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Discussions

Climate change and drought effects on rural income distribution in the Mediterranean: a case study for Spain

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Climate change and drought effects on rural income distribution in the Mediterranean

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Abstract

This paper examines the effects of climate change and drought on agricultural outputs in Spanish rural areas. By now the effects of drought as a response to climate change or policy restrictions have been analyzed through response functions considering direct effects on crop productivity and incomes. These changes also affect incomes distribution in the region and therefore modify the social structure. Here we consider this complementary indirect effect on social distribution of incomes which is essential in the long term. We estimate crop production functions for a range of Mediterranean crops in Spain and we use a decomposition of inequalities measure to estimate the impact of climate change and drought on yield disparities. This social aspect is important for climate change policies since it can be determinant for the public acceptance of certain adaptation measures in a context of drought. We provide the empirical estimations for the marginal effects of the two considered impacts: farms' income average and social income distribution. In our estimates we consider crop productivity response to both bio-physical and socio-economic aspects to analyze long term implications on both competitiveness and social disparities. We find disparities in the adaptation priorities depending on the crop and the region analyzed.

1 Introduction

Climate change induced impacts on society have captured an important part of the attention of environmental research in the last decades. We know now that the cost of action is as important to understand and estimate as is the cost of inaction. (IPCC, 2014; Markandia et al., 2014). Most of the economic analyses of the impacts are sector-based and the impacts are usually estimated in physical terms (changes in crop yield, life expectancy, sea level rise, number of species, etc.) and then translated into monetary terms through some macroeconomic model (computable general equilibrium, agent based model, integrated assessment, etc.) (Ciscar et al., 2011; Watkins et al., 2005).

However, market issues are crucial when dealing with adaptation and so estimating the impacts considering direct current incomes at the exploitation level may reveal another part of the picture which is necessary to understand the expected impacts on people.

Even when income inequalities have been revealed as one of the most important drivers for significant changes in the socio-politic framework in the EU after the 2008 economic crisis and with equitable growth now at the forefront of economic debate (Piketty, 2013), not so much attention has been placed on the distributional effects of climate change extreme events and hazards on economic outputs. The focus of economic evaluation efforts so far has been on risks at the average level, but it is becoming clear that adaptation policy needs to face climate driven income inequalities (Quiroga et al., 2015). There are important references in literature pointing to a climate change induced increase in food inequalities (Wheeler and von Braun, 2013; Pindyck, 2013), environmental justice (Adger, 2001; Stern, 2013; Shukla, 2013) and climate induced migrations (Black et al., 2013; Feng et al., 2012) although most of them are usually based on physical units like yields or ingested calories. To date there has been little empirical research on how and where climate change interventions are shaping inequalities. (Marino and Ribot, 2012). Since the environmental justice concept proposes everyone (independently of their income, race, gender, etc) enjoying the same degree of protection from climate hazards, more knowledge related to empirical effects of climate change on income distribution is essential.

This is indeed important in the agricultural sector which is intrinsically linked to rural development and very related with ecosystem conservation. Crop yield changes as a response to climate change projections have been estimated in many interesting studies dealing with climate change impacts (Rosenzweig et al., 2004; González-Zeas et al., 2014; Lobell et al., 2014) and the Mediterranean especially is identified as a major hotspot due to the expected increase in drought risk (Garrote et al., 2007). Particu-

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larly, in Spain, climate change will probably increase water conflicts among sectors, and the reduction of water use for irrigation will be essential to maintain environmental flows and therefore ecosystem sustainability. In this context we have analyzed the response of rain-fed crops to climate conditions including extreme events such as drought. Here we have selected those crops best representing Mediterranean crop systems. Cereals, grapes and olives are the three basic products of Mediterranean agriculture, the ones representing a higher proportion of harvested area, but also with an important cultural heritage in the region.

Here we estimate crop income functions to simulate productivity and incomes distribution as a response to climate change scenarios. Since real world production is usually affected by unobserved factors – like unexpected weather extremes– the manner in which this influence can be separated from the more tangible and traditional inputs, such as land, labour, or capital is at the heart of a new debate on the appropriate identification strategies for addressing endogeneity and collinearity problems to avoid simultaneity and selection biases that are common in most of production function estimates (Petrick and Kloss, 2013; Yasar et al., 2008). We estimate the production function using the approach of Olley and Pakes (1996) that allows us to combine both control traditional inputs and estate variables – such as climate, and avoid the mentioned biases.

