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Review

An ensemble experiment of mathematical programming models to assess socio-economic effects of agricultural water pricing reform in the Piedmont Region, Italy

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A R T I C L E I N F O

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A B S T R A C T

The Piedmont Region in NW Italy has recently deployed an ambitious and pioneering agricultural water pricing reform aimed at integrating and effectively enforcing EU's Water Framework Directive principles of cost recovery, polluter-pays and affordability. This paper develops a multi-model ensemble framework encompassing 5 mathematical programming models (2 Positive Mathematical Programming models, 2 Positive Multi-Attribute Utility Programming models and 1 Weighted Goal Programming model) that represent the observed behavior of socioeconomic agents to: 1) simulate the impacts of the Piedmontese water pricing reform on land use allocation and management, water conservation, profit and water tariff revenue; 2) sample modeling uncertainty through the ensemble spread; and 3) explore potential tipping points through use of scenario-discovery techniques. Our research suggests that the key challenge to the reform lies in the management of rice fields, an extensive (17% of the agricultural area), water-demanding and relatively low-added-value crop that nonetheless delivers significant ecosystem services (e.g. water retention) of historical and cultural relevance to the region. The ensemble experiment suggests that rice agriculture rapidly dwindles in the price range 0.012–0.074 EUR/m^3 depending on the model. Before reaching this tipping point, agricultural water pricing can reduce withdrawals up to 1.7%–9.5%, while reducing profit between 4.9% and 5.6% and achieving a 57- to 65-fold increase in water tariff revenue.

1. Introduction

Water scarcity and related crises are among the greatest global societal threats (WEF, 2019). In Europe, water scarcity is particularly felt in the closed or closing basins along the Mediterranean Basin, where inelastic water supply increasingly often falls short of commitments to fulfill growing demand. Restoring the balance in overallocated Mediterranean basins will necessitate demand-side policies that reallocate available resources from commercial uses to the environment while enabling economic growth and increasing social welfare. One such policy is pricing, the only demand-side instrument explicitly mentioned in the EU legal *acquis*. In its Article 9, the EU Water Framework Directive (WFD) 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). Despite this solid legislative basis, the implementation of pricing policies in the EU has been sluggish, also in the agricultural sector, the largest human water use (EEA, 2013). Agricultural water prices are often set independently of the volume used (e.g. on a per area basis) and present low cost-recovery ratios, which prevents incentive-pricing water conservation and reallocation to higher value uses. Although EU bodies have reacted to member states institutional paralysis with lawsuits, ruling from EU judiciary has been dichotomic (Jääskinen, 2014). As a result, 20 years after the adoption of the WFD, no member state in Southern Europe has *implemented* an agricultural water pricing reform that integrates the principles of cost recovery, polluter-pays and affordability as stated in the WFD (Rey et al., 2018).

The Piedmont Region in Northern Italy is set to change this trajectory. On July 24th, 2017, the Piedmont Region introduced two additional *ex-ante conditionalities* to access critical EU's Common

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Agricultural Policy (CAP) funding, namely, i) "harmonization of the methods for quantifying irrigation water withdrawals and effective collection, communication and management of this data", including the compulsory adoption of metering devices; and ii) "introduction of environmental and resource costs in the calculation of water prices", while "observing affordability principle" (Regione Piemonte, 2017). Users not observing the additional *ex-ante conditionalities* will not have access to critical CAP funding. It should be noted that in Italy, regional authorities issue, monitor and enforce water abstraction rights and set the corresponding prices; with national institutions and the relevant river basin authority (the Po River Basin Authority in the case of Piedmont) playing a secondary, advisory role (for a detailed description of the water allocation system in Italy and Piedmont the reader may refer to Santato et al., 2016). Under the current water abstraction regime, agricultural licenses are issued by the Piedmont Region for a maximum of 40 years, and prices are set on a per area basis (average charge: 1.22 EUR/ha) or based on the average flow rate capacity (0.56 EUR/l/s). Piedmont's agricultural water pricing reform is set to transition from the current pricing structure to a fully metered system (EUR/m^3). The new pricing structure, which is available in Regione Piemonte (2017), is based on a comprehensive methodology that first estimates the financial, environmental and resource costs of agricultural water use to then elicit the price increase that would enable a predefined cost recovery ratio; where the targeted cost recovery ratio is set based on a discretionary expert judgement that factors in affordability/disproportionate costs issues.

Recent institutional reports using this methodology foresee an average agricultural water price increase from a 0.00012 EUR/m^3 equivalent under the current pricing structure up to 0.013 EUR/m^3, which is expected to increase the contribution of agriculture to the region's water pricing revenues from less than 1% up to 32% (Frontuto et al., 2020). Noteworthy, the 0.013 EUR/m^3 price increase is set based on experts' opinion: beyond this point the impact of the pricing reform, albeit still moderate in terms of foregone income, is expected to have significant and potentially irreversible impacts on the structure of traditional irrigated agriculture (i.e. rice) and related (ecosystem) processes and services, which are regarded as *disproportionate costs* (Frontuto et al., 2020). Naturally this subjective pricing target needs to be further substantiated through a more profound assessment of irrigators' responses and their impact on economic and environmental (i.e. water conservation) performance, the tradeoffs observed between these two variables, and an analysis of disproportionate costs. To this end, Regione Piemonte and three academic institutions (Università di Torino in Italy, and Universidad de Salamanca and Universidad de Córdoba in Spain) have partnered to develop a comprehensive database and calibrate 5 mathematical programming models that represent the observed behavior of socioeconomic agents in an innovative multi-model ensemble experiment, in order to: 1) simulate the impacts of water pricing reform on land use allocation and management, water conservation, employment, profit and water tariff revenue; 2) sample uncertainty through the model spread (Cloke et al., 2013; IPCC, 2014); and 3) explore potential tipping points, with a focus on rice systems, through a scenario-discovery approach (Marchau et al., 2019). Unlike conventional consolidative modeling based on a single model and a complete probabilistic description of future scenarios, the ensemble experiment offers the advantage of providing policymakers with a more comprehensive overview of possible responses through stress test (alternative forcings/scenarios and models). Outputs from multi-model ensemble and scenario-discovery techniques can in turn be used to identify no-regret water pricing policies through robust decision making methods (Marchau et al., 2019).

The paper is structured as follows: Section 2 introduces the case study area, the Piedmont Region in the northwest of Italy; Section 3 presents the multi-model ensemble framework; Sections 4 and 5 present and discuss, respectively, the results achieved; and Section 6 concludes.

2. Case study area: The Piedmont Region in Italy

The Piedmont Region is located in the Northwest of Italy, has a population of 4,392,526 (2017) and spreads over 25,387 km^2 (Eurostat, 2017). The region is located within the Po River Basin District (PRBD), the largest (24% of Italian territory and 21% of its agricultural area) and most economically relevant Italian river basin (35% of Italian GDP and 30% of agricultural Gross Value Added (GVA)). The region comprises the upper stretches of the PRBD and 43% of its territory is classified as mountainous area (mostly the Alps), making the Piedmont Region a relatively water-abundant basin capable of supporting a water-intensive agriculture comprising 396,000 ha and largely based on annual crops such as rice, corn and cereal fodders (70% of Piedmont's agricultural area). Rice, which is supplied through the third largest artificial watercourse in Italy, the Canale Cavour, with a flow rate of 110 m^3/s and a length of 83 km, is the most iconic crop of the region. Piedmont's rice represents 52% of total production of Italy, which is in turn the largest rice producer in Europe (ISTAT, 2016), and is the largest water user in the region (nearly 31,500 m^3/ha on average) (Augusti et al., 2018), although its profit-to-water use ratio is relatively low compared to that of other crops in the region (1300 EUR/ha on average, as compared to e.g. 1200 EUR/ha profit and 3400 m^3/ha water use for corn) (INEA, 2018). Besides its market relevance, rice supplies relevant ecosystem services, most notably water retention services during the Po River's discharge peak in the spring, with subsequent water release throughout the summer season (about 150 m^3/s discharge in July), which is made available for other uses (Director of the Est Sesia Land Reclamation and Irrigation Board, 2019); but also historical and cultural services (rice production and the construction of related water draining and supply infrastructure in the Piedmont Region started in the mid-15th century) and aesthetic values, with rice fields defining the characteristic range of colors of the Piedmontese plains (blue in spring, green in summer, yellow in early autumn). Grassland is the most relevant crop in mountainous areas and represents 8% of Piedmont's agricultural area. Among permanent crops (12% of agricultural area) vineyard stands out, with the Piedmont Region representing 12% of Italian DOC[1] wine production (see Fig. 1).

