Agricultural Water Management 295 (2024) 108757

Contents lists available at ScienceDirect

Agricultural Water Management

journal homepage: www.elsevier.com/locate/agwat

Irrigation water economic value and productivity: An econometric estimation for maize grain production in Italy

Rebecca Buttinelli [a], Raffaele Cortignani [a,*], Francesco Caracciolo [b]

[a] University of Tuscia, Department of Agriculture and Forest Sciences (DAFNE), Via San Camillo de Lellis, Viterbo, VT 01100, Italy
[b] University of Naples "Federico II", Department of Agricultural Sciences - Economics and Policy Group, Via Università 96, Portici, NA 80055, Italy

ARTICLE INFO

Handling Editor - Dr Z Xiying

JEL classification:
C23 Q12 Q15

Keywords:
Irrigation water
FADN data
Maize
Production function
Shadow price

ABSTRACT

Climate change, characterized by rising temperatures and limited precipitation, has intensified the demand for irrigation water while simultaneously restricting its availability. This challenge poses significant risks to agricultural and food production, particularly in the Mediterranean regions where, recently, water deficits have led to substantial production losses and quality issues. Water is a critical determinant of crops' economic viability, especially for water-intensive crops, making it essential to estimate its economic relevance, especially in the absence of reliable water market prices. This study has two primary objectives: first, to evaluate the shadow price of irrigation water for maize grain at the farm level, which is defined as the value generated by the marginal unit of water consumed; and second, to analyse its heterogeneity. Leveraging a Farm Accountancy Data Network (FADN) panel of 1625 Italian farms over a decade (2010–2020), an econometric production function approach is employed. Moreover, quantile regressions reveal variations in the shadow price linked to geographical, managerial, and structural farm characteristics. Our findings underscore water's key role in economically viable maize grain production, significantly enhancing the productivity of other inputs like fertilizers and pesticides. The average shadow price is 0.29 €/m^3, with a median of 0.20 €/m^3 and water total productivity accounts for one-third of maize's average gross output. Quantile regressions uncover how factors like geographic location, altitude, farm management, irrigation water source, and farm size influence the distribution of water productivity, reflecting either efficient use or scarcity of this resource. Our estimation provides valuable insights for policymakers by offering accurate shadow price estimates for irrigation water in Italian maize grain production. Furthermore, it enhances our understanding of irrigation water's role in the economic viability of this crop, while contributing to support evidence-based water management strategies, identifying vulnerable areas and farms and allowing for future methodological developments.

1. Introduction

Water is necessary for human existence and a key input for several economic activities, including agriculture, which is crucial for the global food supply (Damania et al., 2020). Population growth, urbanization, and the growing demand for food make water an increasingly scarce resource in several areas of the world. In addition, climate change makes adverse weather events more violent, frequent, and less predictable. This is also true for drought, a threat now spreading to areas that do not usually face precipitation constraints or extremely high temperatures (FAO, 2022). Moreover, water is primarily allocated to industrial and civilian uses in the case of water shortages, leading to losses in irrigated crop yields and revenues. However, the rising temperatures and increasing scarcity of precipitation have led to a greater demand for irrigation water, often making groundwater recharge insufficient to counterbalance extractions (Wada et al., 2010). In this scenario, agriculture accounts for 72% of global water extractions and represents 70% of extractions in Mediterranean areas (Berbel et al., 2019; FAO, 2022).

Policies and institutions have failed to face these human and economic implications in the past, and even today, water management policies are struggling to address this complex scenario.[1] In recent decades, the European Union has attempted to promote the rational use of

* Correspondence to: University of Tuscia, Department of Agriculture and Forest Sciences (DAFNE), Via San Camillo de Lellis, Viterbo 01100, Italy
E-mail address: cortignani@unitus.it (R. Cortignani).

[1] Indeed, water has commonly been considered a renewable resource. However, at the International Conference of Water Environment in 1992, it was admitted that the failure to acknowledge the economic value of water has led to waste and inefficient use of this resource (ICWE, 1992).

https://doi.org/10.1016/j.agwat.2024.108757
Received 12 October 2023; Received in revised form 11 January 2024; Accepted 27 February 2024
Available online 8 March 2024

water resources among its Member Countries. One of the fundamental approaches used in this regard has been the adoption of the Water Framework Directive (WFD) (European Commission, 2000), which aims to encourage efficient water use through economic incentives such as Full Cost Recovery (FCR)[2] and the "polluter pays" principle. In 2015, Italy took a step further by introducing mandatory measurements and estimations for irrigation volumes and environmental and resource-related costs associated with such activities (D.M., 31 luglio 2015). However, the number of countries in which water pricing meets the requirements set out by the WFD remains relatively low, with most countries, including Italy, failing to fully comply with these principles (Zucaro, 2014).

In fact, in certain areas, especially where volumetric tariffs are not applied and where metering is not adopted, the quantification of irrigation volumes poses the most significant challenge when analysing water consumption in agriculture. Giannoccaro et al. (2020) highlighted that in Italy, defining access rights to groundwater withdrawals and managing asymmetric information and free riding is a complex matter. Introducing pricing mechanisms and FCR measures, as highlighted by Berbel et al. (2019) and Galioto et al. (2017), is also an ambitious objective that requires the knowledge of water's economic value as well as environmental and related service costs (Gómez-limón and Martin-Ortega, 2013). In addition, recently, the European Green Deal and Farm to Fork Strategy (European Commission, 2019)have further emphasized the need for natural resource preservation, leading to the new Common Agricultural Policy (CAP) design which, among many other goals, aims to help the WFD reach its objectives.[3]

Considering the urgent need for sustainable water resource management, driven by policies aimed at preserving natural resources and by climate change threats, such as rising temperatures and reduced water availability, the estimation of water economic value and productivity arises as a powerful tool to thoroughly understand the key economic aspects of water use. However, the estimation of water economic value is particularly difficult when market prices are absent or distorted and, in such circumstances, it is primarily feasible using simulated market or "shadow prices" (Young, 2005). Several definitions of water shadow prices exist in the literature (He et al., 2007): For irrigation water, they can be either based on the value of water alternative use (e.g., different users or different time) or farmer's behavior. In this study, we consider the latter circumstance, in which the economic mechanism behind water consumption is based on two main assumptions: farmers are price takers (for outputs and inputs) and profit maximizers. Thus, they will use water up to the point where its price will be equal to the added value derived from using a marginal unit of this input (Williams et al., 2017). Bierkens et al. (2019), following this approach, stated that water shadow price denotes the value of crops produced per marginal unit of water consumed, given the quantity of other inputs. Therefore, estimating the shadow price is crucial for the optimal allocation of scarce water resources and the efficient functioning of water markets.

Under these assumptions, this study aims to assess the relevance of irrigation water in agricultural production. Specifically, it seeks to estimate the irrigation water shadow price for maize grain production at the farm level leveraging data from a sample of 1625 farms over Italy spanning from 2010 to 2020. Maize grain was selected as the focal crop due to its economic importance among irrigated crops and its vulnerability to market volatility and climate change threats. Italy, ranking as the fourth-largest maize producer in the European Union (Erenstein et al., 2022), relies heavily on maize in various supply chains, including Parmigiano Reggiano production, where silage fodder as feed is prohibited (Mantovi et al., 2015). Nonetheless, water deficits have forced many parts of Italy to rationalize or suspend irrigation water, resulting in yield losses and concerns related to crop quality (CREA, 2021). Moreover, this situation could worsen due to the increasing occurrence of extreme weather events, e.g., water scarcity (IPCC, 2019; Rosenzweig et al., 2014), especially in Mediterranean countries (Hristov et al., 2020; Lionello and Scarascia, 2018), including Italy (Mereu et al., 2021).

Several methods have been proposed to estimate water shadow price, most of which rely on production functions (Johansson et al., 2002). This strand of literature mainly focuses on estimating the irrigation water shadow price for river basins (Garciá Suárez et al., 2019; Koundouri et al., 2014; Mesa-Jurado et al., 2010; Williams et al., 2017) or at the national scale (Kiani and Abbasi, 2012; Takatsuka et al., 2018; Veninga, 2017), and it rarely uses detailed microeconomic data to estimate shadow prices for irrigation water at the farm scale (Mesa-Jurado et al., 2010; Koundouri et al., 2014). While previous studies have already estimated irrigation water shadow prices for various crops at the Country or River Basin level, this study contributes to the existing literature by focusing on maize grain production in Italy at the farm level. An econometric production function approach coupled with detailed microeconomic data spanning a decade was adopted to derive reliable estimates. Furthermore, quantile regression was implemented to better understand the factors influencing water irrigation shadow prices among farms. By providing accurate and up-to-date estimates of water shadow price and its variability, this study can help suggest evidence-based water management strategies and identify vulnerable areas or clusters of farms that may be particularly vulnerable to water-related challenges.

The paper is structured as follows: Section 2 briefly overviews water shadow price definitions and estimation methods. Section 3 describes data and methodology specifying the econometric models, production function form, and shadow price estimation procedure. Section 4 presents econometric estimates and the obtained results. Section 5 discusses the implications of these results. Finally, conclusions are provided in Section 6.

2. Shadow prices of irrigation water: a brief overview

The variety of theoretical frameworks in approaching the estimation of shadow prices of irrigation water is associated to multiple definitions, each contingent on different underlying economic mechanisms such as the value of alternative use or farmer behavior (He et al., 2007) and relying on different methodologies. While this section does not intend to be an exhaustive overview, it does offer a brief overview that addresses some theoretical and methodological issues in the analysis of irrigation water shadow prices.

2.1. Definitions and assumptions

Among the various definitions, Bierkens et al. (2019) use the following definition: "*The shadow price of water reflects the value of crops that can be produced by the marginal unit of water consumed, given the quantity of the other inputs*." This definition is based on the assumption that farmers are price takers (for outputs and inputs) and profit maximisers; as rational agents, farmers use water up to the point where its price equals the added value derived from using a marginal unit of this

[2] WFD makes of FCR principle one of its pillars: in Article 9 it is stated that Member States must take account of the principle of recovery of the costs of water services, including environmental and resource costs in accordance with the "polluter pays" principle. This, with the aim to provide an adequate incentive for users to use water resources efficiently. This incentive had to be given through the adoption of effective economic instruments of pricing, and, as underlined by Gallego-Ayalal et al. (2011), volumetric pricing has primarily been seen as the most suitable tool, since accurate water-metering is considered a necessary condition to estimate appropriate costs for water usage in agriculture. See Berbel and Expósito (2020) for an overview on WFD water pricing and cost recovery.

