Article

Do Irrigation Water Requirements Affect Crops' Economic Values?

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Abstract: The irrigation water requirements of different crops are becoming a pivotal driver for the governance strategies of water allocation and management. This paper estimates the impact of irrigation water requirements on economic value in terms of the yields and gross saleable production of 13 different crops cultivated in the Emilia-Romagna region (Italy) over the 2010–2020 period by exploiting a generalized propensity score matching approach. Results show that the overall irrigation water requirements affect crops' economic value. There is a causal effect of water irrigation on economic value: positive only for high levels of water irrigation in the case of yields, while it reverses and assumes a concave shape for gross saleable production. However, the effect is mediated by the irrigation water requirements of different crops. In water scarcity conditions, the allocation of water to arboreal crops, given the effect of water irrigation on gross saleable production, is also positive for small quantities of water. This paper can help guide the design of more sustainable water management strategies and agricultural development policies to face climate change.

Keywords: irrigation requirements; water allocation; territorial governance; FADN-RICA

1. Introduction

Climate change affects the agriculture and agri-food sector from different perspectives and through different channels. Among them, a special role is played by water scarcity. Indeed, the deep changes across the overall water cycle have brought about unconventional, and extreme, drought and flood events which represent major climate stressors for crop production [1]. These events affect the agriculture and agri-food sector, both in the short and in the long term. For instance, while on the one hand, crops could be damaged by floods, on the other, a drought extended over time can affect soil quality and its essential role within the ecosystem. At the same time, crops are stressed by increasing temperatures, as the ones experienced during 2022 and 2023, where rain deficits accumulated in the last part of winter (Figure 1 for the EU scenario) went along with high temperatures in the subsequent summer.

AREAS OF CONCERN - EXTREME WEATHER EVENTS
Based on weather data from 1 February 2022 until 18 March 2022

(c) EC - Joint Research Centre
MARS AOC - MARCH 2022
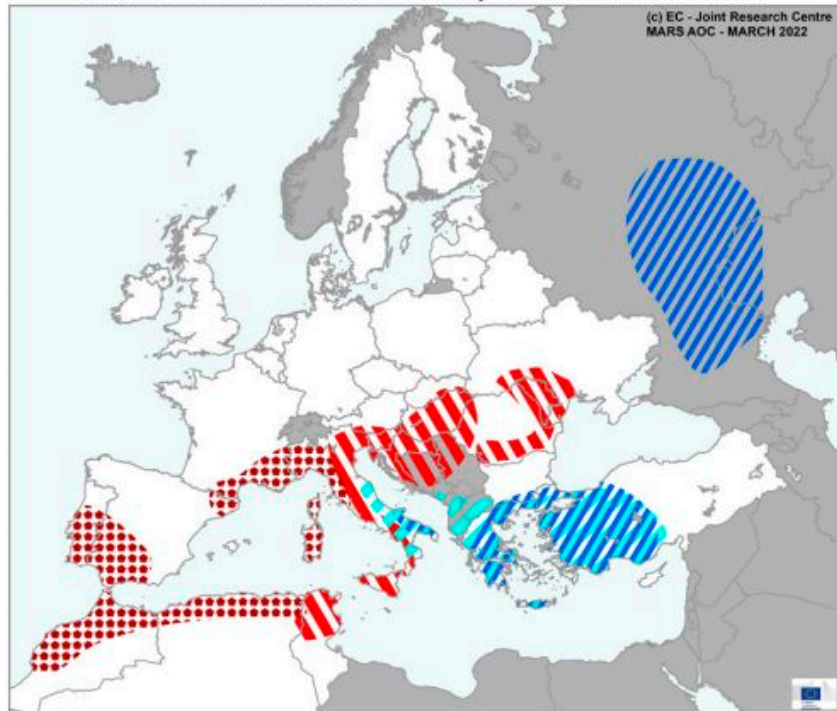
Rain deficit		Cold spell	
Drought		Rain surplus	

AREAS OF CONCERN - EXTREME WEATHER EVENTS
Based on weather data from 1 February 2023 until 17 March 2023

(c) EC - Joint Research Centre
MARS AOC - MARCH 2023
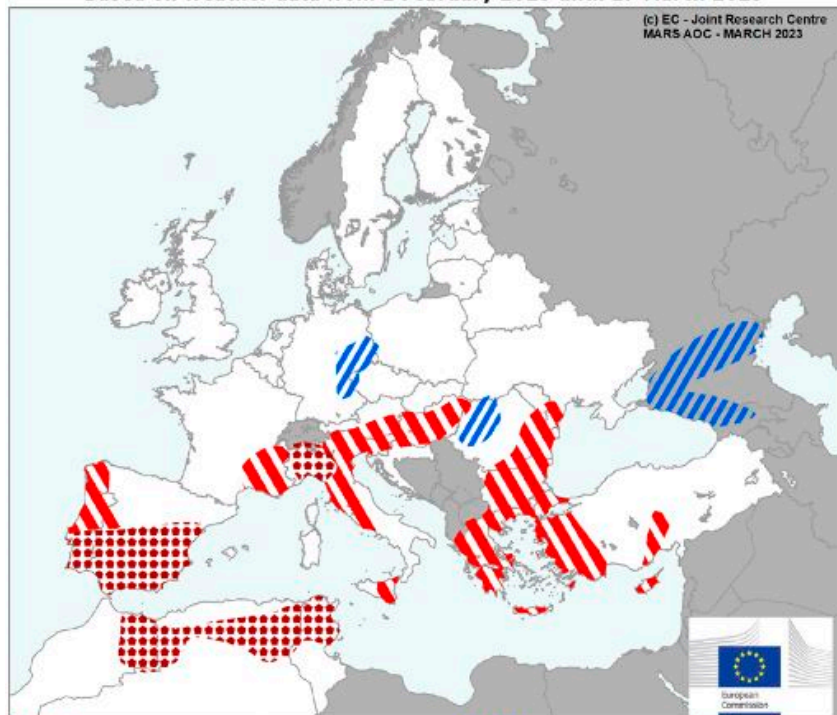
Drought		Rain surplus	
Rain deficit			

Figure 1. JRC Bulletin for winter tail in 2022 [2] and 2023 [3].

Agriculture is a water intensive sector, and actors (mainly farmers) are constantly facing irrigation criticalities.

According to the Water Exploitation Index provided by the European Environmental Agency, most EU countries account for water stress conditions, especially in the Mediterranean basin [4]. Italy is no exception and indeed it displays the 5th highest value of the Water Exploitation Index +[5] among European Union countries in 2019. The Water Exploitation Index + correlates water consumption as a fraction of renewable freshwater resources. Generally, values below 20% are considered to be good while values above 40% testify to severe water stress. In 2019, Italy's value was 57%. It is worth mentioning that this ranking also remarks the stronger tie between irrigation and agriculture displayed by countries in Southern Europe, whose water resources are thus inevitably more stressed [6].

According to the JRC Bulletin [7,8], some Italian regions, such as the Po valley, faced the driest and hottest years ever recorded in 2022 and 2023. In this context, irrigation is enriched by a mitigation strategy dimension to deal with climate change since (i) it protects crops from climate variability and (ii) reduces crop temperatures, especially during heatwaves [9,10]. However, the availability of water irrigation is itself linked to climate dynamics. In particular, global warming and extreme events can affect crop production through many channels, such as the increasing demand for water from farmers and producers, and the volume and geographical diffusion of water bodies suitable for irrigation [11].

According to the existing literature, irrigation water requirements assume a key value for the agricultural, and agri-food sector, not only for agronomic reasons (i.e., the need for water as an input), but also for the economic value that in the actual climate scenario has been reached [12]. From the economic perspective, in fact, the economic value of water irrigation is mainly shaped by supply scarcity, which converts water in the nature of both an excludable club good (shared irrigation) as well as a rival common-pool good (natural water basins). The management of water irrigation therefore becomes a complex issue that countries and regional authorities organize in different ways.

