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Article

Do Water Rights Affect Technical Efficiency and Social Disparities of Crop Production in the Mediterranean? The Spanish Ebro Basin Evidence

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Abstract: The coming agenda for the European Common Agricultural Policy includes more incentives for the environmental compliance of farmer's activities. This will be particularly important in the case of water risk management in Mediterranean countries. Among the new challenges is the need to evaluate some of the instruments necessary to comply with the Water Framework Directive requirements that emphasize the management of water demand to achieve the environmental targets. Here we analyze the implications of changing water rights as a policy response to these challenges. We analyze two important aspects of the decision: (i) the effects on the crop productivity and efficiency and (ii) the effects on the rural income distribution. We provide the empirical estimations for the marginal effects on the two considered aspects. First, we calculate a stochastic frontier production function for five representative crops using historical data to estimate technical efficiency. Second, we use a decomposition of the Gini coefficient to estimate the impact of irrigation rights changes on yield disparity. In our estimates, we consider both bio-physical and socio-economic aspects to conclude that there are long term implications on both efficiency and social disparities. We find disparities in the adaptation strategies depending on the crop and the region analyzed.

Keywords: technical efficiency; yield inequality distribution; climate change adaptation; water policy; agricultural policy

1. Introduction

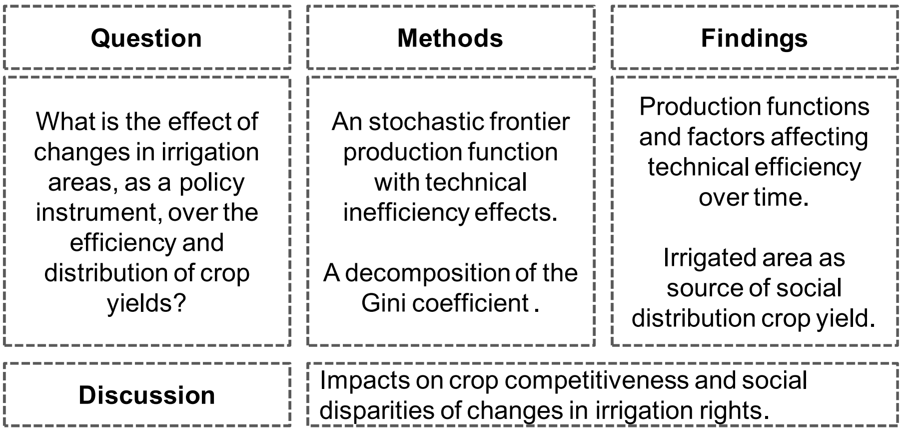
Due to the increasing water conflicts among sectors induced by climate change, the crop response to water pressure is one of the main concerns of climate change adaptation policy [1,2]. Particularly, the agricultural sector is the largest user of total available water accounting for over 70% of the total water available at the global level and even more in the Mediterranean region ([3]). This is mainly used for irrigation, so changes in water rights play an important role in the sustainability of worldwide ecosystems [4]. Despite this, agricultural water management is still very inefficient, and only a fraction of the water applied in this sector is, in fact, used for plant growth [5]. The modernization of irrigation systems plays an important role in targeting water efficiency. This limitation in water resources management includes Spain and many other European Union states [6,7], especially as climate change will probably increase water conflicts among sectors, and reducing the water use for irrigation will be essential to provide for the environmental flows and, therefore, ecosystems sustainability [8,9].

Agricultural research has given priority to the adaptation of crop yields to water pressure focusing on the incentives for increasing water efficiency [6] or water pricing instruments [10]. However, an important instrument used by water authorities is the management of irrigation rights. In this scenario, reductions in irrigation water supply or reductions in irrigated areas are two possible instruments to have important water savings. It seems that at least in the short term, important reductions in irrigation area could have not so severe implications in crop production [11,12], especially for rainfed cereals (wheat and barley) [8]. Crop production simulations as response to different water area scenarios are analyzed and the impacts, although important, are not as severe as expected, at least in the short term. Reductions of up to 30% on irrigated areas may produce reductions of 2% to 15% depending on the crop. This seems to indicate a high farmer's adaptive capacity, which can include the development and wide use of dry resistant crop varieties and crop rotation. This paper focuses on the long run effects of reductions in irrigation areas on farm technical efficiency and income distribution. Here we do not discuss legal issues on how the water quantity restrictions are specified and allocated (freely or by auctions) but we analyze the implications of implementing these restrictions on water rights, concretely in which respect to reduction on irrigated land areas.

According to the implementation's timetable of the Water Framework Directive (WFD), in the short run, EU members must accomplish environmental objectives. Focusing on the economic part, the WFD introduces two key principles. (i) It solicits to water consumers, as industries, farmers and households, to pay the costs of water related services they receive; (ii) The Directive calls on Member States to include an economic analysis of the assessment of water resources (in example, characterization), and examine both profitability as the costs and benefits of diverse options in the decision-making process [13]. Therefore, an economic evaluation of water management activities is necessary. The review of current concessions of the irrigated land area could be a potential policy instrument to accomplish the legal requirements of the WFD [8,14] and we focus on the analysis of water demand reduction for agricultural use through decreasing on irrigated areas.

Our study is centered on the Spanish Ebro river basin, which is located in the Northeast of the Iberian Peninsula in the Mediterranean region. Nowadays, there are not explicit restrictions on the irrigated area in the Ebro river basin, but there exist big socio-economic conflicts about the possibility of transferring water to other highly stressed basins in the area. We focus on the analysis of the implications of water demand reduction for agricultural use based on the decrease of irrigated areas, taking into account Common Agricultural Policy (CAP) reforms and other related variables. Our analysis considers two economic aspects: (a) First we analyze the changes in the efficiency of the agricultural systems through a stochastic frontier production function at the base of historical data for the Ebro basin in Spain; (b) Second, we explore the distributional aspects computing the marginal effect of changes on irrigated area over incomes distribution, using a decomposition of the standard Gini coefficient. Figure 1 shows a general perspective of the paper objectives, methods and findings.

Figure 1. Steps on the analysis.



The paper is structured as follows: (a) Second section shows the description of the data and the integration of the methods for the estimation of crop production functions, efficiency models and the distributional effects on incomes; (b) Third section shows and describes the main results on efficiency and inequality distribution for some crop yields in the basin; (c) Final section presents the conclusions of this paper.

2. Methods

In this paper, we explore the impacts of changes in irrigated areas on production functions, considering water policies, socio-economic, agricultural and environmental effects. Our analysis integrates two essential components in the economic perspective of water effects: efficiency and equity implications. We apply two widely used methodologies for efficiency and income distribution respectively to integrate the bio-physical and socio-economic components that have been usually analyzed separately. In a first step we estimate a stochastic frontier production function to analyze technical inefficiency effects. Then we calculate the associated Gini index and the decomposition factors of this index to evaluate inequality effects for the considered crops and sites.