[3] In fact, the European Court of Auditors in 2021 published a special report stating that past CAP policies have failed to promote sustainable water use in agriculture (ECA Special Report 20/2021, Sustainable water use in agriculture: CAP funds more likely to promote greater rather than more efficient water use).

input (Williams et al., 2017). While this definition provides a snapshot of the actual irrigation water economic value at the farm level, it has several advantages as well as limitations. One of its main advantages is that it allows one to precisely pinpoint the maximum price a farmer would be willing to pay for the last unit of irrigation water used, thus making it particularly relevant for short-term policy considerations. It provides a practical framework for assessing irrigation water productivity, which is essential for farmers who operate under stringent budget constraints and face immediate production decisions. On the flip side, this definition intentionally sidesteps some complexities. Unlike more comprehensive approaches like those by Young and Loomis (2014), it does not incorporate broader environmental or opportunity costs, nor does it explicitly consider the temporal aspect of irrigation water allocation (Elnaboulsi, 2001; Young and Loomis, 2014). Indeed, this study follows the aforementioned definition, without delving into long-term environmental externalities, the value of water in alternative uses, or the intertemporal efficiency or opportunity costs that may emerge in longer-term scenarios. In this specific context and under these assumptions, the shadow price aligns with the marginal value (He et al., 2007; Wang and Lall, 2002). Limitations can be seen as calculated, as a narrower perspective is common because farmers often prioritize maximizing their current profits and may not account for the availability of water in the future when making decisions. We assume, then, that farmers aim to maximize their current net returns and that the shadow price is determined through free competition among them.

2.2. Methodologies and limitations

Several methods exist to estimate the shadow price of irrigation water. According to Young (2005), there are two main methods: deductive and inductive. Deductive methods use logical processes and rely on economic postulates, such as profit and utility maximization, whereas inductive methods rely mainly on econometrics and statistics. Among deductive methods, the most popular are the Residual Value Method (RVM) (Berbel et al., 2011; Hellegers and Davidson, 2010; Ziolkowska, 2015), General Equilibrium Models (GEM) (Jiang et al., 2014; Smith et al., 2015) and Mathematical Programming (MP) (Liu and Chen, 2008; Rosegrant et al., 2000). Under RVM, it is assumed that all inputs except for water are priced at market rate. The price of irrigation water is then calculated as the ratio between the net returns from crop production and the total quantity of water used for irrigation. As for MP, this method derives the optimal allocation of resources, including water, based on objective functions such as profit maximization or cost minimization.[4] For analyzing the broader, economy-wide implications of changes in water use and availability, General Equilibrium Models are often preferred (Jiang et al., 2014; Smith et al., 2015).

However, the aforementioned methods have several limitations. RVM, upon which most deductive methods are based, estimates water value by deducting costs from predicted revenues. It requires the assumption that all markets are perfectly competitive, with the exception of the water market. Additionally, this method requires a thorough estimation of input costs, which can be challenging when dealing with inputs that are not priced on markets—for example, assets owned by the firm like land and machinery. Under these circumstances, a certain degree of uncertainty is inevitable, and omitting or misrepresenting some input costs will inevitably lead to an overestimation of water value. Similarly, both MP and GEM, rely heavily on theoretical assumptions and may oversimplify complex economic relationships.

Inductive procedures include econometric estimations of the production function or water demand (Bruno and Jessoe, 2021; de Bonviller et al., 2020; Scheierling et al., 2006), Hedonic Pricing, Contingent Valuation (Calatrava and Garrido, 2005; Li et al., 2021), Choice Experiments (Rigby et al., 2010), Stochastic Frontier Analysis (SFA) (Coelli and Orion, 2013; P. Koundouri et al., 2014a) and Data Envelopment Analysis (DEA), or a combination of both (Shen and Lin, 2017). Inductive methods are more reliable when data are available. Given an accurate specification of the production function that captures the relationship between water and production, these estimates can provide a reliable assessment of shadow prices using experimental (field experiments) or observational (primary or secondary) data (Mesa-Jurado et al., 2010).[5]

Among its various applications, Njuki and Bravo-Ureta (2019) employed a Cobb-Douglas stochastic production function to determine the shadow price of irrigation water in the US. In a similar vein, Bopp et al. (2022) applied this method to Chilean wine grape production, Conradie et al. (2006) to South African vineyards, and Coelli and Orion (2013) to wine grape production in Eastern Australia. More recently, Nouri-Khajebelagh et al. (2021) estimated the average water shadow price for various crops in Iran. In different contexts, Bellver-Domingo et al. (2019) derived the irrigation water shadow price by analyzing the avoided environmental cost through water desalination using distance function estimation. Irrigation water shadow price estimates based on distance functions were also used by Riera and Brümmer (2022) in Argentina, by Koundouri et al. (2014b) and Koundouri et al. (2014a) in Greece and by Li et al. (2019) in the Beijing- Tianjin-Hebei city region in China.

Bierkens et al. (2019) utilized macro data and a Cobb-Douglas production function to estimate the irrigation water shadow price for various crops in 11 countries, including Italy. Similar studies have been conducted to estimate green water economic value in the Czech Republic (Grammatikopoulou et al., 2020) and South Florida (Takatsuka et al., 2018). Veninga (2017) applied a translog production function to calculate irrigation water shadow prices for maize, sugarcane, and citrus in twelve countries, among them, Italy, where groundwater extraction is the primary water source. Garciá Suárez et al. (2019) assessed the impact of increased irrigation volumes on the total biomass yield in the High Plains River Basin, US. A table concisely summarizing key features of some relevant studies using the production function approach is available in Appendix (Table A1).[6]

While previous studies have mainly focused on estimating the economic value of irrigation water for crops at the country or river basin scale using secondary or primary macro data, our study estimates the water irrigation shadow prices for Italy using detailed microeconomic data, which offers two significant advantages. Firstly, using farm-level accurate and reliable data over 10 years enhances the accuracy of the shadow price estimates. Secondly, by estimating the shadow prices at the farm level, we can identify the circumstances or areas in which irrigation water productivity is most affected by water scarcity or efficiency. This approach aids in better resource allocation and identification of vulnerable farms or territories. Furthermore, a better understanding of the factors affecting shadow prices at the farm level could aid in the development of more effective strategies and interventions for water management.

[4] Distinct approaches are employed such as linear programming (Dayananda et al., 2023; Esmaeili and Shahsavari, 2015; Liu et al., 2009; Schmitz et al., 2013; Shi et al., 2014; Weerahewa and Dayananda, 2023), revealed preference models (Pérez-Blanco and Gutiérrez-Martín, 2017) and positive mathematical programming (Lionboui et al., 2018; Rodríguez-Flores et al., 2019).

[5] Among others, Baniasadi et al. (2020) and Jana (2018) use several methods, including production function, to obtain water shadow price to monetize environmental impacts of excessive groundwater extraction in Iran and the use of wastewater in aquaculture.

[6] Although not exhaustive, Table A1 in the appendix illustrates the diversity of functional forms, variables, and contexts used in recent irrigation water valuation research. This highlights the complexity and context-specific nature of the studies considered.

3. Materials and methods

3.1. Data

This study focuses on Italian maize grain farms, leveraging a Farm Accountancy Data Network (FADN) sample that provides detailed information at both farm and crop levels. FADN is the only source of microeconomic data based on harmonized bookkeeping principles. Based on national surveys, it aggregates data on 68,000 farms, representing almost 5 million EU farms, 90% of the European UAA and Standard Output. The Italian sample comprises 11,000 farms, whose data are stratified by region, size, and type of farming (TF). The data include Gross Output, land, crop-specific variable costs, work-related costs for families and employed workers, and irrigation water volumes.

To ensure the homogeneity of the sample and enable accurate attribution of measured costs at the farm level to the specific crop (particularly work-related expenses), we selected an unbalanced panel of 1625 farms growing irrigated maize grain, and excluded those with livestock, for the period 2010–2020; a total of 5224 observations were analysed. Northern Italy regions (predominantly Lombardy, Piedmont, Friuli-Venezia Giulia, Emilia-Romagna, and Veneto) accounted for 87.3% of the sample, Central Italy for 11%, and the South for 1.7%. The majority of farms were family-run (67.5%), and corporate entities comprised only 18% of the sample. In terms of economic size, 48% of the observations' Standard Production ranges from 50,000 to 100,000 €, while 35.7% ranges from 8000 to 50,000 € and only 16.3% exceeds 100,000 €. Concerning water sources, a significant part of the sample relied on Water User Associations (WUA) infrastructures (78.1%), while the rest relied on self-supply irrigation.

In fact, in Italy, WUA are the primary administrators of irrigation water and play an essential role in planning the responsible use of this resource.[7] These associations typically consist of organized groups of water users, such as farmers and agricultural communities who collectively manage and allocate water for irrigation purposes. The infrastructure associated with WUAs often includes a network of canals, ditches and water distribution systems that serve as conduits for irrigation water. These structures are designed to facilitate the distribution of water, involving the scheduling and coordination of water deliveries to ensure that each member receives their allocated share during the irrigation season, which typically goes from spring (March-April) to the end of the summer (September-October). The characteristics of irrigation across various regions of the country are shaped by a combination of hydrogeological, topographical, environmental, and historical factors and these influence both the infrastructure and the management of water provision. [8]

Table 1 presents sample descriptive statistics for key variables that are utilized in the estimation of shadow prices. These variables include the total agricultural area measured in hectares, family and employed labor quantified in work units, and a range of cost factors—namely, land value, work costs, machinery, pesticides, and fertilizers—all expressed per hectare for the cultivation of maize grain. The table also includes data on the volumes of irrigation water, also denominated per hectare.

.

3.2. Econometric Model

Following the definition provided by Bierkens et al. (2019), the water shadow price has been estimated by calculating the value of maize that can be produced using a unit of irrigation water.

From an empirical standpoint, the shadow price can be obtained by estimating the production function and taking its partial derivative of the production function concerning irrigation water. The production function (Eq. 1) describes the relationship between crop production and various marketable inputs (such as seeds, fertilizers, and pesticides), labor, land, and water.

$$Y = f(L, W, F, P, \mathrm{VC}, \mathrm{WR}, M, T, R) + e \tag{1}$$

Here, Y represents the Maize Grain Gross Output; L, land; W, water; F, use of fertilizers; P, use of pesticides; VC, other variable costs; W*R*, labor, and M, use of machinery. All the aforementioned quantities are expressed as monetary values, except for water, which is expressed in volume (m^3). In addition, T represents average annual temperatures (°C) and R is the average annual precipitation (in 100 mm) at the provincial level. These variables are included to capture the effect of climate variability.[9]

For each observation, the expenditure on each input utilized for maize grain production was assessed in Euros (€). Land (L) is constructed by identifying the annual expenditure of rented land and attributing a return of 2% on the land value for owned land. F, P, and VC represent annual expenditures on maize production, with VC encompassing costs such as quality certifications, energy consumption, subcontracting, marketing, seed procurement, and machinery renting. The costs related to water supply are included in the variable VC and concern the fees charged by WUAs, as for the costs related to self-supply, this amount depends mainly on the energy cost required for pumping or transportation, which, in turn, is influenced by the well's depth and pumping or distribution system adopted.

Labor (W*R*) comprises both employed labor, whose cost is obtained from FADN Balance Sheets, and family labor, whose compensation includes an hourly wage reflecting the opportunity cost and a reward for the managerial work of the entrepreneur. M represents the owned machinery work expenditure and encompasses fuel, insurance, maintenance, and machine operator payments. W indicates the water irrigation volumes for maize grain production, covering both the farms' self-supplied water services and those served by WUAs.