In Italy, water issues are a regional policy concern, as established by the 2005 Constitutional Reform. Within each region, but with variable forms, there are reclamation and irrigation consortia, which are public law subjects that deal with the maintenance of land reclamation infrastructures and agriculture[13,14].Within the specific Italian framework, it is not mandatory to be part of a consortium, nor it is compulsory to buy the irrigation services of one of them. Still, everyone which falls under the consortium administrative area has to pay a fee since many of its activities in the field benefit heterogeneous subjects (farmers, factories and citizens). Consortia set a collective irrigation network which, under a regional policy point of view, allows for better water management. For example, the entire administrative area of Emilia-Romagna is covered by the operations of many different consortia, thus giving researchers the possibility to carry out analyses on a higher level. According to the National board of consortia, slightly more than half the national territory (59.47%) is covered).

In this context, the contribution of this paper is to investigate, for the first time in the literature, the effect of irrigation water requirements on the economic value at the territorial level by using quasi-experimental techniques for causal estimations, looking at the entire agricultural sector of an entire region, and considering different outcome of economic value. More specifically, the aim of the paper is to address the following research questions:

RQ1: Do irrigation water requirements affect crops' economic values?

RQ2: If yes, to what extent does the impact of water irrigation on economic value depend on water endowment?

RQ3: Does the impact change across crop production?

Building on the most recent existing literature [15], we answer these questions by looking at the production of 13 crops in one of the EU's Mediterranean regions where the agricultural sector is most relevant and that has been one of the most stressed by water

crisis (Emilia-Romagna, Italy) and conducting the analysis at the NUTS3-crop level over the 2010–2020 period (Table A1). The crops included in the sample are: Actinidia, alfalfa, corn, grape, green bean, melon, onion, peach, pear, potato, soy, sugar beet and tomato (processing).

We use data from the Italian Farm Account Data Network European database (i.e., RICA), complemented by official territorial statistics (source: EUROSTAT) and agrometeorological data (source: ISTAT).

Methodologically, the analysis exploits generalized propensity score matching (GPS) methods for continuous treatment where the treatment is the irrigation water requirements (in the rest of the paper we refer to irrigation water requirements as IWR) [16]. As far as the economic outcome variables are concerned, we use yields and gross saleable production. The gross saleable production includes the revenues strictly connected with the agricultural activity.

This paper contributes to the strand of the literature about natural resource management and sustainable agricultural production in several ways. First of all, to the best of our knowledge, it is the first contribution that empirically estimates the relation between water requirements and economic value and presents results that can be useful to design sustainable development policies.

Secondly, our analysis provides results also at the crop level for different crops, rather than for only the production of one crop or at an aggregate level (agriculture). Given the heterogeneity across crops, and their agronomic requirements, it is particularly relevant to conduct the analysis separately across crops. In fact, the findings can provide insights for policy makers and practitioners to manage crop transition across territories in response to the predicted climate change. In this paper we look at one specific agriculture system, but the analysis can be easily replicated for other regions or at the national level to better inform policy makers and institutions.

The rest of the paper is divided as follows: Section 2 provides a short presentation of existing literature, describes data and the applied methodology; Section 3 presents the results; and Section 4 concludes and offers some policy reflections.

2. Materials and Methods

2.1. Literature

Several studies exist that investigate the economic value of irrigation. Negri et al. [17] study the impact of climate change events in the U.S, especially in temperature and precipitation, on the decision to adopt irrigation by looking only at the production perspective. They adopt a micro-founded multi output production model to simulate different climatic scenarios and provide estimates of what would be happened with different farmer's choices: irrigation is indeed adopted as a response to variations in the tails of temperature and precipitation distribution, but they are not the only explanatory variables as farm size and soil condition have a role as well.

Da Cunha et al. [18] carry on a two-stage study in the Brazilian scenario by considering (i) how climate influences irrigation adoption and (ii) how farmer adaptation to climate affects land values. They highlight that socioeconomic and agronomic variables as well as climatic ones are important in the decision process. Indeed, they show that, ceteris paribus, small farms tend to irrigate less than big commercial ones, due to the highly heterogeneous and relevant costs of irrigation, which are not so easy to manage for small farms.

By using the World Bank dataset for South America, Seo [19] investigates whether public adaptation to climate change is different from the private one. The focus is on irrigation and its dual nature, i.e., private or public schemes and finds that public schemes are characterized by their lump-sum nature thus conducting either to too much or too little water supply.

At the same time, a different strand of literature focuses on the offsetting effect of irrigation against climate change. Among others, Tack et al. [20] look at the mitigating

effect of irrigation on wheat crops in severe high temperature conditions and they find that irrigation could offset the estimated negative impact on wheat yields (−8%) of every one-degree Celsius increase in temperature. Zaveri and Lobell [21] focus on India over the 1970–2009-period and conclude that irrigation allowed the achievement of higher wheat yields. By the construction of a counterfactually inspired scenario, they confront the observed output, i.e., the one with irrigation and the unobserved one, i.e., the one identified by irrigation levels and weather of 1970, supposing they were steady throughout time. In Li and Troy [22], a central part is dedicated to the impact of specific climatic variables on the difference between irrigated and rainfed crop yields and concludes that irrigation's impact on it us variable but positive, and that for some crops (wheat), it is better not to irrigate as the impact on water resources is stronger than the benefit from irrigation.

Finally, the role of irrigation in agriculture is assessed in [15]: the authors stress that irrigation water has a relevant role in agriculture, but it seems not more important, less relevant even, than the type of farming and variable costs borne by the farm.

Methodologically, the existing literature has mainly adopted three approaches, which have, however, some criticalities and do not allow for the estimation of the causal impact. First, some papers investigate water irrigation issues by adopting the so-called residual value method, as described by Young and Loomis [23]: the value of production is decomposed by the value of each one of its inputs minus one, i.e., irrigation water, thus attributing to the latter the full residual value. While the main advantage of this approach is that it is straightforward and provides easily read results, the main disadvantage is that, accepting the neoclassical framework, it also attributes all kinds of things that affect the production function but that were not possible to detect to water value.

A different group of studies relies on the stated preferences approach [24]. The value of the water irrigation is accounted here starting from what the sample of people interviewed declare, i.e., their willingness to pay. This methodology has some limitations: (i) the necessity of a well-selected sample, (ii) the construction of a structured survey; and (iii) the nature of the analysis are a few of the main weaknesses of this approach. However, they have been demonstrated to be quite useful when speaking of non-market benefits. Lastly, some of the existing papers exploit the hedonic price approach [11,25]. However, the assumption of perfect market competition, and thus that land prices are a perfect function of its attributes is critical for the reliability of the analysis.

2.2. Data

To conduct the analysis, we rely on a dataset that we arrange from different sources of data and that include a set of climatic, agronomic and socioeconomic variables at the NUTS3-crop-year level over the 2010–2020 period.

Climatic data come from the Italian Agenzia regionale per la prevenzione, l'ambiente e l'energia dell'Emilia-Romagna (Arpae) that provides daily records from 1961 to 2020 about precipitation and minimum and maximum temperatures [26] (Available at https://dati.arpae.it/dataset/erg5-eraclito. Last access on 1 April 2023.). Starting with them, we calculated the following agroclimatic indicators. First, we calculated the 90th percentile of the entire time series at NUTS3 level for minimum and maximum temperature (IS_TNover90p and IS_TXover90p). We quantified the total amount of days with temperature above the 90th percentile and defined a heatwave when there were at least three consecutive days over the 90th percentile and the heatwave number (TN_HWN and TX_HWN) as the total of the heatwaves across one year [27].As stated in [27], it is possible to apply the abovementioned heatwave definition either in terms of maximum temperature (TX) or minimum temperature (TN). For precipitation, we considered the days with effective rainfall as the days with precipitation above 2.5 mm (0.1 inch) and the days with heavy rainfall as the ones characterized by precipitation above 25 mm (1 inch) [17] (IS_rainydays and IS_Heavyrainydays, respectively).We are aware of the many existing linkages between the paucity of precipitation in winter and drought problems in the subsequent summer, but we will not address this topic in this work. We will focus mainly on

what happens during the irrigation season (IS), which usually goes from April to October. However, the evidence arising from the data drove us to define it as the time span that goes from the first decade of March to the last decade of November.

