under rainfed agriculture; otherwise, it is zero or negative (Peña-Haro et al., 2014). For our case study in the SLD, a_i, b_i, and d_i were elicited using data from field experiments, combined with simulation outputs from a process-based agronomic model (Peña-Haro et al., 2014). The rationale for the use of simulations on top of field experiments in the calibration of the crop-water production function comes from the need to account for the complex impact and variability of different factors governing crop growth and yield other than water. If a researcher calibrates a production function using only a field experiment on water-yield relationship, she would be ignoring other factors that are responsible for the variation in crop yields from year to year (temporal variability) and across space (spatial variability). In fact the same plot, cultivated year after year in an identical way, without a priori limitations of any element (nutrients, water, other), has a temporal variability in yields due to climatic conditions, soil, etc. Similarly, there is also spatial variability across plots. To account for this variability, the literature on crop-water production functions complements field experiments with simulation models. By combining field experiments with process-based crop growth models, it is possible to capture the interacting effects of farmers' intra-seasonal irrigation decision-making, stochastic weather conditions, and physical and socio-economic water supply constraints on seasonal crop yield response to water. A recent review and application (through Aquacrop-OS) on how to simulate crop-water production functions using field experiments and process-based agronomic models is available in Foster and Brozović (2018). We adopt a similar approach in our model, where we use the process-based GIS-based Environmental Policy Integrated Climate (GEPIC) model (Liu et al., 2007) to account for temporal and spatial variability (GEPIC is the distributed GIS version of EPIC). The calibration results for the crop-water production functions of irrigated crops in the SLD are available in Section 4.1.1. Note that the production functions adopted in our paper are local and only have validity in the context of the area where they have been developed.

The variable costs function $c_i(y_i(w_i))$ adopts a linear form with respect of yield (in kg/ha), as follows:

$$c_i(y_i(w_i)) = e_i y_i(w_i) + f_i \tag{21}$$

Variable costs include plants and seeds, fertilizers, phytosanitary products, spare parts and repair services, subcontracting, hired labor and other supplies. Although national statistics only report two measures of variable costs per year and crop (under rainfed and irrigated agriculture), variable costs will typically be higher (lower) the higher (lower) the yield (e.g. more labor during harvest). We adjust the crop-water production function to account for this by making the variable costs of crop i a linear function of yield with a fixed (f_i, a parameter representing the minimum threshold for variable costs) and a variable

Table 2
PMAUP model data inputs.

Variable	Abbreviation used	Data provider	Ref. year	Granularity
Crop portfolio (% over total surface)	x_i		2015	Hectares per crop at municipality level (NUTS4)
Crop yield (kg/ha) and water applied (m^3/ha) (crop-water production function, annual crops)	y_i, w_i	Adapted from Fabeiro Cortés et al. (2003); ITAP (2005) and Peña-Haro et al. (2014)	2000 and 2009	Water basin level
Crop yield (kg/ha) and water applied (m^3/ha) (crop-water production function, permanent crops)	y_i, w_i	Adapted from Jiménez et al. (2004) and Peña-Haro et al. (2014)	2000 and 2009	Water basin level
Crop yield (kg/ha) (only for the variance and covariance matrix)	y_i	Adapted from MAGRAMA (2015)	2008–2015	Agricultural District (*Comarca*)
Prices (EUR/kg)	p_i	MAGRAMA (2015)	2008–2015	National (NUTS1)
Costs (EUR/ha) and subsidies (EUR/ha)	c_i, s_i	Adapted from MAPA (2019)	2008–2015	Agricultural District
Number of working days (days/ha)	N_i	Adapted from MAPA (2019)	2008–2015	Region (NUTS2)

Source: Own elaboration. MAGRAMA (2015)

(e_i) component, calculated as follows:

$$e_i = \left(c_{i,\ irrigated} - c_{i,\ rainfed}\right) / \left(\left(\max\left(y_i(w_i)\right)\right) = min\left(y_i(w_i)\right)\right) \tag{22}$$

$$f_i = c_{i,\ rainfed} \tag{23}$$

where $c_{i,\ irrigated}$ are the average values of longitudinal data on variable costs for crop i under irrigated agriculture, $c_{i,\ rainfed}$ are the average values of longitudinal data on variable costs for crop i under rainfed agriculture, $\max(y_i(w_i))$ is the maximum yield attainable in the crop-water production function for crop i and $\min(y_i(w_i))$ represents rainfed yield for crop i. If no rainfed alternative is available for crop i, $\min(y_i(w_i))$ and $c_{i,\ rainfed}$ equal 0.

