Italian Economic Journal
https://doi.org/10.1007/s40797-024-00290-6

RESEARCH PAPER

Water Demand Elasticity in Agriculture: The Case of the Central Emilia Irrigation Water District

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Received: 24 July 2023 / Accepted: 5 August 2024

Abstract
We estimated the water demand elasticity through an econometric approach applied to a large dataset of water demand observations for an irrigation water district in the Emilia-Romagna region (Italy). Elasticity has been estimated also by considering sub-samples of crops and irrigation technologies. The results show water demand inelastic to price, with heterogeneity among crops and irrigation systems. More precisely, we find higher levels of water demand responsiveness for efficient irrigation systems (drip and sprinkler) than for traditional irrigation technologies such as furrow systems. In the paper we provide various potential interpretations to this heterogeneity among crops and irrigation systems.

Keywords Agricultural water management · Water demand elasticity · Emilia-Romagna · "Just in case irrigation"

JEL Classification Q12 · Q25

1 Introduction

Water pricing and cost recovery are at the centre of the economic instruments currently used for water management. The international debate on pricing water as a measure to cope with water scarcity started in 1992 with the Dublin principles during the United Nations International Conference on Water and the Environment (United Nations

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Published online: 24 October 2024 Springer

1992). The Dublin principles defined water as an economic good with an intrinsic economic value that should be sustainably managed (Savenije and van der Zaag 2002; Somanathan and Ravindranath 2006). The EU Water Framework Directive (WFD, Dir 2000/60 CE) also reflects the principle of cost recovery of water services as a critical measure to achieve sustainability goals.

Water pricing is an economic tool that stimulates farmers to reduce the use of water and optimise its allocation (Wheeler et al. 2015) by assigning opportunity costs to water as a productive factor and guiding water allocation in order to obtain the highest economic return (Ward and Michelsen 2002). Volumetric tariffs could be used to stimulate farmers to adopt more effective strategies such as crop substitution (Varela-Ortega et al. 1998) and technological innovation (Pronti et al. 2023). Furthermore, water tariffs can create revenues for suppliers (Saleth and Dinar 2005) and allow for cost recovery implementation (Dinar and Mody 2004; Rogers 2002).

Compared to other environmental regulatory instruments, such as command-and-control methods (e.g., technological standards, water quotas), a water tariff can reduce the overall cost of implementing and controlling the effectiveness of water conservation policies (Bjørner et al. 2021). The reason is that profit-maximising farmers can adjust their water demand according to their individual policy adaptation costs, which are different for each and are not directly observable by authorities (Dinar and Mody 2004; Massarutto 2003). Moreover, pricing methods can stimulate lasting incentives for technological innovation, while command-and-control methods provide incentives for innovation only until compliance is achieved (Lago et al. 2015).

The effectiveness of water tariffs depends on the characteristics of demand and, more specifically, on water price elasticity—the measurement of how the quantity demanded of a product responds to a change in its price (Olmstead et al. 2007)—is extremely important for policy-making (Somanathan and Ravindranath 2006; Wheeler et al. 2008). An erroneous assessment of water demand elasticity can lead to water tariff policy failures due to either overpricing water, thereby lowering farmers' income due to high water costs, or underpricing water, thereby assigning excessively low opportunity costs that incentivise over-irrigation[1] (Kahil et al. 2015; Molle 2009).

There are multiple examples of irrigation water demand elasticity derived from econometric analyses, however most of them only rely on cross-sectional data (Scheierling et al. 2006). Moreover, scarce information exists on water price elasticity when considering both heterogeneous agricultural production and irrigation systems (Massarutto 2003). The literature on water demand elasticity in agriculture is discussed in more detail in Sect. 2.

The objective of this paper is to estimate the demand elasticity for irrigation water, by considering the heterogeneity of agricultural production and irrigation systems. In doing this we used a large panel dataset of plot-level observations for an Irrigation Water District located in Emilia-Romagna region in northern Italy. Feasible generalized least squares (FGLS) models and ordinary least squares (OLS) models with a fixed effect have been used to estimate water demand elasticity for the whole region

[1] We consider over-irrigation as providing water in a greater quantity than required by the plant. The water is thus not fully utilized by the plants, since some of it is 'lost' through percolation or evaporation. In reality, excess water is never lost because it can feed groundwater, however, it is not used efficiently for crop irrigation.

under study. Moreover, elasticity has been estimated for a series of combinations of subsamples of crops and irrigation systems while controlling for weather conditions and other heterogeneities between observations. In our view, combining crop subsamples and irrigation technologies is important to understanding the main responses of water demand to water prices.

This paper focuses on the elasticity of water demand at the intensive margin without considering crop substitution, since our objective is to estimate the elasticity of water demand in the short run by considering whether water tariffs can be considered as a tool to incentivise optimal and efficient water use. Another way of looking at our strategy is to consider how farmers respond to water tariffs in terms of water use to consider only the water demand elasticity instead of considering production adjustments that may occur in the medium or in the long run.

The main research questions of this paper are:

RQ1 *What is the demand elasticity for water irrigation to water tariffs in the area under study?*

RQ2 *Are there any heterogeneities between irrigation technologies in terms of water demand elasticity?*

RQ3 *Are there any heterogeneities between crops in terms of water demand elasticity?*

The paper is structured as follows: in Sect. 2, a brief literature on irrigation water demand elasticity is presented; in Sect. 3, materials and methods are discussed; in Sect. 4, the analytical results are shown. Section 5 is a discussion of the main findings; Sect. 6 discusses the main limitations of the study before providing some conclusions in Sect. 7.

2 Water Demand Price Elasticity in Agriculture

The main element of uncertainty in the efficacy of water pricing interventions in agriculture concerns a farmers' policy response to changes in water prices (Kahil et al. 2015). An accurate measure of water demand elasticity is thus crucial for determining effective water pricing policies designed to simultaneously alleviate pressure on water resources and improve fiscal impact (e.g., simultaneously avoiding burdens on farmers' incomes and increasing water authority revenues) (Iglesias et al. 1998).

In the extant literature, the effect of water price elasticity on water price policies remains unclear (Balali et al. 2011; Cooper et al. 2014; Dinar and Mody 2004). Results of empirical analyses are not always consistent; they depend on a variety of local conditions linked to water systems and on other aspects, such as socioeconomic, geographical, and institutional factors (Scheierling et al. 2006). Findings are case-specific and affected by the specific methodological choices. Therefore, in the water economics literature, there is no general consensus on the effect of price on water demand; consequently, the impact of tariff policies on farmers' irrigation decisions remains uncertain (de Fraiture and Perry 2002; Molle and Berkoff 2007).

Agricultural water demand mainly depends on farmers' production decisions (e.g., the amount of land to irrigate and non-irrigated crop types), irrigation technology, physical water productivity, farmers' characteristics, local environmental conditions, and the market structure. However, other factors that are not directly observable, such as technical, environmental, social, institutional, and behavioural factors, can also influence water demand (Massarutto 2003). These elements vary widely across countries and regions, depending on the geographical, socioeconomic, financial, political, and infrastructural conditions, limiting considerations of water demand and elasticity to case-by-case studies (Dinar and Mody 2004; Molle and Berkoff 2007).

In general, empirical studies on agricultural water management show that water demand is inelastic to both large and small changes in the price of water and that the quantity of water demanded is not responsive to pricing policies (Krause et al. 2003; Molle and Berkoff 2007). Water demand was found to be inelastic in the first major research studies (Ogg and Gollehon 1989; Nieswiadomy 1985; Zilberman 1984), and later confirmed in subsequent investigations (Caswell et al. 1990; Moore et al. 1994). Through a meta-analysis of the studies available at the time, Scheierling et al. (2006) found an average price elasticity of − 0.48, but with a relatively large standard deviation of 0.53. The authors found strong heterogeneity between the elasticity levels in each scientific article analysed (varying between − 0.001 and − 1.97), revealing that the variability of the estimates is strongly case-dependent. Other seminal studies found that water demand is completely inelastic (Hendricks and Peterson 2012; Massarutto 2003). Schoengold et al. (2006) found a slightly stronger elasticity, of − 0.79, compared to previous studies, nonetheless they also found that increases in water prices led to limited reductions in water demand. Zuo et al. (2016) confirmed those results using a stated preference survey on the selling price of water entitlements on the Australian irrigation market; they estimated a water demand elasticity of − 0.57.

Other studies found that farmers' water demand is more elastic. For example, Wheeler et al. (2008) and Bonviller et al. (2020) analysed the Australian water market and found average elasticities for water demand to price of − 1.51 (elastic) and − 1.05 (unitary elastic),[2] respectively. Both studies also showed that other factors besides the price of water can influence water demand, for example drought, product price, seasonal effects, inputs related to irrigation (i.e. type of fuel and electricity prices) and crop type (de Bonviller et al. 2020; Wheeler et al. 2008).

Other analyses found that water demand elasticity is non-linear with threshold effects implying that water demand is elastic only after a certain price level (Berbel et al. 2018; Berbel and Expósito 2022; de Fraiture and Perry 2002; Expósito and Berbel 2017; Gómez-Limón and Riesgo 2004; Varela-Ortega et al. 1998). The authors found that: (i) for low water price ranges, water demand is inelastic because water costs are lower than the potential economic risks of losing yields and of water savings (Berbel and Expósito 2022; Gómez-Limón and Riesgo 2004); (ii) for medium price ranges, water demand becomes elastic as farmers adapt to increasing costs due to crop patterns and water saving technologies (Berbel et al. 2018; Expósito and Berbel 2017); and (iii) for high price ranges, water demand is again inelastic since only high value

[2] Wheeler et al. (2008) considered Australian water markets and a time series of total water market allocations for the short term (− 0.52) and the long term (− 0.89). They also highlighted large fluctuations within the irrigation season (− 1.71 to − 4.14). The study by de Bonviller et al. (2020) was based on Australian groundwater markets, which could explain why, differently from Wheeler et al. (2008), they found a unitary elasticity of − 1.05.

crops are irrigated at steep water prices when profit margins continue to be positive, while cultivation is halted when excessive water prices make irrigation unprofitable[3] (de Fraiture and Perry 2007; Gómez-Limón and Riesgo 2004).

The principal causes of the different levels of elasticity can be identified in the alternatives for substituting water as an input in the production process (i.e. the higher the level of water substitutability, the higher the elasticity). The main strategies that farmers can adopt to cope with an increase in water prices, in addition to water consumption reduction, are crop substitution (technical factors) and technology substitution (structural factors).

In a recent study focused on south of Italy, Mirra et al. (2023) found great heterogeneity in demand slopes and water demand elasticities by farm types. They suggest that to optimize the effectiveness of water tariff policies in presence of heterogeneity in elasticity, price discrimination strategies may allow for a better allocation of water resources among farmers. This may lead to an increase in overall water use efficiency at the macro level. In fact, famers who are more willing to pay for water (i.e., farms with lower elasticity) will be the ones who will continue to use water even in presence of price increases, because they will be less able to adapt their irrigation strategies (e.g., long-term investments such costly irrigation structures or crop specialization with low level of adaptability such as orchards). Conversely, farmers with higher levels of adaptability, due to various structural and technical factors, will reduce water demand.

In empirical works, water demand elasticity is derived by using a variety of methods, which are basically divided into two categories: mathematical programming (MP) and econometric analysis. The lack of observations which cover a broad range of prices has encouraged scholars to use MP methods (linear, quadratic, and stochastic approaches) to derive water demand elasticity by simulating optimisation models (Bontemps and Couture 2002). The main approach for assessing elasticity measures with MP is through the derivative of the dual solutions, which are interpreted as water shadow prices (Elbakidze et al. 2017; Howitt et al. 1980). MP has many advantages especially for predicting the agent's response to policy or environmental changes, but this methodology relies on strong assumptions (e.g., a focus on profit maximisation, the agent's access to perfect information and strong constraints on irrigation technology) (Mieno and Brozović, 2017).