The choice to use economic variables rather than quantities derives from the characteristics of the Italian FADN data. While this dataset provides extensive and detailed information on both individual farms and specific crops, it includes data on both the type of fertilizers and pesticide use. This results in significant heterogeneity in both the formulations and types of products used. While it might be possible to differentiate between organic and inorganic fertilizers distinguishing among various types of pesticides, and more importantly, various units of measurements are not always feasible. This could have introduced a bias in the creation of variables and, subsequently, in the estimation process. For this reason, in alignment with common practices in the literature (see, among others Latruffe et al., 2023; Zhu et al., 2012; Zhu and Lansink, 2010), we have chosen to use monetary values. However, we have chosen to differentiate between inputs rather than aggregating them into a single variable. This approach allows us to maintain a finer level of detail and provides more specific insights for each of the inputs under consideration.

Table 2 lists all variables used in the econometric model.

Empirically, the production function is estimated following the Cobb-Douglas specification(Cobb and Douglas, 1928) :

$$Y = \alpha \prod_{i=1}^{N} X_i^{\beta_i} + e \tag{2}$$

Where X represents the vector of inputs including water (W), and β are the estimated parameters vector reflecting input elasticities on production, α is the intercept while e is the error component. This equation can

[7] The National Association of Management and Protection Consortia for Land and Irrigation Waters (ANBI) estimates that approximately 59.47% of the national territorial surface is covered and managed by WUAs.

[8] see Dono et al. (2019) and INEA (2011) for a comprehensive overview of irrigation sector in Italy.

[9] The source used for climate data is the ISTAT database (Italian National Institute of Statistics) for the years 2010–2020.

Table 1
Descriptive statistics of the farm sample – unit of measure, description, mean, and standard deviation.

Variable	UM	Description	Mean	Sd
Total Agricultural Area	Ha	Agricultural Land (Owned and Rented)	44.47	62.09
Family Labor	2300 hours/ unit	Total Family Work Units	1.15	0.68
Employed Labor	2300 hours/ unit	Total Employed Work Units	1.27	0.94
Area	Ha	Hectares of Land under Maize Grain	19.48	34.70
Gross Output	€/ha	Maize Grain Gross Output per hectare	1867.17	610.97
Land Value	€/ha	Return on Land under Maize Grain (2% of owned land value + rents) per hectare	479.99	435.79
Work	€/ha	Maize Grain Total Work Cost per hectare (both Family and Employed Work)	399.80	414.69
Machinery	€/ha	Maize Grain Machinery Costs (only owned machinery) per hectare	484.96	635.55
Pesticides	€/ha	Maize Grain Pesticides Costs per hectare	120.46	70.70
Fertilizers	€/ha	Maize grain Fertilizers Costs per hectare	252.74	138.05
Variable Costs	€/ha	Maize grain Variable Costs per hectare (certifications. energy. subcontracting. marketing. seeds)	329.23	173.93
Water Volumes	m^3/ha	Irrigation Water volume per hectare	1003.61	985.84

Table 2
Description of variables used in the production functions estimation.

Variables		UM	Description
Y	Production	€	Gross Output per year
L	Land	€	Return on land capital (2% of land value) + rents
W	Water	m^3	Water Volume per year
VC	Variable Costs	€	Crop-specific variable costs per year (certifications. energy. subcontracting. marketing. seeds)
F	Fertilizers	€	Expenditure per year
P	Pesticides	€	Expenditure per year
WR	Labour	€	Expenditure on family and employed work per year
M	Machinery	€	Expenditure on owned machinery work per year
T	Temperatures	°C	Average annual temperatures at the provincial level
R	Rainfall	100 mm	Average annual rainfall volumes at the provincial level

be rewritten as Eq. 3 for estimation purposes:

$$\ln Y = \ln\alpha + \sum\nolimits_{i=1}^{n}\beta_i \ln X_i + e \tag{3}$$

Vector β includes a specific parameter related to water elasticity, β_w (Eq. 4):

$$\beta_w = \frac{\partial \ln \quad Y}{\partial \ln \quad W} \bullet \frac{W}{Y} \tag{4}$$

Eq. 2 can be rearranged to derive the partial derivative of Eq. 1 with respect to the water input (W), as illustrated in Eq. 5:

$$\frac{\partial \ln \quad Y}{\partial \ln \quad W} = \beta_w \quad \bullet \frac{Y}{W} \tag{5}$$

The Cobb-Douglas specification assumes that all inputs are substitutes, and the elasticity of substitution between inputs is constant. This limitation can be overcome through a translog specification of the production function. The latter provides a more flexible range of substitution options than those limited by the constant elasticity of substitution assumed in the Cobb-Douglas function. The translog production function is expressed as follows:

$$\ln Y = \alpha + \sum\nolimits_{i=1}^{n}\beta_i \ln X_i + \frac{1}{2} \quad \sum\nolimits_{i=1}^{n}\sum\nolimits_{j=1}^{n}\beta_{ij} \quad \ln \quad X_i \ln X_j + e \tag{6}$$

Where X represents the vector of inputs including water (W); β, estimated parameters vector; α, intercept; and *e,* error component. As before, β includes a specific parameter related to water elasticity, β_w (Eq. 6). The marginal productivity of irrigation water is expressed as the partial derivative of Eq. 5 with respect to the water input (w), as in Eq. 7:

$$\frac{\partial \ln \quad Y}{\partial \ln \quad W} \bullet \frac{Y}{W} = (\beta_w + \sum\nolimits_{j=1}^{n}\beta_{wj}\ln X_j) \bullet \frac{Y}{W} \tag{7}$$

Where all the variables are the same as in Eq. 6.

In both Cobb-Douglas and translog specifications, in order to account for environmental factors characterizing the varying context of each farm over time, we included average temperature and precipitation at the provincial level per year. By following Coelli et al., (1999) and Rahman et al., (2009) we assume that the environmental factors, enter in the production function linearly.[10] The constant term α was augmented to:

$$\alpha_{i,t} = a + \gamma_1 T_{i,t} + \gamma_2 R_{i,t} \tag{8}$$

With γ_1 and γ_2 are parameters that quantify the influence of average annual temperature and precipitation, respectively on agricultural production, providing a more comprehensive and nuanced analysis.

From an empirical perspective, a weighted fixed-effects specification was estimated. Several methodological issues emerge when elasticities and Total Factor Productivity (TFP) are estimated using traditional methods such as OLS. This is because productivity and input choices are correlated, which causes simultaneity or endogeneity problems (Beveren, 2012; Wooldridge, 2009). In addition, if market entry and exit are not allowed, selection bias will emerge. Several estimators have been proposed to address these biases, including those developed by Olley and Pakes (1996) and Levinsohn and Petrin, 2003, 2004. However, by assuming that firm-specific productivity is time-invariant,[11] it is possible to estimate production functions using a fixed-effects estimator (Pavcnik, 2002), as done by several studies focusing on the marginal productivity of irrigation water (Bierkens et al., 2017; Grammatikopoulou et al., 2020; Veninga, 2017). Moreover, the fixed-effects estimator addresses potential sources of endogeneity that may arise from the exclusion of time-invariant variables in the estimates (Baltagi, 2008). In addition, using an unbalanced panel, we overcome the self-selection bias.

Upon calculating shadow prices according to Eq. 7, a quantile regression (Koenker and Bassett, 2013) was estimated, which enabled us to identify farm characteristics associated with various levels or quantiles of shadow prices.

[10] We assume the separability of precipitation and temperature variables from the other production inputs in our model. This assumption is based on the spatial and temporal scales at which these environmental factors are measured. Specifically, they are calculated as annual averages at the provincial level, and as such, do not represent moment-to-moment variations in weather that might directly interact with other production inputs. Instead, these variables serve to characterize the broader climatic landscape or ecosystem within which the farms operate. In this context, they are conceptually distinct from the production inputs, thus justifying their separable treatment.

[11] The marginal productivity of water is unlikely to be affected by productivity or “innovation” shocks that could affect the efficiency of this input in maize production over-time.

Table 3
Description of the quantile regression independent variables and share of total sample (%).

Types of variables	Variables	Share (%)
Geographic Area	North	87.3
	Central	11
	South	1.7
Altimetric Area	Plain	76.8
	Hill	21.5
	Mountain	1.7
Irrigation Water Source	WUA	77.8
	Surface Water	10.3
	Groundwater	11.9
Farm Management	Family-run	67.5
	Mainly Family labor	24.9
	Mainly Employed Labor	4.1
	Other (Subcontracting, only employed labor)	3.5
Farm Size (ha)	<5	3.3
	1–15	30.9
	15–40	33.6
	> 40	32.2

$$Qp(\tau \mid \mathbf{z}) = \theta(\tau) + \mathbf{z}'\gamma(\tau) + u(\tau) \quad (9)$$

Table 3 reports all the variables used in the quantile regression. In particular, we rely on the first and the third quartiles, $\tau = 25$ and $\tau = 75$, and on the differsence between them, $\Delta = Qp(25)–Qp(75)$, to immediately note which characteristics of the farm are associated with relatively low and high levels of shadow price, while $\gamma(\tau)$ parameters can be estimated by using the estimator described by Hunter and Lange (2000). The independent variables represent territorial, structural, and managerial farm characteristics. Among territorial attributes, we consider geographic and altimetric location while we examine farm size for structural factors. Lastly, regarding organizational aspects, we consider labor organization, specifically the proportion of family or employed labor and irrigation water sources.

4. Results

As the Cobb-Douglas function is a restricted form of a translog, we compared these functions using an F-test (Greene, 2002); and the results showed that the translog production function fitted the data significantly better. Moreover, as the Hausman test suggests, a fixed-effects model was employed rather than a random-effects specification. To the latter, year fixed effects have been included to control for systematic temporal variability. Table 4 presents the estimated parameters of the translog production function and their significance levels. The estimated parameters for the Cobb-Douglas model are presented in the Appendix (see Table A2), alongside the parameters for the translog model without fixed effects over years (see Table A3).

Only the linear parameter of irrigation water was significant, revealing its role in maize production. The coefficients further revealed the significant complementarity of water with fertilizers (0.027) and work (0.011). However, a negative relationship was observed between water and pesticides (-0.026). The coefficients associated with climatic variables are not statistically significant, neither for Temperatures nor Rainfall. This is likely because these variables, representing annual means at the provincial level, have their effects absorbed by the annual fixed effects.[12]

After estimating the parameters, we calculated the value of water elasticity for gross maize output, which showed an inelastic response to irrigation water, with an average water elasticity of 0.08. Half of the farms in the sample showed an elasticity value ranging from 0.06 to 0.10. Additionally, the average water shadow price, calculated using Eq. 6, was found to be 0.29 €/m^3, with a median of 0.20 €/m^3 (Table 5). The water shadow price for half of the farms within the sample ranged from 0.10 €/m^3 to 0.39 €/m^3.

[12] Excluding year-level fixed effects results in minor, statistically insignificant changes to the parameters, except for the climatic variables, which in that specification become indeed significant (see Table A3).

Table 4
Weighted fixed effects model estimates for the translog production function and their Standard Errors (St. Err.) and significance levels.