Risk avoidance (z_2) is obtained as the profit variability (measured through the variance and covariance matrix) attached to the profit maximizing combination of land ($\overline{X}$) and water inputs ($\overline{W}$) minus the profit variability attached to the land (X) and water input (W) allocation chosen by the agent (recall attributes are defined so that "more-is-better") (Gómez-Limón et al., 2016):

$$z_2\ (\boldsymbol{X}, \boldsymbol{W}) = \overline{\boldsymbol{X}}^t VCV\left(\boldsymbol{\pi}\left(\overline{\boldsymbol{W}}\right)\right)\overline{\boldsymbol{X}} - \boldsymbol{X}^t V\ CV(\boldsymbol{\pi}(\boldsymbol{W}))\boldsymbol{X} \tag{24}$$

where $VCV(\boldsymbol{\pi}(\boldsymbol{W}))$ is the variance and covariance matrix of the gross variable margin, and π is a vector that contains the per hectare gross margin of each crop π_i. Note that information on yields under deficit irrigation for the crops in the SLD is available for a maximum of two years. While this makes possible to calibrate a crop-water production function $y_i(w_i)$ using a combination of field data and agronomic model simulations (Peña-Haro et al., 2014) (see Section 4.1), insufficient longitudinal data on crop yield for alternative water application levels precludes the calculation of a variance and covariance matrix that differentiates between crop and water application levels. Alternatively, we can obtain the variance and covariance matrix using observed longitudinal data on yield per crop available in official statistics, which is obtained as total irrigated (rainfed if observed) crop production at an agricultural district level divided by the surface of that irrigated (rainfed) crop in that agricultural district (i.e. without distinguishing water application levels). This means we have only one (two, if the series is available for both rainfed and irrigated technique) longitudinal series per crop, instead of one longitudinal series per crop and water application level. Thus, risk avoidance is assumed to be the same for different levels of water applied for the same crop. This is a limitation of the model that can only be addressed with additional longitudinal data that is currently unavailable.

Hired labor avoidance (z_3) is measured as the difference between the labor requirements of the profit maximizing combination of land ($\overline{X}$) and water inputs ($\overline{W}$) minus the labor requirements of the alternative/simulated land (X) and water input (W) combination (recall attributes are defined so that "more-is-better"):

$$z_3\ (\boldsymbol{X}, \boldsymbol{W}) = \sum_i \overline{x_i} N_i(y_i(\overline{w_i})) - \sum_i x_i N_i(y_i(w_i)) \tag{25}$$

where:

$$N_i(y_i(w_i)) = g_i y_i + h_i \tag{26}$$

$$g_i = \left(N_{i,\ irrigated} - N_{i,\ rainfed}\right) / \left(\left(\max\left(y_i(w_i)\right)\right) - min\left(y_i(w_i)\right)\right) \tag{27}$$

$$h_i = N_{i,\ rainfed} \tag{28}$$

where $N_{i,\ irrigated}$ are the average values of longitudinal data on labor requirements (number of days) per hectare for crop i under irrigated agriculture, $N_{i,\ rainfed}$ are the average values of longitudinal data on labor requirements per hectare for crop i under rainfed agriculture. If no rainfed alternative is available for crop i, $\min(y_i(w_i))$ and $N_{i,\ rainfed}$ equal 0.

3.4. Data

Table 2 summarizes data inputs for the PMAUP and crop-water production function model and related data providers.