Econometric regression is rarely applied to the analysis of water demand elasticity, the measurement of water in agriculture is poorly implemented (Lika et al. 2017) and data regarding water tariff is scarce. Despite this, some empirical analyses based on econometric applications have been used in the literature to estimate the elasticity of water demand (Scheierling et al. 2006). However, most of the econometric analyses conducted so far are cross-sectional, which may reduce the accuracy of the estimated

[3] When prices are low, the threshold effects depend on technical substitution (changing irrigation technology and/or switching to less water intensive crops), which reflect changes in the input composition of the farmers' production function. The changes determine the elasticity of the demand curve—which represents the substitution of water with capital and labour as a strategy adopted (based on irrigation technology and/or type of crop) by farmers to cope with the increasing price of water (Renzetti 2002). At certain price levels, the demand curve becomes inelastic due to the end of input substitution possibilities and the increasing disadvantages in agricultural production due to the excessively high opportunity cost of water (Berbel and Gómez-Limón 2000; de Fraiture and Perry 2007; Expósito and Berbel 2017).

elasticities, mainly due to endogeneity problems arising from unobserved and time-invariant heterogeneity (Bontemps and Couture 2002; Havranek et al. 2018; Mieno and Brozović, 2017) which can be partially solved by using panel data (Wooldridge 2010). To the best of our knowledge, econometric analysis using panel data to estimate the elasticity of irrigation water demand has only been used by Schoengold et al. (2006) for surface water and by Hendricks and Peterson (2012) for groundwater.

3 Materials and Methods

3.1 Case Study and Data Description

The Emilia-Romagna region (ERR) accounts for the largest share of irrigated land in Italy. Its agricultural sector is one of the biggest in the country (Pérez-Blanco et al. 2016). Although, water endowments in the area can be considered relatively abundant compared to other Mediterranean areas, in recent years, the regional irrigation system has been put under considerable strain due to severe droughts and thus increased pressure on its water resources (Pérez-Blanco et al. 2016; Vezzoli et al. 2015). The ERR government has boosted its water conservation policy interventions through Irrigation Water Districts[4] in its region by incentivizing improvements in irrigation efficiency by introducing pricing instruments for irrigation (El Chami et al. 2011).

The dataset employed in this study includes the water tariffs and the volume of water distributed by the Central Emilia Irrigation Water District (CEWD) (*Consorzio di Bonifica dell'Emilia Centrale* in Italian) in two ERR provinces: Reggio-Emilia and Modena. The area served by the CEWD has the highest regional production value (ERR 2019a), and many of the famous high-value certified agri-food products are produced there (such as Parmigiano-Reggiano cheese, balsamic vinegar from Modena, Lambrusco wine, and crops with protected geographical indications) (ERR 2019b).

The ERR's most important agricultural products include field crops (alfalfa, maize, meadows), vineyards, and orchards (mainly pears and to a lesser degree apples, peaches, and other fruits). Other crops like soybeans, sugar beets, tomatoes, and watermelons are also grown. The average irrigated area, volume of water used, and water tariffs per type of crop and irrigation system are reported in Table 1. The farmers served by the CEWD do not possess large farms, and the plots tend to be small on average; the typical farm size is 4.9 ha (standard deviation is 6.41 ha). The descriptive statistics of the variables used in this study are shown in Table 2; they show that for the same crop, the average volume of water used typically increases from drip to sprinkler, and from sprinkler to furrow systems.

Over the years, the CEWD experimented with different types of tariff schemes, from flat to volumetric, up to 2015. The different tariffs schemes applied over the years impacted the cost of water, ranging from 0 to 0.0489 euro per m^3 (see a summary of all the tariffs in Appendix, Sect. 1). We highlight that the objective of the paper is to

[4] Irrigation Water Districts are the lowest institutional level of public authority in agricultural water management under Italian law and they are responsible for implementing the EU Water Framework Directive (WFD) at the local level (Bazzani et al. 2005; Dono et al. 2019; Gazzetta Ufficiale della Repubblica Italiana 2006).

Table 1 Mean irrigated areas and water tariff per crop and irrigation system

Crop	Irrigation system	Average irrigated area (ha)	Water volume (m^3 per ha)	Water tariff (€ per m^3)	No. of obs.
Alfalfa	Drip	3.61	776	0.0238	10
Alfalfa	Furrow	3.53	1225	0.0253	235
Alfalfa	Sprinkler	4.74	1023	0.0226	3339
Maize	Drip	1.82	1184	0.0204	49
Maize	Furrow	2.53	3575	0.0321	99
Maize	Sprinkler	3.60	1298	0.0230	3947
Meadows	Drip	5.18	1687	0.0222	1
Meadows	Furrow	4.92	1278	0.0245	5895
Meadows	Sprinkler	6.48	1199	0.0244	150
Pears	Drip	2.40	7695	0.0000	817
Pears	Furrow	2.70	4605	0.0258	225
Pears	Sprinkler	2.82	2235	0.0220	1511
Soybeans	Drip	3.67	1469	0.0284	2
Soybeans	Furrow	1.96	2854	0.0289	18
Soybeans	Sprinkler	2.96	1977	0.0278	405
Sugar beets	Drip	1.73	889	0.0248	2
Sugar beets	Furrow	5.14	1430	0.0236	20
Sugar beets	Sprinkler	5.36	1010	0.0253	796
Tomatoes	Drip	2.65	334	0.0274	80
Tomatoes	Furrow	6.20	996	0.0273	5
Tomatoes	Sprinkler	5.63	849	0.0260	486
Vineyards	Drip	6.25	341	0.0251	1578
Vineyards	Furrow	3.74	1259	0.0238	3031
Vineyards	Sprinkler	5.85	847	0.0261	6178
Watermelons	Drip	8.30	1505	0.0249	236
Watermelons	Furrow	4.65	4189	0.0249	3
Watermelons	Sprinkler	6.64	1887	0.0246	73

Note: Average irrigated area is considered across time and plots. Water tariffs vary among crops and irrigation technologies (for further details see Appendix 1—Sect. 1)

assess the price elasticity of water demand, therefore we focus not only on the use of a volumetric tariff, but on the variation of water prices that is related to the diversity of water tariffs charged in the CEWD during the timeframe considered.

The CEWD was created in 2009 by the merger of two former local Irrigation Districts—the *Consorzio di Bonifica Parmigiana Moglia Secchia* and *Bentivoglio-Enza* Reclamation Consortium—that applied two tariff schemes. Until 2015, water users used their previous tariffs (flat and two-part). In 2016, in compliance with the WFD, the CEWD implemented a new water tariff scheme for all water users based on

Table 2 Descriptive statistics of variables with variations

Variable	Mean	Std. dev.	Min	Max	Observations
Water demand per ha (m^3/ha)	2004.04	2363.50	0.00	49,356.00	30,443
Log of water demand per Ha	7.16	0.93	− 6.40	10.81	30,443
Water tariff (m^3/Ha)	0.03	0.01	0.00	0.05	30,443
Log (water tariff) (m^3/Ha)	− 3.82	0.80	− 6.42	− 3.02	30,443
Irrigated area (Ha)	3.69	4.02	1.00	83.00	30,443
Log of irrigated area	0.99	0.73	0.00	4.42	30,443
Aridity Index JFM (unitless)	1.90	0.77	0.67	3.16	30,443
Aridity Index AMJ (unitless)	0.62	0.19	0.33	1.00	30,443
Aridity Index JAS (unitless)	0.53	0.16	0.38	0.86	30,443
Aridity Index OND (unitless)	1.86	0.45	1.21	2.57	30,443
Alfalfa (dummy)	0.12	0.32	0.00	1.00	30,443
Forage (dummy)	0.02	0.14	0.00	1.00	30,443
Maize (dummy)	0.13	0.34	0.00	1.00	30,443
Meadows (dummy)	0.20	0.40	0.00	1.00	30,443
Pears (dummy)	0.07	0.25	0.00	1.00	30,443
Soya (dummy)	0.01	0.12	0.00	1.00	30,443
Sugar beets (dummy)	0.03	0.16	0.00	1.00	30,443
Tomatoes (dummy)	0.02	0.14	0.00	1.00	30,443
Vineyards (dummy)	0.35	0.48	0.00	1.00	30,443
Watermelons (dummy)	0.01	0.10	0.00	1.00	30,443
Year 2014 (dummy)	0.14	0.34	0.00	1.00	30,443
Year 2015 (dummy)	0.17	0.38	0.00	1.00	30,443
Year 2016 (dummy)	0.17	0.37	0.00	1.00	30,443
Year 2017 (dummy)	0.20	0.40	0.00	1.00	30,443
Year 2018 (dummy)	0.13	0.34	0.00	1.00	30,443
Drip irrigation (dummy)	0.09	0.29	0.00	1.00	30,443
Furrow irrigation (dummy)	0.32	0.47	0.00	1.00	30,443
Sprinkler irrigation (dummy)	0.59	0.49	0.00	1.00	30,443
Water Basin 1 "Enza Cerezzola" (Dummy)	0.04	0.18	0.00	1.00	30,443
Water Basin 2 "Enza Gattatico" (Dummy)	0.00	0.06	0.00	1.00	30,443
Water Basin 3 "River Po" (Dummy)	0.68	0.46	0.00	1.00	30,443
Water Basin 4 "River Secchia" (Dummy)	0.09	0.29	0.00	1.00	30,443
Water Basin 5 "Po Boretto" (Dummy)	0.18	0.38	0.00	1.00	30,443
Water Basin 6 "Po Cavazzoli" (Dummy)	0.00	0.06	0.00	1.00	30,443

Note: Table A1 in Sect. 1 of the Appendix describes the variables with variations (overall, between, within) used in the econometric models a two-part tariff scheme that uses a cost recovery approach with the goal of increasing water efficiency use and recovering operational and maintenance costs. The new two-part tariff scheme has a fixed fee that covers the CEWD's basic service costs and a variable fee, based on the volumetric component, that increases in price based on specific coefficients that consider different types of service costs, crop water intensity, and rivalry for water sources (see Appendix, Sect. 1 for further details).

The water tariff is set at the beginning of each irrigation season and communicated to users. Payment for irrigation service due from the irrigators is required at the end of the irrigation season and is mandatory to be served by CEWD in the following irrigation season.

Direct water metering is impossible because water is served mainly through a network of open canals. Therefore, the volume of water for each supply is measured indirectly by considering the canal flow rate, the capacity of the water structure, and the water delivery duration[5] (CEWD 2017).

The statistical observations of the CEWD dataset comprise the statistical universe. They represent the total water demand managed by the CEWD in the area considered (the Reggio-Emilia province and part of the Modena province) for surface irrigation. Water requests are aggregated yearly by considering the total amount of water demanded for plots, and water tariffs are calculated as the average tariff paid during the year. This is done since the implementation of volumetric tariffs (as of 2016), different water prices, can be charged depending on the time of year of the water demand (in- or out-of-season).

The final dataset is a yearly unbalanced panel at plot farm level that covers the period from 2013 to 2018; it includes a total of 28,738 observations and 9097 different plots. The CEWD dataset includes information on water demand, irrigated land, irrigation systems and water tariffs at the plot level. The same dataset was used by Pronti and Berbel (2023) to analyse the impact of the introduction of the volumetric water tariff on farmers who were previously not subject to such tariff scheme, using a natural experiment (difference-in-differences). Although the dataset is the same, they focused on a different research question considering a specific subset of the dataset, whereas in this analysis we use all available observations (vs. a subset) focusing on irrigation water elasticity by using a log–log model. The two analyses do not overlap and are complementary.

In this case study, water tariffs are very low and farm water costs are negligible. It should be noted that the water tariffs considered in our case study refer only to the cost of accessing the irrigation canal, without considering cost of pumping (i.e. users must pump water themselves from the open canal, which is an expensive activity for the farmer).

Water tariffs can be considered as exogenous since we control for all the forms of potential endogeneity due to simultaneity and omitted variables related to the water tariff components (i.e. crop type, irrigation technology, water basin). In addition, we provide a set of robustness checks on potential endogeneity of the tariff variable in

[5] Unfortunately, we do not have access to the actual calculations made by the CEWD for providing water.