Agriculture represents 3.5% of the Piedmontese GVA, above the national average of 2.8% (Banca D'Italia, 2018), and 75%+ of the regional water withdrawals, approximately 5000 million m^3/y (Regione Piemonte, 2018). Agricultural water use has significantly increased during the last 50 years due to wide-scale adoption of irrigated fodder and corn. This is coupled with a sustained reduction in average precipitation and in the number of rainfall days, and retreating Alps' glaciers (Regione Piemonte, 2018). As a result, the basin-wide water exploitation index (ratio of withdrawals to renewable resources) has increased from less than 20% (no water stress) to between 35% and 65% (severe water stress) over the last two decades (EEA, 2016). ARPA Piemonte (2018) estimates that half of Piedmont Region water bodies are already affected by water scarcity during the irrigation campaign and do not reach the good ecological status. Scarcity is amplified downstream in the PRBD, where more vulnerable regions dependent on the runoff generated within the Piedmont Region, such as the Emilia Romagna Region, are located.

3. Methods: the multi-model ensemble

Conventional consolidative modeling relies on a known set of possible states and related probabilities to identify a single optimal strategy through optimization in a single-model environment. Learning is acquired through observation, interpreting signals that constrain the set of possible states and updating probabilities according to Bayes' rule;

[1] *Denominazione di Origine Controllata* (controlled designation of origin): quality assurance for Italian wine.

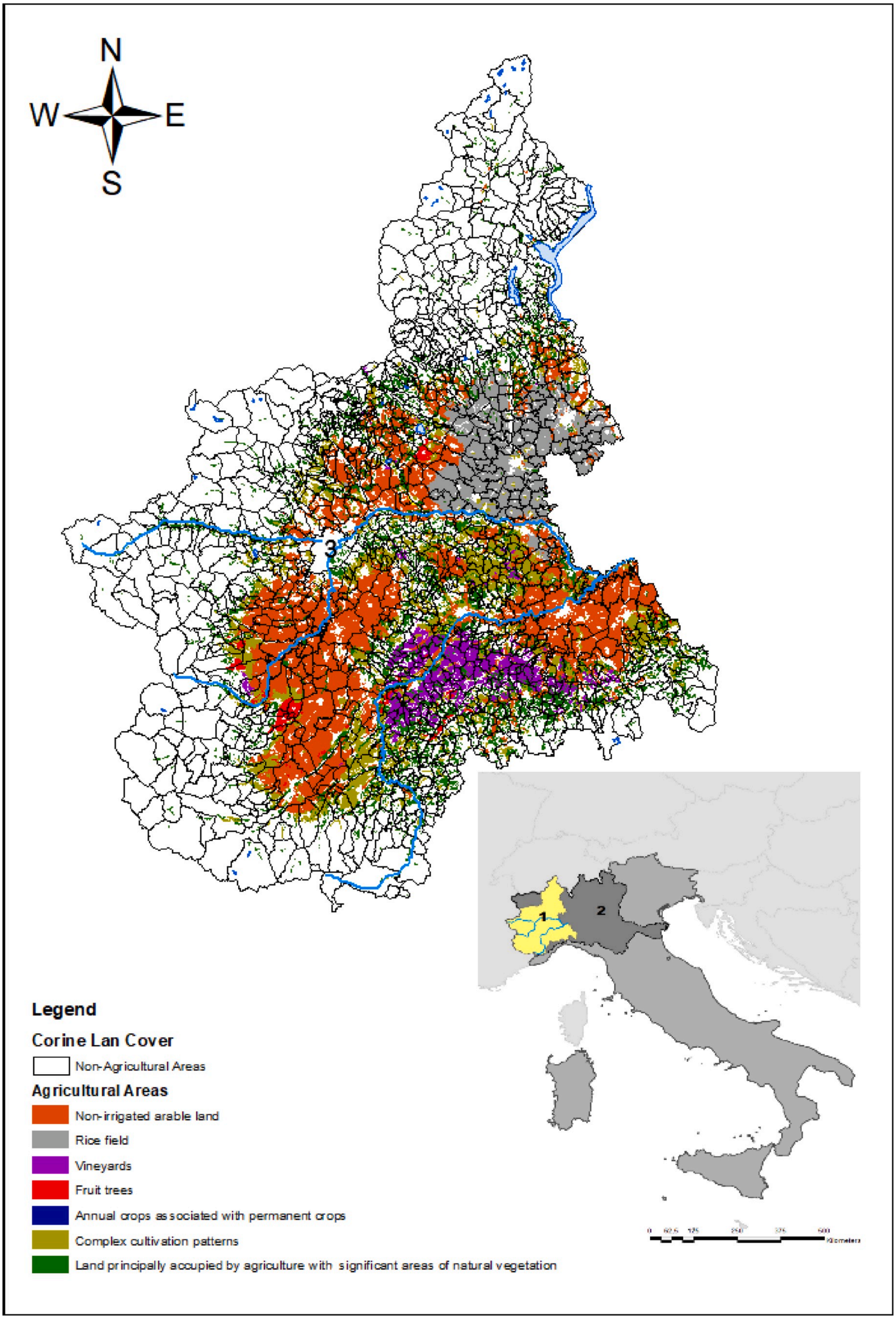

Fig. 1. Location of the Piedmont Region in Italy and detail of agricultural land use.
Legend: 1 Piedmont region, 2 Po River Basin District, 3 Po River.
Source: own elaboration from CORINE land cover (EEA, 2018).

and revising model design in order to better represent observed decisions. However, modeling errors arising from "parameter and structural uncertainties in the model design" (Tebaldi and Knutti, 2007) and the "impossible task" (Marchau et al., 2019) of accurately forecasting all possible future states in non-mechanistic complex socio-ecological systems imply that conventional consolidative modeling may not be capable of predicting contingencies arising from policy choices (Hino and Hall, 2017), including catastrophic and potentially irreversible outcomes (tipping points). In our research, modeling and scenario uncertainties are addressed through: i) a multi-model ensemble framework that samples modeling uncertainty through the model spread (this section); and ii) the use of scenario-discovery techniques to relate alternative simulation scenarios (water pricing scenarios in this case) to their implied consequences (see Section 4.1) (Marchau et al., 2019). The ensemble is populated with 5 positive economic calibrated models: 2 Positive Mathematical Programming (PMP) models, 2 Positive Multi-Attribute Utility Programming (PMAUP) models and 1 Weighted Goal Programming (WGP) model. The following sub-sections present the basics of the 3 modeling families and the 5 models considered. For a more detailed description of each ensemble component, the reader may refer to Howitt (1995) and Júdez et al. (2002) (PMP) (Gómez-Limón et al., 2016; Gutiérrez-Martín and Gómez, 2011); (PMAUP); and Sumpsi et al. (1997) (WGP).

3.1. Economic calibrated models: objective function and domain

Economic calibrated models for agricultural water management represent the pattern of yields, revenues and costs at different scales, from farm to agricultural district (Harou et al., 2009). In these models, agents (clusters in our application to the Piedmont Region, see Section 3.5) decide on crop mix and timing, investments and water application in an optimization framework that aims to maximize a single or multi-attribute objective function within a domain. This complex choice is usually "reduced to a decision on the crop portfolio", where each solution represents a "unique combination of crop, timing, investments and water application" (Pérez-Blanco et al., 2017). The general formulation of the utility maximization problem is as follows:

$$Max\ U(\mathbf{X}) = (f(z_1(\mathbf{X}), \ldots, z_p(\mathbf{X}), \ldots, z_m(\mathbf{X})) \tag{1}$$

Subject to:

$$x_i \geq 0 \tag{2}$$

$$\sum_{i=1}^{n} x_i = 1 \tag{3}$$

$$\mathbf{X} \in F \tag{4}$$

$$\mathbf{X} \in \mathbb{R}^n \tag{5}$$

$$z_1(\mathbf{X}), \ldots, z_m(\mathbf{X}) = \mathbf{Z}(\mathbf{X}) \in \mathbb{R}^m \tag{6}$$

where $U(\mathbf{X})$ is the utility/objective function.

Agents in the model decide on the *crop portfolio* $\mathbf{X} \in \mathbb{R}^n$, a vector representing the fraction of land allotted to each one of the n individual crops available x_i $(i = 1, \ldots, n)$, so to maximize utility through the provision of utility-relevant attributes $z_1(\mathbf{X}), \ldots, z_m(\mathbf{X})$ (i.e. there are up to m relevant attributes), such as profit or avoided risk. Each attribute $z_1(\mathbf{X})$, …, $z_m(\mathbf{X}) \in \mathbf{Z}(\mathbf{X})$in the model is defined so that "more-is-better", i.e. increasing the provision of one attribute while keeping the provision of the remaining attributes constant increases utility. Accordingly, "less-is-better" attributes such as risk or management complexity are transformed into avoided risk/management complexity. Note that each crop portfolio $\mathbf{X}$ yields a *unique* provision of attributes $z_1(\mathbf{X})$, …, $z_m(\mathbf{X})$. Rational agents in the model will choose the crop portfolio that yields the provision of utility-relevant attributes that maximizes utility within the domain F.