4. Results

4.1. Calibration results

4.1.1. Calibration of the crop-water production functions

Crop-water production functions for annual crops in the SLD (namely, wheat, barley, corn, onion, garlic) were generated combining field data and agronomic simulations using the GEPIC model (Liu et al., 2007), building on previous work by Peña-Haro et al. (2014) in the SLD.

Table 3
Calibration results of the crop-water production functions for the main crops in the SLD.

	a ($kg.\frac{ha}{m^6}$)	b ($\frac{kg}{m^3}$)	d ($\frac{kg}{ha}$)	Correlation
Wheat	-0.00111	4.9830	1788.0	0.72
Barley	-0.00081	3.5000	1700.0	0.96
Corn	-0.00033	5.5398	-5399.2	0.88
Garlic	-0.00010	2.7000	3511.3	0.98
Onion	-0.00159	27.7090	-35848.7	0.87
Almond	-0.00004	0.4553	302.2	0.96

Source: Own elaboration.

Table 4
Calibration results and calibration residuals of the PMAUP model.

Attribute (z_p)	z_1	z_2	z_3	e_m
Parameter value (α_p)	0.915	0.079	0.006	1.42%

Source: Own elaboration.

GEPIC is a distributed version of the EPIC model (Williams et al., 1983) through a loose coupling between ArcGis and the EPIC model. In our application to the SLD, GEPIC was calibrated using the outcomes of field experiments that assessed the effect of water applied on the yield of annual crops. Field experiments were conducted in 2000 and 2009 growing seasons at the experimental station "Las Tiesas" in the SLD (Fabeiro Cortés et al., 2003; ITAP, 2005). Paired values of crop yield per level of applied water in the field experiments v. modelled yield were compared using regression analysis in order to calibrate the production functions. Crop responses to different water application values in the different type of soils and climatic areas were simulated in order to generate enough variability to fit the coefficients of the crop-water production functions. Note that since the production of corn and onion is considered unfeasible under rainfed agriculture in the SLD, the *d* parameter adopts a negative value for these crops.

Since there are no process-based agronomic models that simulate ligneous crops, crop-water production functions for ligneous crops in the SLD (almond) were directly calibrated from observed data using the results of deficit irrigation field experiments developed by the ITAP near the SLD area (Jiménez et al., 2004). Accordingly, crop-water production functions for almond trees do not account for the complex impact and variability of different factors governing crop growth and yield other than water. We consider nonetheless that having a production function with limitations is preferrable to ignoring a relevant crop in the case study area, and therefore have chosen to include this production function in the model.

Calibration results for the crop-water production functions in the SLD are reported in the Table 3. The table also reports the correlation between the values estimated with the agronomic model and the ones simulated with the quadratic function: the values range from 0 (worst performance of the quadratic function) to 1 (best performance) (Peña-Haro et al., 2010). The reader is referred to Peña-Haro et al. (2014) for a more detailed discussion of the results, methods and a discussion on the precision of the calibrated model.

4.1.2. PMUAP model calibration

PMAUP model calibration results and residuals for the SLD are shown in Table 4.

The columns α_1, α_2 and α_3 display the parameter values of the Cobb-Douglas utility function for the attributes profit (z_1), risk avoidance (z_2) and hired labor avoidance (z_3), while e_m is the average calibration residual. Calibration results show that the most relevant attribute driving agents' decisions is profit. Risk avoidance has also a relevant role in explaining the behavior of irrigators in the SLD. The attribute measuring management complexity avoidance (z_3) is marginally relevant. Caution must be exercised in interpreting the results. For example, it cannot be inferred that a high risk avoidance parameter will yield a low profit variability, since choices are ultimately constrained by the feasible region. Nonetheless, attribute parameters offer valuable insights on agent's preferences and can serve to project behavior, provided calibration errors are low. In the case of the SLD, metrics for performance evaluation are satisfactory, with a "very low" average calibration residual (Pérez-Blanco et al., 2015).