	Parameter	St. Err.	
Land	0.143	0.111	
Water	-0.065	0.025	***
Variable Costs	0.120	0.167	
Fertilizers	0.879	0.143	***
Pesticides	0.370	0.130	***
Work	0.340	0.091	***
Machinery	-0.028	0.034	
Land×Water	-0.005	0.004	
Land×Variable Costs	-0.043	0.026	*
Land×Fertilizers	-0.019	0.027	
Land×Pesticides	-0.081	0.025	***
Land×Work	-0.013	0.016	
Land×Machinery	-0.004	0.006	
Water×Variable Costs	0.004	0.009	
Water×Fertilizers	0.027	0.008	***
Water×Pesticides	-0.026	0.008	***
Water×Work	0.011	0.005	**
Water×Machinery	0.002	0.002	
Variable Costs×Fertilizers	-0.089	0.049	*
Variable Costs×Pesticides	-0.170	0.046	***
Variable Costs×Work	-0.090	0.029	***
Variable Costs×Machinery	0.005	0.012	
Fertilizers×Pesticides	-0.033	0.043	
Fertilizers×Work	-0.080	0.029	***
Fertilizers×Machinery	-0.007	0.010	
Pesticides×Work	0.070	0.024	***
Pesticides×Machinery	0.015	0.010	
Work×Machinery	0.000	0.009	
Land^2	0.088	0.014	***
Water^2	0.003	0.003	
Variable Costs ^2	0.196	0.030	***
Fertilizers ^ 2	0.015	0.033	
Pesticides ^2	0.092	0.027	***
Work ^2	0.020	0.011	*
Machinery^2	0.000	0.003	
Temperatures	-0.026	0.030	
Rainfall (100 mm)	-0.007	0.006	
Constant	-0.054	0.734	

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Obs.: 5224. Adjusted R-Sq: within = 0.50, between = 0.78, overall = 0.73. All the variables are expressed in logarithms, except for Temperatures and Precipitations.

Fig. 1 shows the predicted marginal and total water productivity for irrigation volumes that align with the requirements for Italy (4000–6000 m^3/ha). We observed that the marginal productivity of irrigation water for maize (i.e., the shadow price) exhibits diminishing marginal returns with decreasing productivity for higher volumes, as indicated by the blue line. On the contrary, the total water productivity (in red) showed an increasing trend, although at a decreasing rate. It starts higher in the initial section and decreases as marginal productivity decreases. The estimated water shadow price for the aforementioned irrigation volumes ranges from 0.02 to 0.04 €/m^3. Total water productivity ranges between 620 and 670 €/ha, accounting for approximately one-third of the maize grain total gross output.

The insights provided by Fig. 1 are crucial for pricing mechanisms. Assuming no adjustment of other production inputs, if prices exceed

Table 5
Summary statistics of estimated water elasticity and water shadow price (€/m^3): mean, standard deviation (St. Dev.), 25th percentile (p25), 50th percentile (p50), and 75th percentile (p75).

	Mean	St. Dev.	p25	p50	p75
Water Elasticity	0.08	0.03	0.06	0.08	0.10
Water Shadow Price (€/ m^3)	0.29	0.26	0.10	0.20	0.39

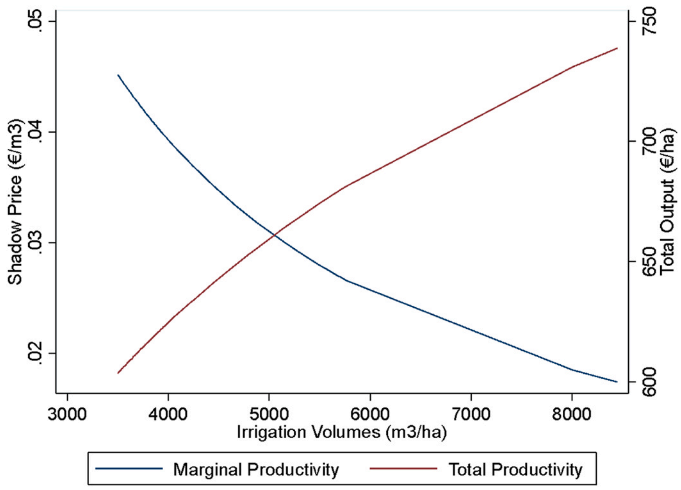

Fig. 1. Estimated Marginal Productivity (in blue) and Total Water productivity (in red) for maize grain.

0.05 €/m^3, they will surpass the value of the marginal productivity of water. In the short term, farmers may choose to reduce irrigation water use, resulting in a decrease in overall production of approximately one-third, with potentially important consequences within the overall supply chain.

While the above-mentioned results provide an average estimation of shadow prices and productivity, it is essential to note that different farms may have different shadow prices or productivity levels for water use. This underscores the significance of farm-level analysis in identifying the variability of water productivity and its association with farm characteristics: estimated shadow price distribution has been analyzed using quantile regressions to detect the influence of several farms' characteristics on water irrigation economic value. The first (Q1, $\tau = 25$) and third quartiles (Q3, $\tau = 75$) were considered to highlight the differences between low and high-water marginal productivity levels (Table 6). The model also highlights a negative trend, with shadow prices decreasing over time. The estimated parameters show significant differences between geographical areas at the Q3 level, with the *Central* Regions showing lower marginal productivity than *Northern* Regions (-0.150). The altitudinal area shows significant differences in Q1, where the shadow price is inversely proportional to the altitude. The Irrigation Water Source highlights a significant positive difference between *Groundwater* and *WUA* in Q3 (+0.060). Concerning farm management, *Family-Run* farms show lower shadow prices than farms with *Mainly Employed Labor* (+0.028) or *Mainly Family Labor* in Q1 (+0.033), while farms relying on subcontracting solely on employed labor show lower shadow prices in Q3 (-0.143). Farm Size, instead, shows significant differences with increasing acreage: *Medium Farms* (15–40 ha), especially, show a gap with *Small Farms* (< 5 ha) equal to −0.046 and −0.153, respectively, in Q1 and Q3. Table 7 presents the estimated shadow prices for Q1 and Q3 deriving from the quantile regressions.

Table 6
Quantile regressions estimates, standard errors (in parentheses), and significance levels for structural, managerial and geographical variables considered.

	Parameters			
	Q1		Q3	
Geographic Area **North**	-		-	
Central	-0.001		-0.150	***
	(0.007)		(0.057)	
South	-0.007		0.045	
	(0.045)		(0.092)	
Altimetric Area **Plain**	-		-	
Hill	-0.037	***	0.045	
	(0.007)		(0.055)	
Mountain	-0.086	***	0.030	
	(0.022)		(0.141)	
Irrigation Water Source **WUA**	-		-	
Surface Water	0.014		0.015	
	(0.010)		(0.023)	
Groundwater	0.014	**	0.060	**
	(0.008)		(0.030)	
Farm Management **Family-run**	-			
Mainly Family labor	0.033	***	-0.026	**
	(0.007)		(0.012)	
Mainly Employed Labor	0.028	**	-0.041	
	(0.013)		(0.031)	
Other	-0.011		-0.143	***
	(0.007)		(0.031)	
Farm Size **<5 ha**	-		-	
5–15 ha	-0.042	*	-0.122	***
	(0.023)		(0.029)	
15–40 ha	-0.046	**	-0.153	***
	(0.023)		(0.035)	
> 40	-0.042	*	-0.129	***
	(0.022)		(0.034)	
Time	-0.059	***	-0.138	***
	(0.008)		(0.029)	
Intercept	0.149	***	0.523	***
	(0.024)		(0.030)	

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$, Std. Err. are in parentheses.
Significance (*) shows the difference from the baseline (in bold).

5. Discussion

Our analysis underscores the relevance of water irrigation for maize grain in Italy and shows that water is an essential input for maize production, especially because of its contribution to other inputs' productivity. Both Cobb-Douglas and translog-derived elasticities showed low values, implying that maize grain production response to water was rigid on average. However, translog estimation allowed the detection of synergies between water and other inputs, highlighting the mutual dependence between water and fertilizers, which can enhance the contribution of both inputs to maize grain production (Hernández et al., 2015; Sadras, 2005; Zhou and Turvey, 2014). The same phenomenon occurs for water and work, suggesting the importance of water in more intensive production systems. Conversely, the negative relationship between water and pesticides suggests a positive contribution of water to maize grain quality and a reduction in sanitary risks (Medina et al., 2015; Wu et al., 2010). Lastly, the climate variables demonstrate no significant contribution. This finding aligns with Di Paolo and Rinaldi's (2008) observation that in Mediterranean regions, rainfall alone may not substantially impact maize grain production without supplemental irrigation water.[13]

The estimation of the water shadow price indicates water's contribution to crop productivity and assesses its economic value. The derived estimated average value stands at 0.29 €/m^3 and the median at 0.20 €/m^3. This analysis is based on a national sample of detailed micro-economic data; therefore, this variability could influence the average shadow price. Italy is characterized by strong territorial, climatic, and pedologic heterogeneity. Therefore, the median value is a more robust indicator. Our results are in line with the water shadow price obtained by Veninga (2017), whose value ranges between 0.19 and 0.53 \$/m^3 (0.18 and 0.50 €/m^3) and D'Odorico et al. (2020), who estimate water value as the farmers' willingness to pay (WTP) for a marginal unit of irrigation water and show a global average price of 0.16 \$/m^3 (approximately 0.15 €/ m^3). Finally, Bierkens et al. (2019) also estimated the same average price for maize grain in Italy. All these works analyzed less recent data and estimated irrigation water shadow prices

[13] Rainfed maize production is not widely observed in Italy, and this can be attributed to the predominance of intensive production methods and specific climatic and soil conditions.

Table 7
Estimated shadow prices (quantile margins both in Q1 and Q3) with significance levels relative to the baseline (in bold) for structural, managerial and geographical variables considered.

		Shadow Price			
		Q1		Q3	
Geographic Area	***North***	**0.111**		**0.400**	
		(0.002)		(0.013)	
	Central	0.110		0.251	***
		(0.009)		(0.055)	
	South	0.104		0.445	
		(0.036)		(0.079)	
Altimetric Area	**Plain**	**0.117**		**0.380**	
		(0.003)		(0.007)	
	Hill	0.080	***	0.426	
		(0.007)		(0.039)	
	Mountain	0.031	***	0.410	
		(0.027)		(0.158)	
Irrigation Water Source	**WUA**	**0.111**		**0.379**	
		(0.003)		(0.008)	
	Surface Water	0.125		0.395	
		(0.006)		(0.025)	
	Groundwater	0.094	*	0.439	**
		(0.010)		(0.043)	
Farm Management	**Family-run**	**0.101**		**0.400**	
		(0.003)		(0.010)	
	Mainly Family labor	0.134	***	0.374	
		(0.007)		(0.013)	
	Mainly Employed Labor	0.130	*	0.359	
		(0.015)		(0.041)	
	Other	0.090		0.257	***
		(0.005)		(0.022)	
Farm Size (ha)	**<5 ha**	**0.153**		**0.519**	
		(0.015)		(0.053)	
	5–15 ha	0.111	**	0.397	**
		(0.003)		(0.013)	
	15–40 ha	0.107	***	0.365	***
		(0.005)		(0.014)	
	> 40	0.110	**	0.390	***
		(0.005)		(0.014)	

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$, Std. Err. are in parentheses.
Significance (*) shows the difference from the baseline (in bold).

at the country scale; hence, a comparison must be made carefully. The same is true for studies that rely on different approaches and focus on the same crop. Berbel et al. (2011) estimated a shadow price of 0.07 €/m^3 while Ziolkowska (2015) and El-Gafy and El-Ganzori (2012) estimated a value ranging between 0.004 and 0.12 €/m^3 for Texas and Kansas, respectively. Finally, de Brito and de Azevedo (2022) showed a higher value (0.14 \$/m^3) in Brazil, and Kiprop et al. (2015) estimated a price of 0.13 €/m^3 in Kenya.