The individual attributes that conform the attribute set $\mathbf{Z}(\mathbf{X})$ used in the calibration and simulation of the models are described in the following paragraphs. We explored the relevance of three attributes in the ensemble, namely: expected gross variable margin (z_1), risk avoidance (z_2) and total labor avoidance (z_3), a proxy for management complexity.

- Expected profit, measured as the expected gross variable margin (z_1). This is the only attribute considered in single-attribute mathematical programming models (PMP models in this ensemble). It is obtained as the summation of the expected per hectare gross margin of each crop π_i (obtained as price (in EUR/kg) times yield (in kg/ha) plus coupled subsidies minus the variable costs (in EUR/ha)) multiplied by that crop's land share (x_i):

$$z_1(\mathbf{X}) = \sum_i x_i \overline{\pi}_i \tag{7}$$

where $\overline{\pi}_i$ is the average gross margin for each crop i in the period 2008–2016, i.e. the summation of the observed gross margin of crop i for every year during the period 2008–2016, divided by the number of years with available data in the series. In the case of PMP models, an additional shadow cost is added to profit during calibration. Note that all variables used to calculate profit (prices, yield, subsidies, costs) are exogenous. In the case of prices, this implies that crops' demand is perfectly elastic. Such "small open economy assumption" (Schöb, 1998) is consistent with EU reports showing that "patterns of crop price variations are similar for all member states" (Kampas and Rozakis, 2017). Admittedly, regional differences in prices may arise, especially in face of asymmetric shocks such as the pricing policy discussed here. This could be modeled e.g. coupling the ensemble framework presented in this paper with a general equilibrium macroeconomic model (Parrado et al., 2019). The development of a multi-system ensemble goes beyond the scope of the present research; we nonetheless reflect on this in the conclusions, where we propose a multi-model and multi-system ensemble as a means to explicitly model crops' demand and prices endogenously, while accounting for modeling and scenario uncertainty.

- Risk avoidance (z_2), measured as the difference between the profit variability of the profit maximizing crop portfolio $\widehat{\mathbf{X}}$ and that of an alternative crop portfolio $\mathbf{X}$ (Bartolini et al., 2007):

$$z_2\ (\mathbf{X}) = \widehat{\mathbf{X}}^t VCV(\pi)\widehat{\mathbf{X}} - \mathbf{X}^t VCV(\pi)\mathbf{X} \tag{8}$$

where $VCV(\pi)$ is the variance and covariance matrix of profit in the time period for which data is available (2008–2016). The first term in the right-hand side of the equation, $\widehat{\mathbf{X}}^t VCV(\pi)\widehat{\mathbf{X}}$, yields the risk of the profit maximizing crop portfolio, while the second term, $\mathbf{X}^t VCV(\pi)\mathbf{X}$, yields the risk of the observed crop portfolio. Provided there is a tradeoff between risk and profit (the higher the profit, the higher the risk) (Gutiérrez-Martín and Gómez, 2011), risk avoidance ($z_2\ (\mathbf{X})$) will be positive.

- Total labor avoidance (z_3), a *proxy* for management complexity avoidance (Bartolini et al., 2007; Sumpsi et al., 1997) measured here as the difference between the total (family plus hired labor) expected (i.e. multi-annual average) labor requirements of the crop portfolio with the highest possible labor requirements within the domain, $\overline{\mathbf{X}}$, and those of an alternative crop portfolio $\mathbf{X}$.

$$z_3\ (\mathbf{X}) = \sum_i \overline{x_i} N_i - \sum_i x_i N_i \tag{9}$$

where N_i is the expected total labor requirements per hectare of crop i.

Note that in PMP models profit is the only utility-relevant attribute explored in the objective function, while the WGP and the two PMAUP models also explore the relevance of risk and management complexity aversion (multi-attribute). Accordingly, some of the constraints that conform the domain are not applicable/binding to all models, i.e. those referring to risk aversion and management complexity attributes do not apply in single-attribute PMP models.

The set of constraints that conform the domain F used in the calibration and simulation of the models are described in the following paragraphs.

- *Land availability.* Available agricultural land is assumed constant and equals the summation of observed agricultural land uses (see equations (2) and (3)).
- *Water availability.* It is assumed that water abstraction licenses remain constant before and after every simulation run, i.e.:

$$\sum_{i=1}^{n} w_i x_i \leq w \tag{10}$$

where w_i is crop i's specific water requirements and w is the total water allotment in the Piedmont Region.

- *Climate and soil.* Since each agricultural area/climatic region has its own soil and climatic characteristics, agents in the model can only grow those crops that are observable in the database (Essenfelder et al., 2018).

$$\sum_{i=1}^{n} y_i x_i = 0 \,\middle|\, y_i \in \{0,1\} \tag{11}$$

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

- *Crop-specific constraints.* Some crops in the portfolio have an upper and/or lower area bound because of specific policy restrictions. In our application to the Piedmont Region, this restriction is used to set a minimum/maximum threshold for ligneous trees of ±5%. Admittedly, since the pricing policy instrument is designed to work in the long run, it could result in major crop portfolio changes involving permanent crops, which could eventually go beyond the 5% threshold. On the other hand, the reduction or expansion in the acreage of permanent crops beyond the 5% threshold would result in significant (dis)investments with potentially large impacts on e.g. carbon sequestration, whose economic value is not accounted for in the models, which focus on yearly market variables (notably profit) (Essenfelder et al., 2018). Accurately modeling agent's responses in terms of permanent crops necessitates the inclusion of other relevant variables, notably carbon prices and/or Payments for Ecosystem Services, which are at present being tested in the European context; yet, this is beyond the scope of this paper. Against this backdrop, setting a minimum/maximum threshold for ligneous trees is common practice in the literature (Gutiérrez-Martín and Gómez, 2011; Parrado et al., 2019).
- *Crop rotation.* In some cases, it is possible to observe that two or more crops rotate with each other. For example, if farmers in an area yearly rotate wheat with sunflower, aggregation over a sufficient number of farms (e.g. at a municipality level) typically results in a similar surface of wheat and sunflower (Gómez-Limón et al., 2016). Accordingly, the surface of wheat in the simulations cannot exceed the surface of sunflower, and vice versa. If the surface of sunflower (wheat) becomes binding and decreases below the surface of wheat (sunflower) (e.g. due to higher water prices), the surface of wheat (sunflower) must decrease to match that of sunflower.

3.2. Calibration

Economic calibrated models follow an inductive approach that aims to eliciting the parameters of an objective/utility function capable of reproducing observed agents' choices within a domain/set of constraints, in order to accurately predict future responses to policy shocks through simulation. Noteworthy, each modeling family considered explores one specific functional form for the objective function: additive (WGP), Cobb-Douglas (PMAUP) and quadratic (PMP).

The **WGP** approach used in our ensemble framework relies on the calibration method developed by Sumpsi et al. (1997) to elicit the parameters of a multi-attribute, additive objective function. Note that due to the definition of the attributes above, our application includes a non-linear component in the additive objective function through the risk attribute. WGP allows for both single- and multi-attribute specifications, which makes the approach consistent with the Theory of Planned Behavior (TPB) (Ajzen, 1991). The TPB argues that decision-making is driven by "the multiple attributes of objects (including but not limited to profit) and farmers' beliefs regarding these attributes" (Pérez-Blanco et al., 2017). TPB's theoretical construct is substantiated by a large body of empirical research on the relevance that attributes other than profit, such as risk aversion or management complexity aversion, have in explaining agent's behavior and choices (see e.g. Gómez-Limón et al. (2016)). On the other hand, use of an additive function may lead to over-specialized responses and even corner solutions: the agent sets the crop that delivers highest utility at the maximum level until a binding constraint prevents further specialization, which often results in a characteristic "jumpy behavior" (Graveline, 2016).

PMP is possibly the most popular economic calibrated model to assess the behavior of agricultural agents, and irrigators in particular (Graveline, 2016). PMP relies on non-linear objective functions to calibrate and accurately reproduce observed agent behavior. Through the use of non-linear functions, PMP avoids unrealistic outcomes such as corner solutions or abrupt discontinuities in agent's responses, yielding instead smooth calibration results (Howitt, 1995). Due to these obvious advantages, PMP has been consistently used to assess agricultural and water policies, including water pricing, in several regions worldwide (Graveline, 2016). PMP calibration uses "information contained in dual variables of calibration constraints, which bound the solution of the original linear programming problem to observed activity levels" to "specify a non-linear objective function such that observed activity levels are reproduced by the optimal solution of the new programming problem without bounds" (Heckelei and Britz, 2005). This is done in three steps: (i) an additional area constraint that bounds the model calibration results to observed choices is introduced in the domain and the dual values associated to the constraint for each crop obtained; (ii) these dual values are used to add a non-linear component to the utility function (typically a quadratic cost function, or shadow cost); and (iii) the utility non-linear function obtained in (ii) is maximized subject to a similar set of constraints to those considered in the original problem, which perfectly reproduces the observed agent's behavior (Henry de Frahan et al., 2007). The main critique to PMP modeling regards the challenge of providing an "economic or technological rationale for the non-linear terms in the objective function" (Heckelei et al., 2012). As a result, a modeler needs to resort to *ad-hoc* arguments to elucidate the outcomes of PMP models following a policy shock (Graveline, 2016). Moreover, while PMP has modeled risk aversion in a single-attribute environment through the use of mean-variance approach, its single-attribute approach struggles to explicitly measure and account for the utility-relevance of alternative attributes such as management complexity aversion. The ensemble framework in this paper relies on the classic calibration method (PMP_1) (Howitt, 1995) and a variation proposed by Júdez et al. (2002), that skips the first step using the average rent of land as dual value (PMP_2).