2.1. Data

We focus our analysis on five crops in the Ebro river basin. These crops have been selected for being the most representative according to the total agricultural area in the basin. The selected crops are: alfalfa, wheat, grapevine, maize and barley. They all account for almost 55% of the total agricultural area in this region. Barley, grapevine and wheat represent primarily rainfed crops while alfalfa and maize exemplify mainly irrigated production (Table 1). Wheat, barley and maize are cereals of prime importance in the Mediterranean, as well as in all EU Member States. These kinds of crops occupy 40% of the total used agricultural area in the EU and about 47% in the Ebro basin [15]. Spain is the first European country in the production of dried alfalfa, and in 2010 it became the second main exporter of this crop (Spanish Association of Manufacturers of Alfalfa dehydrated—AEFA). Spain is also one of the largest wine producers in the world in terms of planted area, production and value, where the Ebro basin plays an important role in terms of high added value.

Table 1. Percentage of agricultural area and prevalent crop system in the Ebro basin.

Crop	% of the Total Agricultural Area	Dominant Cropping System
Wheat	17.0%	Rainfed
Barley	26.4%	Rainfed
Maize	2.2%	Irrigation
Alfalfa	4.4%	Irrigation
Grapevine	4.2%	Rainfed
Total	54.2%	

We use an unbalanced panel of observed historical data for the period 1976–2002 and for 15 provinces in the Ebro river basin. A full description of the variables considered in the study and the data source are summarized in Table 2.

Here we consider the linkages among socio-economic and bio-physical aspects affecting the production and efficiency. Among socio-economic factors we have included the effects of labor and technology, access to irrigation and water use, the socio-economic level measured through the Human Development Index [16], indicators on policy changes (MacSharry and Agenda2000 CAP reforms). The biophysical effects include some geographic and agro climatic factor like altitude, location, temperature, precipitation and a drought indicator.

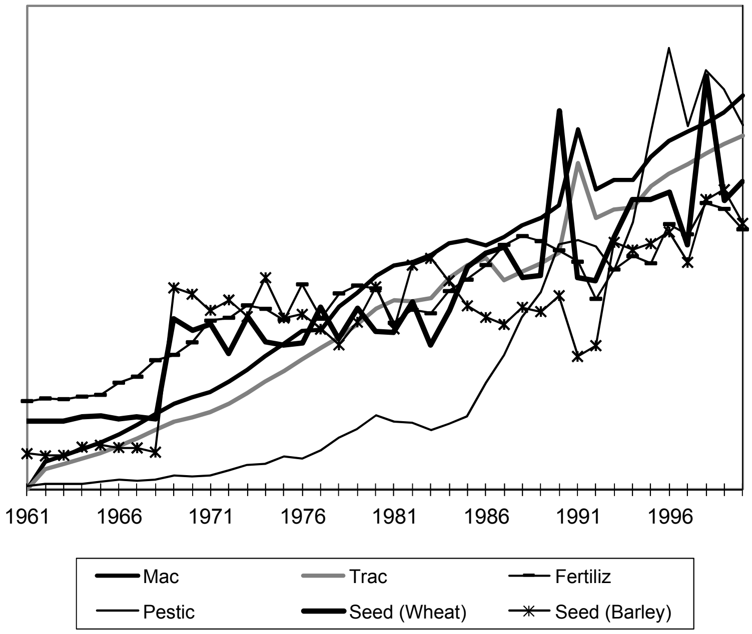
To characterize an indicator of technological factors we generated a variable to combine the different kinds of fertilizers (nitrogen, phosphate, and potash fertilizers) and machinery like tractors and combines. The data were obtained from FAO [17]. These inputs are ordinarily highly correlated and can cause multicollinearity problems in regression analysis. Figure 2 shows the historical evolution and the correlation among some of the technological factors in Spain, such as the increase on combines (Trac) and other machinery (Mac) used in the production, the generalization of the use of nitrogen fertilizers (Fertiliz) and the introduction of improved varieties (seeds). In Spain, the improvements in technical and biological factors is highly correlated since has occurred at the same time as a result of the concentration process in the agricultural sector ([18]).

Table 2. Description of variables.

Type of Variable	Contribution to the Analysis	Name	Definition	Unit	Source of Data (*)
Socio-economic factors	Output	Y_{it}	Crop yield at a site in year t	T/ha	MARM
	Input factor	$Tech_{it}$	Proxi of technological development. Derived from Principal component analysis (PCA) of fertilizers and machinery in year t	Standardized units	Own elaboration from FAOSTAT
	Input factor	L_{it}	Total employment of agricultural sector at a site in year t	1000 people	LFS; INE
	Input factor	$Irrig_{it}$	Net water needs of crops in year t	mm/month	CHEBRO
	Input factor	$Irrig\_area_{it}$	Irrigated area by crop type	Ha	MARM
	Efficiency driver	$\%Irrig\_area_{it}$	Irrigated area by crop type as proportion of total agricultural area (%)	Ratio	MARM
	Efficiency driver	HDI_{it}	Human Development Index at a site in the year t (%)	Index	IVIE; Bancaja
	Efficiency driver	$MacSharry_t$	Dummy variable equal to 1 after MacSharry Reform introduction in 1994, 0 before this year	1 or 0 as a function of the introduction of the reform	Own elaboration
	Efficiency driver	$Agenda2000_t$	Dummy variable equal to 1 after Agenda2000 Reform introduction in 2001, 0 before this year	1 or 0 as a function of the introduction of the reform	Own elaboration
	Time trend	t	$t = 1$ for 1976, $t = 27$ for 2002.	Year sequence	Own elaboration
Bio-phisical factors	Efficiency driver	$Altitude_i$	Total area in Km^2 by altitude zone: 0–600, 601–1000 and more than 1000 m of altitude	Km^2	INE
	Input factor	$Area\_ebro_i$	Dummy variables indicating the 3 main areas of the basin: Northern, Central and Low Ebro	1 or 0 as a function of the area	Own elaboration
	Input factor	$Prec_{it}$	Total precipitation at a site in the year t	mm/year	AEMET
	Input factor	T_Mean_{it}	Average temperature at a site in the year t	°C	AEMET
	Input factor	Dro_{it}	Dummy variable indicating drought year (1 for drought years, 0 in other cases)	1 or 0 as a function of SPI index	Own elaboration from AEMET

Notes: (*) Statistical Division of the Spanish Ministry of Environment, Rural, and Marine Affairs (MARM); Labor Force Survey (LFS). Spanish Institute of Statistics (INE); Planning Hydrographic Office Ebro basin Authority (CHEBRO); Spanish Meteorological Agency (AEMET); Valencian Institute of Economic Research (IVIE); Savings Bank of Valencia, Castellón and Alicante (Bancaja).