Sect. 4.2. In panel data econometrics, attrition[6] can be a possible cause of bias (Chadi 2021; Cheng and Trivedi 2015; Wooldridge 2010). We also tested attrition by using the approaches proposed by Diggle (1989) and Ridout and Diggle (1991) and found that attrition patterns in our datasets can be considered as random and unremarkable. The attrition tests are in Sect. 2 of the Appendix.

Unfortunately, data on costs, energy consumption, income and productivity of farms are not available. For general information and with the aim of providing an adequate picture of the level of water cost on local farms, we report in Table 2 some water cost indices considering the crops included in the CEWD dataset (FADN 2022). To overcome the lack of economic data, we used data from the National Agricultural Accountancy Data Network (FADN) (FADN 2022). In Table 2 are shown the cost of water per irrigated area, the water cost ratio of total variable cost and the water cost ratio of the value of the total sellable production per type of crop using the FADN sample for the whole of Italy, Northern Italy, ERR and the Modena and Reggio-Emilia provinces (MORE).

Water cost represents a small part of the total variable costs of farms, ranging between 0.7 and 5.2% for ERR and between 0.4 and 6.5% for MORE. These values are below the national and Northern Italy averages (6.3–23.1% and 3–19.3%, respectively). Yet, there are water cost differences between crops. Meadows, orchards, and vineyards have the highest ratio of water cost to total water cost, whereas water costs are relatively low for watermelons and tomatoes. Finally, water cost represents on average 1.4 and 1.2% of the total production value for ERR and MORE, respectively (Table 3).

We merged our dataset with the seasonal aridity index (AI) for each plot.[7] The AI is the ratio of the accumulated precipitation and the reference evapotranspiration (Steduto et al. 2012); it is used to assess the relative contribution of rain to the potential water needs. The spatial resolution we use refers to the municipality in which each plot is located and is used only for merging the weather variables with our main dataset.

3.2 Methodological Approach

The price elasticity of demand is a well-known concept in economics used for measuring the relative change in the quantity demanded following a unitary change in price (Chiang and Wainwright 2013). Various model specifications and econometric methods have been used to estimate water demand elasticity in agriculture using observational data. Some specifications imply constant elasticities along the curve (such as the log–log functional form), others do not (log-linear, quadratic and translog models)

[6] Attrition is the process of dropout from a panel study, it happens specially in surveys when some respondents do not participate to all the waves of the survey. Attrition if systematic can lead to bias in the estimations using panel data (Lugtig 2014).

[7] We used the ERA-Interim dataset of the European Centre for Medium-Range Weather Forecasts (ECMWF) with 25 km^2 grid cell spatial resolution; the external climatic data were merged by considering the georeferenced data of the municipalities where each plot was located. Multiple weather variables were included to account for seasonal variations (maximum and minimum temperatures, accumulated precipitation, and reference evapotranspiration) (ECMWF 2020).

Table 3 Water cost per irrigated area (Ha), water cost on total variable costs (%), water cost on total production value (%). Source: own elaboration on FADN data (FADN/RICA 2022)

Crop	Water cost per irrigated ha (€/ha)				Water cost/total variable cost (%)				Water cost/total production value (%)			
	Italy	North	ERR	MORE	Italy	North	ERR	MORE	Italy	North	ERR	MORE
Maize	107	88	30	25	11.36	9.20	4.36	3.42	5.71	4.73	1.74	1.40
Meadows	72	60	15	24	23.05	19.29	5.23	6.52	9.24	5.89	1.67	2.34
Orchards	211	151	150	–	11.30	5.25	5.18	–	3.37	1.63	1.61	–
Soybeans	77	77	24	14	11.81	11.77	4.64	3.37	5.77	5.72	2.03	1.28
Sugar beets	64	64	35	22	6.28	6.28	4.84	2.78	3.66	3.66	1.71	0.84
Tomatoes	385	137	74	191	8.39	3.74	2.87	4.27	3.05	1.37	1.02	1.91
Vineyards	181	163	118	38	11.41	6.61	5.05	2.17	2.31	1.83	1.15	0.36
Watermelons	427	143	29	14	9.98	2.97	0.67	0.43	4.28	1.21	0.35	0.15
Average	191	110	59	47	11.70	8.14	4.11	3.28	4.68	3.26	1.41	1.18

Note: North = Emilia-Romagna, Lombardy, Piedmont, Veneto and Friuli Venzia Giulia, ERR = Emilia-Romagna, MORE = Modena and Reggio-Emilia Provinces. The orchards category includes: apricots, cherries, plums, apples, peaches and pears

(Espey et al. 1997; Kim 1992; Oum 1989). The most common model specification used to estimate water demand functions is the log–log.

Our baseline model is a log–log regression model with fixed effects at plot level (Eq. 1). The use of a panel at plot level can avoid macrogeographical aggregation issues by observing directly at the micro level the demand for water without averaging the data at a higher spatial level (Mieno and Brozović 2017). Additionally, the use of fixed effects models can reduce endogeneity problems due to unobserved heterogeneity (Wooldridge 2005). Moreover, we included year fixed effects to capture exogenous effects which can alter the model estimations (e.g., extreme weather conditions and climate anomalies, specific macroeconomic circumstances, and yearly market conditions, such as international trade and crop prices).

We decided to consider plot observations since we are interested in focusing mainly on the effects of water tariff on water demand and, in our opinion, plots are the most suited level of observation. We emphasise again that our study focuses on the elasticity of water demand at the intensive margin, focusing on farmers' reactions in water demand to water tariffs in the short term and not considering farmers' adaptation strategies (i.e., extensive margin) such as land use change or changes in irrigation technologies. This could have been done using farm-level or basin-level observations, the interest could shift to adaptation strategies to rising tariffs, but that is not the aim of this paper; furthermore, the length of the observation period (5 years) and the limited geographical area (two provinces) considered does not allow for strong cross-sectional variations to study farms adaptation strategies. That type of an assessment could be better obtained in a national or supranational study. Nonetheless, we believe our study is representative of many other cases in Italy and in Europe since it shares numerous similarities with other European agricultural regions.

The logarithm of the total yearly water demand at the plot level is used as the dependent variable, and the logarithm of the yearly average tariff of water paid per cubic meter (m^3) by farmers at the plot level is used as the independent variable of interest. Several controls have been added. Our baseline model is shown in reduced form in Eq. (1), while the extended model is shown in Eq. (2).

$$Log(y)_{i,t} = \alpha + \beta Log(x)_{i,t} + \gamma Z_{i,t} + \rho B_m + \tau_t + \delta_i + u_{i,t} \tag{1}$$

where $y_{i,t}$ is the total volume of water demanded per hectare for each plot i in year t. Irrigation demand is made directly by farmers to the CEWD, which calculates the total amount of water needed to serve the plots based on an irrigation plan compiled annually by its water users which includes details on the type of irrigation system used and the crop plan. This means that the total amount of water demanded is not decided directly by the farmer; instead, it is optimised by the CEWD.

$x_{i,t}$ is the yearly average water tariff per m^3 of water used for plot i in year t. The average tariff of water demanded in the econometric model is the average of the tariff paid for each cubic metre delivered for each water request made by farmers during the irrigation season (year t). The tariff does not depend on the total quantity of water received; it is calculated considering other factors; therefore, problems of simultaneity bias are not present. See Appendix, Sect. 1 for more details.

$Z_{i,t}$ is a set of control variables: (i) the size of the plot; (ii) the irrigation system used (dummy) for plot i in year t; (iii) the seasonal AI for plot i at time t; and (iv) the type of crop cultivated (dummy) on plot i in year t. We use crop dummies to capture the specificity of each type of crop production which can be related also to economic, marketing, and production aspects (e.g., fertilizer and pesticide costs, labour intensity) which are not directly observable in our data (e.g., production costs, water needs, productivity, type of selling markets). Furthermore, the use of irrigation system dummies can help overcome the problem of non-observed economic and production aspects (e.g., energy costs).

Moreover, we use dummy variables to control for the water basin in which the plot is located, as the CEWD has different subzones[8] B_m. By using water basin dummies as control variables, we take into account geographical and institutional heterogeneities at the sub-regional level within the CEWD, which includes past water pricing policies adopted in mixed form within the different subzones before 2016. τ_t is a year dummy; δ_i is the plot fixed effect for taking into account unobserved plot heterogeneity (such as the unobserved characteristics of farmers including their experience, and soil quality of the plot), which could cause bias and inconsistent estimates (Wooldridge 2010, 2005). α is the constant term, $u_{i,t}$ is the idiosyncratic error with zero mean, and σ_u^2 is the variance (Wooldridge 2010). In Eq. (2), the baseline model is in extended form.

$$\begin{aligned} Log(Water\ demand\ per\ Ha)_{i,t} = \alpha &+ \beta Log(Water\ price)_{i,t} \\ &+ \gamma_1 Log(Irrigated\ area)_{i,t} + \gamma_2 Furrow_{i,t} \\ &+ \gamma_3 Drip_{i,t} + \theta_i \sum_{s=1}^{4} AI_{s,i,t} + \omega_i \sum_{c=1}^{C-1} Crop_{n,i,t} \\ &+ \rho_i \sum_{m=1}^{M-1} Water\ Basin_m + \tau_t + \delta_i + u_{i,t}, \end{aligned} \tag{2}$$

where s, c and m are the subscript for the seasonal AI, the number of crop types and the number of water basins, respectively.

The AI is used as a synthetic dimension of several weather variables, as in Koundouri et al. (2006), and it is calculated following the Consultative Group for International Agricultural Research (CGIAR) (2019). Quarterly AIs are employed for different seasons[9] as climatic control variables and are computed as the ratio of the value of the accumulated precipitation (measured in mm) of a specific season and the accumulated reference evapotranspiration (measured in mm) for each season (Allen and FAO 1998; Villalobos et al. 2016). This method of computation results in a unitless proxy measure

[8] There are six in total: Enza Cerezzola, Enza Gattatico, Po, Secchia, Po Boretto, and Po Cavazzoli.

[9] The AIs are calculated for each season as follows: $AI_{season} = AccumPricip/ET0$. The seasons are divided into Winter (January, February, March), Spring (April, May, June), Summer (July, August, September), and Autumn (October, November, December).

of a crop's water requirement satisfied by seasonal rainfall[10] (Allen and FAO 1998; CGIAR 2019).

The data include the following crop types: alfalfa, maize, meadows, pears, soybeans, sugar beets, tomatoes, vineyards, and watermelons. Other crops with low and negligible observations or with generic definitions that cover various crops (e.g., "orchards", "forage" and "vegetables") are omitted.[11] Irrigation systems are divided into the macro irrigation categories such as drip, sprinkler, and furrow. Both the crops and irrigation technologies for the crops are fixed for one year but may change from year to year.

As expected, all correlations among crops and irrigation technologies are statistically significant at the 0.01 level. The correlations are especially strong for meadows with furrow irrigation systems (0.70) and sprinkler systems (− 0.57). For the other categories, the correlations seem to be small and acceptable for our analysis (between − 0.25 and 0.30 for all the other categories). The correlation between crops and irrigation systems indicates that these factors are strictly connected. The only crop type that has a strong correlation with the irrigation technology used is meadows; it has a positive correlation with furrow irrigation, and a strongly negative correlation with sprinkler irrigation. Other crops also have a correlation with irrigation technology, but it is less strong. A correlation matrix of crops and irrigation technologies is available in Appendix Sect. 2 (Table A7).