Water and agronomic data were gathered from Consorzio di Bonifica per il Canale Emiliano Romagnolo (CER), which is a second level consortium whose activities pertain to an important part of the region and consist in information on the irrigated dimension of acreage and yields for the area of interest.

In particular, we collected IWR by the means of Irriframe [28], a digital platform developed by CER whose utility to support better water management practices in Europe has already been proved [29].

Data on gross saleable production and the characteristics of the local agricultural sector come from the Italian Farm Accountancy Data Network database, i.e., RICA (FADN, 2022). The FADN is the most important source of annual micro-economic data for agricultural holdings within EU. One of its greatest advantages lies in the harmonized and standardized practice of its construction, which makes comparisons between countries possible. The Italian sample is made up of 10,764 farms. In extracting data from FADN, we used the following criterion: we considered every fully irrigated crop as irrigated, i.e., when the entire acreage dedicated to that particular crop was irrigated (see https://rica.crea.gov.it/ for more information, last access on 1 April 2023). Lastly, data from ISTAT was used to cover possible observation gaps in the acreage and yields item, while data on per capita GDP come from EUROSTAT. See Table 1 for source and descriptive statistics of the variables we used while Table A2 for their definition.

Table 1. Variables used in our analysis and their source. Author's elaboration.

Source	Variable	Obs	Mean	Std. Dev.	Min	Max
FADN	Economic Dimension of Farms	609	3.289	0.329	2.327	4.389
	Gross Saleable Production (EUR)	588	6427	4811	379.7	28,442
Arpae	IS_TNover90p (number of days)	609	41.75	11.87	8	67
	IS_TXover90p (number of days)	609	49.43	13.53	15	81
	TN_HWN (number of heatwaves)	609	5.156	1.457	1	8
	TX_HWN (number of heatwaves)	609	6.350	1.843	3	11
	IS_rainydays (number of days)	609	56.99	12.89	33	85
	IS_Heavyrainydays (number of days)	609	4.210	2.815	0	16
Cer-ISTAT	Yields (quintals/ha)	609	301.6	214.6	22	850
	Acreage (ha)	584	5919	10,055	32.96	133,905
Irriframe	IWR (mm/ha)	609	33.95	12.48	8.048	74.47
Eurostat	Percapita_GDP (million EUR)	609	32,942	4476	23,972	42,403

2.3. Research Scenario

The final sample is an unbalanced panel of 8 NUTS3 areas of the Emilia-Romagna region and 13 different crops followed from 2010 to 2020 for a total of 609 observations. The sample does not include the NUTS3 Rimini due to its inadequate data coverage.

Emilia-Romagna is one of the most productive regions in Italy for the agricultural and agri-food sector. It accounted for approximately 9.16% of the national gross domestic product in 2021 and for the 11.8% of the value of the national agricultural output in 2020). Its geographical position allows for the existence of a high-quality and highly heterogenous food industry, as proven by the 44 European protected denomination items. According to 7th Agricultural Census data mentioned by Emilia-Romagna Region, within Emilia-Romagna the utilized agricultural area (UAA) is equals to 1045 thousands of hectares, about the 79% of the total agricultural area, in slightly decrease of 1.8% and 2.6%, respectively from 2010.

The region has a milder climate compared to other Italian regions. Still, it has not been immune to climate change. Figure 2 depicts anomalies only considering maximum and minimum temperature: to this definition, it seems quite clear that 2014 has been the coolest year of our time span of interest. Instead, to look at the hottest ones, we would have to at least simultaneously consider both temperature and precipitation: as described by Figure 3, the 2012–2013 pair as well as 2017 emerge.

Figure 2. Days over the 90th percentile for minimum and maximum temperature (**left**) and number of heatwaves (**right**). Author's elaboration on ARPA-E data. Notes: IS_TNover90p and IS_TXover90p expressed as number of days, while TN_HWN and TX_HWN as number of heatwaves.
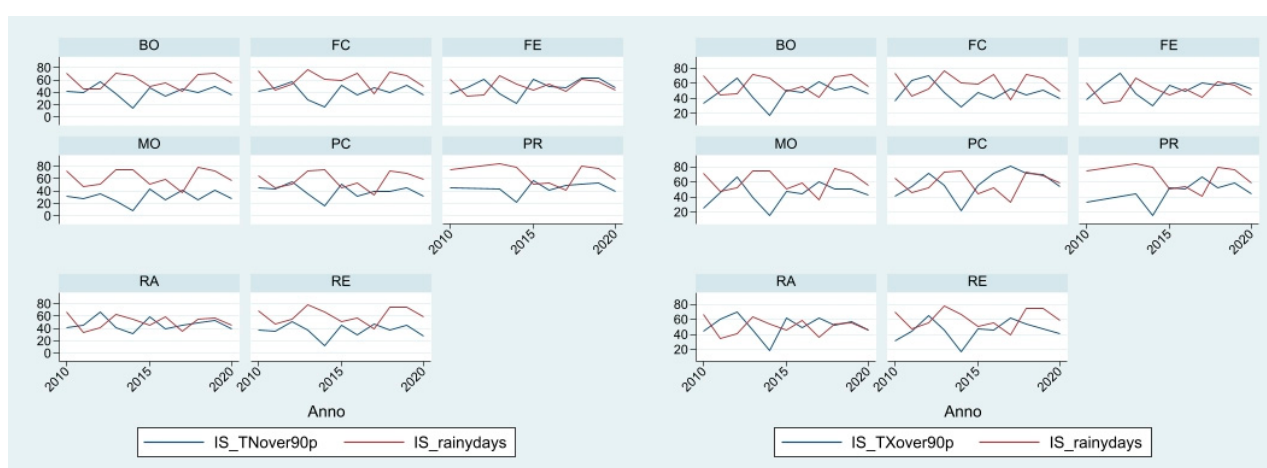

Figure 3. Temperature and precipitation at NUTS3 level. Author's elaborations on ARPA-E data. Notes: IS_TNover90p, IS_TXover90p and IS_rainydays expressed as number of days.

Finally, we do not have data regarding the full stock of water available for irrigation within every NUTS3 area. Instead, we have data on crop water requirements, defined as IWRthat for its inherent characteristics we can consider as the crops' minimum demand for water or, roughly speaking, the inferior threshold of irrigation water. Given that the IS

generally goes from the first decade of March to the final decade of November, IWR is calculated as the average water demand by crop j not over the entire IS, but only over the exact period of its irrigation. We plotted the unitary heterogenous IWR across crops and for time t at the NUTS3 level (Wit) and did the same for yields (Yit) in Figure 4.

Figure 4. *Wit* and *Yit* by NUTS_3 area. Authors' elaborations on CER and Arpae data. Notes: Wit is expressed in mm/ha/year and Yit is expressed in quintals/ha/year.

On average, a decrease in demanded water emerges, with a particularly falling movement for Bologna, Ferrara, Ravenna and Reggio Emilia. The same trend does not hold for yields which do not follow a decreasing path, but rather a more irregular one. According to the Emilia-Romagna Region (2021), the 2020/2010 delta of the yields for the crops considered within our analysis was a decrease of 18% (see https://statistica.regione.emilia-romagna.it/agricoltura/produzione-lorda-vendibile-a-prezzi-correnti). It is interesting to note that three out of the four abovementioned areas are in the eastern part of the region, which lacks abundant water resources and is strongly dependent on CER services.