PMAUP models "build on the axioms of revealed preference to construct a multi-attribute objective function that is both consistent with an observed (and finite) set of choices and prices and suitable as a basis for empirical analysis" (Parrado et al., 2019). PMAUP replaces the dual variables that would traditionally be added to the objective function to make calibration possible in PMP with agent's preference parameters represented as shares of a non-linear (typically Cobb-Douglas) utility function, the arguments of which are competing attributes (e.g. profits v. avoided management complexity). PMAUP is a data and computationally intensive approach consistent with the TPB that has been used to empirically explore the relevance of attributes other than profit (Gómez-Limón et al., 2016; Gutiérrez-Martín and Gómez, 2011), particularly during the last decade, propelled by expanding frontiers in computational power and micro-data. Yet, since only observed behavior is used as an input and assumptions are limited (no engineering-based yield functions, no assumptions of fixed proportions, no limitation to profits as the sole relevant attribute of farmers), the calibration of PMAUP models is challenging where there is a large number of choice variables (several alternatives in the crop portfolio) and cross-sectional variation is low (time-series variation might be confounded with other trends), which may lead to some instability in the model calibration that is difficult to rationalize (e.g. abrupt changes in parameter values following the introduction of an additional attribute). The ensemble framework in this paper relies on two specific calibration methods: the projection method (Gutiérrez-Martín and Gómez, 2011) (PMAUP_1) and the iteration method (Gómez-Limón et al., 2016) (PMAUP_2).

3.3. Management of uncertainty and robust decision making

Apart from PMP, which is a special case where the estimated residual is adjusted to zero, all economic calibrated models considered in our ensemble yield calibration residuals, which can be used to assess the internal performance of each model (readers can refer to Annex I in the supplementary material for a complete description of the calibration residuals used in the ensemble models). This does not mean PMP models can perfectly forecast behavioral responses to policy shocks; there remain "significant" sources of uncertainty outside calibration residuals, including those models where residuals are adjusted to zero (Phillips et al., 2001). Note also that calibration residuals are not directly comparable between families of models, since modeling errors are independent (Cloke et al., 2013).

The difficulty in assigning a reasonable metric of uncertainty to each model is at the core of the use of multi-model ensemble frameworks. Admittedly, forecasts from different models do not have the same likelihood; however, since we do not know their probability and to the extent modeling errors are independent, we can explore uncertainty through the model spread (IPCC, 2014). It would be possible as well to apply Laplace "Principle of insufficient reason" to assume the ensemble behaves as a Bayesian System, and obtain a "best estimate" as the simple arithmetic mean of the forecasts from each model in every scenario considered. This approach may nonetheless assume more than is granted by available evidence (recall the likelihood of forecasts from different models is unknown) (Hino and Hall, 2017); to avoid maladaptation, this research adopts a robust decision making approach that minimizes regret.

Robust decision making is a method that uses results from several simulation runs (using alternative models and/or scenarios through scenario-discovery techniques) to connect policy makers with model(s) capable of exploring uncertainty, so to identify robust adaptation options as those that "perform well compared to alternatives" (Marchau et al., 2019) and "hedge against uncertainty" (Graveline, 2019). Robust decision making process typically follows an iterative process between researchers and stakeholders/policy makers in five steps (Marchau et al., 2019). *Step 1* involves the definition of the decision-making framework, which in our case involves the exploration of alternative agricultural water pricing strategies through simulation, leveraging on scenario-discovery and multi-model ensemble techniques. *Step 2* is the evaluation of the proposed pricing strategies (see Section 4.1). *Step 3* assesses vulnerabilities to pricing strategies, notably through the identification of potential tipping points (Section 4.2). *Step 4* assesses the tradeoffs between alternative strategies and involves the identification of robust policies that avoid tipping points and unfavorable surprises (decision-making process) (Section 4.2). The decision-making process can be implemented through the use of heuristics (expert judgement), through mechanistic constrained optimization algorithms, or through a combination of both (Marchau et al., 2019). If the 4 steps above do not yield a satisfactory outcome, an additional *Step 5* can be included to explore alternative adaptation strategies. This step was not necessary in our research, since the task commissioned from Regione Piemonte explicitly demanded an analysis of incremental volumetric water prices in the agricultural sector, and no alternative policy was considered.

3.4. Data

Data was collected for the period 2008–2016, with 2016 as the calibration year. The database includes 28 crops representing 95% of total irrigated surface in the region. All attributes are defined so that "more-is-better" and are quantities of dimension one (i.e. normalized) (Gómez-Limón et al., 2016). Table 1 summarizes data inputs and related data providers.

The only non-primary data source in the database are water withdrawals. The water abstraction license regime in Italy is "byzantine and substandard" (Santato et al., 2016): relevant data gaps on water withdrawals exist, and public statistics underestimate actual water use. According to Regione Piemonte (2018) estimates, total withdrawals from irrigation amount to 5000 million m^3/year; while ISTAT (2010) water use statistics (primary data source) set total withdrawals in the region at 0.7 billion m^3/year. To circumvent this data mismatch, we measured irrigation water withdrawals using the per crop irrigation water consumption estimates and irrigation efficiency data from Augusti et al. (2018), and obtained a figure of 4750 million m^3 annual withdrawals.

3.5. Economic agents and results aggregation

The decision variable (i.e. land use) is available at a municipality level. This means that we have 1204 potential economic agents for the models. During the robust decision-making process, policy makers and stakeholders argued in favor of aggregating these 1204 units into more tractable agents that could yield easy-to-understand results and better inform their decisions. In order to define tractable agents for the calibration and policy simulation, this paper follows the work by Gómez-Limón et al. (2012) and handles municipalities as local aggregation units that can be grouped into clusters. To this end, we first obtain

Table 1
Models' inputs and data providers.

ID	Data provider	Variable	Ref. year	Disaggregation
Agricultural land use	Sistemapiemonte (2018)	Crop portfolio	2016	Hectares per crop at a municipality level
Crop yields, prices and costs	INEA (2018)	Crop yields (kg/ha), prices (EUR/kg) and costs (EUR/kg)	2008–2016	Per crop and province (NUTS3)
Water withdrawals and consumption and irrigation technology	Adapted from Augusti et al. (2018)	Water withdrawals, water consumption (m3/ha) and irrigation technology (%)	2016	Per crop at regional level (water withdrawals and consumption); at regional level (irrigation efficiency)
Working days (labor)	INEA (2016)	Number of working days	2016	Per crop at a regional level (NUTS2)

Source: own elaboration.