We test for the heteroscedasticity and autocorrelation by using the White test and the Wooldridge test, both of which indicate that the data are heteroscedastic and serially correlated, respectively (Wooldridge 2010). Thus, we employed clustered standard errors at plot level to obtain robust estimates as was done in other similar studies (Bertrand et al. 2004; Gehrsitz 2017; Mieno and Brozović, 2017). Doing so relaxes the assumption of homoscedasticity and allows for cross-sectional changes in the individual variance and for correlation within individual groups (Hansen 2007a), which leads to consistent estimations when the dimension of the panel is large and there are a sufficient number of clusters (Hansen 2007b). Moreover, to verify robustness, the model is run using a FGLS regression with fixed effects. This method relies on first-order autoregressive disturbance terms, producing an unbiased, robust, and consistent estimation in the presence of autocorrelation (Hansen 2007a). In the Sect. 3 of the Appendix, we offer a sensitivity analysis of the clustering structure by changing the variable used to cluster standard errors. The results are found to be robust.[12]

Both econometric approaches (OLS and FGLS) are applied to the whole sample and then to various split-sample analyses of irrigation technologies and crops, both

[10] AI values lower than 1 indicate that the precipitation in the considered period fails to satisfy the water requirement of the crop, while values greater than 1 indicate that the accumulated rainfall for the period is higher than the accumulated reference evapotranspiration (CGIAR 2019). AI levels lower than 0.65 indicate arid areas (CGIAR 2019). The data used are from the ERA-Interim dataset of the ECMWF, with a definition at the cell level of 25 km^2 spatial resolution (ECMWF 2020).

[11] We removed these macro classes of crops since they were not a specifically identifiable crop type, but merely a generic group of crops. Moreover, those observations were a negligible part of the dataset (observation delated as percentages of total observations: Forage 1.96%, Other Arable Crops 1.07%; Other Orchards 1.49%; Vegetables 1.08%).

[12] We use the plot, year, plot and year, farm, farm and year, water basin, and water basin and year.

individually and combined,[13] to consider the potential heterogeneities of elasticities among different production systems and irrigation technologies. The analysis of elasticity by individual crop and irrigation technology is important to understand if there are heterogeneities in water demand responses to tariffs.

To retain information on the whole demand curve and prevent data truncation and deletion, water tariffs with zero values, occurring when flat tariffs were applied for certain plots, are transformed since the logarithm of zero is not defined (Weninger 2003). To reduce bias, the transformation follows other empirical studies dealing with logarithmic functions by adding a very small quantity to the zero values[14] (Friedlaender et al. 1983; Gilligan and Smirlock 1984; Kim 1987). In Sect. 3 of the Appendix, we conduct a sensitivity analysis in which we compare different transformations of zeros to avoid the truncation of our dataset.[15]

4 Results

4.1 Main Findings

We find in general that water demand is inelastic to price (the values of the estimated coefficients in absolute terms are all below one) indicating that the demand for water is not proportionally responsive to changes in the tariff of water. By considering the whole sample (without splitting the sample in groups of crops or technologies), a 1% change in the tariff of water induces an average reduction of − 0.27% (with confidence interval (CI) − 0.29; − 0.25) in the water demanded at the plot level (Table 4 Column 1). This result is consistent with previous studies indicating inelastic water demand in agriculture, such as the meta-analysis by Scheierling et al. (2006), who find an average price elasticity of − 0.48. Table 4 provides the results for the full sample and the irrigation technology models. Table 5 presents the results of the crop models, and Table 6 shows the results of crops combined with irrigation technologies. In each table, the estimations of the elasticities are highlighted for all the econometric models (simple log–log, the FGLS regression). The results of the estimations are very similar among all the econometric models, indicating that our econometric estimations are

[13] We take into account the irrigation technology and crop combinations with higher frequency in our CEWD dataset, using as a rule of thumb a frequency of at least 100 observations.

[14] Such studies suggest adding a value in the order of 0.001 or 10% of the sample mean to avoid altering the distribution and, consequently, the logarithmic transformation (Bellégo and Pape 2019). The zero values in our datasets represent 8.5% of the total, and although they constitute a residual part of the data, they are transformed to avoid truncating our sample. Since our analysis deals with tariffs close to 0, we check the effect of the transformation on the logarithmic function with different simulations. The addition of 10% of the minimum value in the distribution to the zero values is chosen to reduce the noise in the data caused by the transformation. Finally, sensitivity checks are performed regarding the robustness of the transformation and regarding the avoidance of any change in the structure of the model (Bellégo and Pape 2019) by examining the kernel density estimation of the transformation distribution of both the estimated dependent variable and the independent variable, which fit a normal distribution.

[15] We show that our strategy of adding to zero values a 10% of the minimum water price value in the distribution is robust and does not alter the results of our analysis, the estimated elasticity remains stable also adding values in a range between 3 to 30% of the minimum price value observed, while it increases slightly by adding 50% of the minimum nonzero value.

Table 4 Estimation of water elasticity to water tariff for the whole sample and for subsamples of irrigation technologies

Variables	(1) Total sample	(2) Drip	(3) Furrow	(4) Sprinkler
Dependent variable				
Log (water m^{3}per HA)				
OLS FE				
Log (water tariff)	– 0.271***	– 0.445***	– 0.210***	– 0.326***
	(– 25.85)	(– 5.874)	(– 16.16)	(– 17.90)
Observations	28,738	2670	9342	16,726
R-squared	0.232	0.248	0.275	0.228
Number of plots	9097	817	2495	6284
Robust S.E. (clustered)	Yes	Yes	Yes	Yes
FGLS				
Log (water tariff)	– 0.278***	– 0.418***	– 0.216***	– 0.355***
	(– 25.00)	(– 6.245)	(– 17.09)	(– 17.85)
Observations	19,641	1853	6847	10,442
R-squared	–	–	–	–
Number of plots	6654	606	1998	4151
Robust S.E.	Yes	Yes	Yes	Yes
Controls				
Year FE	Yes	Yes	Yes	Yes
Plot FE	Yes	Yes	Yes	Yes
Seasonal Aridity Index	Yes	Yes	Yes	Yes
Irrigated area	Yes	Yes	Yes	Yes
Crop type	Yes	Yes	Yes	Yes
Irrigation technology	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

robust. Only slight differences arise for pears and sugar beets. The tables with all the estimated coefficients for all the models are available in in Sect. 4 of the Appendix (from Table A10 to A15).

Although water demand is estimated to be inelastic in general, a few differences between technologies and crops do arise. When considering the subsamples of irrigation technologies (Table 4), furrow irrigation systems are the most inelastic (Table 4, Column 3), with a coefficient of – 0.21 (CI – 0.23; – 0.18). Sprinkler and drip irrigation systems show a slightly higher responsiveness to changes in water tariffs, with coefficients of – 0.33 (CI – 0.36; – 0.29) and – 0.44 (CI – 0.59; – 0.3), respectively (Table 4, Columns 2 and 4). Given that the confidence intervals of the estimates for sprinkler and drip irrigation systems overlap slightly, we performed a Wald statistical test on the coefficients of the interactions of each technology with the tariff of water

Table 5 Estimation of water elasticity for subsamples of different crops

Variables	(1) Alfalfa	(2) Maize	(3) Meadows	(4) Pears	(5) Watermelon	(6) Tomato	(7) Sugar Beet	(8) Soya	(9) Vineyard
Log (water m^3 per HA)									
OLS with FE									
Log (water tariff)	− 0.310***	− 0.297***	− 0.194***	− 0.634**	− 0.551***	− 0.514***	− 0.316***	− 0.240	− 0.336***
	(− 10.25)	(− 7.943)	(− 13.23)	(− 2.487)	(− 5.270)	(− 7.303)	(− 3.234)	(− 1.147)	(− 5.537)
Observations	3584	4095	6046	2100	312	571	818	425	10,787
R-squared	0.214	0.228	0.303	0.384	0.304	0.380	0.254	0.159	0.213
Number of plots	1925	2185	1523	454	129	348	569	327	2895
Robust (cluster plot)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FGLS									
Log (water tariff)	− 0.320***	− 0.278***	− 0.220***	− 1.179***	− 0.527***	− 0.371*	− 0.687***	0.381	− 0.348***
	(− 8.613)	(− 6.167)	(− 16.49)	(− 3.140)	(− 4.368)	(− 1.725)	(− 3.620)	(0.938)	(− 8.615)
Observations	1659	1910	4523	1646	183	223	249	98	7892
R-squared	–	–	–	–	–	–	–	–	–
Number of plots	877	1042	1250	407	69	153	169	74	2441
Robust	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls (all models)									
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plot FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal Aridity Index	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Irrigated area	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crop type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Irrigation tech. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 6 Estimation of water elasticity to water tariff for subsamples of representative combinations of irrigation technologies and crops

Variables	(1) Alfalfa sprinkler	(2) Alfalfa furrow	(3) Maize sprinkler	(4) Meadows furrow	(5) Meadows sprinkler	(6) Pears drip	(7) Pears sprinkler	(8) Soya sprinkler	(9) Tomato sprinkler	(10) Watermelon drip	(11) Sugar beet sprinkler	(12) Vineyard drip	(13) Vineyard sprinkler	(14) Vineyard furrow
Dependent variable														
Log (water m^3 per HA)														
OLS with FE														
Log (water tariff)	− 0.309***	− 0.152	− 0.306***	− 0.191***	− 0.284	− 1.393	− 0.787	− 0.254	− 0.534***	− 0.523***	− 0.308***	− 0.195	− 0.391***	− 0.276***
	(− 10.00)	(− 0.635)	(− 8.092)	(− 13.05)	(− 0.743)	(− 1.442)	(− 0.649)	(− 1.197)	(− 7.458)	(− 4.548)	(− 3.078)	(− 0.567)	(− 3.917)	(− 4.360)
Observations	3339	235	3947	5895	150	712	1352	405	486	236	796	1578	6178	3031
R-squared	0.219	0.199	0.235	0.308	0.122	0.345	0.439	0.121	0.419	0.311	0.258	0.253	0.198	0.255
Number of plots	1802	137	2113	1456	109	173	322	314	306	91	553	470	1834	841
Robust (clustered)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FGLS														
Log (water tariff)	− 0.330***	1.955	− 0.284***	− 0.217***	4.553	− 1.492**	− 0.723	0.379	− 0.472**	− 0.494***	− 0.688***	− 0.00845	− 0.506***	− 0.295***
	(− 7.116)	(0.316)	(− 6.142)	(− 16.36)	(0.777)	(− 2.221)	(− 1.309)	(0.935)	(− 2.354)	(− 3.806)	(− 3.594)	(− 0.0481)	(− 8.434)	(− 5.036)
Observations	1537	98	1834	4439	41	539	1030	91	180	145	243	1108	4344	2190
R-squared	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Number of plots	819	53	1014	1225	29	144	270	68	127	53	165	373	1460	672
Robust	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls (all models)														
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plot FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Aridity Index	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Irrigated area	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crop type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Irrigation technology	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

in a fully specified model to test whether the coefficients are significantly different. The statistical test strongly rejected the hypothesis of the equality of the estimated coefficients, indicating that they are all significantly different.[16]

Water elasticities are heterogeneous among crop types (Table 5). Cattle-grazing crops (meadows and alfalfa), which are irrigated principally with furrow irrigation, are inelastic but with different intensities (− 0.19 for meadows—CI − 0.22; − 0.16; − 0.31 for alfalfa—CI − 0.37; − 0.25) (Table 5, Columns 1 and 3). Sugar beets and maize also have a strongly inelastic water demand curve, although sprinklers are their main irrigation system (Table 5, Columns 7 and 2). Conversely, watermelons (drip irrigation) and tomatoes (sprinkler irrigation) are slightly more responsive to water tariff, and therefore, their water demand curve is slightly less inelastic, with approximately − 0.5 of elasticity (-0.55 for watermelons—CI − 0.76; − 0.34; − 0.51 for tomatoes—CI − 0.65; − 0.38)[17] (Table 5, Columns 5 and 6). This result could mainly depend on the irrigation systems used which is correlated in some cases to the type of crop (e.g., meadows with furrow and maize with sprinkler). The water demand for the vineyards category is generally inelastic (− 0.34—CI − 0.45; − 0.22). An explanation for the inelastic demand of vineyards may lie in the high value of wine, for which water is an essential input and the cost is a small share of the total cost of the final product.