Figure 2. Historical evolution and correlation among the technological factors affecting crop productivity in Spain. Source of data: [8] y FAOSTAT.



	Mac	Trac	Fertiliz	Pestic	Seed
Mac	1.00	1.00	0.92	0.87	0.86
Trac	1.00	1.00	0.90	0.88	0.86
Fertiliz	0.92	0.90	1.00	0.78	0.88
Pestic	0.87	0.88	0.78	1.00	0.84
Seed	0.86	0.86	0.88	0.84	1.00

When introducing these highly correlated factors separately in the model, multicolinearity problems emerge producing inaccuracy in the significance tests. This makes it difficult to understand which factors are relevant to explain the productivity changes. To avoid this problem in the estimation of the model, we generated a new variable called $Tech_{it}$, using principal component analysis (PCA) [19,20]. This method consists in combining a large number of variables into a smaller number of related variables, retaining as much information as possible of the original variables. We use the first component that has an Eigenvalue greater than 1 (Eigenvalue of the Component 1 = 4.25) and it explains 85% of the variability of data as an indicator for technology ($Tech_{it}$) [21]. In our case, this first component presents high and positive correlations with all the technological factors considered; and then reflects the size of technology. That is, the greater quantity of fertilizers, machinery, *etc.* we have, the higher scores on the first principal component we obtain.

We have introduced a geographical variable to capture the agro climatic regional differences among the locations in the Northern, Central or Low Ebro region. Although the climate in this basin is mostly Continental-Mediterranean, important differences exist in the middle part of the basin, which includes some parts of Semi-Arid climate and in the northwest corner which is mainly Oceanic.

Since climate patterns vary across the regions and so do the crop processes, the farmers modify their response according to these variations (for example, through changes in the planting and harvesting dates). We initially introduced quarterly indexes but the temperature and precipitation indexes affecting production were different in each county due to the climate patterns differences so the model was not so comparable and serious multicolineality problems arise. Moreover, in some cases we missed the compensation processes that sometimes occur with water scarcity. Sometimes in the Mediterranean, the plasticity of the crops that are quite used to drought can deal with some water scarcity in the usual growing period and it is compensated by late precipitation through growing processes adaptation [22]. In order to make the model comparable among the regions and to allow farmers autonomous adaptation we used total annual precipitation instead of precipitation of the main growing season that suffer important disparities among the regions and also across the years.

Drought characterization is also difficult, given their spatial and temporal properties and a non-general accepted definition [23]. To characterize drought (Dro_{it}) in this study, we use the frequently used Standardized Precipitation Index (SPI, [24]). In a broad concept, this index is based on the probability of precipitation for any time scale. It is calculated as the difference in accumulated precipitation between a selected aggregation period and the average precipitation for that same period. For this study, we follow previous works in Spain [25,26].

Here we do not consider the effects of the energy factor. This is a very complex factor affected by important price variations—the energy price has increased more than 70% in the last 10 years in Spain. To consider the energy factor, it will be necessary to control for price volatility and we preferred to keep our production function in physical units instead of considering the model in monetary terms, which is standard in the efficiency model literature since the relationship is non-monetary, that is, a production function relates physical inputs to physical outputs.

2.2. Stochastic Frontier Production Function with Technical Inefficiency Effects

In this paper, the technical efficient effects of the stochastic frontier production function are modeled in terms of water management variables such as irrigated area. We consider Cobb-Douglas stochastic frontiers with neutral technological progress in which the technical efficiency effects are modeled for the five different crops in all provinces of the Ebro basin for unbalanced panel data [27–29]. The Cobb-Douglas production function was chosen because of its simplicity and validity in different works [30,31]. Nevertheless, we also tested the trans-log function, but Cobb-Douglas specification was preferable in all the cases due to the collinearity problems and the low degrees of freedom in the trans-log specification. Production functions have been obtained in order to estimate technical efficiency effects and their distribution across the whole basin.

We follow the Battese and Coelli [28] and Huang and Liu [29] models specification, that estimate inefficiency levels of particular economic agents and also explains their inefficiency in terms of possible explanatory variables. Some advantages of this approach are that, first, it avoids the inconsistency problems of the two-stage approach used in other empirical works when analyzing the inefficiency determinants and, second, is the inclusion of two types of uncorrelated errors which one of them allows for the presence of measurement errors or other forms of statistical noise in the model, while with non-parametric approaches all deviations from the frontier are assumed to be due to inefficiency (the works of [32] and [33] are excellent surveys of efficiency frontiers). The model can be expressed as:

$$Y_{it} = \exp(f(x_{it}, \beta) + V_{it} - U_{it});\ i = 1,....,N,\ t = 1,....T \quad (1)$$

where Y_{it} is logarithm of the production of the *i-th* “firm” in *t-th* period. $f(x_{it}, \beta)$ is a given function of $k \times 1$ vector of (transformations of) x_{it} input factors of the *i-th* site in *t-th* period of observation (see

Table 2 for detailed explanation) and a vector of unknown parameters, β. V_{it} is a vector of random variables accounting for statistical noise in outputs, which is assumed to be *iid*, ($V_{it} \overset{iid}{\sim} N(0,\sigma_v^2)$) and independent of U_{it}, where U_i is a random variable which is assumed as the technical inefficiency in production and is *iid* truncated at zero, $U_i \overset{iid}{\sim} N^+(z_{it}\delta,\sigma_u^2)$.

Our general models for all studied crops follow the next form:

$$\ln Y_{it} = \beta_0 + \sum_{j=1}^{J} \beta_j \ln x_{jit} + \beta_{it} t + V_{it} - U_{it} \tag{2}$$

This formulation (Cobb-Douglas) is frequently used in recent researches. *t* is the time trend; in other words it is a variable added here to measure the Hicks-neutral technical change. According to these models, the technical inefficiency is defined as:

$$U_{it} = z_{pit}\delta + W_{it} = \delta_o + \sum_{n=1}^{N} \delta_p z_{pit} + \delta_{it} t + W_{it} \tag{3}$$

where, z_{pit} is a $1 \times m$ vector of the all technical inefficiency explanatory variables (efficiency drivers, see Table 2 for detailed explanations) in a site *i* over time; δ is an $m \times 1$ vector of unknown coefficients; and W_{it} is a random error term which is assumed to be independently distributed as a truncated normal with mean zero and variance σ_W^2, such that point of truncation is $-z_{pit}\delta$. Then the technical efficiency is defined as: $TE_{it} = exp(-U_{it}) = exp(-(\delta_o + \sum_{p=1}^{J} \delta_p z_{pit} + \delta_{it} t + W_{it}))$. Given the assumptions of the model, the predictions of individual "agent" technical efficiencies are calculated from their conditional expectations: $TE_{it} = E[exp(-u_{it}) \mid \varepsilon_{it}]$. Measures of technical efficiency relative to the production frontier in the *t-th* year can be expressed as: $TE_i = E(Y_i^* \mid U_i, X_i) / E(Y_i^* \mid U_i = 0, X_i)$.