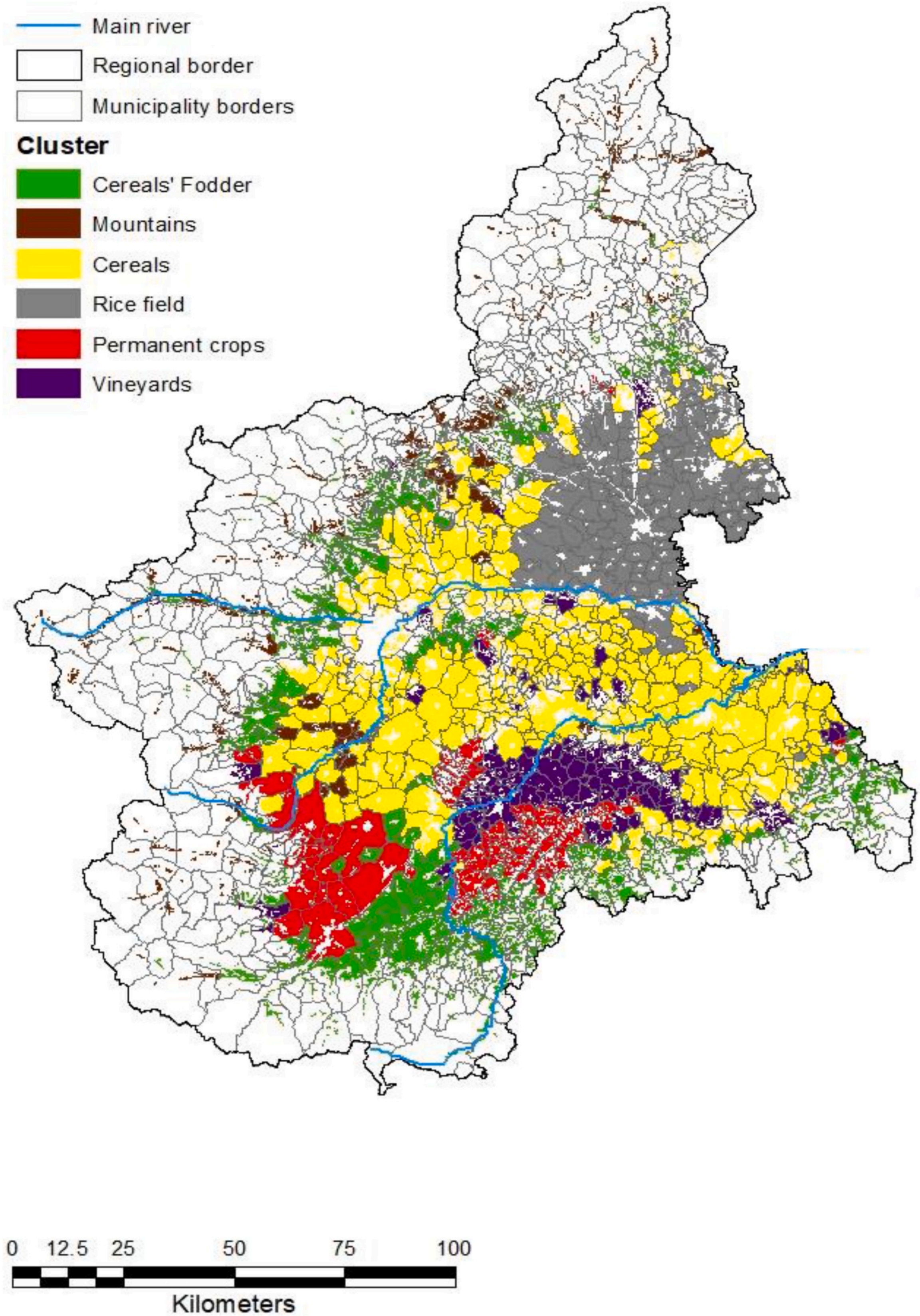

Fig. 2. Piedmont agricultural clusters.
Source: own elaboration.

information on the relevant data inputs described above for 1204 unique aggregation units/municipalities. We then employ a hierarchical aggregation procedure using the Euclidean distance measure and the Ward's agglomeration algorithm to maximize the internal homogeneity of clusters (Murtagh and Legendre, 2014). The results of the hierarchical clustering are usually presented in dendrograms from which, after visual inspection, the number of clusters is selected. The visual criterion can nonetheless be misleading and inefficient in identifying the optimal number of clusters, and this research adopts instead numerical criteria. Different indices have been proposed to find the optimal number of clusters. Following Charrad et al. (2014), we use a set of 30 indices instead of just one of them. The clustering procedure is performed using the NbClust package of the R software and is available in Annex II in the supplementary material, along with the list of the indices used. Note that the results of the different indices may not be univocal; when this happens, a simple majority rule is applied, which in our case led to 6 clusters as optimal grouping (Charrad et al., 2014) (see Fig. 2).

The resultant clusters are: C1 – Cereals and cereal fodders, which features cereals (29%), cereal fodders (60%) and permanent crops (6%); C2 – Mountains, largely devoted to the production of fodders (48%) and corn (42%); C3 – Cereals, including corn (29%), wheat (22%) and cereal fodders (28%); C4 – Rice (76% of land use in the cluster); C5 – Permanent crops, which encompasses vineyards (12%), other permanent crops (25%) and cereals (32%); C6 – Vineyards (48% of land use). These clusters are the agents of the mathematical programming models in the ensemble. Calibration results for these agents are presented in Annex III in the supplementary material.

Notably, simulation results using clusters as agents do not differ significantly from those obtained using individual municipalities as agents, which ensures consistence between the two aggregation levels while allowing for an easier-to-understand presentation of the results using a tractable number of agents (6 clusters v. 1204 municipalities).

Finally, results are aggregated at regional level as the weighted mean of the 6 clusters using clusters' land use shares as the weighting variable; i.e. attribute values for the Piedmont Region for every simulation run are obtained as the simulated attribute value for each cluster (per hectare), times the cluster's corresponding land use share. On the other hand, the crop portfolio at a regional level is obtained from the aggregation of the simulated crop portfolios for every cluster.

4. Results

4.1. Simulation

Once the five models are calibrated, they are used to run a number of simulations in which water prices are increased from 0 (baseline scenario) to 0.2 EUR/m^3 (i.e. 1666.7 times higher than the original price of 0.00012 EUR/m^3) at 0.002 EUR/m^3 intervals. Such pricing scenarios were co-developed with Regione Piemonte following a series of iterations (see Robust decision-making steps in Section 3.4). After every simulation run, agents in the model reassess their crop portfolio choices so to maximize their utility function within the domain. The result is a database representing the socio-economic effects of agricultural water pricing reform under multiple plausible futures, which is used to detect pricing policies that may potentially lead to contingencies/tipping points and underpin the implementation of a robust pricing policy.

Fig. 3 summarizes crop portfolio responses by ensemble component/model for relevant crops, namely fodders, corn, rice, wheat and grassland. The complete results including all crops are presented in Annex IV in the supplementary material. Fig. 3 also includes a "best estimate" obtained as the arithmetic mean of the forecasts from ensemble components in every scenario considered. It should be recalled that the "best estimate" is merely informative, since the likelihood of forecasts from different models is unknown, and the objective of this work is finding a robust pricing policy.

Overall, ensemble simulation results for the Piedmont Region show a

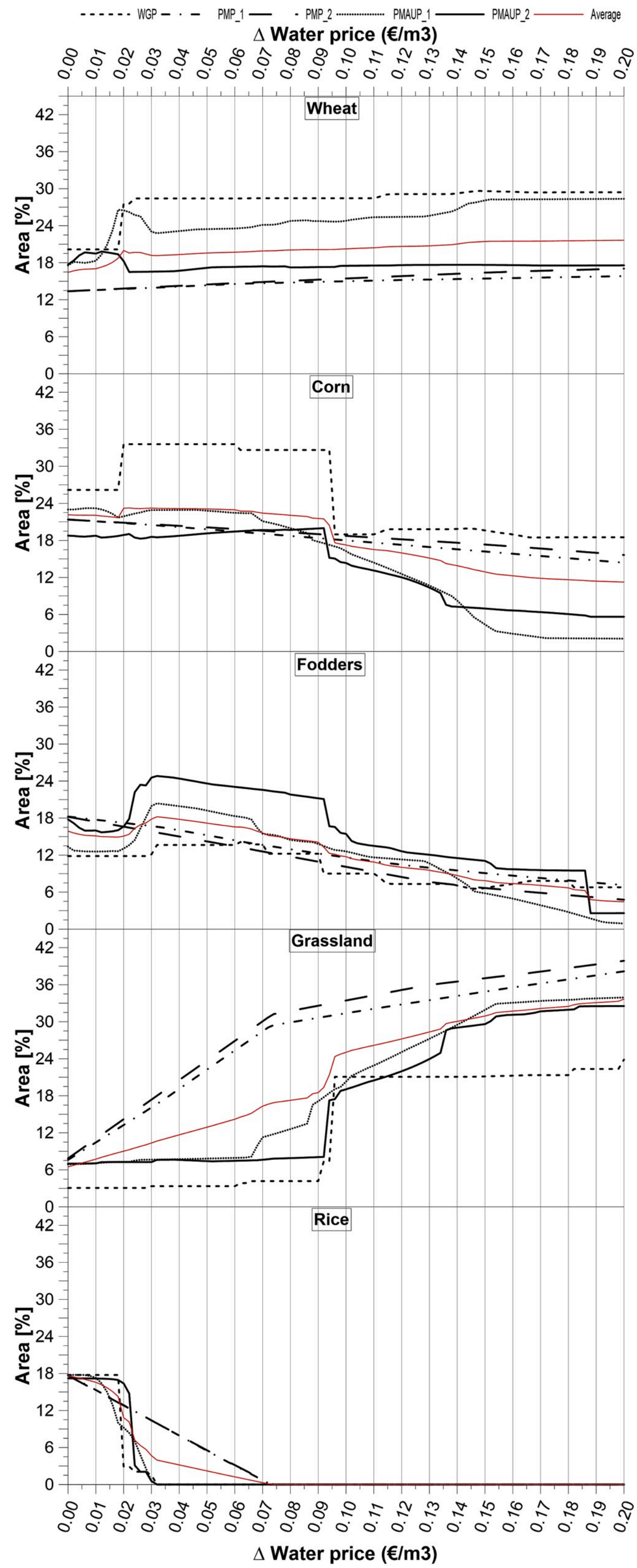

Fig. 3. Crop portfolio responses to incremental water prices for selected crops. Source: own elaboration.

trend towards the progressive substitution of water-intensive crops, such as corn and cereal fodders, by rainfed crops (wheat and grassland), although adaptation patterns to incremental prices may differ between models. For the case of cereal fodders, acreage reduction is constant and consistent across models. A similar trend is observed for corn, which nonetheless shows higher resilience to price increases and retains a relevant crop portfolio share throughout all simulations. Note that the land share of corn and cereal fodders (models WGP, PMAUP_1 and PMAUP_2) may experience some acreage expansion in the price range 0.012–0.032 EUR/m^3, as irrigators adapt to the new water price by substituting rice by less water intensive crops. Such land use changes are not observed in PMP models, where corn and cereal fodders experience a continued decrease and rice is substituted solely by grassland.