Pears yield puzzling results. Pears are the crop with the highest level of elasticity, showing heterogeneous estimates of elasticity among the econometric models, inelastic for the OLS model (− 0.63—CI − 1.13; − 0.13) and elastic for the FGLS model (− 1.18—CI − 1.92; − 0.44), respectively (Table 5 Column 4). All the models show estimated coefficients that are statistically significant (with 5 and 1% significance for the OLS and FGLS results, respectively) when considering all the irrigation systems in the sample. This may be due to the fact that pears are mainly irrigated with precision irrigation systems (sprinklers and drip irrigation) which have a high level of water control resulting in a more elastic reaction to water tariff changes. The only crop that does not show statistically significant elasticity is soya.

When considering the combination of irrigation technology and crops (Table 6) the results are consistent with those of Table 5 for most of the individual crops combined with their main irrigation system, whereas the statistical significance disappears when crops are combined with less typical irrigation systems (e.g., alfalfa and meadows with sprinklers).

[16] Wald test for joint equality of all the coefficients. H0: All Coeff tech*water price are equal; H1: All Coeff are different. $F(2, 9096) = 5.00$ Prob > $F = 0.0068$. Wald test for equality of the coefficients for sprinkler and drip. H0: sprinkler = drip; H1: sprinkler $\neq$ drip. $F(1,9096) = 9.99$ Prob > $F = 0.0016$.

[17] Additionally, in this case, as the CIs of tomatoes and watermelons overlap slightly, we performed a Wald test, as in the previous fn. H0: coeff tomatoes*water price = coeff watermelons*water price; H1: tomatoes $\neq$ watermelons. The test strongly rejected the H0. $F(1, 9096) = 12.08$; Prob > $F = 0.0005$.

Vineyards in combination with furrow irrigation is more inelastic (− 0.28—CI − 0.4; − 0.15) than the sprinkler method (− 0.39—CI − 0.59; − 0.19),[18] whereas the coefficient for drip irrigation is not statistically significant (Table 6, Columns 12–14).

The results also differ when considering the subsample of pears combined with different irrigation technologies. It is elastic for drip irrigation in the FGLS model which indicates an elastic water demand, with an estimated coefficient of − 1.49 and statistical significance at the 5% level (CI − 2.81; − 0.17), while for all the other econometric models and irrigation systems (sprinkler and furrow), the estimated coefficients are not significant (Table 5). The variability in the estimated coefficients among the different econometric models indicates that the results related to pears should be taken with caution.

4.2 Robustness Tests

We performed a double robustness test to confirm the exogeneity of the water tariff variable and remove all possible concerns of its potential endogeneity in our analysis. First we used the control function approach suggested by Wooldridge (2010), who employs a two-step procedure to test the endogeneity of the regressors. The author regresses the potential endogenous variable on a set of exogenous regressors as well as an instrument that satisfies an exclusion restriction. Then the endogenous variable, all the exogenous variables (excluding the instrument used in the first step) and the residuals obtained in the first step are entered into the outcome equation on the right-hand side.

The endogeneity test is thus a simple Wald test on the residual term obtained in the first stage, considering its statistical significance once inserted into the second stage equation. If the standard error of the coefficient of the residual is statistically significant, the variable regressed in the first stage (in our case, the logarithm of the water tariff) must be considered endogenous and an instrumental variable (IV) approach must be used, otherwise the variable can be considered exogenous.

The test is used with clustered standard error to deal with heteroskedasticity. The control function approach is described in more details in the 6th chapter of Wooldridge (2010). The whole regression with all the estimated coefficients is shown in the Appendix (Sect. 5). In our case we used as an instrumental variable that satisfies an exclusion restriction the aridity index in autumn season (*AI OND*), which is exogenous, and it does not affect the dependent variable (logarithm of water demand) since it represents the level of aridity at the end of the irrigation season (from October to December) when agricultural production is stopped. Our instrument is correlated to the level of humidity during the irrigation season (*AI JFM*, *AI AMJ*, *AI JAS*), but does not directly influence the water demand because the irrigation season is finished during its reference period and is therefore not related to drought events or low levels of humidity which can directly drive irrigation needs.

[18] We employed the same strategy described in footnotes 14 and 15 for the overlapping of the confidence intervals of the coefficients. All the estimated elasticities for vineyards in combination with furrow and sprinkler irrigation systems are significantly different. H0: vineyards*furrow = vineyards*sprinkler; H1: vineyards*furrow ≠ vineyards*sprinkler. The test strongly rejected the H0. $F(1, 9096) = 8.42$; $Prob > F = 0.0037$.

Table 7 Robustness tests (control function approach and 2SLS) for the potential endogeneity of log (water tariff)

Control function approach test for endogeneity	
Log (water tariff)	− 0.285***
t-stat	(− 13.66)
Vhat	0.0150
t-stat	(0.675)
P-value	0.500
IV water tariff endogenous AI OND as instrument	
Log (water tariff)	− 0.284***
t-stat	(− 13.61)
Hansen J-test (like Sargan test but used when using clustered s.e.)	0.000 (equation exactly identified)
Endogenity test H0: log (water tariff) is exogenous	0.349
P-value	0.5546

The results of the endogeneity test, using the control function approach, are shown in Table 7, where the non-significance of the variable *vhat* (the residual of the first-stage regression) is considered a statistical test with H0 indicating that the variable under analysis—*Log* (*Water tariff*)—is exogenous (Wooldridge 2010). Since the t-stat is lower than the critical values and the P-value is higher than 0.1, we cannot reject H0; therefore, we cannot state that the variable under scrutiny is non-exogenous (we do not reject H0). Thus, *Log* (*Water tariff*) is considered exogenous.

The second test was done running an OLS two stage least square regression using the method proposed by Baum et al. (2024) with fixed effects and clustered standard errors. As in the previous robustness test, we used the aridity index in autumn (*AI OND*) as the excluding restriction. We focused our attention on the endogeneity test and the overidentification test of the Hansen J test instrument. The former tests the null hypothesis that the specified endogenous regressors can actually be treated as exogenous; the test statistic is distributed as chi-squared with degrees of freedom equal to the number of regressors tested.

The latter, the Hansen J test,[19] considers the joint null hypothesis that the variables used are valid instruments (i.e., uncorrelated with the error term), and that the excluded instruments are correctly excluded from the estimated equation. Under the null hypothesis, the test statistic is distributed as chi-squared, and a rejection of H0 casts doubt on the validity of the instruments (Baum et al. 2024).

Both of the tests we ran did not reject their respective H0 (t-statistics lower than the critical value and P-values higher than 0.1), therefore we can state that the *Log (Water tariff)* variable is not endogenous, and that the *AI OND* variable is a valid instrument. Moreover, both estimated values of elasticity are similar to the value found in the main analysis (Table 4, Column 1), the only difference is in the larger standard errors found

[19] Usually this test is performed using the Sargan statistic under the assumption of homoschedasticity; the Hansen J statistic is used in presence of heteroskedasticity and autocorrelation and it allows the use of robust or clustered standard errors (Baum et al. 2024).

in the robustness tests, but this is normal in the two approaches used. Finally, since our tests confirmed that the water tariff is exogenous, the OLS approach should be preferable to the IV approach, given that the latter is less efficient (Wooldridge 2010).

5 Discussion

5.1 Water Demand (In)elasticity

Many studies have found that water demand is inelastic to price. Our results confirm that water demand is generally inelastic, suggesting that CEWD farmers have a low response to water prices, which is in line with previous studies such as Caswell et al. (1990), Zilberman (1984), Hendricks and Peterson (2012), Schoengold et al. (2006) and Zuo et al. (2016). Therefore, our study suggests that for this case study farmers' response to water pricing policies is low, which may limit water tariffs as an incentive to reduce water use. This means that water demand response is less than proportional to price changes, which is quite intuitive since water does not have many substitutes as an agricultural input in the short run.

This may be because water tariffs can only cover a limited part of the real economic value of water. Farmers may not only consider water price to evaluate their irrigation strategies, but the total economic value of water used for irrigation.

Following Ward and Michelsen (2002), the economic value of water can be defined as the amount that a rational water user is willing to pay for a water resource that reflects his/her willingness to forego other types of water consumption. This depends on the total amount of water available and water price levels, in fact, the greater the amount of water users served the less water available, so the higher the cost-opportunity of water use. This leads to a higher value of water when water prices increase incentivizing water users to employ water for the most profitable use (e.g., high-value crops).

Therefore, inelastic water demand seems to be perfectly rational from farmers' point of view both in the short term and when water prices are low. The elasticity of water demand may change when considering potential water substitution, such as in the long run with technological innovation, which can improve water efficiency, or with high water prices, when the total economic value of water may become higher. However, estimates of water demand elasticity in the long-term are difficult to obtain, and existing literature is scant (Berbel and Exposito 2020).

We found that irrigation technologies and crops may determine the level of responsiveness due to different elasticities, but still all elasticities estimated by crop, by technology and by combination of both gave values less than -1, indicating that in general water demand is inelastic to water price.

Therefore, our findings also highlight that water pricing per se may be a limited incentive tool to control for water over-extraction. Water pricing policies can be supported by institutional cooperation and water markets, as stated by Albiac et al. (2020). Water markets are based on tradable water rights defined on a limited base depending on the status of water resources (i.e., 'cap and trade' system). This instrument is more flexible than water tariffs (which works as an environmental tax) allowing to achieve cost-effectiveness of the policy with a market price of water that leads to efficient use of water use at the lowest total cost (Perman et al. 2011).

In fact, depending on the farm's internal cost structure and the farmer's adaptability to water restriction (e.g., technological flexibility, lower costs to switch to more efficient irrigation systems, annual or permanent crop), farmers with lower adaptability will purchase water permits, while farmers with higher adaptability will reduce water use and sell their water rights. In addition, the use of water markets can also provide a dynamic incentive to technological innovation boosting irrigation efficiency at the water basin level (Perman et al. 2011).

Nevertheless, our findings do not necessarily mean that farmers remain impervious to pricing and water tariff policies, but rather that they respond less than proportionally to price changes. In terms of policies, this implies that water tariffs can be only effective if current water costs increase significantly, but this may consist in large negative effects on agricultural incomes.

5.2 Heterogeneity of the Elasticity with Different Irrigation Technologies

Our estimations indicate that the response of water use to price varies among the irrigation systems and crops with increasing levels of responsiveness for more efficient technologies, which contradicts published studies based on either MP models or analytical agroeconomic models (Berbel et al. 2018).

Our most interesting finding is related to the differences and heterogeneity in water demand elasticities between irrigation technologies and this is in line with the findings of Mirra et al. (2023) who found heterogeneity among different types of farms classified by irrigation systems and crop specialization. Although conclusions are similar, our research is based on econometric analysis of a large dataset meanwhile Mirra et al. (2023) used a MP approach. Another difference between our study and Mirra et al. (2023) is that the latter consider on-demand irrigation service at the plot gate through pressurised pipeline (i.e., tariff equals marginal variable cost for water service), whereas in our case the tariff includes only the cost of delivering water at the open canal without considering the pumping cost from the canal to the plot. However, this is not an issue for our empirical setting, since by controlling for irrigation technologies, crops and using fixed effects all other irrigation costs are considered. Our estimated elasticities suggest that drip irrigation is more responsive to water tariffs than sprinkler irrigation and that sprinkler systems are more responsive to water tariffs than furrow systems; this is confirmed by our models which refer to subsamples of crops and combinations of crops and irrigation systems.

These results are slightly in contrast with some theoretical models which show opposite findings such as Berbel et al. (2018), Berbel and Mateos (2014)[20] and with other empirical works, such as those by Hendricks and Peterson (2012), Caswell et al.

[20] Berbel et al. (2018) and Berbel and Mateos (2014) were based on analytical models without uncertainty assumptions in which farmers showed lower elasticity under higher-precision systems. In their analysis, the authors considered the following standard efficiency (E) values for furrow, sprinkler, and drip irrigation systems: E = 0.60, E = 0.85, and E = 0.95, respectively. Conversely in our case, the elasticities have an inverse correlation with the level of water control in the form of drip (the most elastic), sprinkler, and furrow (the least elastic) systems.