Our study is centred on Spanish farms, located in the Mediterranean region. Nowadays, there are explicit restrictions on water availability in most of the Spanish river basins and there are big socio-economic conflicts especially in the agricultural sector. We focus the analysis on the implications of drought increase due to climate change on rural income distribution. Our analysis considers two economic aspects: (a) first we analyze the drivers for the agricultural systems productivity through a semiparametric method which uses 1990–2013 data for incomes at the farm level in the different river basins in Spain; (b) second, we explore the distributional aspects computing the marginal effect of changes on seasonal rainfall distribution, using a decomposition of the standard Gini coefficient.

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This paper is organized as follows: Sect. 2 focuses on the steps within the methodology, models and data. Section 2.1 details the climate change scenarios considered for the simulations; Sect. 2.2 presents the econometric model for the Olley and Pakes crop productivity estimation, Mediterranean crops, Gini index decomposition. Section 2.3 explains the Gini index for measuring income distribution and the decomposition to calculate the marginal effects of drought. Sections 3.1 to 3.3 present the results for the production functions, the simulations of productivity changes for the different scenarios and the calculations for the changes in income distribution.

2 Methods

This paper provides an assessment of the distribution of incomes as a response to climate change induced increase in droughts in the Mediterranean. Our analysis integrates two essential components in the economic perspective of adaptation policy: productivity and equity implications. We first integrate the bio-physical and socio-economic databases to characterize the nature state variables and management factors affecting production and link these components which have been usually analyzed separately. In a second step we estimate a semi-parametric production function to analyze productivity drivers and climate elasticity. Third, we calculate the associated Gini index and the decomposition factors of this index to evaluate inequality marginal effects for the considered crops and sites. Then we select the climate change scenarios and we simulate production and income distribution according to these climate scenarios.

2.1 Agricultural production function simultaneous estimates: observed inputs and unobserved productivity shocks

As we have mentioned in the objectives, our main goal in the paper is to analyze the drought induced changes in the distribution of incomes that are definitively based on productivity. So we first need to define and estimate a productivity measure. The Olley and Pakes (1996) approach assumes that incumbent farms decide at the beginning of each period whether to continue to participate in farming activity, depending on their productivity level, which in turn depends on their production factor (it corrects the selection bias). To this end, investment (i_{it}) is considered as a proxy for the unobserved productivity shocks. Also, this method corrects the simultaneity bias arising from the fact that farms choose their level of input once they know their level of productivity. We assume that farmers produce a homogeneous product with Cobb–Douglas technology. Simultaneity exists between the choice of inputs and productivity since productive farms are more likely to make capital investments to increase the future value of the farm. Therefore, the farm's decision to invest in further capital, implies that future productivity is increasing in the current productivity shock, so farms that experience a large positive productivity shock in period t will invest more in period $t+1$. The Olley and Pakes (1996) semi-parametric method accounts for these issues.

There is also a selection bias since farms only stay in business if the liquidation value is smaller than the anticipated future value of profits. Achieving this requires a second step to estimate survival probabilities, which will then allow to control for selection bias. In our implementation, we estimate the probability of survival by fitting a probit model. Details on the production function are placed in Appendix A. In order to analyse the effects of climate we can examine these coefficients that represent climate-elasticity (or semi-elasticity to be more precise), that can be defined as the percentage change in the function's output as a result of one unit change in the level of a climate variable. For example, the average temperature coefficient indicates the percentage change in monetary outcome for the farms due to an increase in one degree in the average temperature.

Marginal product – the change in output resulting from employing one more unit of a particular input, assuming other inputs are kept constant (Brewer, 2010) – has been calculated for analyzing the drought effect.

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2.2 Measuring rural income distribution: a decomposition of the Gini index with regard to social equity

To characterize the inequality distribution of the agricultural output, we use the Gini coefficient decomposition proposed by Pyatt et al. (1980) and Shorrocks (1982), and extended by López-Feldman et al. (2007), 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 of its simplicity and its desirable properties. In a general context, it fulfils the properties of mean independence, population size independence, symmetry, and Pigou Dalton transfer sensitivity (Haughton and Khandker, 2009). However, this tool presents two main shortcomings: (i) not easy decomposability as entropy measures, and (ii) difficult statistical testability for the significance of changes in the index over time. Haughton and Khandker (2009) suggested that the latter 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. 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 (Quiroga et al., 2014; Sadras and Bongiovanni, 2004; Seekell et al., 2011). In a general context, it ranges from zero (equal distribution) to one (perfect inequality).