Rice responses to price shocks are heterogeneous and complex: while WGP and PMAUP models predict a significant reduction of rice beyond a price increase of 0.008 EUR/m^3 (PMAUP_1) and 0.018 EUR/m^3 (WGP and PMAUP_2), PMP models show a smooth reduction in acreage along price increases. In a series of interviews with representatives from the regional authority, river basin authority and Piedmontese land reclamation and irrigation boards, all stakeholders showed concern regarding this potential outcome, which had already been identified in a previous report as a critical barrier to the pricing reform (Frontuto et al., 2020) due to its potentially irreversible impact on the structure of traditional irrigated agriculture (i.e. rice) and related (ecosystem) processes and services of historical and cultural relevance to the region. Finally, like corn, cereal fodders and rice subside, grassland and wheat expand their acreage along with price increases.

Most water conservation is achieved at the 0.008–0.032 EUR/m^3 interval (0–0.074 EUR/m^3 for PMP models), when rice is replaced by less water-intensive corn/cereal fodders and rainfed crops in all the models, and water withdrawals fall from an average of 7000 m^3/ha to 1800 m^3/ha (see Fig. 4). Price increases below 0.012 EUR/m^3 slightly affect cereal fodders and yield modest water conservation figures. Price increases in the range of 0.034–0.19 EUR/m^3 for PMAUP and WGP models and 0.07–0.19 EUR/m^3 for PMP models lead to the gradual substitution of fodder and corn by rainfed crops, reducing water withdrawals from 1800 to 800 m^3/ha. Further price increases >0.19 EUR/m^3 meet an inelastic demand curve and are ineffective towards water conservation in the price range considered. This is explained because i) water withdrawals have already been removed from marginal lands and are now concentrated in highly productive areas capable of absorbing the price shock; and ii) agronomic restrictions, including crop rotations and planting constraints. Notably, although irrigators can reduce or expand permanent crops such as vineyard, we set a lower and upper bound of ±5% deviations from the original crop area. This is done to prevent significant capital (dis)investments, including the disruption in the provision of carbon sequestration services, which may conflict with other policies such as the Common Agricultural Policy (Essenfelder et al., 2018). Note that this constraint does not become binding until price increases beyond 0.19 EUR/m^3 due to the profitability of vineyards in the Piedmont Region.

Profit (see Fig. 5) falls consistently along price increases in both single-attribute PMP and multi-attribute PMAUP models, although the impact on PMP models is initially higher due to the presence of the quadratic cost function, which penalizes the shift towards less water intensive and/or rainfed crops that occupy a marginal area in the observed crop portfolio. WGP features a characteristic "jumpy" behavior where profit typically decreases but can also increase despite growing water prices.

The impacts of agricultural water pricing on employment (hired and family labor) is reported by the three multi-attribute ensemble components (PMAUP_1, PMAUP_2 and WGP). Initially employment increases along with prices, as rice is substituted by more labor-intensive corn. After a price increase of 0.096 EUR/m^3, when corn starts to decline consistently in all multi-attribute models, labor decreases as well (see Fig. 6). Note that information on employment (hired labor) is valuable to obtain information on GVA beyond profit/gross margin (the other component of GVA being labor income). For consistency among single- and multi-attribute models, this study reports information on profit and employment separately.

Water tariff revenue refers to the public revenue obtained directly from water pricing. Tariff revenue does not include other impacts on public revenue e.g. through a reduction in the income tax due to declining farmers' profits. Simulation results show that tariff revenue typically increases along with higher prices, although there are some significant exceptions where price increases trigger the substitution of water-intensive crops by less water intensive and rainfed crops (see Fig. 7). This is particularly visible for rice in the price range 0.012–0.074 EUR/m^3 for all models in the ensemble, and for corn in the price range 0.084–0.094 EUR/m^3 for multi-attribute PMAUP and WGP models. In

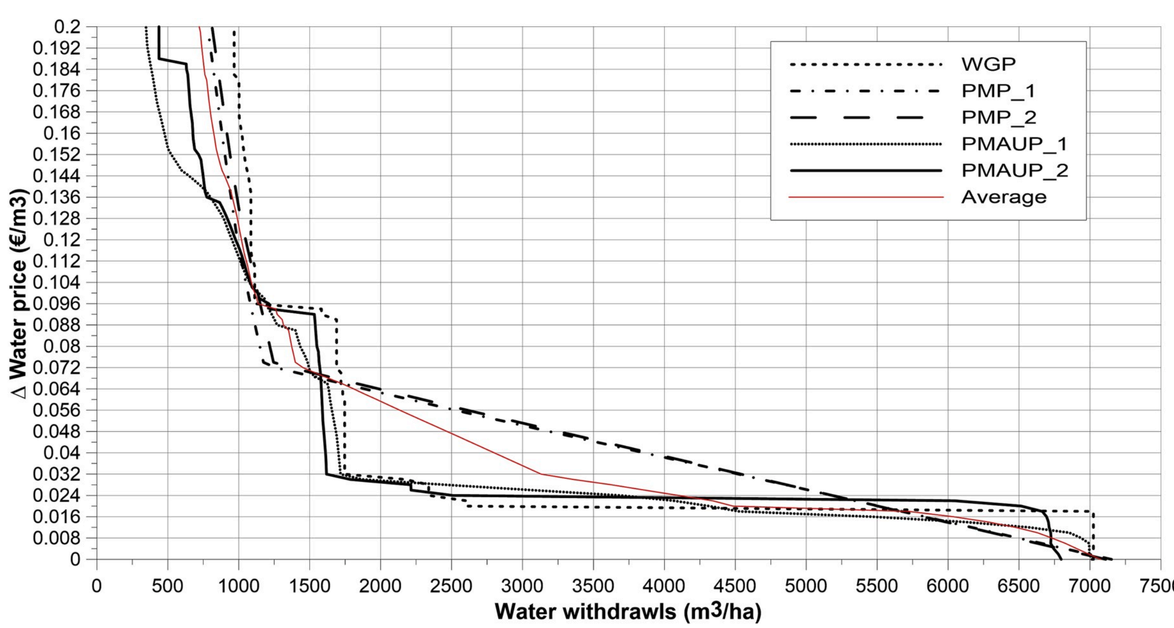

Fig. 4. Agricultural water demand curve.
Source: own elaboration.

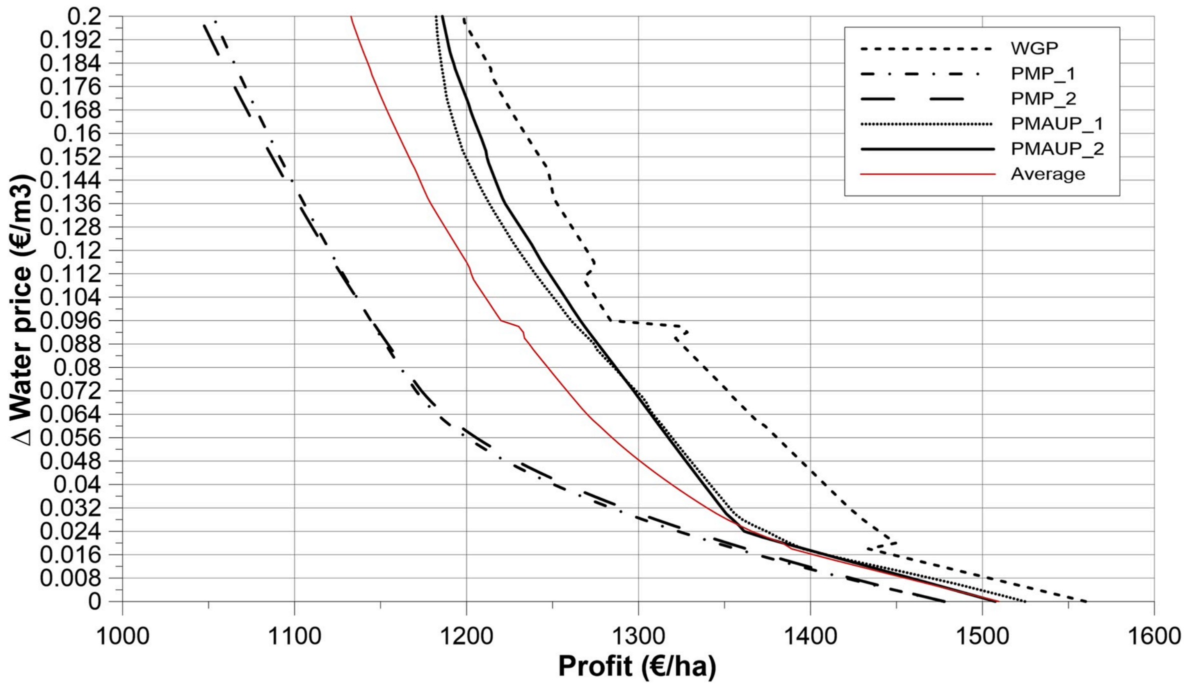

Fig. 5. Profit.
Source: own elaboration.

these instances, the water conservation effect overcomes the price increase effect and tariff revenue falls.