2.4. Methodology

According to Negri et al. [17], the farmer's decision-making process can be defined as follows:

$$\pi_I(P, W, \omega, N, \theta) = max_X[PY - WX - \omega T_I]: Y\epsilon Y(X, \theta, N, T_I)$$
$$\pi_D(P, W, N, \theta) = max_X[PY - WX]: Y\epsilon Y(X, \theta, N, T_D)$$
(1)

where *I* and *D* indicates irrigated and dryland, respectively; *Y*(.) are the production possibilities set by constraints on technology, land (*N*), land quality (θ), i. e., soil and climate and irrigation capacity (*T*); *P* and *W* are the exogenous output and input prices; *Y* and *X* are agricultural output and input, respectively; *T* represents the discrete choice whether to adopt irrigation or not and ω is the irrigation cost.

Aimed at the achievement of the optimum possible profit level, each farmer will decide whether to adopt irrigation. However, in our analysis, IWR is not directly linked to profit, rather it is linked to gross saleable production generating endogeneity and self-selection issues. To solve it, we rely on generalized propensity score matching (GPS) for

continuous treatment [16]. The GPS extends the binary treatment proposed by Rosenbaum and Rubin [30] to continuous treatment scenarios with the aim of balancing the distribution of covariates in the treated and control group [31]. Several papers recently used this approach to evaluate agrifood policies, including [32,33]]. In this paper, in fact, all NUTS3 crop observations are treated (irrigated), but with different levels of treatment. Thanks to the GPS we are, therefore, capable of estimating how the impact changes for different levels of treatment intensity.

From the empirical perspective, the GPS first assigns a score in terms of treatment probability and second, it compares observations with the most similar score in order to isolate the performance ascribable to the treatment. Then, it estimates the causal impact of a unitary change in the treatment level by using the dose–response function approach. The model produces two outcomes: the dose–response function (DRF) and the treatment effect function (TEF).

In this paper, we considered IWR as the treatment and looked at the yields and gross saleable production as proxies of economic values. Due to the absence of data on the exact amount of supplied water, IWR can be considered a good proxy of the latter given that irrigation water gravitates around IWR and is surely correlated with it. Operationally, the GPS model, as illustrated in Hirano and Imbens [16] and Imbens [34] relies on the assumption of weak confoundedness. If we define $Y_i(t)$ as the potential outcome of the individual i when exposed to the treatment t, then we can formulate it as follows:

$$Y(t) \perp T|X \quad \forall t \in T. \tag{2}$$

It means that, given the covariates X for each individual, the potential outcome is orthogonal with respect to the treatment assignment. This assumption derives directly from Rosenbaum and Rubin [30] and in its original form, it involves the unbiasedness of the difference between the treatment and control means as the average treatment effect. In the GPS case, it is not necessary for this to hold, and indeed the weak unconfoundedness only requires the conditional independence of each value of the treatment, not the joint one [16].

One of the main utilities of GPS allows us to observe not only the average irrigation effect on yields (μ), but also the marginal one (m),

$$\mu(t) = E[Y_i(t)]$$
$$m(t) = [Y(t+1) - Y(t)]. \tag{3}$$

In other words, we need to construct a function that allows us to operate the best comparison among our units. This function is the propensity score and is a function of the covariates of each unit. More precisely, it is the conditional probability of receiving the treatment, given the covariates:

$$r(t, x) = f_{T|X}(t|x) \tag{4}$$

which, in turn, leads us to the define the GPS as $R = r(t, x)$. Another trait of the methodology is the balancing property, namely:

$$X \perp I(T = t)|r(t, x) \tag{5}$$

where $I(.)$ is the indicator function. Equation (5) states that within layers marked by the same value of the propensity score, the probability that $T = t$ is not dependent upon the value of X.

At this point, the practical implementation of the GPS is divided into three parts [35]. The first requires the estimation of the propensity score $r(t, x)$. Treatment is assumed to be normally distributed, conditional on covariates. Since our treatment does not follow this path, we use an ln transformation and then tested its normality by the skewness and kurtosis test:

$$g(T_i)|X_i \sim N[h(\gamma, X_i), \sigma^2] \tag{6}$$

where $g(.)$ is the transformation of our treatment and $h(.)$ is function of covariates (X_i) with linear and high order terms, dependent on a vector γ of parameters. To complete the first step, we estimate the GPS as [35]:

$$\hat{R}_i = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} \exp\left[-\frac{1}{2\hat{\sigma}^2}\left(g(T_i) - h(\hat{\gamma}, X_i)\right)\right] \tag{7}$$

where $\hat{\sigma}^2$ and $\hat{\gamma}$ are estimated from Equation (6). If Equation (5) holds, we can consider observations within the same layer to be identical among them, orthogonally with respect to the actual treatment level. The second part of the procedure deals with the conditional expectation of the outcome given the treatment (T) and GPS (R) [35]. We estimate the following:

$$\varphi[E(Y_i|T_i, R_i)] = \vartheta(T_i, R_i, \alpha) = \alpha_0 + \alpha_1 T_i + \alpha_2 T_i^2 + \alpha_3 R_i + \alpha_4 R_i^2 + \alpha_5 T_i R_i \tag{8}$$

with α being a vector of parameter estimates whose meaning is not of particular relevance to the selected model, setting aside their statistical significance [35].

Finally, we average the estimated regression function over the GPS at any level of the treatment to obtain the DRF [35]. More precisely:

$$E[\widehat{Y(t)}] = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}[t, \hat{r}(t, X_i)] = \frac{1}{N}\sum_{i=1}^{N}\varphi^{-1}[\hat{\vartheta}(t, \hat{r}(t, X_i); \hat{\alpha})]. \tag{9}$$

3. Results

3.1. Main Results

Starting from our first research questions (RQ1), the aim was to estimate the impact of IWR on the economic value (yields and gross saleable production) of crop production. In addition, we were interested in evaluating whether this effect depends on treatment (irrigation) endowment (RQ2).

Overall, IWR exerts a significant effect on yields as depicted by the DRF (Figure 5a) (RQ1). The left-side panel of the figures reports the DRF providing graphical representations of the relationship between WD and yields, while the right-side panel depicts the TEF, that is, the first derivative of the respective DRF. The middle line refers to the function, while the top and bottom lines represent 95% confidence intervals. See Table A3 for model validation. This result is mainly in line with Tack et al. [16] that demonstrated how irrigation is an effective tool to support yield, even if with extreme climate change conditions, and Zaveri and Lobell [17] that concluded a positive increasing benefit of irrigation on wheat yields.
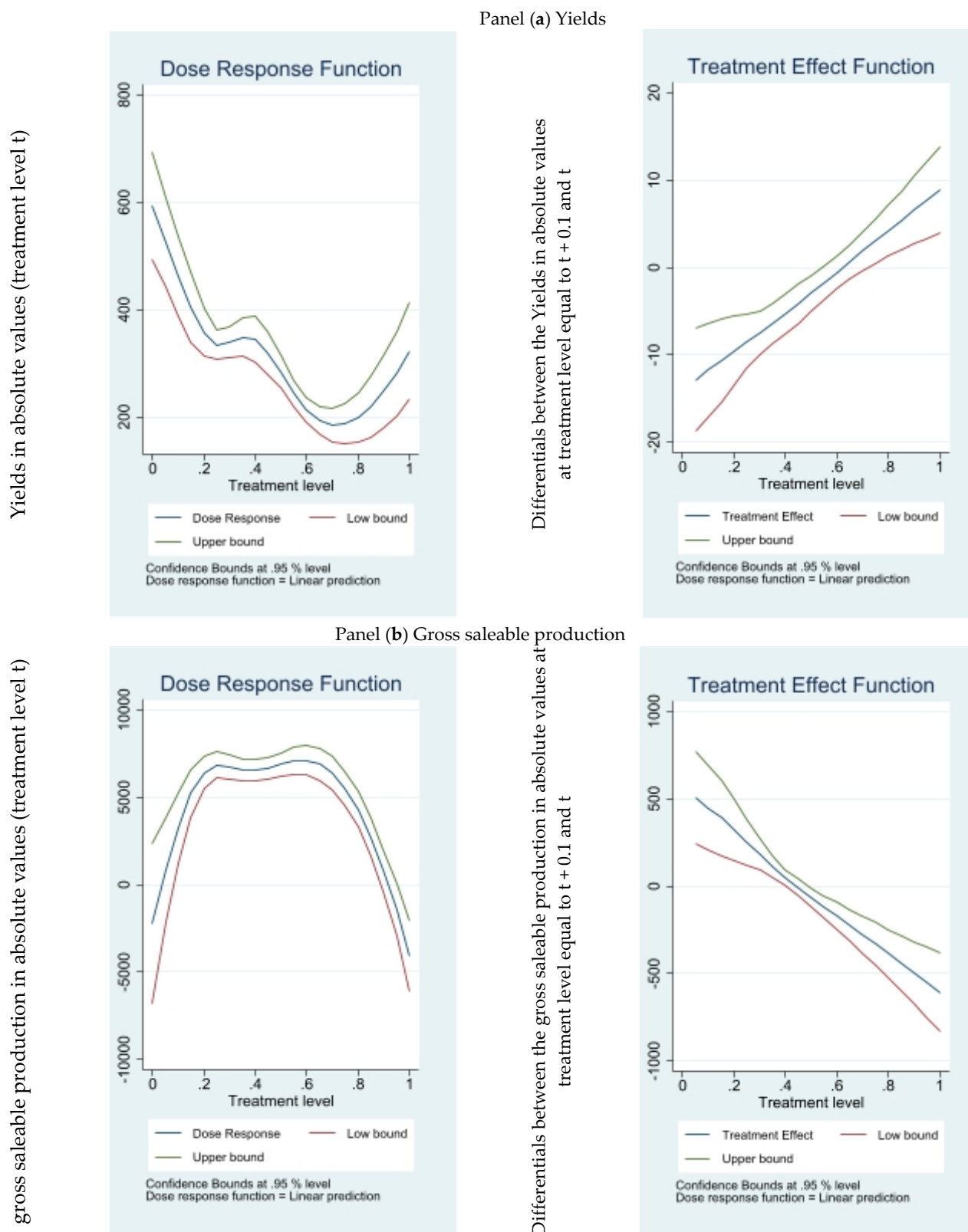
Panel (**a**) Yields