The parameters of the model were estimated with the Maximun-Likelihood (ML) method. Then, we have used the parameterization of Battese and Corra [34] and we replace σ_V^2 and σ_U^2 with $\sigma^2 = \sigma_V^2 + \sigma_U^2$ and $\gamma = \sigma_U^2 / \sigma_V^2 + \sigma_U^2$. The parameter γ must be between 0 and 1, where the starting value can be obtained using an iterative maximization process [35]. To achieve the objective of this work, we apply the methodology described above including two general variables to characterize water use, which were defined in the data section (net water needs and irrigated area). We run hypothesis test to examine if there is constant returns-to-scale technology. For this analysis, the null hypothesis can be formulated as: $Ho : \gamma = 0$, which indicate that there not exist technical inefficiency; and $Ho : \delta_i = 0$ which specify that there is no technical inefficiency effects. In order to identify the specific impact of each factor in the technical efficiency, the marginal effects of each variable included in the specification was also calculated.

2.3. Distributional Efficiency Using the Decomposition of the Gini Coefficient

To characterize the inequality distribution of the agricultural output, we use the Gini coefficient decomposition proposed by Pyatt *et al.* [36] and Shorrocks [37], and extended by Lerman and Yitzhaki [38], which includes the marginal impact of different sources on overall yield inequality, focusing on the impact of water related variables. The Gini coefficient is probably the most common inequality measure, because its simplicity and its desirable properties. This concentration ratio is widely used in many fields of economics as well as in ecology and agronomics, but there are fewer applications in agricultural and environmental economics together ([39–41]). In a general context, it ranges from zero (equal distribution) to one (perfect inequality), and fulfills the properties of mean independence, population size independence, symmetry, and Pigou Dalton transfer sensitivity ([42]). However, this tool presents two main lacks, not easy decomposability as entropy measures, and a difficult statistical testability for the significance of changes in the index over time. Haughton and Khandker [42] suggested that this last lack is not a real problem because confidence intervals can usually be produced by means of bootstrap techniques. Taking into account these considerations, we use this approach. Then, this methodology develops how each source's contribution to the Gini coefficient could be observed as the product of its share on total output, its own source's Gini coefficient, and its correlation with the total output and can be expressed as:

$$G_{tot} = \sum_{k=1}^{K} S_k G_k R_k \tag{4}$$

where G_{tot} represents the Gini coefficient for the total yield; S_k is the share of component *k* in the total yield, this implies the question of how important the source is respect to total yield; G_k represents the relative Gini of source *k*, this part try to measure how equally or unequally distributed the income source is; R_k is the Gini correlation between yield from source *k* and the total yield distribution $R_k = Cov\{y_k F(y)\}/Cov\{y_k F(y_k)\}$, implying the question of how the income source and the distribution of total income are correlated. This decomposition of Gini coefficient is a good measure to help us understand the determinants of inequality, and allows estimating the effect of small changes in a specific source of yield (income) on inequality, maintaining the other sources constant. Then, the decompostition of the overall Gini into specific source factor effects has been derived from Lerman and Yitzhaki [38]. The authors show that the partial derivative of the overall Gini coefficient with respect to a percent change *e* in the source factor *k* is equal to:

$$\frac{\partial G_{tot}}{\partial e_k} = S_k \left(G_k R_k - G_{tot} \right) \tag{5}$$

In this paper, for example, we include the irrigated area as a source factor. If we consider the relationship between irrigated area and crop yield, the interpretation of this decomposition will be the following: if irrigated area source represents a large share of total crop yield, it could probably have a large impact on inequality. If crop yield is equally distributed ($G_k = 0$), it cannot affect inequality, even if its magnitude is large. However, if this crop yield source is large and unequally distributed (S_k and G_k are large), it could either increase or decrease inequality, depending on which farmers, at which points in the crop yield distribution, earn it. If the crop yield source (irrigated area) is unequally distributed and flows disproportionately toward those at the top of the crop yield distribution (R_k is positive and large), its contribution to inequality will be positive. However, if it is unequally distributed but targets poor farmers, the crop yield source may have an equalizing effect on the crop yield distribution.

3. Results

3.1. Production Functions and Factors Affecting Technical Efficiency over Time

Table 3 shows the estimated crop production functions for the five crops in the study. We selected the Cobb-Douglas production function form for all studied crops, first, due to its simplicity and validity [30] and its acceptance in the literature of production functions in agricultural economics [8,43,44] and second, due to the inherent problem of collinearity presented by the translog functions. Specifically, when we estimate the translog specification, we observe highly correlation between the new explanatory variables, high variance inflation factor and severe problems for the condition numbers (taking into account the guidelines reported in [45]), then we choose to try with a different specification of the model (Cobb-Douglas) using the same data and it produces shifts suggesting weak collinearity problems. For all crop models, we tested the significance of the γ parameter, we reject the null hypothesis that γ equals zero, which indicates that σ_u^2 is not zero and the term U_{it} representing inefficiency is significant in the model.

Table 3. Cobb-Douglas crop production functions.