The estimated water shadow price is also consistent with the current pricing imposed by WUAs,[14] the primary organization responsible for the distribution of irrigation water in Italy. However, it should be noted that WUA tariffs mainly aim to recover water delivery and distribution costs. Considering the estimated shadow price as an indication of water pricing would be inaccurate, our price could be viewed as an estimate of water resource value, not accounting for water-related costs, externalities, or opportunity costs as WFD requires. However, any pricing imposed above the marginal productivity level would present a potential constraint for the producer, considering that according to our estimation, total water productivity accounts for one-third of the maize average gross output. In such a scenario, farmers would have to choose between reducing water usage, which could lead to a loss of production, and optimizing the overall production process by reducing water usage and adopting novel technologies in the long term.[15] The results of these strategies depend on local and regional characteristics as well (Hatfield et al., 2011).

Shadow price heterogeneity could reflect multiple scenarios and even water availability or efficient usage; a higher price reveals a water shortage or lower efficiency in water allocation, while a lower price reveals the opposite. Considering the first quartile (Q1), that is, farms not constrained by water availability, the Geographic Area does not show a significant difference. In contrast, the altimetric area shows that the water shadow price decreases with increasing altitude levels, reflecting greater water availability for *Hill* and *Mountain*. This result could also highlight the greater productivity of water in traditional maize-growing areas, such as Po Valley. In contrast, where water is scarce, this constraint mainly affects the most productive areas (*Northern Italy*). At the Q1 level, Farm Management shows a higher price for *Mainly Employed Labor* and *Mainly Family Labor* farms, revealing greater efficiency in *Family-Run* farms and *Subcontracting* or *Only Employed Labor* farms, which is in line with the findings of Speelman et al. (2008). Instead, at the Q3 level, management plays a role especially in *Subcontracting* or *Only Employed Labor* farms, that show a significantly lower price, likely reflecting higher efficiency in irrigation water management. *Small farms* (<5 ha) were the most vulnerable in both Q1 and Q3, possibly because of the greater incidence of water-related costs, making them more susceptible to water shortages. These results are consistent with those of Speelman et al. (2008) and Gadanakis et al. (2015), who found that farmers need to develop economies of scale to be more efficient and achieve input cost savings.

Concerning irrigation water sources, when farmers rely on groundwater, the marginal productivity is lower in Q1, indicating a lower shadow price compared to that obtained for farms relying on WUAs infrastructure. Considering that WUAs impose seasonal programming and farmers must schedule irrigation volumes and shifts before the sowing season, this result could depend on greater flexibility in irrigation schemes for farms relying on groundwater. WUAs usually carefully plan the irrigation season and the planning process typically takes into account factors such as anticipated water availability, crop water requirements and historical usage patterns. These schedules aim to strike a balance between providing a consistent water supply for irrigation needs and managing water resources. However, water availability can be highly variable, especially in regions prone to seasonal fluctuations or drought conditions. When water availability becomes limited WUAs may need to implement restrictions on water delivery. For example, they might prioritize supplying water for high-value crops or essential agricultural activities. As a result, there may be occasions when water delivery is curtailed or restricted to ensure equitable distribution during periods of scarcity. However, this can also reveal lower efficiency and suboptimal use of water resources. The main costs incurred by self-supplied farms concern infrastructure, delivery, and water extraction, which translates to fewer constraints on resource usage (Gómez and

[14] Tariffs for irrigation vary widely and are influenced by individual WUAs and regional regulations. In Northern Regions, they are based on irrigated or irrigable areas, while in Central and Southern regions, they depend on water volume or irrigated crops in compliance with the Water Framework Directive. In addition, tariffs can take various forms, including flat rates, volumetric rates, or tiered structures and some WUAs also impose fixed annual fees to cover service access and administrative costs. On average, volumetric rates typically range from 0.10 to 0.40 €/m^3 while the cost per m3 of well water is highly variable due to factors like the well's depth and operational expenses, making precise estimation challenging.

[15] Among these, precision farming, digitalization, and more efficient management of water productivity are promising strategies (Hatfield and Dold, 2019), coupled with the adoption of soil conservation measures, such as the introduction of legume crops in modern cropping systems (Stagnari et al., 2017; Wreford and Topp, 2020). The most common crop management practices include crop cultivar diversification, scheduling of planting dates, early maturing crops, drought-tolerant cultivars, and crop rotation (Dono et al., 2016; Pais et al., 2020; Yang et al., 2019, 2021)

Pérez Blanco, 2012). Where farms are constrained by water availability or are less efficient in this input allocation (Q3) the most affected farms are self-supplied farms (groundwater). The use of a support decision tool (smart irrigation), recycling water at the farm level, has been proven to have a positive effect on water efficiency at the farm scale (Gadanakis et al., 2015) and collective action in irrigation management (Chaudhry (2018), seems to improve on-farm water use efficiency. However, Wang (2010) found that farmers adopting well, or mixed irrigation exhibited higher water efficiency than those using river irrigation, probably because of greater flexibility and less water wastage during transportation. However, these results often depend on social and territorial characteristics, making comparisons inappropriate.

In summary, small and family-run farms are the most affected by water shortages, especially where water is already scarce. Where water is not very scarce, improving the efficiency of irrigation water use in farms located on the *Plain* can contribute the most to maize productivity. Concerning water irrigation sources, it must be highlighted that if water is scarce, thanks to seasonal planning, WUAs can probably guarantee farmers a more efficient water distribution and lower risks or production losses. Concomitantly, groundwater allows greater flexibility when water is not scarce, potentially leading to the suboptimal use of this resource. However, it has to be reminded that Italian WUAs can follow different pricing approaches: Northern Regions often apply a fixed cost per year or crop, while Southern Regions mainly use a volumetric approach. In the latter, farmers could be pushed to search for alternative water sources (groundwater) to reduce water-related costs and compensate for water scarcity (Cortignani et al., 2018). Hence, farmers' responses to water shortages should be further examined when they rely on both irrigation sources, to establish whether a substitution or additional effect exists between them. For this reason, it is crucial to analyze the economic value of water in detail, highlighting variations and differences across territories, areas, and types of farms, to develop strategies to balance the economic value of water with its environmental significance and to ensure sustainable water usage practices in agriculture (Bozzola and Swanson, 2014).

6. Conclusions

The results of our analysis have several potential applications, including establishing the relevance, productivity, and economic value of irrigation water and allowing for further methodological development. We found that water is a crucial input for making maize grain economically viable, emphasizing the significant dependence of this crop on water, and the contribution of this resource to other inputs' productivity. This is particularly significant because Italy is the fourth-largest maize grain producer in the EU, and Northern Regions account for 85% of the Italian maize agricultural area. Maize plays a strategic role in several supply chains, particularly in Parmigiano Reggiano production, which does not allow the use of silage fodder (Mantovi et al., 2015). Moreover, if imposed prices surpass the value of the marginal productivity of water, farmers may choose to reduce irrigation water use resulting in losses in overall production of approximately one-third, or to replace maize with rainfed crops (Aldaya et al., 2023; Sapino et al., 2022). Consequently, a shortage in maize production could result in greater dependence on imports and economic losses in several Italian agricultural sectors.

Moreover, our water shadow price estimation can assist policymakers in partially fulfilling the requirements of the WFD by estimating the resource value, which assesses water relevance and scarcity, and by identifying vulnerable areas and clusters of farms, taking into account Italy's territorial and productive heterogeneity. Additionally, our estimation facilitates the assessment of each input's impact on output, allowing the distinction between fertilizers and pesticides. Combining these results with a Mathematical Programming approach could lead to the estimation of flexible models, establishing economic, social, and environmental impacts on farms resulting from a reduction in chemical input use, as required by the F2F targets (Cortignani et al., 2022). Importantly, it should be noted that our estimation of the water shadow price for irrigation neglects any other economic returns derived from the overall supply chain; namely, it does not include the contribution of maize to downstream or upstream supply chains. As such, the provided estimation only indicates the direct economic value of water for maize production and does not reflect the full value of water's contribution to the supply chain and economy. Further, our analysis presumes that unobserved firm-specific water productivity does not vary over time and does not consider external productivity shocks that could influence the level of inputs used by the farmer. Moreover, our analysis does not account for intertemporal efficiency and opportunity costs associated with water use. In specific circumstances where extraction costs are notably high or where externalities have a significant impact, the estimated shadow price in our study may be lower than in an assessment that includes these considerations. These limitations should be kept in mind when interpreting the estimated shadow price of water.

In conclusion, our estimation serves as a starting point for further research and analysis that incorporates these additional factors to establish a more accurate assessment of water's value and its impact on agricultural production and supply chains. Integrating social, environmental, and economic factors is crucial for achieving sustainable water use practices that account for the total value of water as a vital resource for agriculture and the economy.

CRediT authorship contribution statement

Rebecca Buttinelli: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Francesco Caracciolo:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Raffaele Cortignani:** Funding acquisition, Project administration, Resources, Supervision, Writing – original draft, Writing – review & editing.

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.

Data Availability

The authors do not have permission to share data.

Acknowledgements

This study was carried out within the Agritech National Research Center and received funding from the European Union Next-GenerationEU (PIANO NAZIONALE DI RIPRESA E RESILIENZA (PNRR) – MISSIONE 4 COMPONENTE 2, INVESTIMENTO 1.4 – D.D. 1032 17/06/2022, CN00000022). This manuscript reflects only the authors' views and opinions, neither the European Union nor the European Commission can be considered responsible for them.

Appendix

Table A1
Functional forms, dependent and independent variables, case studies and concerned crops in the recent literature estimating irrigation water shadow price using production function approach.