Panel (**b**) Gross saleable production

Figure 5. GPS1-Effects of irrigation on yields (Panel a) and gross saleable production (Panel b). Full sample. Panel (a) yields. Notes: We used bootstrap methods to obtain the dose–response function standard errors and confidence intervals which are included in the figures as the lower and upper bounds [35]. Models have been estimated with the constant. Yields are expressed in quintals/ha.

Some differences, however, emerge when we look at different treatment levels (RQ2). The dose–response function has, in fact, a convex form (with the exception of treatment

levels between 0.2 and 0.4) suggesting that the positive effect of irrigation on yields emerges only for a high level of treatment (irrigation). The TEF, which reports the outcome as increasing due to the unitary increment of the treatment, confirms it: the effect increased more for the last third of the treatment distribution.

The convex form of the DRF reversed and became concave when considering the impact of irrigation on gross saleable production (Figure 5, Panel b). The former indeed positively affects the latter, but following a decreasing path, as highlighted by the TEF: once the maximum has been reached, to increase the treatment leads to a loss in gross saleable production.

Overall, these results confirm the existing literature. Ruberto et al. [15] found that irrigation is a determinant factor affecting crops' economic values, but it is not more relevant than other internal and external elements.

3.2. Heterogeneity Analysis

The effect of irrigation can be influenced by the agronomic characteristics of different crops and their higher or lower water intensity nature. This heterogeneity has been underlined by Li and Troy [18] concluding that some crops are unsustainable given that they need too much water.

Crop differences also emerged in this paper. By looking at the DRFs of Figure 5a: some crops are characterized by high yield volumes yields and low IWR volumes (before treatment level 0.4) while others by low yield volumes and high IWR volumes (between 0.4 and 1). Therefore, we decided to investigate this heterogeneity, especially whether the effect of the treatment differs across crops (RQ3). Therefore, we replicated the analysis by splitting the sample into two-subsamples according to the yield, above and below 350 quintal/ha. The first sample included lower water intensity crops, whereas the second one included higher water intensity crops. Descriptives for the subsamples are provided by Tables 2 and 3 and suggest that while crops included in the group above the turning point are mainly non-arboreal crops, the other group is mainly composed by arboreal crops which account for higher irrigation water requirements, but also for higher gross saleable production.

Table 2. Descriptive statistics.

Lower Water Intensity Crops			
Crop	**Freq.**	**Percent**	**Cum.**
Alfalfa	13	6.070	6.070
Melon	1	0.470	6.540
Onion	36	16.82	23.36
Potato	32	14.95	38.32
Sugar beet	72	33.64	71.96
Tomato (Processing)	60	28.04	100
Total	214	100	
Higher Water Intensity Crops			
Actinidia	38	9.620	9.620
Alfalfa	23	5.820	15.44
Corn	72	18.23	33.67
Grapes	59	14.94	48.61
Green bean	24	6.080	54.68
Melon	23	5.820	60.51
Onion	2	0.510	61.01
Peach	53	13.42	74.43
Pear	50	12.66	87.09
Potato	6	1.520	88.61

Soy	45	11.39		100
Total	395	100		

Table 3. Gross saleable production and IWR.

	Lower Water Intensity Crops				
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Gross Saleable Production	210	5280	3214	624.5	20,537
IWR	214	29.25	11.09	8.048	72.95
	Higher Water Intensity Crops				
Gross Saleable Production	378	7065	5401	379.7	28,442
IWR	395	36.49	12.47	8.933	74.47

We separately re-estimated the model for the two subsamples (Figures 6 and 7).