Dependent Variable: ln(Yield)					
Explanatory Variables	**Wheat**	**Maize**	**Grapevine**	**Alfalfa**	**Barley**
Tech	0.0818 ***	−0.0327 **	0.0058	0.0074	0.0800 ***
	[0.022]	[0.014]	[0.026]	[0.012]	[0.021]
ln(L)	0.1359 *	−0.2176 ***	−0.5492 ***	−0.0713 **	0.0835
	[0.070]	[0.053]	[0.095]	[0.028]	[0.072]
Cent_Ebro	−0.0931	−0.1030 **	−0.3556 ***	−0.0542	−0.0701
	[0.075]	[0.045]	[0.100]	[0.037]	[0.072]
Northern_Ebro	−0.3647 ***	−0.1185 *	−0.7678 ***	−0.1121 **	−0.3980 ***
	[0.137]	[0.070]	[0.198]	[0.051]	[0.114]
ln(Irrig)	0.0488 *	0.0558 **	−0.1740 **	0.1418 ***	−0.0084
	[0.025]	[0.022]	[0.069]	[0.013]	[0.022]
ln(Irrig_area)	−0.0301	0.0381 ***	0.1350 ***	0.0243 ***	−0.0527 ***
	[0.023]	[0.012]	[0.020]	[0.008]	[0.020]
ln($Prec_{year}$)	0.1851 ***	0.0245	−0.0262	0.1374 ***	0.1072 *
	[0.065]	[0.041]	[0.078]	[0.032]	[0.062]
ln(T_Mean_{year})	−0.8508 **	−0.1174	1.5134 ***	0.3849 ***	−1.2215 ***
	[0.371]	[0.188]	[0.439]	[0.130]	[0.279]
Dro	−0.1297 **	−0.0258	−0.1471 **	−0.0195	−0.2269 ***
	[0.051]	[0.035]	[0.058]	[0.029]	[0.050]
T	0.0035	0.0198 ***	0.0098	0.0073 **	−0.0017
	[0.007]	[0.005]	[0.008]	[0.004]	[0.007]
Constant	1.5550	1.9793 ***	−0.5115	0.7496	3.6684 ***
	[1.416]	[0.604]	[1.120]	[0.456]	[1.022]
Observations:	276	239	164	306	265

Notes: Standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Crop production processes mostly present the expected signs according to the agricultural processes. The technical component impact in yield is positive for all crops in our study, except for maize. We need to mention here that the data in the analysis are not farm level data but regional agregated data. For this reason, the specific contribution of one variable to the productivity should be analyzed in regional terms. For example, a negative sign of technology factors can be interpreted as the contribution of the most technified farms to the maize production is less that the ones that are not so technified. This makes sense since maize is not a so extensive cereal in Spain like others like wheat or barley.

The agricultural labor shows a negative and significant impact on the yield of maize, grapevine, and alfalfa. However we can find some studies related to the agricultural sector with this non-normal sign [27,46–48]. There are some explanations about this sign. (a) This variable is at the macro level and we can observe decreasing returns to scale when additional labor move from other sectors to agricultural sector; (b) Another explanation is that as national agricultural productivity increase, farmers can produce more food with less labor; (c) Moreover, it is reasonable to think that there is a labor surplus activity; this means that it is hiring more labor than the recommended level at a marginal productivity level [47]; (d) The regional farms dedicated to these crops are in fact family farms, and then this variable could be showing a camouflaged unemployment problem. Irrigation has also a positive and significant impact in wheat, maize and alfalfa. This fact implies that reductions in water availability for irrigation will cause a decrease of crop yields. We can observe that the coefficient for ln(irrig) in grapevine is negative what is due to the fact that grapevine is a rain fed crop and in this area include very high quality production (La Rioja, Rivera del Duero, Penedes, Navarra DO, *etc.*) where only deficit irrigation is being applied to maintain yield during drought periods ([8]) since exceed water can affect the wines quality. Therefore, when scarcity problems arise, the water for irrigation is increased to maintain the crop, but still worse outputs can be expected due to the drought effects. In contrast, for the same crop, the coefficient for ln(irrig_area) is positive since it is still relevant the protective effect of this deficit irrigation during important water scarcity periods since in other case the yields can be dramatically reduced and even the vineyards resulting damaged for several periods. Irrigation area also has an important impact on maize grapevine, and alfalfa. Drought has a negative and significant impact for wheat, grapevine and barley, which are mainly rainfed crops, while irrigated crops do not show evidence of significant impact of drought.

Factors explaining changes in the technical inefficiency model are in Table 4, where a negative sign in the estimates implies that the variable has a positive effect on the efficiency. The geographic variables introduced with altitude variables indicate that an increase in altitude increases technical inefficiency in all crops. This implies that crops in the higher altitude areas are less efficient than the crops in the lower altitude areas. The results of the efficiency model suggest that irrigated area has a positive and significant effect over the technical efficiency in all the studied cases (irrigated and rainfed crops). The human development index shows a negative impact for maize, this seems to indicate that more developed sites are more efficient in this cases. In addition, we observe a positive impact for barley, the reason may be that barley is mostly grown in marginal environments, receiving modest inputs.

It is important to observe the effect of Common Agricultural Policy Reforms over the efficiency. Agenda2000 reform, which had a significant and positive effect on wheat and barley crop yield inefficiency. The impact of MacSharry reform differs across the crops, presenting a negative and significant impact for maize production, but positive in the case of wheat crop.

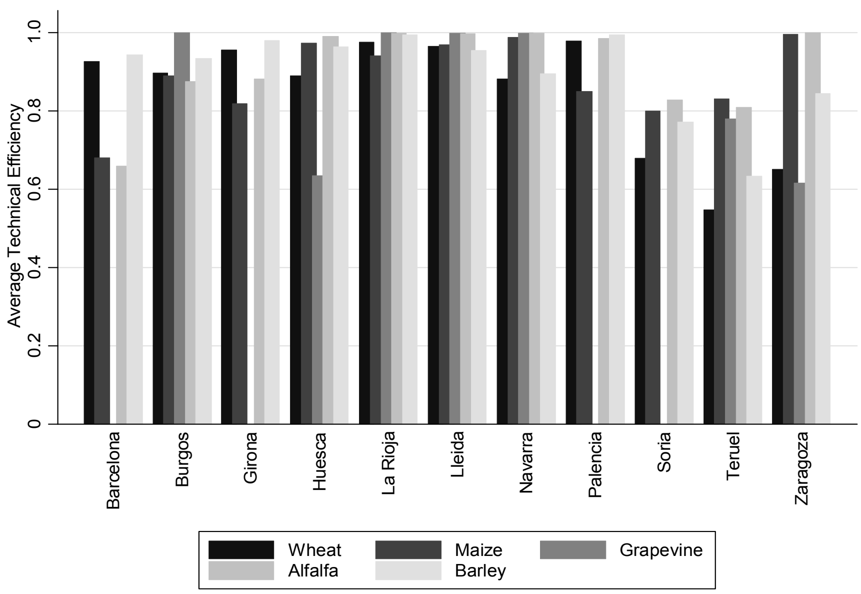
Figure 3 shows the regional predicted technical efficiencies for each crop. The average technical efficiency in the Ebro basin during the period 1976–2002 is 85% for wheat, 91% for alfalfa, 87% for grapevine, 89% for maize and 86% for barley relative to the crop's own potential output. This means that the existing production technology is used almost efficiently (85%–91%). Looking the regional distribution, La Rioja presents the higher technical efficiency—specially referred to wheat, maize and grapevine—and Teruel and Soria show the lower one.