4.2. Robust decision making

Robust decision making was implemented following the steps described in Section 3.3. In *Step 1*, the two leading authors, policy makers (Regione Piemonte) and stakeholders (representatives from Land Reclamation and Irrigation Boards) gathered in a *kick-off* meeting to discuss and agree on the methodological approach to the research, and the initial set of pricing scenarios. In *Step 2,* preliminary results obtained using the approach agreed in Step 1 were presented and

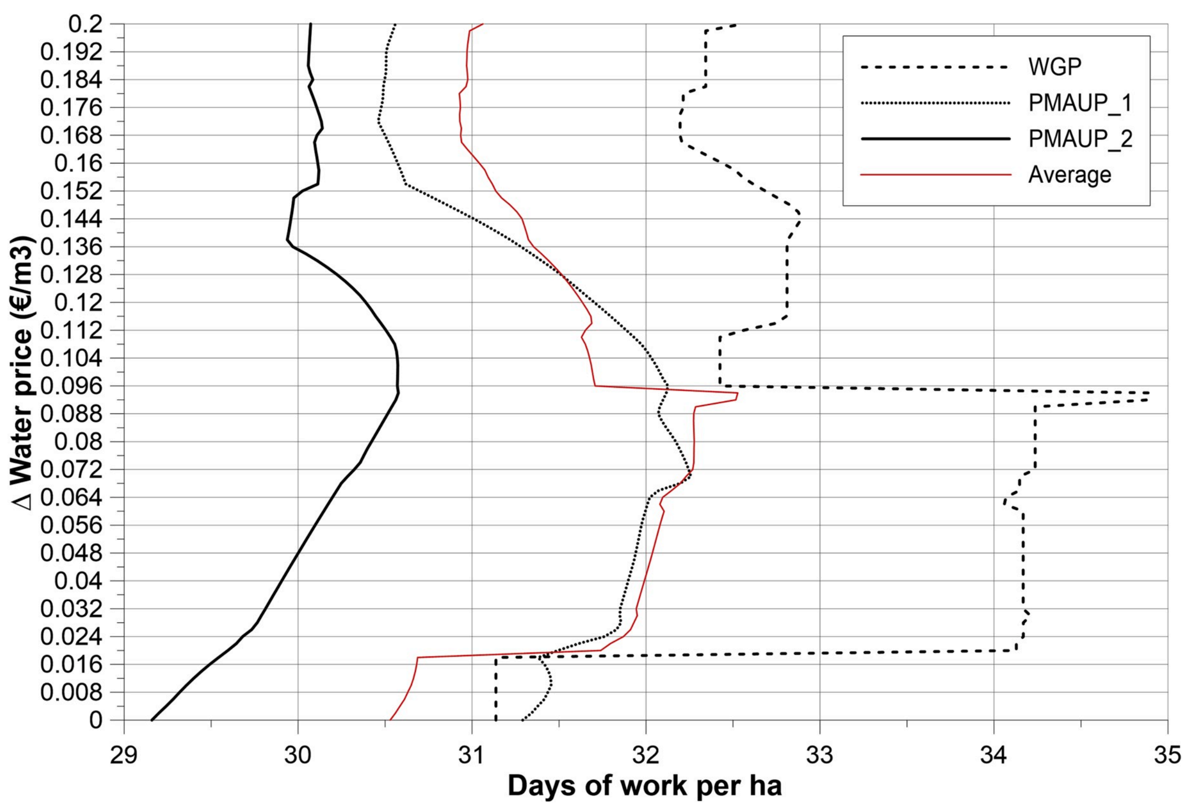

Fig. 6. Employment.
Source: own elaboration.

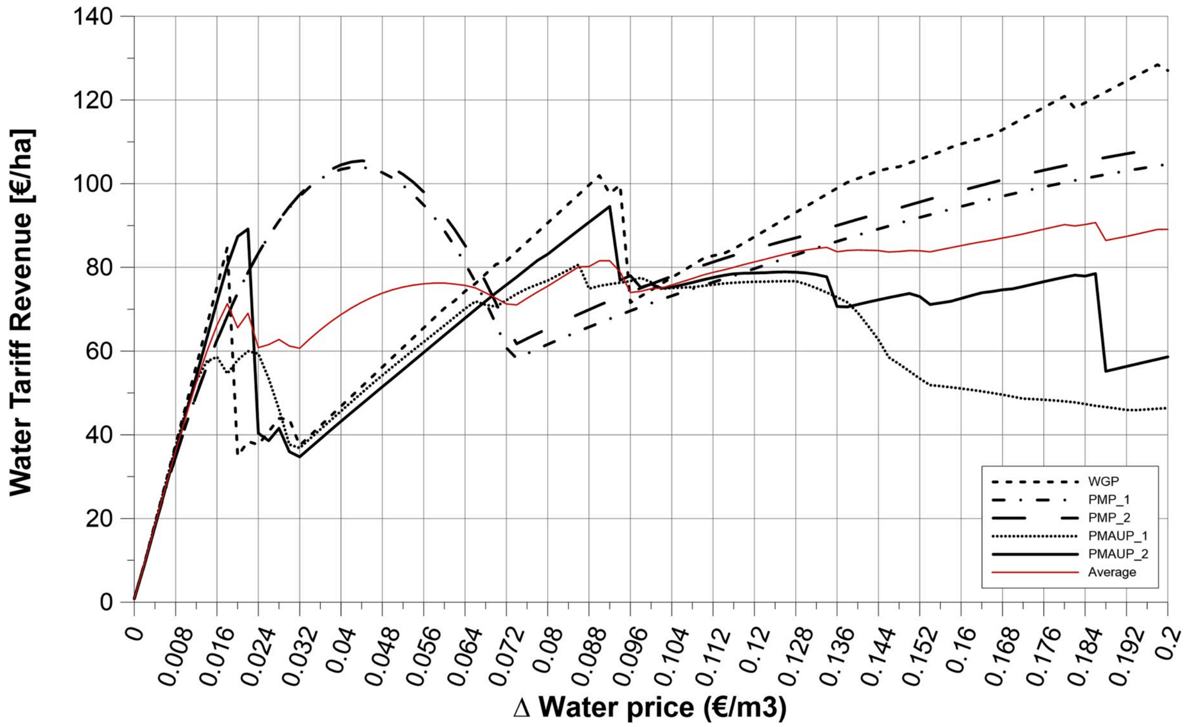

Fig. 7. Tariff revenue.
Source: own elaboration.

discussed in a second meeting. The range of pricing scenarios was revised and delimited to increase detail (from an initial range of 0–1 EUR/m^3 at 0.01 EUR/m^3 intervals to a range of 0–0.2 EUR/m^3 at 0.002 EUR/m^3 intervals, which remained unchanged), and the ensemble approach and its components were validated. In *Step 3*, the results obtained in Step 2 were used to assess vulnerabilities to pricing strategies.

At the beginning of the research, policy makers and stakeholders had already shown concern on the impact that water pricing policies may have on traditional rice fields and permanent crops, most notably vineyard. Simulations showed resilience of the latter crop to price increases; in contrast, rice systems were found to be highly vulnerable, with their area completely disappearing in *all* ensemble components in the price range 0.032–0.074 EUR/m^3. This was somewhat expected due to its intensive use of water (nearly 31,500 m^3/ha on average) and relatively low return as compared to alternative crops in the region (average, 1300 EUR/ha). As shown in the previous section, multi-attribute models suggest a rapid reduction in rice area in the interval 0.008–0.032 EUR/m^3, while single-attribute PMP models predict a less sharp, yet steady decrease in the interval 0–0.074 EUR/m^3. Among multi-attribute models, PMAUP_1 predicts a smooth decline of rice in the interval 0.008–0.012 EUR/m^3, which becomes more pronounced in the interval 0.012–0.018 EUR/m^3 (44% of rice area has already disappeared at this point) and again in the interval 0.02–0.032 EUR/m^3, after which rice systems disappear; PMAUP_2 predicts a faster decline of rice area, which goes from 18% to 0% of agricultural area in the interval 0.02–0.024 EUR/m^3; while WGP predicts the almost complete withdrawal of rice from the crop portfolio after prices increases of 0.02 EUR/m^3 (83% of the original area), followed by a progressive reduction of the remaining rice area in the interval 0.02–0.032 EUR/m^3. This suggests the existence of a tipping point for rice systems beyond a price increase of 0.012–0.02 EUR/m^3 for 3 of the 5 ensemble components.