(1990), and Zilberman (1984), who state that higher degrees of irrigation precision reduce water use, thereby causing inelastic demand to price. In other words, those studies state that water demand elasticity using precision irrigation systems as drip and sprinkler is lower than when using traditional systems such as furrow systems. In general, MP and agroeconomic models use higher water price levels, while our analysis is focused on low levels of observed water prices (null to 0.0489 EUR/m^3). Moreover, MP analysis makes general assumptions regarding the full knowledge and profit-maximising behaviour of farmers (Elbakidze et al. 2017) that are often far from their actual (and real) behaviour toward water pricing policies.

Among other possible causes, the differences in elasticity among irrigation technologies can be justified as a matter of weather uncertainty and risks in irrigation decisions. Farmers are strongly affected by the effect of climate on crops. The uncertainty regarding water efficiency and the crop response to irrigation doses may explain the high use of water in the case of less monitorable technologies, particularly when water prices are very low and there are no water quotas. This explanation is in line with Graveline et al. (2012) who highlight uncertainty and risk factors as important elements of the farmers' adaptation strategy to changes in water availability or changes in water costs (e.g. the adoption of deficit irrigation or supplementary irrigation) (Cortignani and Severini 2009; Graveline and Mérel 2014).

The heterogeneous responsiveness of the different crop and irrigation systems to water tariffs found in our study may be linked to perceived risks and uncertainties of potential crop yield losses due to the wrong irrigation can play a role in irrigation decisions. Although our model could not explicitly consider farmers' risks and uncertainties, this argument can be supported by considering both the control and the accuracy of water application of the different irrigation systems. Indeed, pressurised systems (sprinkler and drip) allow for the frequent (daily) and precise use of water with a significant degree of uniformity, which implies that farmers know that all their plots receive water, approximately at the needed time and in the quantity they decide, and that no part of their fields suffers from water shortages.

This argument suggests that the greater level of water application control of drip and sprinkler irrigation systems results in sharper reactions to tariff changes because farmers can control better the application of water in all the parts of the plot reducing then the risk of yield losses. In contrast, furrow irrigation, which has a lower level of water application control, is more inelastic to price due to the higher potential yield loss (and foregone profits) when water crop requirements are not met compared to the low cost of over-irrigation.

The explanation of our results is consistent with the Babcock (1992) "just in case" model for the use of agricultural inputs which states that for a risk-averse farmer, when agricultural yields are difficult to predict and their variations strongly depend on the application of a specific input (for Babcock, nitrogen fertiliser), farmers tend to overuse that input with the aim of reducing the risk of yield loss. This effect is amplified when the variance in yields increases due to climatic factors, such as precipitation and temperature (Babcock 1992).

Our findings are in line with this theory since the lower the water control level of the irrigation system (e.g., furrow irrigation), the higher the risk of yield loss when water applications remain below the minimum crop water requirement, the higher the degree of water overuse. For this reason, water price elasticity increases from furrow systems (less responsive) to sprinkler and drip systems (slightly more responsive). Conversely, the higher the control of the irrigation system, the greater the reaction to water tariff shifts.

Another potential explanation on diversity of responses among irrigation systems can be related to a higher intrinsic irrigation cost for sprinkler and drip irrigation than furrow. Those costs can be related to each irrigation technologies which we cannot account for since in our case study they are not observed. Those can be energy costs for pumping water from the canal to the open field, other can be costs of labour needed for irrigation such as installation of irrigation gears or other equipment necessary for irrigation activities, or other technical costs not directly observable such as information costs. In fact, although furrow irrigation uses a larger amount of water, those irrigation related costs (e.g., energy for pumping, labour) can be much less than sprinkler and drip. Therefore, sprinkler and drip technologies can be more sensitive to rise in water tariff.

5.3 Heterogeneity of the Elasticity with Type of Crops

From our results, irrigation technologies seem to be the most important driver of water demand elasticity, but this might not be the only aspect influencing elasticity. In a vast literature review, Scheierling et al. (2006) found that less elastic estimates are obtained with high-value crops and this is confirmed also by our findings.

We found slightly heterogeneous elasticities between crops (i.e. market-oriented products—tomato, pears, watermelons—showed a slightly higher level of elasticity than non-market oriented products—Alfalfa, Maize, Sugar Beet, Soya, Vineyard, Meadows),[21] which are mainly driven by the irrigation technology adopted (i.e., crops and irrigation systems are highly correlated), but this could also depend on crop yield responses to deficit irrigation. In fact, for market-oriented products (such as fruits and vegetables), which usually have higher value per quantity of product than non-market-oriented products, we found slightly higher levels of elasticity (but still within the range of inelastic demand).

For those products deficit irrigation can be used as a strategy to improve both the quality of the final products and to increase the marginal value of water productivity when irrigation constraints are present (Geerts and Raes 2009). This may further justify why we found high-value crops (i.e. tomatoes, watermelons and pears) slightly more elastic to water tariffs than low-value crops, which contradicts the theory that states high-value products show higher water demand elasticities (Scheierling et al. 2006).

An important aspect to be emphasised considering high-value crops is that meadows, which present the lowest responsiveness levels to water tariffs in all the model considered, are cultivated as fresh fodder for the cattle reared to produce Protected Designation of Origin (DOP) Parmigiano Reggiano. Therefore, meadows should be considered as a compulsory basic raw material used in a DOP high-value chain, which

[21] We consider 'market-oriented' products as those intended to be sold directly to the market (e.g. fruit and vegetables), while 'non-market-oriented' products are agricultural products intended to be processed or used in other supply chain processes.

may also explain why this crop and furrow irrigation, which is the principal irrigation system used to irrigate this crop, showed the lowest level of response to water tariffs (meadows and furrow irrigation show high correlation).

This was also highlighted by Giannoccaro et al. (2022), who estimated a water demand curve using averages of the amount of water farmers would be willing to save at each price from a choice experiment study on agri-environmental payment scheme in the region of Apulia. They found that farmers whose crops receive high value from irrigation (e.g., table grape and processing tomato) are not willing to accept compensatory payments to reduce their water demand.

The total economic value of water used for irrigation can therefore be a key factor in the effectiveness of water pricing policies. In fact, a farmer will not only consider the cost of water for her/his irrigation decisions, but will consider the total cost of water in terms of the value of production that could be lost by reducing water demand. Considering this, total economic value of water (even if it is not directly considered in this study) may also explain why water demand elasticity is generally inelastic suggesting that farmers react little to price incentives.

Thus, water pricing policies can only be effective if the tariff does not only reflect the cost of water but is also proportional to the value of water in the farmer's final product. This also highlights the importance of considering the diversity of reactions in water demand due to different pricing, which may be a combination of several multidimensional factors such as technological aspects, direct costs of irrigation (e.g. irrigation equipment, cost of water), indirect costs of irrigation (e.g. agronomic knowledge and techniques related to irrigation activities), crop reaction to water reduction, marginal cost of water and the overall value of water in terms of the final product.

5.4 Further Policy Implications

Our results highlight that water tariff policies for reducing over-irrigation are ineffective as a tool to control over-irrigation because of the inelasticity of water demand to water prices. Water institutions with the objective to improve water use efficiency should use tailored interventions to improve water conservation with a "user pays"[22] principle approach as suggested by Perez-Blanco et al. (2016) and Dinar et al. (2015).

This principle is totally integrated in the 'cost recovery principle' which is the cornerstone of the WFD (Article 9) indicating that water pricing policies should create incentives for the users to use efficiently water resources internalizing environmental externalities and reducing over-consumption through effective price mechanisms (Berbel and Exposito 2020).

By doing so, the pricing policy should not stop at the recovery of the direct cost incurred by the water provider, but also considering all the whole aspects to ensure the long-term sustainability of water services (WAREG 2023). In this context, as suggested by Mirra et al. (2023), price discrimination policies that take into account

[22] The 'user pays' principle is a variant of the more famous 'polluter pays' principle (according to which the costs of pollution prevention and control measures should be borne by the person responsible for the pollution) suggesting that the user of a natural resource should bear the costs of depletion of natural capital (EEA 2023).

the diversity of technical and structural factors that may drive the heterogeneity of elasticities can produce an overall more efficient level of water demand.

In this case study, the tariffs applied by the CEWD to have access to irrigation channel resulted in very low prices (the maximum price applied was 0.05€ per m^3) and low tariff charged (price x quantity) in the range of 5.1–110.1 EUR/ha,[23] which is a negligible part of the total production costs that leads to a low level of response in terms of water demand reduction by farmers. Giannoccaro et al. (2022), even if they did not focused on elasticity, presented an estimated water demand curve with prices ranging between 0.1€ per m^3 to 0.5€ per m3, tariff values between two to ten times more than the maximum found in our study highlighting as the water tariff applied by the CEWD are still aimed exclusively to financial cost recovery and they are consequently low.[24]

Considering this we may state that our results could suggest that water tariffs considering only a partial cost-recovery (i.e., based only on the recovery of capital and investment costs, the costs of water infrastructures, services costs, and the costs of operation and maintenance), do not enable strong water demand reductions since water prices are too low for the internalization of environmental externalities (Berbel and Exposito 2020).This is in line with the findings of authors who found non-linear water demand elasticities (Berbel et al. 2018; Berbel and Expósito 2022; de Fraiture and Perry 2002; Expósito and Berbel 2017; Gómez-Limón and Riesgo 2004).

Those authors state that for low water prices, demand for water is inelastic, while it increases for medium prices and becomes inelastic again for high prices. With low prices, the potential risk of yield losses can be perceived as higher than the overall cost of water. The demand for water is inelastic because the price threshold at which water demand starts to be elastic has not yet been reached. This could be the case here, and therefore the low level of farmers responsiveness to water price changes could depend on the general low level of water tariffs set by a partial cost-recovery approach. But this should be further verified using specific models accounting for non-constant elasticity.

Considering that water costs represent a negligible part of agricultural costs (see Table 3), CEWD has room to increase water tariffs to implement water policies as a tool for environmental sustainability including environmental costs (i.e., the costs of environmental damage imposed by water users and resource costs which are opportunity costs due to resource depletion) complying with full-cost recovery approach of Article 9 of the WFD (Berbel and Exposito 2020).

In addition, the current pricing system adopted by CEWD could include additional costs for inefficient irrigation technologies (e.g., furrow systems) to incentivise a switch to more efficient irrigation systems (e.g., drip or sprinkler systems), while compensating for the inelasticity of water demand of these systems, which makes it difficult to use a pricing system to reduce over-irrigation. Alternatively, CEWD could

[23] The numbers represent the 10th and 90th percentiles of the water cost per ha. The mean is 47.30 EUR/ha and median is 27.82 EUR/ha.

[24] Again, we emphasize that water tariffs used in Giannoccaro et al. (2022) refer to on-demand irrigation service, in which water is delivered to the plot gate through pressurised pipeline. In our case study, water tariffs are lower than the Giannoccaro et al. (2022)'s case because water is not delivered through pressurised pipeline and it must be pumped by the farmer, which is a costly activity.

provide smart-metering systems to control the real water requirements of crops in order to reduce over-irrigation by inefficient systems due to uncertainties in water flow control.

6 Limitations

A limitation of our study is that the available data do not provide farm-specific economic and production information, such as labour intensity, energy costs, crop yields, revenues and costs. We have partially controlled for these aspects by using crop and irrigation technology dummies, which should be linked to economic and production aspects. But, in future studies the use of specific economic and production controls (if available) could improve the estimation of water price elasticity.

Unfortunately, we were not able to discuss our interpretations on the findings with CEWD's technical experts, therefore all potential causes of the different level of elasticity found among different crops and different irrigation systems discussed in this paper lack a technical validation of practitioners on the field. In any case, we firmly believe that all interpretations provided are consistent with the literature on agricultural water management.