Functional Form	Dependent Variable	Independent Variables	Case Study	Crop	References
Translog	Crop Production (t)	Area (ha) Employment in agriculture (1000 person) Agricultural Value Added per Worker ($) Green water use ($km^3$) Blue water + non-renewable groundwater (km^3) Fertilizers (kg/ha)	China, Egypt, India, Iran, Italy, Mexico, Pakistan, Saudi Arabia, South Africa, Turkey, USA	Sugarcane, Maize, Citrus	Veninga, (2017)
	Biomass output per acre (t/acre)	Fertilizers (quantity index) Chemicals (quantity index) Precipitation (inches) Irrigation water (ratio of irrigated area to total cropland) Degree Days	High Plains Aquifer, USA	All crops produced in a county	Garciá Suárez et al. (2019)
Cobb Douglas	Value of crop products sold ($)	Employment in cropland (number of FTEs) Amount of surface water usage in cropland (acre-ft/yr) Amount of groundwater usage in cropland (acre-ft/yr) Ratio of surface water on total water Rate of land share of irrigated lands out of the total cultivated croplands Rate of fertilized lands out of the total cultivated lands	South Florida, USA	Croplands products (mainly sugarcane and citrus)	Takatsuka et al., (2018)
	Crop Production (kg/year/AA)	Agricultural Land (ha) Energy (kg di oil equivalent per year/AA) Water (green water e irrigation water in mc/year/AA	China, Egypt, India, Iran, Italy, Mexico, Pakistan, South Africa, Spain, Turkey, USA	Wheat, Potato, Maize, Rice, Citrus	Bierkens et al., (2019)
	Production output (t)	Labour (1000 persons) Fertilizers (kg) Pesticides (kg) Harvesting equipment (n. of harvesters) Transport fuel (terajoule) Green water use (m^3) Harvested crop area (ha)	Czech Republic	Cereals (Wheat, Barley, Maize, Oats, Triticale)	Grammatikopoulou et al., (2020)
Several Forms	Yield (kg/ha)	Seed (kg/ha) Fertilizers (kg/ha) Pesticides (kg/ha) Machinery Costs ($) Manpower (man days) Irrigation water (m^3/ha)	Ardabil Plain, Iran	Wheat, Potato, Alfalfa, Barley, Canola	Nouri-Khajebelagh et al., (2021)

* Green water (evapotranspiration), blue water (withdrawal from rivers, surface water and renewable groundwater) and non-renewable groundwater (Oki et Kanae, 2006

Table A2
Estimates of the Fixed-Effects Cobb Douglas Production Function and their Significance Levels

Variable	Parameter	Std. Err.	
Land	0.131	0.025	***
Water	0.011	0.003	***
Variable Costs	0.188	0.028	***
Fertilizers	0.241	0.024	***
Pesticides	0.207	0.042	***
Work	0.096	0.035	***
Machinery	0.000	0.006	
Temperatures	- 0.074	0.021	***
Rainfall (100 mm)	-0.003	0.003	
Intercept	4.286	0.362	***

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$, Std. Err. Are in parentheses. Obs.: 5224.
Adjusted R-Sq: within = 0.41, between = 0.79, overall = 0.74.

Table A3
Weighted fixed effects model estimates for the translog production function and their Standard Errors (St. Err.) and significance levels.

Variable	Parameter	Std. Err.	
Land	0.139	0.112	
Water	-0.070	0.025	***
Variable Costs	0.059	0.169	
Fertilizers	0.848	0.144	***
Pesticides	0.331	0.132	***
Work	0.390	0.092	***
Machinery	-0.053	0.034	
Land×Water	-0.004	0.004	
Land×Variable Costs	-0.044	0.027	*
Land×Fertilizers	-0.021	0.027	
Land×Pesticides	-0.079	0.026	***
Land×Work	-0.019	0.016	
Land×Machinery	-0.007	0.006	
Water×Variable Costs	0.004	0.009	
Water×Fertilizers	0.028	0.008	***
Water×Pesticides	-0.029	0.008	***
Water×Work	0.012	0.005	**
Water×Machinery	0.001	0.002	
Variable Costs×Fertilizers	-0.088	0.049	*
Variable Costs×Pesticides	-0.153	0.046	***
Variable Costs×Work	-0.098	0.030	***
Variable Costs×Machinery	0.010	0.012	
Fertilizers×Pesticides	-0.050	0.044	
Fertilizers×Work	-0.067	0.029	**
Fertilizers×Machinery	-0.005	0.011	
Pesticides×Work	0.083	0.024	***
Pesticides×Machinery	0.015	0.010	
Work×Machinery	-0.001	0.009	
Land^2	0.096	0.014	***
Water^2	0.004	0.003	
Variable Costs ^2	0.200	0.031	***
Fertilizers ^ 2	0.021	0.033	
Pesticides ^2	0.090	0.028	***
Work ^2	0.008	0.011	
Machinery^2	0.003	0.003	
Temperatures	-0.079	0.017	***
Rainfall (100 mm)	-0.006	0.003	*
Constant	0.802	0.669	

Note: *p < 0.1; **p < 0.05; ***p < 0.01. Obs.: 5224. Adjusted R-Sq: within = 0.48, between = 0.78, overall = 0.72. All the variables are expressed in logarithm, except for Temperatures and Precipitations.

References

Aldaya, M.M., Gutiérrez-Martín, C., Espinosa-Tasón, J., Ederra, I., Sánchez, M., 2023. The impact of the territorial gradient and the irrigation water price on agricultural production along the first phase of the Navarra Canal in Spain. Agric. Water Manag. 281, 108245 https://doi.org/10.1016/J.AGWAT.2023.108245.

Baltagi, B.H., 2008. Econometric Analysis of Panel Data. John Wiley & Sons Ltd,, Chichester.

Baniasadi, M., Zare' Mehrjordi, M.R., Mehrabi Boshrabadi, H., Mirzaei Khalilabad, H.R., Rezaei Estakhrooye, A., 2020. Evaluation of negative economic-environmental externalities of overextraction of groundwater. Groundwater 58, 560–570. https://doi.org/10.1111/gwat.12933.

Bellver-Domingo, A., Fuentes, R., Hernández-Sancho, F., 2019. Reclaimed water and irrigation: a cost-benefit analysis for desalination of WWTPs effluents. Desalin. Water Treat. 166, 193–201. https://doi.org/10.5004/dwt.2019.24556.

Berbel, J., Expósito, A., 2020. The theory and practice of water pricing and cost recovery in the water framework directive. Water Alter. 13, 659–673.

Berbel, J., Mesa-Jurado, A., Pistón, J.M., 2011. Value of irrigation water in guadalquivir basin (Spain) by residual value method. Water Resour. Manag. 25, 1565–1579. https://doi.org/10.1007/s11269-010-9761-2.

Berbel, J., Borrego-Marin, M.M., Exposito, A., Giannoccaro, G., Montilla-Lopez, N.M., Roseta-Palma, C., 2019. Analysis of irrigation water tariffs and taxes in Europe. Water Policy 21, 806–825. https://doi.org/10.2166/wp.2019.197.

Beveren, I.Van, 2012. TOTAL FACTOR Product. ESTIMATION 26, 98–128. https://doi.org/10.1111/j.1467-6419.2010.00631.x.

Bierkens, M.F.P., Reinhard, S., de Bruijn, J.A., Veninga, W., Wada, Y., 2019. The Shadow Price of Irrigation Water in Major Groundwater-Depleting Countries. Water Resour. Res. 55, 4266–4287. https://doi.org/10.1029/2018WR023086.

Bopp, C., Jara-Rojas, R., Bravo-Ureta, B., Engler, A., 2022. Irrigation water use, shadow values and productivity: Evidence from stochastic production frontiers in vineyards. Agric. Water Manag. 271, 107766 https://doi.org/10.1016/j.agwat.2022.107766.

Bozzola, M., Swanson, T., 2014. Policy implications of climate variability on agriculture: Water management in the Po river basin, Italy. Environ. Sci. Policy 43, 26–38. https://doi.org/10.1016/j.envsci.2013.12.002.

Bruno, E.M., Jessoe, K., 2021. Using price elasticities of water demand to inform policy. Annu. Rev. Resour. Econ. 13, 427–441. https://doi.org/10.1146/annurev-resource-110220-104549.

Calatrava, J., Garrido, A., 2005. Modelling water markets under uncertain water supply. Eur. Rev. Agric. Econ. 32, 119–142. https://doi.org/10.1093/eurrag/jbi006.

Chaudhry, A.M., 2018. Improving on-farm water use efficiency: Role of collective action in irrigation management. Water Resour. Econ. 22, 4–18. https://doi.org/10.1016/j.wre.2017.06.001.

Cobb, C.W., Douglas, P.H., 1928. Theory of production. Am. Econ. Rev. https://doi.org/10.1007/978-4-431-54433-3_9.

Coelli, T., Orion, S., 2013. The technical efficiency of wine grape growers in the murray–darling basin in Australia. Wine Econ.

Coelli, T., Perelman, S., Romano, E., 1999. Accounting for environmental influences in stochastic frontier models: with application to international airlines. J. Product. Anal. 11, 251–273.

Conradie, B., Cookson, G., Thirthle, C., 2006. Efficiency farm size west. cape grape production: pooling small datasets 74, 334–343.

Cortignani, R., Dell'Unto, D., Dono, G., 2018. Recovering the costs of irrigation water with different pricing methods: Insights from a Mediterranean case study. Agric. Water Manag. 199, 148–156. https://doi.org/10.1016/j.agwat.2017.12.016.

Cortignani, R., Buttinelli, R., Dono, G., 2022. Farm to Fork strategy and restrictions on the use of chemical inputs: Impacts on the various types of farming and territories of Italy. Sci. Total Environ. 810, 152259 https://doi.org/10.1016/j.scitotenv.2021.152259.

31AD D.M., 31 luglio 2015. Ministero delle Politiche agricole alimentari e forestali: Approvazione delle linee guida per la regolamentazione da parte delle Regioni delle modalità di quantificazionedei volumi idrici ad uso irriguo.

D'Odorico, P., Chiarelli, D.D., Rosa, L., Bini, A., Zilberman, D., Rulli, M.C., 2020. The global value of water in agriculture. Proc. Natl. Acad. Sci. U. S. A. 117, 21985–21993. https://doi.org/10.1073/pnas.2005835117.

Damania, R., Desbureaux, S., Hyland, M., Islam, A., Moore, S., Rodella, A.-S., Russ, J., Zaveri, E., 2020. The economics of water scarcity and variability. Oxf. Rev. Econ. Policy. https://doi.org/10.1093/oxrep/grz027.

Dayananda, D., Weerahewa, J., Weerasooriya, S.A., 2023. Resource-use efficiency and environmental sustainability in the village tank cascade systems in the dry zone of Sri Lanka: An assessment using a bio-economic model. Front. Sustain. Food Syst. 7 https://doi.org/10.3389/fsufs.2023.1084973.

de Bonviller, S., Wheeler, S.A., Zuo, A., 2020. The dynamics of groundwater water markets: Price leadership and groundwater demand elasticity in the Murrumbidgee, Australia. Agric. Water Manag. 239 https://doi.org/10.1016/j.agwat.2020.106204.

de Brito, P.L.C., de Azevedo, J.P.S., 2022. Economic value of water for irrigation in São Francisco River Basin, Brazil. Appl. Water Sci. 12 https://doi.org/10.1007/s13201-022-01678-4.

Di Paolo, E., Rinaldi, M., 2008. Yield response of corn to irrigation and nitrogen fertilization in a Mediterranean environment. F. Crop. Res. 105, 202–210. https://doi.org/10.1016/j.fcr.2007.10.004.

Dono, G., Severini, S., Dell'Unto, D., Cortignani, R., 2019. Italy. In: Molle, F., Sanchis-Ibor, C., Avellà-Reus, L. (Eds.), Irrigation in the Mediterranean. Global Issues in Water Policy. Springer,, Cham. https://doi.org/10.1007/978-3-030-03698-0_6.