4.2. Simulation results

We simulate a progressive increase of water prices in the SLD from 0 to 1 EUR/m^3 at 0.01 EUR/m^3 intervals. For each simulation run, we obtain the crop portfolio and water application responses by irrigators and calculate the compensating variation (i.e. monetized foregone utility), foregone income and water saved. Simulations are run using the model setting described in Section 3, which integrates the crop-water production function of irrigated crops into the objective function and allows for adjustments at the intensive, extensive and super-extensive margin (W-PMAUP). The results thus obtained are subsequently compared with those from an alternative classic PMAUP model setting (C-PMAUP) where the continuous agronomic production functions are substituted by point values that represent average expected production under irrigated and/or rainfed agriculture for each crop (i.e., a maximum of two points per crop), thus allowing only for extensive and super-extensive margin adjustments (Pérez-Blanco and Gutiérrez-Martín, 2017). The difference between the modeling outcomes from these two model settings reveals the net effect of intensive margin adjustments on the expected economic and environmental performance of water pricing. Note that only the W-PMAUP model is calibrated: the C-PMAUP model uses the same parameters obtained for the W-PMAUP, with different crop-water production functions (point values representing crop yield under rainfed and irrigated agriculture, instead of continuous crop-water production function). If we calibrated both models separately, considering a continuous production function for the W-PMAUP and point values for the C-PMAUP, calibration results would differ both because of the alternative model settings *and because of the different data inputs*. In reality, though, intensive margin adjustments are a feasible option, which is indeed frequently adopted by farmers in the SLD and elsewhere, meaning that any model calibrated on a database that

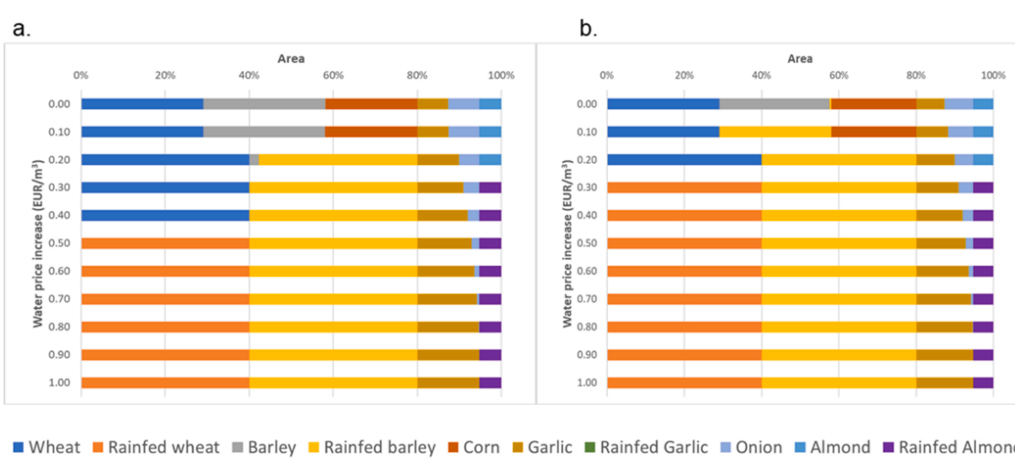

Fig. 3. Extensive and super-extensive margin adjustment (land allocation decisions) in W-PMAUP (a.) and in C-PMAUP model setting (b.) Source: own elaboration.