Panel (**a**) Yields
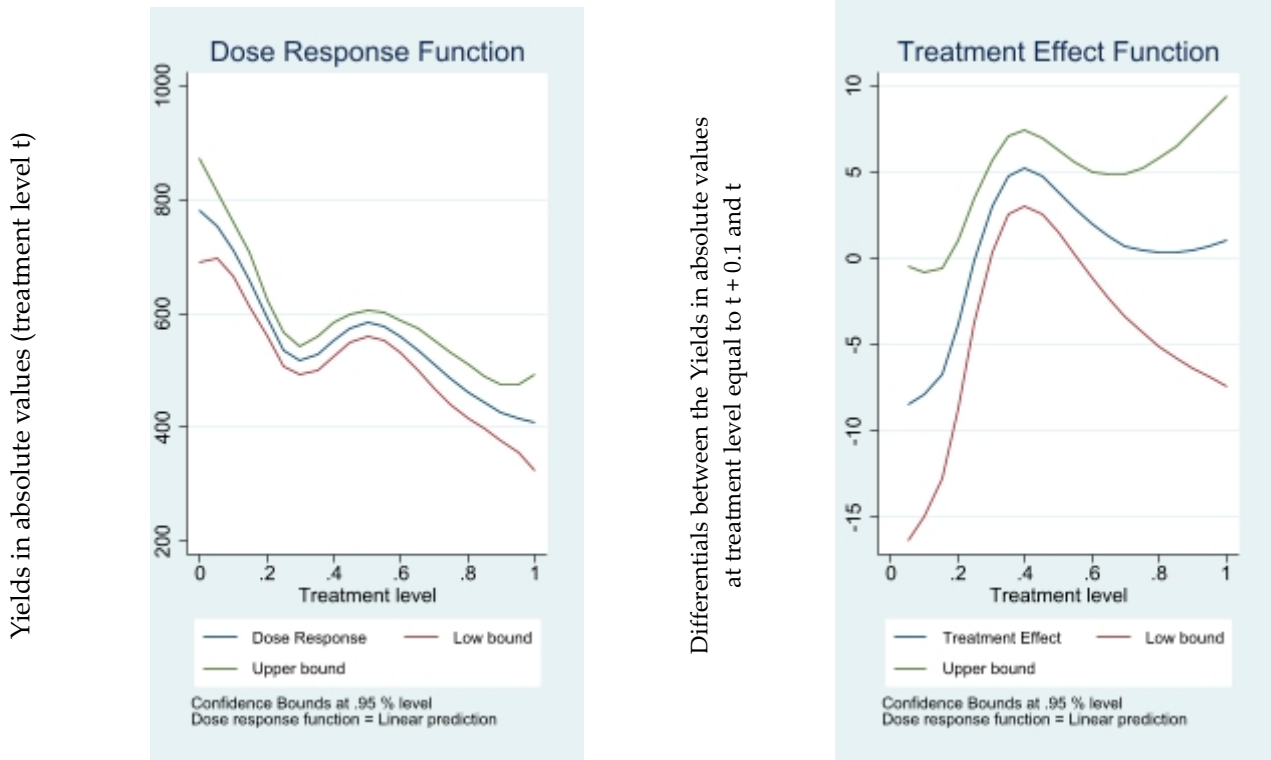
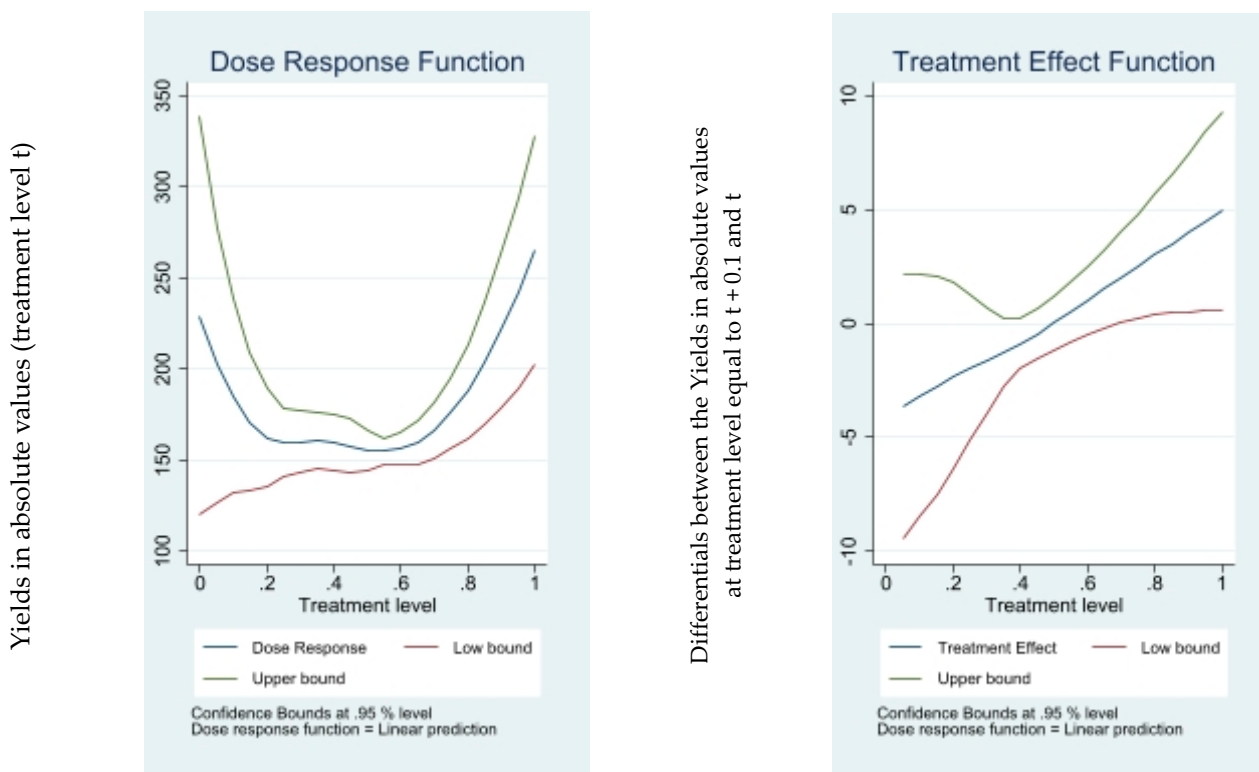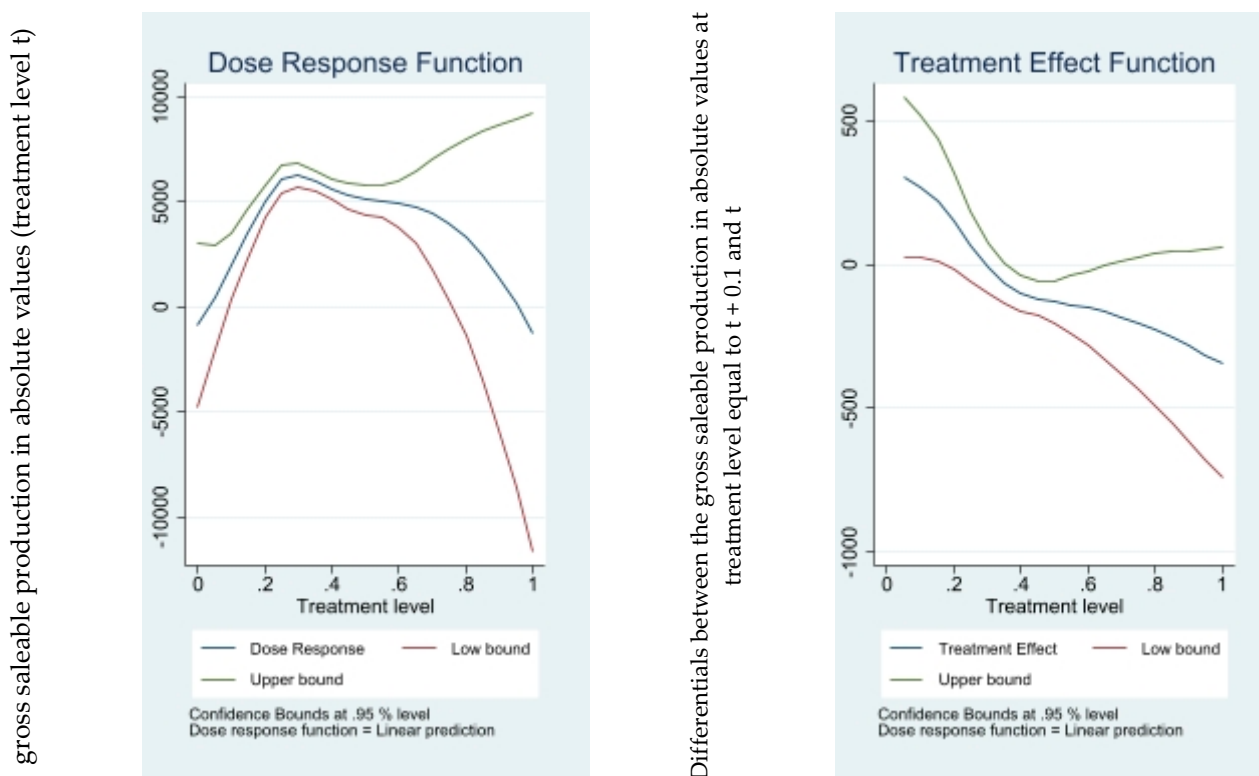Panel (**b**) Higher water intensity crop production

Figure 6. GPS2-Effects of IWR on yields. Panel (**a**) Lower water intensity crop production. Notes: The middle line refers to the function, while the top and bottom lines represent 95% confidence intervals. We use bootstrap methods to obtain the dose–response function standard errors and confidence intervals which are included in the figures as lower and upper bounds [35]. Models have been estimated with the constant. Yields are expressed in quintals/ha and gross saleable production is considered at current prices.