Dono, G., Cortignani, R., Dell'Unto, D., Deligios, P., Doro, L., Lacetera, N., Mula, L., Pasqui, M., Quaresima, S., Vitali, A., Roggero, P.P., 2016. Winners and losers from climate change in agriculture: Insights from a case study in the Mediterranean basin. Agric. Syst. 147, 65–75. https://doi.org/10.1016/j.agsy.2016.05.013.

El-Gafy, I., El-Ganzori, A., 2012. Decision support system for economic value of irrigation water. Appl. Water Sci. 2, 63–76. https://doi.org/10.1007/s13201-012-0029-2.

Elnaboulsi, J.C., 2001. Nonlinear pricing and capacity planning for water and wastewater services. Water Resour. Manag. 15 (1), 55–69. https://doi.org/10.1023/A:1012228611303.

Erenstein, O., Jaleta, M., Sonder, K., Mottaleb, K., Prasanna, B.M., 2022. Global maize production, consumption and trade: trends and R&D implications. Food Secur 14, 1295–1319. https://doi.org/10.1007/s12571-022-01288-7.

Esmaeili, A., Shahsavari, Z., 2015. Water allocation for agriculture in southwestern Iran using a programming model. Appl. Water Sci. 5, 305–310. https://doi.org/10.1007/s13201-014-0192-8.

European Commission, 2000. Directive 2000/60/EC of the European Parliament and of the Council of 23 October 2000 Establishing a Framework for Community Action in the Field of Water Policy. Official Journal L 327, 0001–0073, 22/12/2000.

European Commission, 2019. The European Green Deal. Brussels, com/2019/640 final. – ⟨https://ec.europa.eu/info/strategy/priorities-2019-2024/european-greendeal_en⟩.

FAO, 2022. The State of the World's Land and Water Resources for Food and Agriculture 2021 – Systems at breaking point, The State of the World's Land and Water Resources for Food and Agriculture 2021 – Systems at breaking point. https://doi.org/10.4060/cb9910en.

Gadanakis, Y., Bennett, R., Park, J., Areal, F.J., 2015. Improving productivity and water use efficiency: A case study of farms in England. Agric. Water Manag. 160, 22–32. https://doi.org/10.1016/j.agwat.2015.06.020.

Galioto, F., Guerra, E., Raggi, M., Viaggi, D., 2017. The impact of new regulations on water pricing in the agricultural sector: a case study from Northern Italy. Agric. Econ. Rev. 18, 77–95.

Gallego-Ayalal, J., Gomez-Limon, J.A., Arriaza, M., 2011. Irrigation water pricing instruments: a sustainability assess. Ment. | Tarif. óN. Del. agua De. Riego.: Una evaluacióN. De. la sostenibilidad. Span. J. Agric. Res. 9, 981–999. https://doi.org/10.5424/sjar/20110904-449-10.

Garciá Suárez, F., Fulginiti, L.E., Perrin, R.K., 2019. What is the use value of irrigation water from the high plains aquifer? Am. J. Agric. Econ. 101, 455–466. https://doi.org/10.1093/ajae/aay062.

Giannoccaro, G., Sardaro, R., de Vito, R., Roselli, L., de Gennaro, B.C., 2020. Policy instruments for irrigation groundwater management. An assessment of farmers' stated preferences. Econ. Agro-Aliment. 22, 1–27. https://doi.org/10.3280/ecag2-2020oa10409.

Gómez, C.M., Pérez Blanco, C.D., 2012. Do drought management plans reduce drought risk? a risk assessment model for a Mediterranean river basin. Ecol. Econ. 76, 42–48. https://doi.org/10.1016/j.ecolecon.2012.01.008.

Gómez-limón, J.A., Martin-Ortega, J., 2013. The economic analysis in the implementation of the water-framework directive in Spain. Int. J. River Basin Manag. 11, 301–310. https://doi.org/10.1080/15715124.2013.823977.

Grammatikopoulou, I., Sylla, M., Zoumides, C., 2020. Economic evaluation of green water in cereal crop production: A production function approach. Water Resour. Econ. 29, 100148 https://doi.org/10.1016/j.wre.2019.100148.

Greene, W.H., 2002. Econometric analysis, 5th ed. Prentice Hall,, Upper Saddle River, NJ.

Hatfield, J.L., Dold, C., 2019. Water-use efficiency: Advances and challenges in a changing climate. Front. Plant Sci. 10, 1–14. https://doi.org/10.3389/fpls.2019.00103.

Hatfield, J.L., Boote, K.J., Kimball, B.A., Ziska, L.H., Izaurralde, R.C., Ort, D., Thomson, A.M., Wolfe, D., 2011. Climate impacts on agriculture: Implications for crop production. Agron. J. 103, 351–370. https://doi.org/10.2134/agronj2010.0303.

He, J., Chen, X., Shi, Y., Li, A., 2007. Dynamic computable general equilibrium model and sensitivity analysis for shadow price of water resource in China. Water Resour. Manag. 21, 1517–1533. https://doi.org/10.1007/s11269-006-9102-7.

Hellegers, P., Davidson, B., 2010. Determining the disaggregated economic value of irrigation water in the Musi sub-basin in India. Agric. Water Manag. 97, 933–938. https://doi.org/10.1016/j.agwat.2010.01.026.

Hernández, M., Echarte, L., Della Maggiora, A., Cambareri, M., Barbieri, P., Cerrudo, D., 2015. Maize water use efficiency and evapotranspiration response to N supply under contrasting soil water availability. F. Crop. Res. 178, 8–15. https://doi.org/10.1016/j.fcr.2015.03.017.

Hristov, J., Toreti, A., Pérez Domínguez, I., Dentener, F., Fellmann, T., Elleby, C., Ceglar, A., Fumagalli, D., Niemeyer, S., Cerrani, I., Panarello, L., Bratu, M., 2020. Analysis of climate change impacts on EU agriculture by 2050 JRC PESETA IV project-Task 3. JRC Tech. Rep. https://doi.org/10.2760/121115.

Hunter, D.R., Lange, K., 2000. Quantile Regression via an MM Algorithm. J. Comput. Graph. Stat. 9, 60–77. https://doi.org/10.1080/10618600.2000.10474866.

ICWE, 1992. The Dublin Statement and Report of the International Conference on Water and the Environment. Development issues for the 21st century, Dublin.

INEA, 2011. Atlante nazionale dell'irrigazione, a cura di Zucaro R. Roma 2011.

IPCC, 2019. Summary for Policymakers. In: Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems [P. R., Shukla, J., Skea, E., Calvo Buendia, V., Masson-Delmotte, H.- O., Portner, D. C. Roberts, P. Zhai, R. Slade, S. Connors, R. van Diemen, M. Ferrat, E. Haughey, S. Luz, S. Neogi, M. Pathak, J. Petzold, J. Portugal Pereira, P. Vyas, E. Huntley, K. Kissick, M. Belkacemi, J. Malley, (eds.)].

Jana, S., 2018. Socioeconomic impacts and cost-benefit analysis of wastewater-fed aquaculture. : Wastewater Manag. Aquac. 269–284. https://doi.org/10.1007/978-981-10-7248-2_14.

Jiang, L., Wu, F., Liu, Y., Deng, X., 2014. Modeling the impacts of urbanization and industrial transformation on water resources in China: An integrated hydro-economic cge analysis. Sustain 6, 7586–7600. https://doi.org/10.3390/su6117586.

Johansson, R.C., Tsur, Y., Roe, T.L., Doukkali, R., Dinar, A., 2002. Pricing irrigation water: A review of theory and practice. Water Policy 4, 173–199. https://doi.org/10.1016/S1366-7017(02)00026-0.

Kiani, R.A., Abbasi, F., 2012. Optimizing Water Consumption Using Crop Water Production Functions. Crop Prod. Technol. https://doi.org/10.5772/29543.

Kiprop, J.K., Lagat, J.K., Mshenga, P., Macharia, A.M., 2015. Determining the Economic Value of Irrigation Water in Kerio Valley Basin (Kenya) by Residual Value Method. J. Econ. Sustain. Dev. 6, 102–108.

Koenker, R., Bassett, G., 2013. No title regression quantiles. J. Chem. Inf. Model. 53, 1689–1699.

Koundouri, P., Babalos, V., Stithou, M., Anastasiou, I., 2014. A micro-econometric approach to deriving use and non-use values of in situ groundwater: The vosvozis case study, Greece. Handb. Econ. Ecosyst. Serv. Biodivers. 423–435. https://doi.org/10.4337/9781781951514.00032.

Koundouri, P., Dávila, O.G., Anastasiou, Y., Antypas, A., Mavrogiorgis, T., Mousoulides, A., Mousoulidou, M., Vasiliou, K., 2014a. An econometric analysis of agricultural production, focusing on the shadow price of groundwater: policies towards socio-economic sustainability. Glob. Issues Water Policy. https://doi.org/10.1007/978-94-007-7636-4_5.

Koundouri, Phoebe, Babalos, V., Stithou, M., Anastasiou, I., 2014b. A micro-econometric approach to deriving use and non-use values of in situ groundwater: The vosvozis case study, Greece. Handb. Econ. Ecosyst. Serv. Biodivers. 423–435. https://doi.org/10.4337/9781781951514.00032.

Latruffe, L., Niedermayr, A., Desjeux, Y., Dakpo, K.H., Ayouba, K., Schaller, L., Kantelhardt, J., Jin, Y., Kilcline, K., Ryan, M., O'Donoghue, C., 2023. Identifying and assessing intensive and extensive technologies in European dairy farming. Eur. Rev. Agric. Econ. 50, 1482–1519. https://doi.org/10.1093/erae/jbad023.

Levinsohn, J., Petrin, A., 2003. Estimating production functions using inputs to control for unobservables. Rev. Econ. Stud. 70 (2), 317–342.

Levinsohn, J., Petrin, A., 2004. Prod. Funct. Estim. Stata Using Inputs Control unobservables 113–123.

Li, G., Shi, M., Zhou, D., 2021. How much will farmers be compensated for water reallocation from agricultural water to the local ecological sector on the edge of an oasis in the Heihe River Basin? Agric. Water Manag. 249 https://doi.org/10.1016/j.agwat.2021.106801.

Li, Y., Li, Z., Cui, S., Chang, S.X., Jia, C., Zhang, Q., 2019. A global synthesis of the effect of water and nitrogen input on maize (Zea mays) yield, water productivity and nitrogen use efficiency. Agric. . Meteorol. 268, 136–145. https://doi.org/10.1016/j.agrformet.2019.01.018.

Lionboui, H., Benabdelouahab, T., Elame, F., Hasib, A., Boulli, A., 2018. Estimating the economic impact of climate change on agricultural water management indicators. Pertanika J. Sci. Technol. 26, 749–762.

Lionello, P., Scarascia, L., 2018. The relation between climate change in the Mediterranean region and global warming. Reg. Environ. Chang. 18, 1481–1493. https://doi.org/10.1007/s10113-018-1290-1.