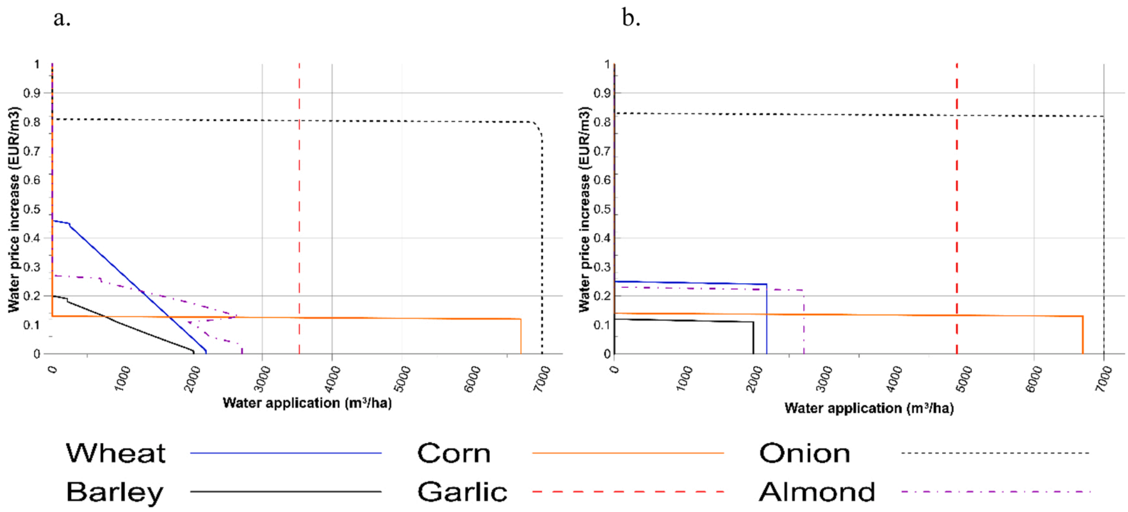

Fig. 4. Intensive margin adjustment (water application decisions) in W-PMAUP (a.) and C-PMAUP model setting (b.) Source: own elaboration.

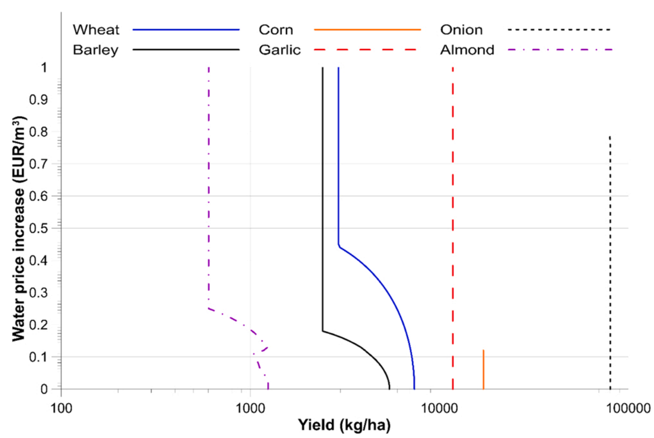

Fig. 5. Yield (kg/ha) per crop in the W-PMAUP model setting under alternative water prices (logarithmic scale).
Source: own elaboration.

excludes this option would incur in data measurement errors. Therefore, we use a single database (the one closer to observed irrigators' decisions, which includes continuous agronomic crop-water production functions) and, once the model is calibrated (W-PMAUP), we replace the continuous agronomic production functions by point values (C-PMAUP) to compare simulation outcomes with both settings, and thus reveal the net effect of intensive margin adjustments.

Fig. 3 and Fig. 4 represent agents' responses to incremental water pricing under the W-PMAUP and C-PMAUP model settings. In terms of land allocation to alternative crops (extensive and super-extensive margin adjustments), both model settings show similar responses in every simulation run (see Fig. 3); albeit dissimilarities arise regarding water application to crops (intensive water adjustment) (Fig. 4). Under the W-PMAUP model setting, agents can respond to higher prices by progressively decreasing the amount of water applied to irrigated crops (deficit irrigation). Deficit irrigation is observed in the W-PMAUP model for all crops with the exception of garlic, the most profitable crop in the case study area, which is fully irrigated in all simulations; and water intensive corn, for which irrigation abruptly stops in both models after a charge increase of 0.13 EUR/m^3. On the other hand, in the C-PMAUP model agents are constrained to apply water in fixed proportions to land, meaning that intensive margin adjustments are not possible and crops receive a constant amount of water inputs until abruptly interrupting irrigation and shifting to rainfed agriculture.