Table 4. Technical inefficiency model.

Technical Inefficiency = U					
Explanatory Variables	**Wheat**	**Maize**	**Grapevine**	**Alfalfa**	**Barley**
$Altitude_{(0–600)}$	0.0007 ***	−0.0006 **	0.0031	0.0003	0.0007 ***
	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]
$Altitude_{(601–1000)}$	0.0001	−0.0002	−0.0024 *	−0.0000	−0.0000
	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]
$Altitude_{(+1000)}$	0.0007 ***	0.0002 **	0.0023	0.0013 ***	0.0008 ***
	[0.000]	[0.000]	[0.002]	[0.000]	[0.000]
%Irrig_area	−0.1226 *	−0.0557 ***	−0.1471 ***	−0.1761 ***	−0.3870 *
	[0.066]	[0.014]	[0.053]	[0.044]	[0.233]
HDI	0.3600	−0.8561 ***	0.5497	−0.2694	0.6372 *
	[0.276]	[0.324]	[0.640]	[0.283]	[0.377]
MacSharry	1.1563 *	−0.1879	0.4204	1.2207	0.7645
	[0.666]	[0.766]	[1.027]	[0.751]	[0.922]
Agenda2000	1.7112 **	2.1257 **	0.9079	0.6947	2.3135 **
	[0.684]	[0.930]	[0.993]	[0.726]	[0.959]
t	−0.2697 *	0.2519 *	−0.1977	−0.0061	−0.3585 **
	[0.141]	[0.144]	[0.315]	[0.141]	[0.178]
Constant	−36.7713	76.0302 ***	−69.3678	22.3471	−60.6567 *
	[23.993]	[28.069]	[52.776]	[24.382]	[33.044]
Observations	276	239	164	306	265

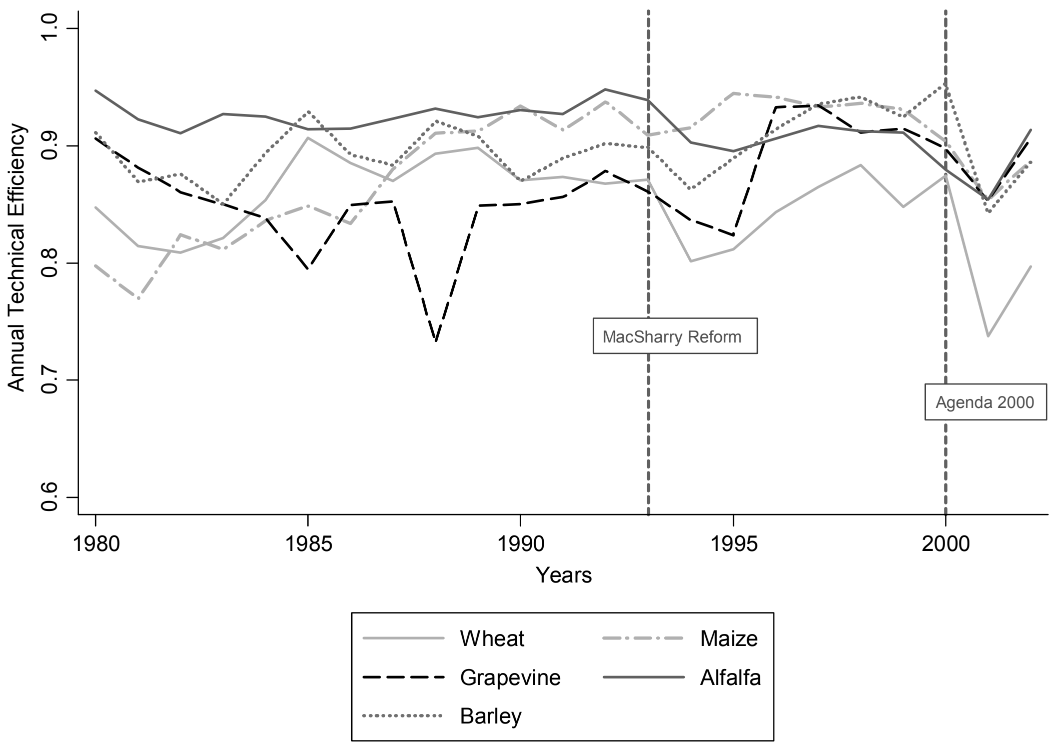
Notes: Standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 3. Predicted average technical efficiency by crop and region.



In Figure 4, we can see that, during the period under study, the average values for maize and grapevine show a general growth in technical efficiency, while wheat and alfalfa shows a light decreased in technical efficiency average. During the period 1992–1994, especially in 1993, from the MacSharry reform incorporation, significant changes can be observed. It is especially significant the reduction in wheat technical efficiency as response to the decoupling process. On the other hand maize seems to react in the opposite way. However, wheat and barley response to Agenda2000 reform's present a significant negative effect. In general our model shows a negative shift in the efficiency's trend from 2000, when both, the Water Framework Directive and Agenda2000 were introduced. Barley and specially wheat seems to show the greater falls as a response to both reforms. Another interesting factor is that during the studied period most of the crops—except wheat, that shows important responses to policies—show a convergence path in technical efficiency, despite their fluctuating trends.

Figure 4. Temporal prediction on average technical efficiency related to PAC policy changes.



3.2. Crop Yield Sources and Their Impact on Social Distribution

Table 5 shows the Gini decomposition and irrigation marginal effects over the crop yields distribution, including the estimation of bootstrapped confidence interval. In general, the results show that an increase on the irrigated area generates a reduction in the Gini coefficient, which means a better income distribution in the rural areas. Therefore, the response of a policy focused on the reduction of irrigated areas can have negative implications on incomes concentration (more inequalities). Particularly, an increase of 1% on the irrigated area imply a decrease of the Gini coefficient around 0.02% in the case of wheat, 0.04% for maize, 0.02% for barley, and near 0.00% for grapevine. The alfalfa crop response is also near to 0.00% but in this case the index shows the opposite effect. These changes are statistically significant, 95% bootstrapped percentile confidence intervals are showed in brackets. Regard to the share of this component in the total yield (S_k), we can see that the response to irrigated area is higher in the case of maize and lower for alfalfa, although both are mostly irrigated crops. In this study, we can observe that G_k ranges between 0.20 for maize and 0.66 for grapevine. This means that irrigated land shows a more unequal distribution of grapevine yield incomes and a more equal distribution for maize yield incomes. This difference can be related to the fact that grapevine is a rain fed crop and therefore moderate rainfall is a factor that contributes to relatively good growth conditions. When farming under relatively good growth conditions irrigation can be a yield risk-increasing factor as it increases the variability of harvests (*i.e.*, largely increase output under good growth conditions).