The decomposition of the overall Gini into specific source factor effects was derived from Lerman and Yitzhaki (1985). It is a good measure to help to understand the determinants of inequality, and allows for estimating the effect of small changes in a specific source of yield (income) on inequality, while maintaining the other sources constant. In this paper, we include drought as a source factor. If we consider the relationship between drought and crop yield, the interpretation of Gini decomposition will be the following: (i) if drought as a source represents a large share of total crop yield, it could probably have a large impact on inequality, (ii) if crop yield is equally distributed, it cannot affect inequality, even if its magnitude is large, and (iii) if this crop yield source is large and unequally distributed, it could either increase or decrease inequality, depending on which farmers, at which points in the crop yield distribution, earn it.

Here we use the Lorenz curves as the most common Gini index representation to analyze how rural inequalities respond to climate change induced drought. The Lorenz curves represent the cumulative distribution function of income distribution. Since a perfectly equal income distribution would be one in which every farmer has the same income, this could be represented by the line $y = x$, also called the "perfect equality" or "equi-distribution" line. In this hypothetical case, N% of rural population would always have N% of the rural income. The Gini Index is the area between the Lorenz curve and the equi-distribution line.

A detailed description of Gini decomposition can be found in Appendix B.

2.3 Data

Since our model considers the interrelation among management factors and climate estate variables, it was necessary to combine several socio-economic and biophysical databases for the analysis. Table 1 shows detailed information about the variables we used, the units and source of the data and main descriptive statistics. We have used SABI database (Iberian Balance sheet Analysis System) that provides information about farm incomes, management factors (land, labour and capital) and spatial farm location. The SABI database is produced jointly by Bureau van Dijk and Informa and comes from the financial information that farms must present to the Companies Registration Office. It is an annual survey which looks at a panel of representative Spanish agricultural farms and contains balance sheet data, cash flow and other data. Our database is an unbalanced panel observed over the period 1990–2013. SABI also provides information about the major digit NACE codes (National Classification of Economic Activities) to which the farms belong. The data are at the farm level and they are provided for different sectors. Here we have analysed the farm incomes from 1990 to 2013 in the most important sectors regarding Mediterranean representative crops: the cereal sector (NACE code A1.1.1), the grape sector (NACE code A1.2.1) and the olive

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sector (NACE code A1.2.6). Our sample includes all the farms providing information for the selected sectors.

The SABI database provides the data in real currency (current EUR), so to consider real increase in purchase capacity and discount the effect of market price increases, we have deflated the current monetary variables into real values with 1990 as the base year, using national account data for Spain (INE, Spanish National Statistics Bureau). Climatic information for the period 1990–2013 has been collected from AEMET (Spanish national meteorological service). Table 1 presents the descriptive analysis of the variables used.

The current work uses the firm's sales volume and it is converted into real terms. With regard to the inputs, labour is measured as the number of workers. In this type of study, the standard practice is to define labour in terms of hours worked but this information is not available. Capital quantity is defined as the market value of capital assets (machineries, tractors, etc.) owned by the farms, in constant prices. Land is defined as the value for the planting area. Material is defined as intermediate spending carried out in the production process (fertilizers, pesticides, energy, etc.).

The farm investment is calculated according to the proposal by Lewellen and Badrinath (1997) as follows:

$$i_{\mathrm{it}} = \mathrm{nf}_{\mathrm{it}} - \mathrm{nf}_{\mathrm{it}-1} + \mathrm{bd}_{\mathrm{it}}$$

where nf is net fixed assets and bd is book depreciation expenses. Theoretically, the model mentioned in the last section requires that investment be strictly positive to invert the investment function. In their empirical implementation, Olley and Pakes (1996) drop all observations with zero investment. Other authors have noted that in practice zero investment is often observed and that the methodology seems to work even when the theory is violated (see, for example, Pavcnik, 2002). Therefore our approach will be to retain all the observations with zero investment but also introduce dummy variables (dummy variables for zero investment interacted with state inputs) to account for these observations, as in Blalock and Gertler (2004) and Breunig and Wong (2008).

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As a robusticity check, we did estimate the model dropping all of the observations with zero investment and the resulting coefficient estimates are similar to those reported below. We add t which is a variable included here to measure the Hicks-neutral technical change that is common among firms in the same sector and autonomous region. A Hicks-neutral technical change is a change in the production function of a farm which satisfies certain economic neutrality conditions. A change is considered to be Hicks neutral if the change does not affect the balance of labour and capital in the products' production function. Factor-neutral (also called Hicks-neutral) technological change is assumed, either explicitly or implicitly, in most of the standard techniques for measuring productivity, ranging from the classic growth decompositions of Solow (1957) and Hall (1988) to the recent structural estimators for production functions (Olley and Pakes, 1996; Levinsohn and Petrin, 2003: Ackerberg, Caves and Frazer, 2006).