Liu, X., Chen, X., 2008. Methods for approximating the shadow price of water in China. Econ. Syst. Res. 20, 173–185. https://doi.org/10.1080/09535310802075349.

Liu, X., Chen, X., Wang, S., 2009. Evaluating and predicting shadow prices of water resources in China and its nine major river basins. Water Resour. Manag. 23, 1467–1478. https://doi.org/10.1007/s11269-008-9336-7.

Mantovi, P., Dal Prà, A., Pacchioli, M., & Ligabue, M., (2015). Forage production and use in the dairy farming systems of Northern Italy.

Medina, Á., Rodríguez, A., Magan, N., 2015. Climate change and mycotoxigenic fungi: Impacts on mycotoxin production. Curr. Opin. Food Sci. 5, 99–104. https://doi.org/10.1016/j.cofs.2015.11.002.

Mereu, V., Gallo, A., Trabucco, A., Carboni, G., Spano, D., 2021. Modeling high-resolution climate change impacts on wheat and maize in Italy. Clim. Risk Manag. 33, 100339 https://doi.org/10.1016/j.crm.2021.100339.

Mesa-Jurado, M.A., Berbel, J., Orgaz, F., 2010. Estimating marginal value of water for irrigated olive grove with the production function method. Span. J. Agric. Res. 8 https://doi.org/10.5424/sjar/201008s2-1362.

Njuki, E., Bravo-Ureta, B.E., 2019. Examining irrigation productivity in U.S. agriculture using a single-factor approach. J. Product. Anal. 51, 125–136. https://doi.org/10.1007/s11123-019-00552-x.
Nouri-Khajebelagh, R., Khaledian, M., Kavoosi-Kalashami, M., 2021. Economic value of irrigation water for major crops in the Ardabil plain, Iran*. Irrig. Drain. 70, 1359–1367. https://doi.org/10.1002/ird.2619.
Olley, B.Y.G.S., Pakes, A., 1996. The Dynamics of Productivity in the Telecommunications Equipment Industry Author (s): G. Steven Olley Ariel Pakes Publ. : Econom. Soc. Stable URL 64, 1263–1297. ⟨https://www.jstor.org/stable/2171831⟩.
Pais, I.P., Reboredo, F.H., Ramalho, J.C., Pessoa, M.F., Lidon, F.C., Silva, M.M., 2020. Potential impacts of climate change on agriculture-A review. Emir. J. Food Agric. 32, 397–407. https://doi.org/10.9755/ejfa.2020.v32.i6.2111.
Pavcnik, N., 2002. Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants, 69, 245–276.
Pérez-Blanco, C.D., Gutiérrez-Martín, C., 2017. Buy me a river: Use of multi-attribute non-linear utility functions to address overcompensation in agricultural water buyback. Agric. Water Manag. 190, 6–20. https://doi.org/10.1016/j.agwat.2017.05.006.
Rahman, S., Wiboonpongse, A., Sriboonchitta, S., Chaovanapoonphol, Y., 2009. Production efficiency of Jasmine rice producers in Northern and North-Eastern Thailand. J. Agric. Econ. 60 (2), 419–435.
Riera, F.S., Brümmer, B., 2022. Environmental efficiency of wine grape production in Mendoza, Argentina. Agric. Water Manag. 262 https://doi.org/10.1016/j.agwat.2021.107376.
Rigby, D., Alcon, F., Burton, M., 2010. Supply uncertainty and the economic value of irrigation water. Eur. Rev. Agric. Econ. 37, 97–117. https://doi.org/10.1093/erae/jbq001.
Rodríguez-Flores, J.M., Medellín-Azuara, J., Valdivia-Alcalá, R., Arana-Coronado, O.A., García-Sánchez, R.C., 2019. Insights from a calibrated optimization model for irrigated agriculture under drought in an irrigation district on the central Mexican high plains. Water (Switz.) 11, 1–23. https://doi.org/10.3390/w11040858.
Rosegrant, M.W., Ringler, C., McKinney, D.C., Cai, X., Keller, A., Donoso, G., 2000. Integrated economic-hydrologic water modeling at the basin scale: The Maipo river basin. Agric. Econ. 24, 33–46. https://doi.org/10.1016/S0169-5150(00)00113-4.
Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A.C., Müller, C., Arneth, A., Boote, K.J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T.A.M., Schmid, E., Stehfest, E., Yang, H., Jones, J.W., 2014. Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. Proc. Natl. Acad. Sci. U. S. A. 111, 3268–3273. https://doi.org/10.1073/pnas.1222463110.
Sadras, V.O., 2005. A quantitative top-down view of interactions between stresses: Theory and analysis of nitrogen-water co-limitation in Mediterranean agro-ecosystems. Aust. J. Agric. Res. 56, 1151–1157. https://doi.org/10.1071/AR05073.
Sapino, F., Dionisio, C.P., Guti, C., García-prats, A., Pulido-velazquez, M., 2022. Influence of crop-water production functions on the expected performance of water pricing policies in irrigated agriculture, 259. https://doi.org/10.1016/j.agwat.2021.107248.
Scheierling, S.M., Loomis, J.B., Young, R.A., 2006. Irrigation water demand: A meta-analysis of price elasticities. Water Resour. Res. 42 (1), 9. https://doi.org/10.1029/2005WR004009.
Schmitz, C., Lotze-Campen, H., Gerten, D., Dietrich, J.P., Bodirsky, B., Biewald, A., Popp, A., 2013. Blue water scarcity and the economic impacts of future agricultural trade and demand. Water Resour. Res. 49, 3601–3617. https://doi.org/10.1002/wrcr.20188.
Shen, X., Lin, B., 2017. The shadow prices and demand elasticities of agricultural water in China: A StoNED-based analysis. Resour. Conserv. Recycl. 127, 21–28. https://doi.org/10.1016/j.resconrec.2017.08.010.
Shi, M., Wang, X., Yang, H., Wang, T., 2014. Pricing or quota? A solution to water scarcity in oasis regions in China: A case study in the Heihe River Basin. Sustain 6, 7601–7620. https://doi.org/10.3390/su6117601.
Smith, R.B.W., Nelson, H., Roe, T.L., 2015. Groundwater and Economic Dynamics, Shadow Rents and Shadow Prices: The Punjab. Water Econ. Policy 1. https://doi.org/10.1142/S2382624×15500149.
Speelman, S., D'Haese, M., Buysse, J., D'Haese, L., 2008. A measure for the efficiency of water use and its determinants, a case study of small-scale irrigation schemes in North-West Province, South Africa. Agric. Syst. 98, 31–39. https://doi.org/10.1016/j.agsy.2008.03.006.
Stagnari, F., Maggio, A., Galieni, A., Pisante, M., 2017. Multiple benefits of legumes for agriculture sustainability. overview 13 (1). https://doi.org/10.1186/s40538-016-0085-1.
Takatsuka, Y., Niekus, M.R., Harrington, J., Feng, S., Watkins, D., Mirchi, A., Nguyen, H., Sukop, M.C., 2018. Value of irrigation water usage in South Florida agriculture. Sci. Total Environ. 626, 486–496. https://doi.org/10.1016/j.scitotenv.2017.12.240.
Veninga, W., 2017. The shadow price of fossil groundwater. MSc thesis Wageningen University. Thesis online collection. WTO, p. 50. ⟨http://edepot.wur.nl/425744⟩, 2223572.
Wada, Y., Van Beek, L.P.H., Van Kempen, C.M., Reckman, J.W.T.M., Vasak, S., Bierkens, M.F.P., 2010. Global depletion of groundwater resources. Geophys. Res. Lett. 37, 1–5. https://doi.org/10.1029/2010GL044571.
Wang, H., Lall, S., 2002. Valuing water for Chinese industries: a marginal productivity analysis Valuing water for Chinese industries: a marginal productivity analysis. Appl. Econ. 34, 759–765. https://doi.org/10.1080/00036840110054044.
Wang, X.Y., 2010. Irrigation water use efficiency of farmers and its determinants: Evidence from a survey in northwestern China. Agric. Sci. China 9, 1326–1337. https://doi.org/10.1016/S1671-2927(09)60223-6.
Weerahewa, J., Dayananda, D., 2023. Land use changes and economic effects of alternative fertilizer policies: A simulation analysis with a bio-economic model for a Tank Village of Sri Lanka. Agric. Syst. 205 https://doi.org/10.1016/j.agsy.2022.103563.
Williams, R.B., Al-Hmoud, R., Segarra, E., Mitchell, D., 2017. An Estimate of the Shadow Price of Water in the Southern Ogallala Aquifer. J. Water Resour. Prot. 09, 289–304. https://doi.org/10.4236/jwarp.2017.93019.
Wooldridge, J.M., 2009. On estimating fi rm-level production functions using proxy variables to control for unobservables, 104, 112–114. https://doi.org/10.1016/j.econlet.2009.04.026.
Wreford, A., Topp, C.F.E., 2020. Impacts of climate change on livestock and possible adaptations: A case study of the United Kingdom. Agric. Syst. 178, 102737 https://doi.org/10.1016/j.agsy.2019.102737.
Wu, F., Bhatnagar, D., Bui-Klimke, T., Carbone, I., Hellmich, R., Munkvold, G., Paul, P., Payne, G., Takle, E., 2010. Climate change impacts on mycotoxin risks in US maize. World Mycotoxin J. 4, 79–93. https://doi.org/10.3920/WMJ2010.1246.
Yang, C., Fraga, H., van Ieperen, W., Trindade, H., Santos, J.A., 2019. Effects of climate change and adaptation options on winter wheat yield under rainfed Mediterranean conditions in southern Portugal. Clim. Change 154, 159–178. https://doi.org/10.1007/s10584-019-02419-4.
Yang, X., Menefee, D., Cui, S., Rajan, N., 2021. Assessing the impacts of projected climate changes on maize (Zea mays) productivity using crop models and climate scenario simulation. Crop Pasture Sci. 72, 969–984. https://doi.org/10.1071/CP21279.
Young, R., 2005. Nonmarket Economic Valuation for Irrigation Water Policy Decisions: Some Methodological Issues. Water.
Young, R.A., Loomis, J.B., 2014. Determining the economic value ofwater: Concepts and methods. Routledge,, Washington, DC.
Zhou, L., Turvey, C.G., 2014. Climate change, adaptation and China's grain production. China Econ. Rev. 28, 72–89. https://doi.org/10.1016/j.chieco.2014.01.001.
Zhu, X., Lansink, A.O., 2010. Impact CAP Subsid. Tech. Effic. Crop Farms Ger., Neth. Swed. 61, 545–564. https://doi.org/10.1111/j.1477-9552.2010.00254.x.
Zhu, X., Demeter, R.M., Lansink, A.O., 2012. Tech. Effic. Product. Differ. Dairy Farms three EU Ctries.: role CAP Subsid. 13, 66–92.
Ziolkowska, J.R., 2015. Shadow price of water for irrigation-a case of the High Plains. Agric. Water Manag. 153, 20–31. https://doi.org/10.1016/j.agwat.2015.01.024.
Zucaro, R., 2014. Condizionalita ' Ex-Ante Per Le Risorse Idriche: Opportunita ' E Vincoli per il mondo agricolo. Inea.