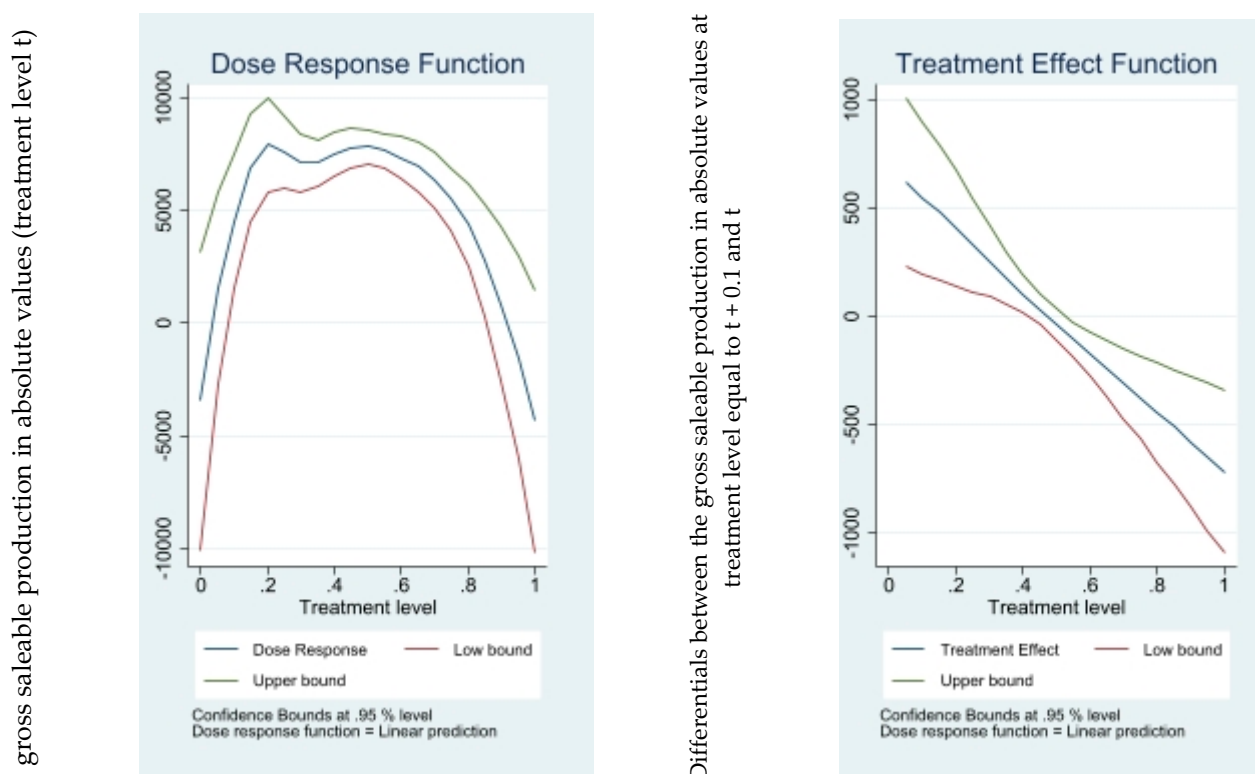Panel (**b**) Higher water intensity crop production

Figure 7. GPS3-Effects of irrigation water requirements on gross saleable production. Panel (**a**) Lower water intensity crop production. Notes: The middle line refers to the function, while the top and bottom lines represent 95% confidence intervals. We use bootstrap methods to obtain the dose–response function standard errors and confidence intervals which are included in the figures as lower and upper bounds [35]. Models have been estimated with the constant. Yields are expressed in quintals/ha and gross saleable production is considered at current prices.

Starting from the effects on yields and lower water intensity crop production (Figure 6a), the left-side panel of the figures reports the DRF providing graphical representations of the relationship between IWR and gross saleable production (a) and yields (b); the right-side panel depicts the TEF, that is, the first derivative of the respective DRF. The findings show that the DRF is concave for both the lowest and highest levels of the treatment, while it assumes a convex shape from 0.2 to 0.4. This evidence suggests that on average, there is a positive effect for a medium level of water irrigation, meaning that the yields of lower water intensity crops do not benefit from a low level of irrigation (as the treatment is not enough to increase yields) or from the highest ones (due to the decreasing marginal productivity of the production factors). Conversely, a medium level of treatment seems to be effective and generates positive and increasing effects.

In the case of higher water intensity crops (Figure 6b), a clearer convex pattern emerges. This suggests that water irrigation is effective in increasing yields only after a certain level of treatment (around 0.5), but after that, it will always remain positive.

Moving to the gross saleable production estimations (Figure 7), lower water intensity crops (Figure 7a) show a concave DRF along the 0.1–0.6 treatment span (the only significant part of the estimations). In this case, in fact, the left-side panel of the figures also reports the DRF providing graphical representations of the relationship between IWR and gross saleable production (a) and yields (b); the right-side panel depicts the TEF, that is, the first derivative of the respective DRF. The results suggest that, on average, while there is a positive effect from the lower level of treatment, there is a negative effect from the highest levels. For higher water intensity crops (Figure 7b), the impact follows a similar trend: no significance before 0.1 and after 0.9, a positive impact corresponding to a lower level of treatment, a null impact for a medium level of treatment, and a negative one for

the higher levels. This suggests that the economic value (i) noticeably benefits from obtaining the first level of treatment (moving from around zero irrigation to a certain degree of it) with a sharp increase in the gross saleable production and (ii) from a medium level of treatment, as they guarantee a certain and constant level of gross saleable production. From the economic perspective, treatment impact on gross saleable production follows the same logic as that of decreasing marginal productivity, as depicted by the TEF: the gains in gross saleable production decrease along the treatment increase, up to the point where they eventually became negative. The clear relevance of the treatment (irrigation) is what we observe in agronomic practices commonly implemented for arboreal crops, such as supplemental irrigation for vineyards.

If we split the group of higher water intensity crops according to the median value of the gross saleable production (Table 4), we find that the upper part is mostly made up of arboreal crops (A), which from the agronomic perspective requires more water irrigation, accounts for higher gross saleable production and maintains a constant economic value over time in comparison with non-arboreal crops (H).

Table 4. Higher 50% gross saleable production.

Variable	Obs	Mean	Std. Dev.	Min	Max
A_Gross Saleable Production	159	11,552	4293	6471	28,442
H_Gross Saleable Production	31	10,251	4141	6518	26,846
A_IWR	164	36.35	10.02	9.918	57.77
H_IWR	43	33.69	16.39	8.933	74.47
A_Yields	164	202.3	62.43	58	320
H_Yields	43	228.4	94.39	51.19	320

4. Discussion and Conclusions

Following the heated debate on water crises and irrigation requirements in a climate change scenario, this study emphasizes the growing importance of irrigation water requirements in shaping governmental strategies for water allocation and management. The research estimates the economic impact of irrigation water requirements on yields and gross saleable production for 13 different crops in Italy over the 2010–2020 period by using GPS methods. The findings indicate:

(i) a causal effect of irrigation water on economic value, with positive impacts observed for high levels of water irrigation in terms of crop yields (RQ1)

(ii) in terms of yields, it is positive only for a high level of water irrigation, while gross saleable production reacts sharply and positively to a low level of treatment and negatively for a higher level of treatment; in the middle, it remains overall stable, but reaches different values depending on the sample (RQ2)

(iii) the effect is mediated by the specific water requirements of different crops (RQ3).

We want to stress that we basically observed three types of crops: the first one (e.g., sugar beet) is characterized by high yield volumes, low water requirements but also low gross saleable production (the decreasing part up to the turning point of the GPS1); the second one is denoted by a lower yield volumes, but higher water requirements as well as higher gross saleable production (e.g., corn); the last one displays mostly arboreal crops which are extremely water demanding (e.g., Actinidia) and that, even though they are not too different in terms of yield volumes form the second group, they show the highest gross saleable production.

Therefore, in terms of water allocation strategies, our findings highlight the need for tailored strategies. The results suggest that, when farmers face strong constraints on water availability, the more efficient solution seems to be to allocate water to arboreal crops, as

the effect of water irrigation on gross saleable production is positive also if small quantities of water are distributed. However, to maintain the highest economic values, a medium level of water allocation is needed. This is in line with the core of efficiency criterion in economics: as depicted in [36], it is better to allocate water to the production of crops for which the productivity is higher. In our case, this has been demonstrated in the case of arboreal crops, confirming what the literature has said while focusing on Norther Italian regions [37].