Table 5. Gini decomposition for irrigated area by crop.

Crop	G	$S_{k = \text{Irrigated area}}$	$G_{k = \text{Irrigated area}}$	$R_{k = \text{Irrigated area}}$	% Change	[95% Conf. Interval]
Wheat	0.22	0.05	0.57	0.25	−0.0166	[−0.0320 to −0.0066]
Maize	0.22	0.12	0.20	0.79	−0.0372	[−0.0491 to −0.0256]
Barley	0.18	0.03	0.46	0.10	−0.0192	[−0.0241 to −0.0136]
Alfalfa	0.16	0.01	0.28	0.62	0.0016	[−0.0004 to 0.0036]
Grapevine	0.32	0.02	0.66	0.41	−0.0032	[−0.0109 to 0.0013]

The Gini correlation between source and total yield is low (0.10 and 0.25) for grapevine and wheat, indicating that, in these cases, irrigated area favors the “poor”, the sites with lower yields. In the opposite site are maize and alfalfa. Observing the wheat, irrigated land has a slight equalizing effect on the distribution of total yield, because although it has a relatively high Gini coefficient (57%), the Gini correlation between source and total yield is low.

3.3. Water Policy Implications on Technical Efficiency and Social Equity

Figure 5 presents together the effect of changes in irrigated area affecting technical efficiency and social inequalities. We can see that in general the impact of these changes on social distribution of incomes is more significant in the areas where the cereals are dominant, and particularly the major impacts on technical efficiency are produced for barley and alfalfa crops. According to the results in the previous section, policies of reducing area under irrigation can be a non-dramatic solution for production [8,11,12], but in the long term they negatively affect the competitiveness and increasing social inequality in agriculture.

Figure 6 shows the marginal effect of the irrigated area on competitiveness and income distribution looking at province level and taking into account the agricultural gross value added. We can observe that in alfalfa production, the marginal impact of irrigated area in the different locations is highly homogenous on technical efficiency and also there is low variation in terms of equity. A different effect can be observed in the case of maize where the distributional aspects seem to be really dependent on the location. In addition, it is interesting to observe that in the case of maize the impact of irrigated area over equity is higher for those regions that are in the extremes in terms of income (less and more development) than those in the average.

Figure 5. Marginal effects of the irrigated area on competitiveness (efficiency) and income distribution (equity) by region in % change.

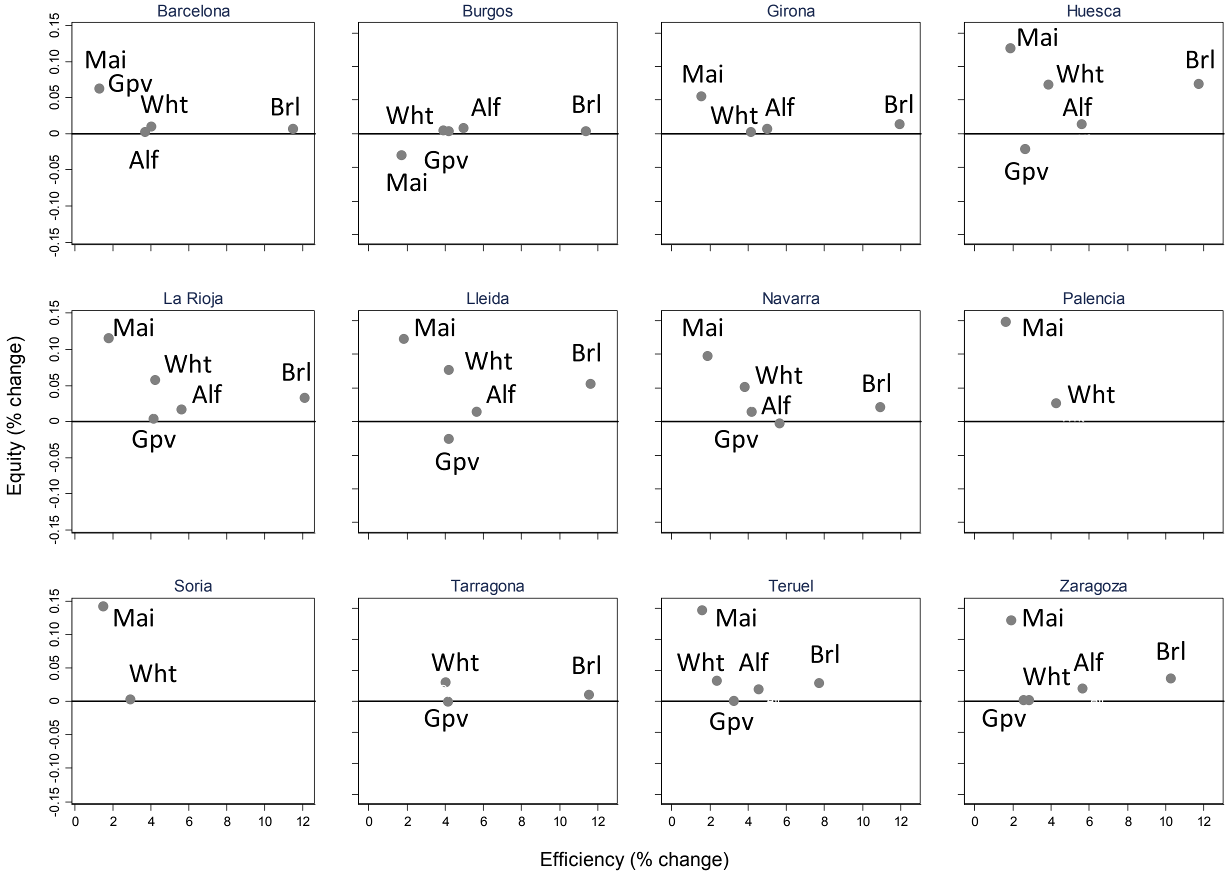
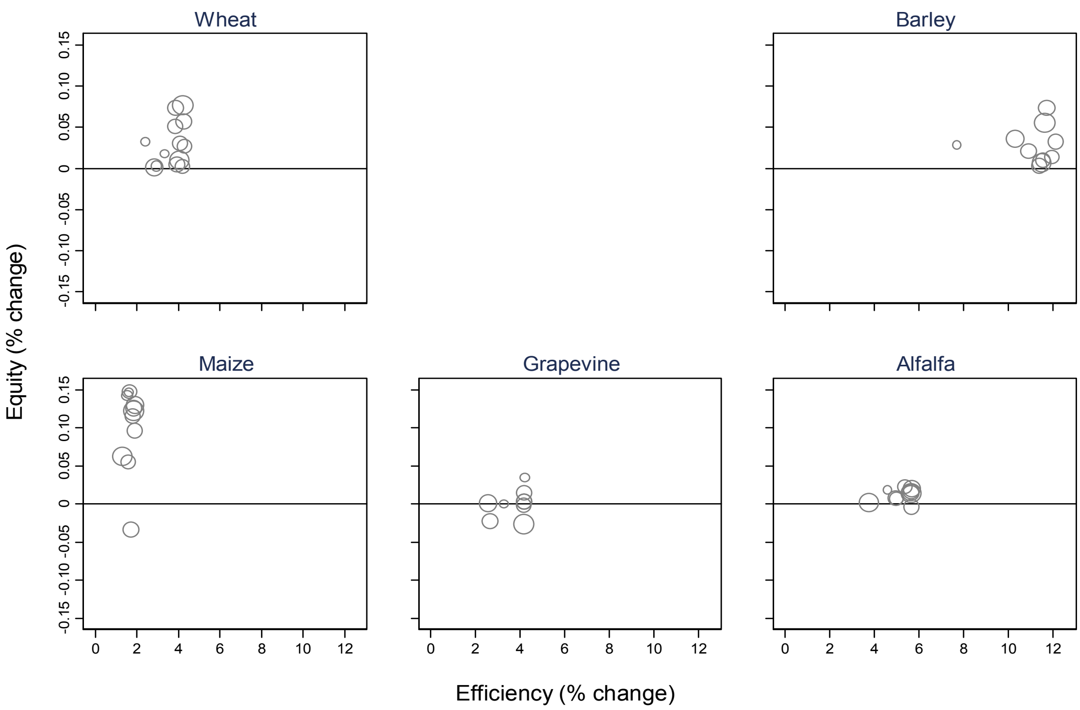