According to Graveline and Mérel (2014), there are three critical factors conditioning intensive margin adjustments: (i) water intensity (water-intensive crops are those that can contribute more significantly towards water saving); (ii) yield elasticity to water use (the higher yield elasticity to water use, the lower deficit irrigation is observed); and (iii) profitability (crops with higher profit will be less affected by deficit irrigation). It can be observed that these three factors explain water application responses to pricing in the W-PMAUP model setting. Garlic, the most profitable crop, can afford a price increase of up to 1 EUR/m^3 without applying deficit irrigation (i.e. a 600–1000% increase in the volumetric cost of water as compared to the observed groundwater pumping costs of 0.1–0.20 EUR/m^3); while in the case of onion, the second most profitable crop, water applied per hectare remains constant until a charge increase of 0.78 EUR/m^3 (a 490–780% water cost increase), at which point onion is replaced by other crops (with deficit irrigation briefly applied in the interim). Barley and wheat are the crops with the lowest yield elasticity to water use; accordingly, deficit irrigation is observed from the initial water price increases, until both crops eventually shift to rainfed agriculture, which happens at a water charge increase of 0.19 (barley) and 0.44 EUR/m^3 (wheat). Almond starts deficit irrigation in the initial simulation runs, with a slight rebound at a 0.12 EUR/m^3 price increase due to a substitution effect with corn. In the case of corn, the high yield elasticity to water application overtakes all the other effects, meaning that irrigated corn is abruptly substituted by less water-intensive crops without intermediary deficit irrigation at a charge increase of 0.12 EUR/m^3.

The possibility to adapt at the intensive margin in the W-PMAUP setting means crop yield per hectare is not constant anymore across the alternative price simulations, as happens in models where water input is applied in fixed proportions to land (C-PMAUP setting). Fig. 5 shows how different water application choices affect yield (in kg/ha) for each crop under the W-PMAUP model setting. For those crops that can be cultivated under rainfed agriculture (wheat, barley and almond), irrigation water is progressively diminished and yield reduces, until irrigation stops altogether and yield equates that under rainfed agriculture.

Fig. 6 shows the water demand curve representing the relationship between water prices and water application, for both the W-PMAUP and C-PMAUP model settings. Simulation results using the C-PMAUP model setting displays a "jumpy" behavior with (quasi-)inelastic responses in the initial and final stretches of the demand function. This outcome is consistent with those coming from the literature on agricultural water pricing under scarcity, where the model structures adopted also ignore deficit irrigation/intensive margin adjustments. On the other hand, the

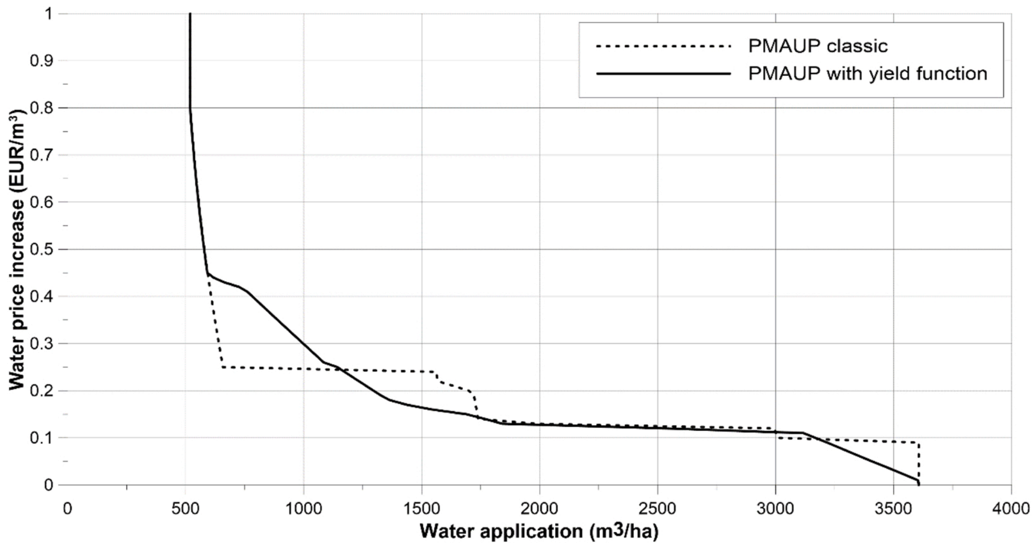

Fig. 6. Agricultural water demand curve.
Source: own elaboration.