Moreover, in our analysis, we consider constant elasticities which could be misleading in the presence of non-linearities in demand. This implies that the diminishing effects of pricing policies or threshold effects cannot be analysed (Chu and Grafton 2020). Therefore, different models, to consider nonlinear and segmented demand curves, should be included in future studies. Such analyses could be conducted by adding quadratic terms or employing so-called piecewise (or segmented) regressions that consider spikes in the regressions (Liu et al. 2016; Olmstead et al. 2007), which cannot be used in our case due to the limited extension of water tariffs ranges.

Moreover, our study focuses on the entire irrigation season without considering different levels of seasonal water demand elasticities (e.g. the flowering and growing stages can be more inelastic, while the ripening phase of crops can be more elastic) (Allen and FAO 1998) because our data have been aggregated at yearly level. Therefore, in interpreting our findings, we should consider that for higher water tariffs and inter-annual timeframes, the results may differ (e.g. irrigation water demand is more elastic in the long term than in the short term) (Scheierling et al. 2006). In fact, crops with different harvesting season may have different degree of flexibility in terms of water demand elasticity. This should be taken into consideration in further studies by using inter-annual estimation of water demand elasticity.

Another limitation of our study is that we only consider the elasticity at the intensive margin (water used per ha), since we use the plot of land as the unit of analysis, in this way, we can estimate only the elasticity of water demand in the short term and focus only on farmers' response to water tariffs in terms of the amount of irrigation water required. We are fully aware that considering the elasticity at the extensive margin is equally important. Indeed, in this way, farm data can be used to consider changes in land use and study how farmers react to changes in water tariffs in terms of irrigated area and crop variety. This is still an empirical question focused more on production aspects but very important, as analysing the elasticity at the extensive margin can provide answers in terms of farmers' land use adaptation strategies to water tariff policies. Further studies should address this topic to provide answers on farmers' medium and long-term adaptation strategies to water pricing.

7 Conclusions

In our paper, we analysed water demand elasticity for CEWD in the provinces of Reggio-Emilia and Modena in the Emilia-Romagna region in Italy. We used a panel data approach with observations at plot level which is not common in the literature.

As found in previous empirical work in this field, our results show that water demand is inelastic to price suggesting that farmers response in water demand are less than proportional to changes in water prices.

Another important finding of our analysis is that we found heterogeneity among irrigation systems. Surprisingly, we found that precision systems (drip and sprinkler) have a more responsive water demand than traditional systems (furrow), which is the opposite to the findings of previously published models (Scheierling et al. 2006).

We also found diversity in water demand responsiveness to tariff by different types of crops. Water demand has been generally found inelastic also when considering combinations of different types of irrigation systems and crops.

Our results highlight the importance of using mixed policy instruments to increase the effectiveness in achieving environmental goals. Indeed, since our analysis confirms that water demand is generally inelastic, the use of water pricing policies alone may not incentivize farmers to internalize externalities of water over-extraction, while adding also other policy instruments to the intervention could be more effective (i.e., water markets or technological standards).

Another option may be the establishment of customized water tariffs to discriminate water prices based on the different level of reactivity to water prices of irrigation technologies and crops to boost effective strategies for conservative water use in agriculture. Such strategies could be implemented by CEWD by modifying the parameters used to calculate the two-part tariff and by introducing an increasing coefficient related to the water demand elasticity levels of the various irrigation technologies.

Considering this case study, the current tariff system adopted by the CEWD should include additional costs for water inelastic crops (such as meadows, vineyards, and maize) and/or inelastic irrigation systems to stimulate a more conservative use of water. Moreover, considering that water costs are a minor percentage of farm costs, CEWD has room for increasing water tariffs as a tool for achieving environmental sustainability.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s40797-024-00290-6.

Acknowledgements The authors would like to thank Arianna Di Paola for her support in the extraction of meteorological data.

Author Contributions Conceptualization and design of study: AP, JB. Acquisition of data and data curation: AP. Methods and analysis: AP. Interpretation of results: AP, JB. Drafting the manuscript: AP, JB. Revising the manuscript critically for important intellectual content: AP, JB. Approval of the version of the manuscript to be published AP, JB.

Funding Open access funding provided by Università Cattolica del Sacro Cuore within the CRUI-CARE Agreement.

Data availability Data are private and we cannot share as public data since we did not receive permission from the owner of data.

Declarations

Conflict of interest We declare that we do not have any conflict or competing interests in regards of this piece of research work. The authors declare that they do not have any form of conflict of interest.

References

Albiac J, Calvo E, Kahil T, Esteban E (2020) The challenge of irrigation water pricing in the water framework directive. Chall Irrig Water Pricing Water Framew Dir Water Altern 13:674–690

Allen RG, FAO (eds) (1998) Crop evapotranspiration: guidelines for computing crop water requirements, FAO irrigation and drainage paper. Food and Agriculture Organization of the United Nations, Rome

Babcock BA (1992) The effects of uncertainty on optimal nitrogen applications. Rev Agric Econ 14:271–280. https://doi.org/10.2307/1349506

Balali H, Khalilian S, Viaggi D, Bartolini F, Ahmadian M (2011) Groundwater balance and conservation under different water pricing and agricultural policy scenarios: a case study of the Hamadan-Bahar plain. Ecol Econ 70:863–872. https://doi.org/10.1016/j.ecolecon.2010.12.005

Baum CF, Schaffer ME, Stillman S (2024) IVREG2: Stata module for extended instrumental variables/2SLS and GMM estimation. Statistical Software Components S425401, Boston College Department of Economics. https://EconPapers.repec.org/RePEc:boc:bocode:s425401

Bazzani GM, Di Pasquale S, Gallerani V, Morganti S, Raggi M, Viaggi D (2005) The sustainability of irrigated agricultural systems under the Water Framework Directive: first results. Environ Model Softw 20:165–175. https://doi.org/10.1016/j.envsoft.2003.12.018

Bellégo C, Pape L-D (2019) Dealing with the log of zero in regression models. SSRN Electron J. https://doi.org/10.2139/ssrn.3444996

Berbel J, Gómez-Limón JA (2000) The impact of water-pricing policy in Spain: an analysis of three irrigated areas. Agric Water Manag 43:219–238. https://doi.org/10.1016/S0378-3774(99)00056-6

Berbel J, Exposito A (2020) The theory and practice of water pricing and cost recovery in the Water Framework Directive. Water Altern 13:659–673

Berbel J, Expósito A (2022) A decision model for stochastic optimization of seasonal irrigation-water allocation. Agric Water Manag 262:107419. https://doi.org/10.1016/j.agwat.2021.107419

Berbel J, Mateos L (2014) Does investment in irrigation technology necessarily generate rebound effects? A simulation analysis based on an agro-economic model. Agric Syst 128:25–34. https://doi.org/10.1016/j.agsy.2014.04.002

Berbel J, Gutiérrez-Martín C, Expósito A (2018) Impacts of irrigation efficiency improvement on water use, water consumption and response to water price at field level. Agric Water Manag 203:423–429. https://doi.org/10.1016/j.agwat.2018.02.026

Bertrand M, Duflo E, Mullainathan S (2004) How much should we trust differences-in-differences estimates?*. Q J Econ 119:249–275. https://doi.org/10.1162/003355304772839588

Bjørner TB, Hansen JV, Jakobsen AF (2021) Price cap regulation and water quality. J Regul Econ 60:95–116. https://doi.org/10.1007/s11149-021-09439-y

Bontemps C, Couture S (2002) Irrigation water demand for the decision maker. Environ Dev Econ 7:643–657. https://doi.org/10.1017/S1355770X02000396

Caswell M, Lichtenberg E, Zilberman D (1990) The effects of pricing policies on water conservation and drainage. Am J Agric Econ 72:883–890. https://doi.org/10.2307/1242620

CEWD (2017) Regolamento Irriguo (Annex 2 No. 188/cms/2017). Consorzio di Bonifica dell'Emilia Centrale

CGIAR (2019) Global geospatial potential EvapoTranspiration & Aridity Index methodology and dataset description, [WWW Document]. Glob Arid PET Database. https://cgiarcsi.community/data/global-aridity-and-pet-database/

Chadi A (2021) Identification of attrition bias using different types of panel refreshments. Econ Lett 201:109777. https://doi.org/10.1016/j.econlet.2021.109777

Cheng TC, Trivedi PK (2015) Attrition bias in panel data: a sheep in wolf's clothing? A case study based on the Mabel survey. Health Econ 24:1101–1117. https://doi.org/10.1002/hec.3206

Chu L, Grafton RQ (2020) Water pricing and the value-add of irrigation water in Vietnam: insights from a crop choice model fitted to a national household survey. Agric Water Manag 228:105881. https://doi.org/10.1016/j.agwat.2019.105881

Cooper B, Crase L, Pawsey N (2014) Best practice pricing principles and the politics of water pricing. Agric Water Manag 145:92–97. https://doi.org/10.1016/j.agwat.2014.01.011

Cortignani R, Severini S (2009) Modeling farm-level adoption of deficit irrigation using Positive Mathematical Programming. Agric Water Manag 96:1785–1791. https://doi.org/10.1016/j.agwat.2009.07.016

de Bonviller S, Wheeler SA, Zuo A (2020) The dynamics of groundwater markets: price leadership and groundwater demand elasticity in the Murrumbidgee, Australia. Agric Water Manag 239:106204. https://doi.org/10.1016/j.agwat.2020.106204

de Fraiture C, Perry C (2002) Why is irrigation water demand inelastic at low price ranges? In: Presented at the paper presented at the conference on irrigation water policies: micro and macro considerations, Agadir, Morocco, p 23

de Fraiture C, Perry C (2007) Why is agricultural water demand unresponsive at low price ranges? In: Molle F, Berkoff J (eds) Irrigation water pricing the gap between theory and practice, comprensive assessment of water management in agriculture. India, pp 94–107

Diggle PJ (1989) Testing for random dropouts in repeated measurement data. Biometrics 45:1255. https://doi.org/10.2307/2531777

Dinar A, Mody J (2004) Irrigation water management policies: allocation and pricing principles and implementation experience. Nat Resour Forum 28:112–122. https://doi.org/10.1111/j.1477-8947.2004.00078.x

Dinar A, Pochat V, Albiac-Murillo J (eds) (2015) Water pricing experiences and innovations, global issues in water policy. Springer International Publishing, Cham. https://doi.org/10.1007/978-3-319-16465-6

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 International Publishing, Cham, pp 151–183. https://doi.org/10.1007/978-3-030-03698-0_6

ECMWF (2020) ERA-Interim dataset, European Centre for Medium-Range Weather Forecasts (ECMWF) [WWW Document]. https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era-interim

EEA (2023) User-pays principle [WWW Document]. Eur Environ Agency. https://www.eea.europa.eu/help/glossary/eea-glossary/user-pays-principle

El Chami D, Scardigno A, Malorgio G (2011) Impacts of combined technical and economic measures on water saving in agriculture under water availability uncertainty. Water Resour Manag 25:3911. https://doi.org/10.1007/s11269-011-9894-y

Chang A, Wainwright K (2013) Fundamental methods of mathematical economics, McGraw Hill India.