Figure 6. Marginal effects by crop and agricultural GVA of the irrigated area on competitiveness (efficiency) and income distribution (equity) in % change. (Area of symbol proportional to Agricultural GVA of the site).



4. Discussion and Policy Implications

The increasing stress on water systems in the Mediterranean due to climate change effects and overuse of ground and surface water reserves amplify existing water conflicts and pressure water availability for agriculture. Furthermore, within the context of increases of water demands and policy developments such as the WFD restrictions context, it is necessary that the management plans for river basin districts are complemented by more detailed management programs that could include adaptation measures such as changes in irrigated land to cope with environmental and sustainability constraints [8].

One of the main policy implications of this paper stresses that initiatives that will reduce irrigated areas will have an adverse impact both on agricultural profitability and social cohesion of the rural sector. Therefore, these sort of water policy instruments should be undertaken cautiously since several indirect implications may arise.

In this sense, it would also be important to better understand the implications of other kinds of water policies that could be alternative measures to ensure sustainability in the agricultural sector, such as (i) enhancing research on dry-resistant crop varieties; (ii) incentives for the expansion of drip irrigation; (iii) considering the possibility of limiting subsidies to rain fed crops (instead of irrigated ones); (iv) water pricing policies, *etc*.

In particular WFD states that from 2010, Member States must ensure that water pricing policies provide adequate incentives for users to use water resources efficiently and that the various economic sectors contribute to the recovery of the costs of water services, including those relating to the environment and resources. This paper shows other important factors including rural development, irrigated land maintenance and the connection with agricultural policies that are also crucial to enhance efficiency in the water for agriculture.

Irrigated agriculture production is highly influenced by the EU policies. In particular, analyzing the interrelationship between the implementation measures to comply with WFD and the changes in the CAP will be determinant for the river basin decision makers in the near future. Since its introduction in 1962, CAP has been in constant evolution through successive reforms. Here we focus on the MacSharry reform (1992) which introduced the system of direct payments during 1993–1999, and was extended by Agenda2000 (2000–2004). In this last reform, rural development became the second pillar of the CAP, bringing some structural measures as environmental subsidies and Least Favored Areas (LFA) subsidies, thus creating an integrated policy to promote development of a sustainable agriculture as well as dynamic rural areas across Europe. The main aim of the CAP is to promote higher liberalization and competitiveness of European agriculture at the international level; however, this objective seems to be opposed to the environmental character of the WFD. In this case, it is important to have a greater knowledge about the impacts of the both policies over crop yields.

As we have mentioned in the results section, the impacts of the MacSharry reform are sensitive to the type of crop. This policy seems to have affected negatively to irrigated cereals (maize) while improving the efficiency for the rain fed cereals (wheat). However, Agenda2000 reform has had a negative influence on the rain fed cereals production efficiency in Spain. The rain fed cereals seem to show the greater falls as a response to both reforms.

Another interesting factor is that during the studied period, most of the crops show a convergence path in technical efficiency that reinforces the idea of agricultural progress being a win-win strategy producing positive externality effects on water efficiency. Therefore, policies oriented to enhance the rural development could be as competitive as pricing instruments.

However, this paper does not attempt to assess the specific impacts of rural development aspects such as agricultural labor structure, rural abandonment, or impacts on agricultural holdings on efficiency and social sustainability. For this purpose, micro models can be formulated at farm household level to study these implications through social indicators. This kind of models has been successfully simulated for other regions in the Mediterranean to evaluate other policy implications like CAP scenarios [13].

5. Conclusions

A major challenge for water policy in the near future is the adaptation of crops to increasing water pressure, since climate change tends to increase the existing water conflicts among sectors. In this paper, we evaluate the effect of changes in irrigation duties over the efficiency and distribution of crop yields in the Ebro river basin in Spain. The results presented here show that in the long term irrigated area has a stabilizing effect on the distribution of the yield of wheat and grapevine, and it also favors the increase of technical efficiency. This means that policies of reducing the area under irrigation can be a non-dramatic solution for production in the short run, but could seriously affect social aspects in the long term since they negatively affect the competitiveness and increase social disparities in agricultural incomes. This study is relevant for the revision of River Basin Management Plans in order to face the specifications of the EU Water Framework Directive (WFD) and national policies taking into account reforms to the CAP, within the context of climate change. The methods presented here can be extended to examine other issues as the effects of modernization on irrigation systems, fertilizer application and agricultural subsidies.

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Author Contributions

The contents of this article are part of Zaira Fernández-Haddad research results in her PhD Dissertation. Sonia Quiroga as advisor of Zaira Fernández-Haddad designed the research topic and developed the theoretical framework of the study. Zaira Fernández-Haddad built on the methodology and technical work with the supervision of Sonia Quiroga and Cristina Suárez which valuable ideas improved the methodology. Paper writing was prepared by all authors.

Conflicts of Interest

The authors declare no conflict of interest.

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