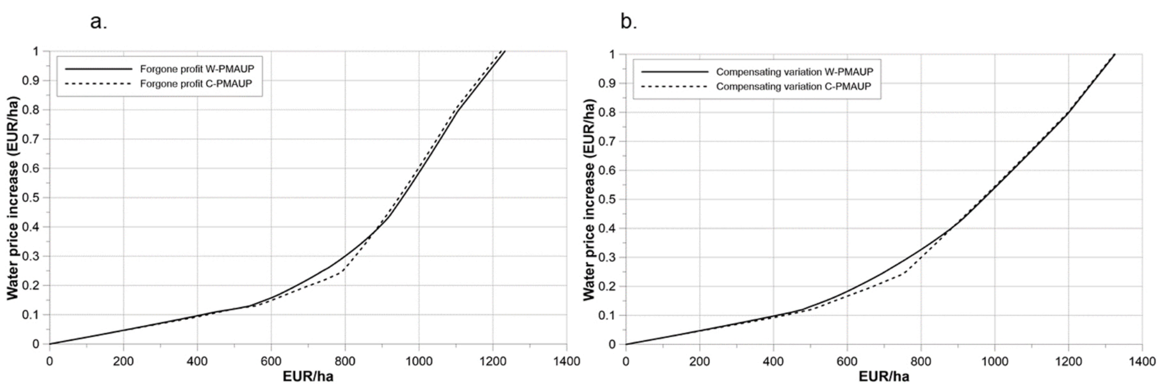

Fig. 7. Forgone profit (a.) and compensating variation (b.), water charges.
Source: own elaboration.

W-PMAUP model setting that allows for deficit irrigation displays a gradual reduction in water use along with higher prices in the initial and middle stretches of the demand function, and a quasi-inelastic response for a price increase of 0.43 EUR/m^3 or higher. This result suggests that having (or not) quasi-inelastic responses in the initial and middle stretches of the demand function is conditional on the model structure/settings choice. The upshot is that where intensive margin adaptation responses are possible in the model, water pricing is cost-effective towards water saving in the initial stretches of the demand function, which thus far have been often assumed to be inelastic. For example, a price increase of 0.09 EUR/m^3, which represents a non-trivial price increase of 45%– 90% in the SLD, is ineffective towards water saving in the C-PMAUP, but can save up to 390 m^3/ha (11% of the average water application of 3606 m^3/ha) in the W-PMAUP model setting. In addition, quasi-inelastic responses in the final stretches of the demand function, while appearing in both model settings, emerge at higher prices in the W-PMAUP (from 0.43 EUR/m^3) as compared to the C-PMAUP model setting (from 0.25 EUR/m^3).

Fig. 7 reports the economic impact of higher prices in terms of foregone profit (a.) and the monetized utility loss or compensating variation (b.), i.e. the amount of money the irrigator would need to achieve his initial utility following price increases. The compensating variation is consistently higher for the C-PMAUP model setting in all simulations, indicating a larger utility loss as compared to the W-PMAUP model setting, which is particularly visible in the charge increase interval between 0.1 EUR/m^3 and 0.4 EUR/m^3 (between 1% and 8% higher compensating variation in the C-PMAUP than in the W-PMAUP model setting). A similar outcome is observed for the foregone profit, which again is higher in the C-PMAUP model setting up to 0.4 EUR/m^3 increase, with a marked gap in the 0.1 EUR/m^3 - 0.4 EUR/m^3 interval (between 0.7% and 8.3% higher foregone income in the C-PMAUP than in the W-PMAUP model setting). The superior economic performance under the W-PMAUP setting is attributable to the increased number of adaptive responses available in the W-PMAUP as compared to the C-PMAUP and reveals the net effect of intensive margin adjustments on economic outputs.