Crops that need lower levels of water appear as the crops that farmers and policy makers should look at not only due to their relevance to the final market (consumers), but also due to their use as inputs in other agrifood production processes. This is the case for alfalfa used in Parmigiano Reggiano PDO production, one of the main economically successful agrifood products of Italy [37]. To what extent crops participate in food value chains, both at the national and global level, should therefore be considered when designing strategic water management strategies. It can have an effect not only on the sustainability of local production systems, but also on their economic competitiveness.

From a policy perspective, this paper highlights how water resource management and governance questions should be addressed by considering both yields and economic value, rather than focusing only on the productivity [38]. Our contribution stresses that it would be a mistake and economically damaging to consider only low water demanding crops as feasible under water scarcity scenarios. This evidence, at least in part, supports the mitigation strategies that have been supported by policy interventions and plans over the last several years.

In addition, given that arboreal crops are crops in which unconventional water use is allowed (i.e., direct and indirect use of wastewater), the importance of arboreal crops in crop allocation becomes even more apparent [39]. Arboreal crops are, in fact, the only type for which the use of wastewater is allowed. The reuse of wastewater is supported by the EU in order to achieve a more sustainable agricultural system. However, its efficiency depends on how policies and interventions are designed.

For example, in the EU, Regulation 2020/741/EU addresses water scarcity issues by introducing a harmonized standard for wastewater reuse in agriculture. The achievement of the best possible solution can be challenging, especially in countries which lack a consistent normative system in regard to the second half of the water utilization cycle, i.e., the depuration and discharge of wastewater. Indeed, the lack of good territorial and crop-tailored regulations is a major driver of the increase in soil and crop damage. With the aim of maximizing the availability of water for farmers, policy makers and local actors have to consider not only natural boundaries and water quality [40], but also economic factors, such as infrastructure costs and the determination of water prices [41]. The provision of high-quality water provided by so-called direct reuse may result in higher prices, which can be unsustainable for farmers, especially those that cultivate low value-added crops. From the economic perspective, the concept of "irrigation water consumption-yield-economic value of crops" should be balanced by adopting a more inclusive and sustainable approach. Even if the main issue remains the problem of maximum optimization between productivity, economic values and physical constraints (water in this case), nowadays, the issue should also be enriched by a more comprehensive sustainability strategy. This is particularly clear if we look, for example, at the Sustainable Development Goals Agenda (SDGs) which attempts to simultaneously achieve the protection, restoration and promotion of the sustainable use of terrestrial ecosystems (SDG 15) and the sustainable management and provision of clean water (SDG 6) with an increase in agriculture productivity (SDG 2). The result, therefore, is a complex challenge of supporting agricultural productivity, with efficient high quality water use, while providing long-term environmental, social and economic sustainability to farmers and citizens. Therefore, to address this issue it is not sufficient to look at yields, but we also need to consider the economic dimension of crops from a more integrated point of view.

Our findings should be considered as explorative and further research needs to be carried out. The estimation of the socio-economic effects of specific irrigation techniques and, in particular, the adoption of wastewater reuse in agriculture is in our research agenda. At the same time, we are interested in investigating how technological choices and socio-cultural dynamics will produce patterns of water use and allocation.

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Data Availability Statement: Data available on request due to restrictions.

Appendix A

Table A1. Crops and NUTS3.

Crops	Actinidia, Alfalfa, Corn, Grape, Green bean, Melon, Onion, Peach, Pear, Potato, Soy, Sugar beet, Tomato (Processing)								
NUTS3-Provinces	ITH51-Piacenza (PC), ITH52-Parma (PR), ITH53-Reggio Emilia (RE), ITH54-Modena (MO), ITH55-Bologna (BO), ITH56-Ferrara (FE), ITH57-Ravenna (RA), ITH58-Forlì-Cesena (FC)								
	BO	FC	FE	MO	PC	PR	RA	RE	Total
Actinidia	10	11	6	0	0	0	11	0	38
Alfalfa	3	2	0	6	8	7	1	9	36
Corn	11	0	11	11	9	9	11	10	72
Grape	11	11	0	11	2	5	11	8	59
Green bean	0	8	0	0	6	0	10	0	24
Melon	8	0	11	5	0	0	0	0	24
Onion	11	8	0	0	9	0	10	0	38
Peach	11	11	11	9	0	0	11	0	53
Pear	11	0	11	10	0	0	11	7	50
Potato	11	9	7	0	0	0	11	0	38
Soy	7	0	8	8	8	0	7	7	45
Sugar beet	11	7	11	9	6	8	11	9	72
Tomato (Processing)	8	5	10	0	11	9	11	6	60
Total	113	72	86	69	59	38	116	56	609

Table A2. Data definitions.

Source	Variable	Definition
Fadn	Economic Dimension of Farms	Average economic dimension of farms, by year and at NUTS3 level. Values from 1 (small) to 5 (big)
	Gross Saleable Production	Gross saleable production for irrigated crops (EUR), by year and crop, at NUTS3 level
Arpae	IS_TNover90p	Number of days during IS in which the minimum temperature went above the 90th percentile of its 1961–2020 distribution.

	IS_TXover90p	Number of days during IS in which the maximum temperature went above the 90th percentile of its 1961–2020 distribution.
	TN_HWN	Number of minimum temperature heatwaves during the IS.
	TX_HWN	Number of minimum temperature heatwaves during the IS.
	IS_rainydays	Number of days with effective rainfall during the IS.
	IS_Heavyrainydays	Number of days with heavy rainfall during the IS.
Cer	Yields	Yields of irrigated crops (quintals/ha), by year and crop, at NUTS3 level.
	Acreage	Acreage of irrigated crops (ha), by year and crop, at NUTS3 level.
Irriframe	IWR	Average irrigation water requirement over the exact period of its irrigation (mm/ha), by year and crop, at NUTS3 level.
Eurostat	Percapita_GDP	Per capita Gross Domestic Product at current market prices (EUR), by year, at NUTS3 level.

Table A3. Estimation of the DRF.

GPS 1-Full Sample.				
	IYields (Quintals/Ha)		Gross Saleable Production (EUR /Ha)	
Variable	Coefficients	SE	Coefficients	SE
WD	−865.569	599.9565	57,081.63 ***	14,732.31
WD (^2)	656.8621	525.6152	−58,377.29 ***	13,250.4
GPS	−175.9433	190.391	−3111.61	4472.597
GPS^2	285.0726	153.6744	−69.52433	3595.859
WD *GPS	−154.2393	233.6022	−5216.351	5469.356
Observations	609		588	
GPS2 Lower (a) and higher (b) water intensity crops				
	A-IYields (Quintals/Ha)		B-IYields (Quintals/Ha)	
Variable	Coefficients	SE	Coefficients	SE
WD	−894.4823 *	513.8982	−412.9934	341.7621
WD (^2)	471.4249	472.1137	454.8758	288.6213
GPS	−356.091 **	167.6097	52.81079	101.4106
GPS^2	−29.08193	133.5734	−2.967697	78.13132
WD *GPS	1059.992 ***	224.9905	−46.00546	116.1592
Observations	214		395	
GPS3- Lower (a) and higher (b) water intensity crops				
	A-Gross Saleable Production (EUR/Ha)		B-Gross Saleable Production (EUR/Ha)	
Variable	Coefficients	SE	Coefficients	SE
WD	34,052.73 **	14,480.93	69,529.67 ***	22,686.64
WD (^2)	−33,620.69 **	13,692.91	−70,070.87 ***	19,574.33
GPS	6062.368	4580.525	−13,683.88 **	6411.992
GPS^2	−697.1769	3628.13	7233.836	4917.609
WD *GPS	−17,208.59 ***	6118.141	−2564.918	7392.32
Observations	210		378	

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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