Step 4 involves the decision on the policy to be adopted. We started by using constrained optimization methods through the utilization of the Minimization of Maximum regret algorithm (MinMax regret). MinMax regret measures regret as "the distance between the indicator for an instrument and the best indicator in a given scenario" (Graveline, 2019). In our case, we are looking for the pricing policy that yields the minimum maximum regret considering results from all models; in other words, the pricing policy that minimizes surprise/tipping points with potential disproportionate costs. The MinMax regret approach does not demand any additional information besides what is already available in the previous section; however, it tends to be highly conservative. Use of the MinMax regret approach suggested a maximum price increase of 0.008 EUR/m^3, i.e. the price at which the maximum regret is 0 (no loss of rice area in any model). At this price increase, water conservation is fairly small (0–650 m^3/ha), profit falls slightly (49–57 EUR/ha) and tariff revenue is quite significant (35–38 EUR/ha).

Constrained optimization methods were subsequently complemented with the use of heuristics through expert judgement, with the aim of exploring more ambitious and *feasible* water conservation-rice area tradeoffs. Through expert judgement, the feasible price increase was expanded to 0.012 EUR/m^3, right before the tipping point identified in Step 3. At a price increase of 0.012 EUR/m^3, the rice area diminishes but the impact is still moderate (16.7% reduction in PMP, 5.6% in PMAUP and 0% in WGP models), water conservation is limited (84–985 m^3/ha), foregone profit is small (73–85 EUR/ha) and tariff revenue is significant (49–56 EUR/ha). It should be noted that this price increase is slightly lower but still close to the 0.013 EUR/m^3 (Frontuto et al., 2020) price increase proposed by experts in a report prior to our analysis.

5. Discussion

Water crisis are among the greatest global societal threats – and Europe is not spared (WEF, 2019). The "total *cost of droughts* over the past thirty years amounts to *EUR 100 billion*", with the yearly average cost *quadrupling* over the same period (EC, 2017). Structural water scarcity is an expanding phenomenon affecting at least 17% of the European territory. 55% of surface water bodies in the EU have failed to meet good ecological status, and although the first cycle River Basin Management Plans predicted a 10% improvement in this figure by 2015, "delays in implementing many of the improving measures" have caused deferrals, further disruptions and *irreversible* damage in the supply of valuable ecosystem services (EC, 2017). Against this backdrop, EU institutions have called on policy makers to find “the right price tag on water” (EC, 2012). Such price should: i) be volumetric to enhance incentive-pricing water conservation; ii) recover not only financial, but also resource and environmental costs to convey adequate price signals; and iii) avoid disproportionate costs through affordable prices for strategic sectors and related users.

Balancing these three aspects has proven to be challenging. While the seminal literature on water pricing substantiates the effectiveness of the instrument towards achieving water conservation (Dinar and Subramanian, 1997), full cost recovery in overallocated basins typically involves a significant increase in prices with non-negligible impacts on income and employment (Perry, 2005). Where water has been historically perceived as plentiful and irrigation techniques have remained essentially unchanged for decades or even centuries, responses to pricing generally involve reducing water use. This results in significant water conservation at low or medium price ranges (Rey et al., 2018), albeit (traditional) agricultural systems may suffer abrupt transformations with non-trivial impacts on the local economy, which can be further amplified economy-wide (Parrado et al., 2019). On the other hand, where autonomous adaptation to water scarcity has given rise to sophisticated and relatively profitable irrigation systems, we may observe high ability to pay and inelastic responses to prices at low or medium price ranges, which results in limited crop portfolio changes despite significant pricing-induced income losses (Zuo et al., 2015). This is e.g. the case of the absolute water scarce basins of southern Spain, where farmers have invested on greenhouses or irrigation modernization, among other techniques (Berbel and Mateos, 2014). The upshot is that farmers will shift to less-water intensive and less profitable crops at relatively high prices, thus increasing the economic costs of water conservation. This can be aggravated by non-virtuous adaptation strategies such as shifting from surface water to more loosely controlled groundwater, thus transferring the overallocation problem to water bodies where norms and regulations are more difficult to supervise and enforce (Gómez and Pérez-Blanco, 2012).

The non-trivial tradeoffs between economic efficiency and water conservation highlighted above raise barriers to the political acceptability of pricing (Rausser et al., 2011), which have *de facto* precluded the implementation of full cost recovery (Berbel and Mateos, 2014). Notwithstanding the difficulty to fully recover water use costs, pricing still represents a powerful incentive that can contribute towards achieving collectively agreed environmental goals if certain conditions are met. For example, where demand is inelastic, pricing can be “leveraged against the high willingness to pay of users” to raise revenues that contribute towards enhancing the environmental status of water bodies (e.g. payment for ecosystem services).

The challenges and opportunities above are observable in our case study area in the Piedmont Region. According to Piedmont Region estimates, achieving full cost recovery necessitates a 2500-fold water price increase (0.30 EUR/m^3 price increase equivalent) (Frontuto et al., 2020), which following our estimates would not only significantly reduce agricultural profit (−36% on average) but also be inconsequential in terms of water conservation beyond a price increase of 0.2 EUR/m^3 (ensemble average) due to increasingly inelastic response to higher prices. Perhaps not surprisingly, experts advising the water policy reform found the costs of such price increase disproportionate, also on the grounds of potential irreversible impacts on the structure of traditional irrigated agriculture, and suggested a (maximum) price increase of up to 0.014 EUR/m^3 (Frontuto et al., 2020). According to our modeling exercise, although the impacts in terms of foregone profit may not be regarded as disproportionate (5%–11% foregone profit in the price increase interval 0.012–0.032 EUR/m^3, up to 20% in PMP at 0.074 EUR/m^3), a price increase beyond 0.012 EUR/m^3 results in the rapid substitution of the traditional Piedmontese rice landscape by rainfed crops and corn, with rice completely disappearing from the crop portfolio following a price increase of 0.032 EUR/m^3 (0.074 EUR/m^3 for PMP). This is expected to have a critical impact on water retention capacity during the summer discharge peak. Furthermore, the forward and backward linkages of agriculture with related economic sectors (e.g. food industry) are likely to amplify the economic impact of rice systems removal, which may also affect historical water drainage and supply infrastructures.

The downside of setting a maximum 0.012 EUR/m^3 price increase is a modest water conservation potential: an ensemble average of 350 million m^3 of water conserved annually, or 6.82% of current withdrawals (between 1.7% and 9.5% depending on the ensemble component). On the other hand, tariff revenues increase consistently and almost peak for some models in the price interval 0–0.012 EUR/m^3 (up to 56 EUR/ha), while profit reduction is relatively low (4.9%–5.7% depending on the model). This suggests that if rice systems are to be preserved, water pricing is not an effective instrument to conserve water, but still retains some potential as a revenue raising tool.

6. Conclusions

This work develops a mathematical programming multi-model ensemble framework to sample uncertainty and underpin robust decision making. This is, to the best of our knowledge, the first ensemble experiment to assess the local impacts of agricultural water policy reform. Its development, implementation and subsequent iterative policy formulation along with stakeholders provided insights into modeling and scenario uncertainty that proved valuable towards the identification of robust pricing policy in the Piedmont Region. The ensemble could be improved through its connection to complementary ensemble experiments that sample uncertainty in physical systems, notably the water system (Cloke et al., 2013), and in other human systems (e.g. macroeconomics, which would allow us to model crops' demand and prices endogenously) (Parrado et al., 2019). Modularity and protocols could be used to connect such complex systems among them, in line with recent contributions to the area of socio-hydrology (Essenfelder et al., 2018). The ensemble could be also expanded through the inclusion of additional mathematical programming models (Graveline, 2016). The individual ensemble components could also benefit from further research through: i) exploration of new attributes in multi-attribute models, such as seasonal forecasts, where this data is available; and ii) expansion of the crop portfolio to explicitly differentiate management techniques in agriculture in general and irrigation in particular. Such improved ensemble could be used to assess the impact of adaptation policies other than pricing in the irrigation sector, to complement our assessment of agricultural water pricing with that of alternative/complementary policies; although the current institutional and legal context and policy agenda suggest the feasibility of such instruments in the Piedmont Region/Italy may be unclear, as previously discussed.

Acknowledgments

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2020.110645.

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