5. Conclusion

This paper integrates a continuous crop-water production function into a PMAUP model to assess the influence of intensive margin adjustments on the expected water saving and economic performance of water pricing. The model is calibrated for an agricultural area in a water scarce agricultural area in southeastern Spain (El Salobral-Los Llanos in the Júcar River Basin), so to factor in climatic, soil and other local factors conditioning the crop yield-water input relationship. Results reveal non-trivial dissimilarities in the economic and water saving performance of the W-PMAUP (intensive, extensive and super-extensive margin adjustments) and C-PMAUP (only extensive and super-extensive margin adjustments) model settings. The quasi-inelastic responses in the initial and middle stretches of the C-PMAUP demand function, which are consistent with findings in the literature on water charges in water scarce areas, are transformed into elastic responses in the W-PMAUP, suggesting a more cost-effective contribution of water pricing towards water saving. Ignoring intensive margin adjustments also tends to overestimate the economic impact of water pricing, with a higher foregone profit and compensating variation obtained in the C-PMAUP model setting as compared to the W-PMAUP model setting in all simulation runs. The compensating variation (foregone profit) is up to 1%–8% (0.7%–8.3%) higher in the C-PMAUP than in the W-PMAUP model setting for the water price increase range 80%– 200%. Given that deficit irrigation is a commonly used adaptation response in the SLD, we argue that ignoring it may not accurately reflect the actual adaptation options available to irrigators, and recommend the use of WPM that integrate crop-water production functions.

The model proposed in this paper can be improved in several ways. Future efforts should aim at gathering longitudinal data on yields for alternative water application levels with high granularity through remote sensing, surveys, field experiments or other means, so to build increasingly accurate site-specific crop-water production functions and more detailed utility-relevant attributes (e.g. through the development of a variance and covariance matrix that differentiates between crop types and water application in the risk avoidance attribute). This will facilitate the application of the model and replication of the experiments elsewhere, a prerequisite to validate the preliminary findings obtained for our case study area in the SLD. Note that although calibration residuals are low in the case study area, performance may be less satisfactory elsewhere, which calls for exploring alternative/additional attributes (e.g. alternative definitions of the management complexity avoidance attribute) and more comprehensive and spatially detailed data (such as water use data) to better define the feasible region, e.g. leveraging on earth observation and in situ monitoring, digital data acquisition and management and predictive analytics. Furthermore, other input (e.g., fertilizer) could be introduced in the production function to consider other aspects of the complex mechanism that govern crop growth and yield, even though this goes beyond the object of this paper, which is to test the performance of a crop-water production function in saving water through pricing. Building multi-model ensemble experiments combining multiple WPM that allow for intensive margin adjustments can help us sample modeling uncertainty and establish confidence intervals for the environmental and economic performance of alternative water conservation policies (Sapino et al., 2020). Beyond multi-model ensembles, decision-making should be also informed by multiple scenarios that complement the pricing simulations in our model, which may in turn reveal far-reaching and under-recognized implications for our policy (Pannell, 2006). For example, our findings rely on the assumption that both water charges *and water allocations* are effectively enforced; however, where agents can resort to alternative sources of water (e.g., through illegal aquifer withdrawals), higher charges may lead to an increase in the use of alternative sources (which calls for complementary policies, such as use of remote sensing and penalties in the case of water theft) (Loch et al., 2020b). Coupling the proposed PMAUP model with a hydrologic model and a river basin management model is also necessary to assess the environmental impacts of water conservation across space, thus supporting the identification of potential distributive issues (e.g. upstream v. downstream water conservation). Finally, accurate estimates on the environmental and resource costs of water are needed to design realistic water pricing scenarios that substitute the hypothesized scenarios adopted in our simulations; albeit these costs are at present difficult to obtain given that there are "few standardized methods" to measure the economic value of water, and there are often "large differences between values obtained through different methods" (UN, 2021b).

Declaration of Competing Interest

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

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