Elbakidze L, Schiller B, Taylor RG (2017) Estimation of short and long run derived irrigation water demands and elasticities. Water Econ Policy 03:1750001. https://doi.org/10.1142/S2382624X17500011

ERR (2019a) Valore aggiunto della produzione agricola regionale, Statistiche Regione Emilia-Romagna. Regione Emilia-Romagna

ERR (2019b) Collezione dop e igp, Statistiche Regione Emilia-Romagna. Regione Emilia-Romagna

Espey M, Espey J, Shaw WD (1997) Price elasticity of residential demand for water: a meta-analysis. Water Resour Res 33:1369–1374. https://doi.org/10.1029/97WR00571
Expósito A, Berbel J (2017) Why is water pricing ineffective for deficit irrigation schemes? A case study in Southern Spain. Water Resour Manag 31:1047–1059. https://doi.org/10.1007/s11269-016-1563-8
FADN (2022) Farm accountancy data network [WWW Document]. FADN database. https://ec.europa.eu/info/food-farming-fisheries/farming/facts-and-figures/farms-farming-and-innovation/structures-and-economics/economics/fadn_en
FADN/RICA (2022) Italian agricultural accounting information network (RICA) of the farm accountancy data network [WWW Document]. RICA Database. https://bancadatirica.crea.gov.it/Default.aspx
Friedlaender AF, Winston C, Wang K (1983) Costs, technology, and productivity in the U.S. Automobile Industry. Bell J Econ 14:1–20. https://doi.org/10.2307/3003534
Gazzetta Ufficiale della Repubblica Italiana (2006) Legislative Decree 152/06, Enviromental Regulations
Geerts S, Raes D (2009) Deficit irrigation as an on-farm strategy to maximize crop water productivity in dry areas. Agric Water Manag 96:1275–1284. https://doi.org/10.1016/j.agwat.2009.04.009
Gehrsitz M (2017) The effect of low emission zones on air pollution and infant health. J Environ Econ Manag 83:121–144. https://doi.org/10.1016/j.jeem.2017.02.003
Giannoccaro G, Roselli L, Sardaro R, De Gennaro BC (2022) Design of an incentive-based tool for effective water saving policy in agriculture. Agric Water Manag 272:107866. https://doi.org/10.1016/j.agwat.2022.107866
Gilligan TW, Smirlock ML (1984) An empirical study of joint production and scale economies in commercial banking. J Bank Financ 8:67–77. https://doi.org/10.1016/S0378-4266(84)80025-4
Gómez-Limón JA, Riesgo L (2004) Water pricing: Analysis of differential impacts on heterogeneous farmers: irrigation water pricing, differential impacts. Water Resour Res. https://doi.org/10.1029/2003WR002205
Graveline N, Mérel P (2014) Intensive and extensive margin adjustments to water scarcity in France's Cereal Belt. Eur Rev Agric Econ 41:707–743. https://doi.org/10.1093/erae/jbt039
Graveline N, Loubier S, Gleyses G, Rinaudo J-D (2012) Impact of farming on water resources: assessing uncertainty with Monte Carlo simulations in a global change context. Agric Syst 108:29–41. https://doi.org/10.1016/j.agsy.2012.01.002
Hansen CB (2007a) Generalized least squares inference in panel and multilevel models with serial correlation and fixed effects. J Econom 140:670–694. https://doi.org/10.1016/j.jeconom.2006.07.011
Hansen CB (2007b) Asymptotic properties of a robust variance matrix estimator for panel data when T is large. J Econom 141:597–620. https://doi.org/10.1016/j.jeconom.2006.10.009
Havranek T, Irsova Z, Vlach T (2018) Measuring the income elasticity of water demand: the importance of publication and endogeneity biases. Land Econ 94:259–283. https://doi.org/10.3368/le.94.2.259
Hendricks NP, Peterson JM (2012) Fixed effects estimation of the intensive and extensive margins of irrigation water demand. J Agric Resour Econ 37:1–19
Howitt RE, Watson WD, Adams RM (1980) A reevaluation of price elasticities for irrigation water. Water Resour Res 16:623–628. https://doi.org/10.1029/WR016i004p00623
Iglesias E, Garrido A, Sumpsi J, Varela-Ortega C (1998) Water demand elasticiy: implications for water management and water pricing policies. In: Presented at the world congress of environmental and resource economists, Venice, p 16
Kahil MT, Connor JD, Albiac J (2015) Efficient water management policies for irrigation adaptation to climate change in Southern Europe. Ecol Econ 120:226–233. https://doi.org/10.1016/j.ecolecon.2015.11.004
Kim HY (1987) Economies of scale in multi-product firms: an empirical analysis. Economica 54:185–206. https://doi.org/10.2307/2554390
Kim HY (1992) The translog production function and variable returns to scale. Rev Econ Stat 74:546–552. https://doi.org/10.2307/2109500
Koundouri P, Nauges C, Tzouvelekas V (2006) Technology adoption under production uncertainty: theory and application to irrigation technology. Am J Agric Econ 88:657–670
Krause K, Chermak JM, Brookshire DS (2003) The demand for water: consumer response to scarcity. J Regul Econ 23:167–191. https://doi.org/10.1023/A:1022207030378
Lago M, Mysiak J, Gómez CM, Delacámara G, Maziotis A (2015) Use of economic instruments in water policy: insights from international experience. Springer, Berlin, Heidelberg, New York
Lika A, Galioto F, Viaggi D (2017) Water authorities' pricing strategies to recover supply costs in the absence of water metering for irrigated agriculture. Sustainability. https://doi.org/10.3390/su9122210

Liu Y, Gao Y, Hao Y, Liao H (2016) The relationship between residential electricity consumption and income: a piecewise linear model with panel data. Energies 9:831. https://doi.org/10.3390/en9100831
Lugtig P (2014) Panel attrition: separating stayers, fast attriters, gradual attriters, and lurkers. Sociol Methods Res 43:699–723. https://doi.org/10.1177/0049124113520305
Massarutto A (2003) Water pricing and irrigation water demand: economic efficiency versus environmental sustainability. Eur Environ 13:100–119. https://doi.org/10.1002/eet.316
Mieno T, Brozović N (2017) Price elasticity of groundwater demand: attenuation and amplification bias due to incomplete information. Am J Agric Econ 99:401–426. https://doi.org/10.1093/ajae/aaw089
Mirra L, Gutiérrez-Martín C, Giannoccaro G (2023) Security-differentiated water pricing as a mechanism for mitigating drought. Impacts insights from a case study in the Mediterranean Basin. Environ Manag. https://doi.org/10.1007/s00267-023-01886-x
Molle F (2009) Water scarcity, prices and quotas: a review of evidence on irrigation volumetric pricing. Irrig Drain Syst 23:43–58. https://doi.org/10.1007/s10795-009-9065-y
Molle F, Berkoff J (eds) (2007) Irrigation water pricing: the gap between theory and practice, Comprehensive assessment of water management in agriculture series. CABI, Wallingford, Cambridge
Moore MR, Gollehon NR, Carey MB (1994) Multicrop production decisions in western irrigated agriculture: the role of water price. Am J Agric Econ 76:859–874. https://doi.org/10.2307/1243747
Nieswiadomy M (1985) The demand for irrigation water in the high plains of Texas, 1957–80. Am J Agric Econ 67:619–626. https://doi.org/10.2307/1241084
Ogg CW, Gollehon NR (1989) Western irrigation response to pumping costs: a water demand analysis using climatic regions. Water Resour Res 25:767–773. https://doi.org/10.1029/WR025i005p00767
Olmstead SM, Michael Hanemann W, Stavins RN (2007) Water demand under alternative price structures. J Environ Econ Manag 54:181–198. https://doi.org/10.1016/j.jeem.2007.03.002
Oum TH (1989) Alternative demand models and their elasticity estimates. J Transp Econ Policy 23:163–187
Pérez-Blanco CD, Standardi G, Mysiak J, Parrado R, Gutiérrez-Martín C (2016) Incremental water charging in agriculture. a case study of the Regione Emilia Romagna in Italy. Environ Model Softw 78:202–215. https://doi.org/10.1016/j.envsoft.2015.12.016
Perman R, Ma Y, Common M, Maddison D, McGilvray J (2011) Natural resource and environmental economics, 4th edn. Pearson Education, Harlow
Pronti A, Berbel J (2023) The impact of volumetric water tariffs in irrigated agriculture in Northern Italy. Environ Impact Assess Rev 98:106922. https://doi.org/10.1016/j.eiar.2022.106922
Pronti A, Auci S, Mazzanti M (2023) Adopting sustainable irrigation technologies in Italy: a study on the determinants of inter- and intra-farm diffusion. Econ Innov New Technol. https://doi.org/10.1080/10438599.2023.2183854
Renzetti S (2002) The economics of water demands, natural resource management and policy. Springer US, Boston
Ridout MS, Diggle PJ (1991) Testing for random dropouts in repeated measurement data. Biometrics 47:1617. https://doi.org/10.2307/2532413
Rogers P (2002) Water is an economic good: how to use prices to promote equity, efficiency, and sustainability. Water Policy 4:1–17. https://doi.org/10.1016/S1366-7017(02)00004-1
Saleth RM, Dinar A (2005) Water institutional reforms: theory and practice. Water Policy 7:1–19. https://doi.org/10.2166/wp.2005.0001
Savenije HHG, van der Zaag P (2002) Water as an economic good and demand management *paradigms with pitfalls*. Water Int 27:98–104. https://doi.org/10.1080/02508060208686982
Scheierling SM, Loomis JB, Young RA (2006) Irrigation water demand: a meta-analysis of price elasticities: meta-analysis of irrigation water demand. Water Resour Res. https://doi.org/10.1029/2005WR004009
Schoengold K, Sunding DL, Moreno G (2006) Price elasticity reconsidered: panel estimation of an agricultural water demand function: price elasticity reconsidered. Water Resour Res. https://doi.org/10.1029/2005WR004096
Somanathan E, Ravindranath R (2006) Measuring the marginal value of water and elasticity of demand for water in agriculture. Econ Polit Wkly 41:2712–2715
Steduto P, Hsiao TC, Fereres E, Raes D (2012) Crop yield response to water, FAO irrigation and drainage paper. Food and Agriculture Organization of the United Nations, Rome
United Nations (1992) The Dublin statement on water and sustainable development [WWW Document]. UN Doc. Gather. Body Glob. Agreem. http://www.un-documents.net/h2o-dub.htm

Varela-Ortega C, Sumpsi JM, Garrido A, Blanco M, Iglesias E (1998) Water pricing policies, public decision making and farmers' response: implications for water policy. Agric Econ 19:193-202. https://doi.org/10.1111/j.1574-0862.1998.tb00526.x

Vezzoli R, Mercogliano P, Pecora S, Zollo AL, Cacciamani C (2015) Hydrological simulation of Po River (North Italy) discharge under climate change scenarios using the RCM COSMO-CLM. Sci Total Environ 521–522:346–358. https://doi.org/10.1016/j.scitotenv.2015.03.096

Villalobos FJ, Testi L, Fereres E (2016) The components of evapotranspiration. In: Villalobos FJ, Fereres E (eds) Principles of agronomy for sustainable agriculture. Springer International Publishing, Cham, pp 107–118. https://doi.org/10.1007/978-3-319-46116-8_9

Ward F, Michelsen A (2002) The economic value of water in agriculture: concepts and policy applications. Water Policy 4:423–446. https://doi.org/10.1016/S1366-7017(02)00039-9

WAREG (2023) Water pricing principles in the EU [WWW Document]. Eur Water Regul. https://www.wareg.org/articles/european-water-pricing-principles/

Weninger Q (2003) Estimating multiproduct costs when some outputs are not produced. Empir Econ 28:753–765. https://doi.org/10.1007/s00181-003-0157-5

Wheeler S, Bjornlund H, Shanahan M, Zuo A (2008) Price elasticity of water allocations demand in the Goulburn-Murray Irrigation District*. Aust J Agric Resour Econ 52:37–55. https://doi.org/10.1111/j.1467-8489.2008.00416.x

Wheeler SA, Bark R, Loch A, Connor J (2015) Agricultural water management. In: Handbook of water economics. Dinar Ariel, Schwabe Kurt, pp 71–86

Wooldridge JM (2005) Fixed-effects and related estimators for correlated random-coefficient and treatment-effect panel data models. Rev Econ Stat 87:385–390. https://doi.org/10.1162/0034653053970320

Wooldridge JM (2010) Econometric analysis of cross section and panel data, 2nd edn. MIT Press, Cambridge

Zilberman D (1984) Technological change, government policies, and exhaustible resources in agriculture. Am J Agric Econ 66:634–640. https://doi.org/10.2307/1240968

Zuo A, Ann Wheeler S, Adamowicz WL, Boxall PC, Hatton-MacDonald D (2016) Measuring price elasticities of demand and supply of water entitlements based on stated and revealed preference data. Am J Agric Econ 98:314–332. https://doi.org/10.1093/ajae/aav022