In our paper, we measure Hicks-neutral technological progress with the time trend in productivity. Assuming neutral technical change implies that the coefficients of the interactions between the yearly trend and the input variables are zero. We also tried to estimate a non-neutral technical progress but the resulting coefficients were not significant, so the Hicks-neutral technological progress was checked as appropriate.

Drought characterization is always a difficult task, given their spatial and temporal properties and no single accepted definition (Tsakiris et al., 2007). In the most general sense, drought originates from a deficiency of precipitation over an extended period of time – usually a season or more – resulting in a water shortage for some activity, group, or environmental sector (NDMC, 2015). Operational definitions help define the onset, severity, and end of droughts. No single operational definition of drought works in all circumstances, and this is a big part of why policy makers, resource planners, and others have more trouble recognizing and planning for drought than they do for other natural disasters (NDMC, 2015).). To characterize drought in this study, we use the commonly used Standardized Precipitation Index (SPI, McKee et al., 1993). 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 (Iglesias et al., 2007; Garrote et al., 2007). We have introduced a geographical variable to capture the differences among river basin locations (Fig. 2) to reflect that climate and management patterns vary across the basins and so do the crop processes and farmers' incomes. All the 10 river basins are represented in the analysis since there are a number of farms included in each of the basins. However, we introduced a dummy variable for differentiating the effects on 5 of them: Duero, Ebro, Guadalquivir, Guadiana and Tajo. This allows us to compare differential marginal effects for these important basins. For example, if we have a significant and positive effect on the variable capturing the Duero river basin effect, this indicates that for this basin the effects are higher than the average effects. For the river basins not represented we just have the average value as reference. Introducing dummy variables allocates differential marginal effects with respect to the representative average value. We consider the most important river basins to allocate these differences.

2.4 Climate change scenarios and drought in the Mediterranean

We analyse the response of crop productivity to climate change through simulations responding to climate scenarios derived from representative concentration pathways of global emissions for the 2050s: the A1B scenarios with a balanced emphasis on all energy sources (around 850 ppm of CO_2) and the E1 scenarios representing stabilisation (458 ppm of CO_2). The source of climate data is the University of East Anglia (Christensen et al., 2011) and those data have been fully described in Iglesias et al. (2011): A1B represents a balanced emphasis on all energy sources with CO_2 level in 2080 of about 850 ppm. E1 is the so-called global "2 °C-stabilization" scenario that is characterised by atmospheric concentrations of 498 ppm CO_2 in the 2080s. This last generation socio-economic scenarios were not developed in the PRUDENCE project but new climate projections have been developed under the Climate Cost project (Christensen et al., 2011; Iglesias et al., 2012). To address uncertainty we use several climate models driven by these representative concentration pathways: A1B: DMIEH5-4; A1B: HADGEM-1 and the E1: DMICM3-1; E1: DMICM3-2; E1: HADGEM2-1.

Table 2 presents the average values for the seasonal average temperatures and total precipitations.

The two selected scenarios represent important differences in mitigation policies. The E1 scenario corresponds to the future emission pathway that is required to limit global warming to no more than 2 °C above pre-industrial levels and the allowable level of CO_2 emissions in this greenhouse gas stabilization scenario corresponds to limiting global warming below this EU target. Significant and early policy actions are required in mitigating greenhouse gas emissions to limit global warming to no more than 2 °C above pre-industrial levels. In the greenhouse gas stabilization scenario the allowable CO_2 emissions increase has to be steadily reduced resulting in a decrease of 56 % in year 2050 and almost 100 % in year 2100. (Roeckner et al., 2011). On the other hand the A1B scenario is part of the SRES scenario families and has been the focus of model inter-comparison studies. E1 and A1B illustrative marker scenarios are about 490 and 850 ppm respectively. (IPCC, 2007; Christensen et al., 2011; Roeckner et al., 2011).

3 Results

3.1 Olley and Pakes production functions estimates

Table 3 shows the estimates for the nature state drivers and management factors elasticities of the statistical function of yield response for the selected Mediterranean crops in the analysis. We can observe that the marginal effects are as expected with regard to traditional inputs. That is, the management factors positively affect the increase in productivity. We can observe that the effect of size (land) is not relevant in determining crop productivity in Spain. That is, there are not significant productivity differences between big and small farms. This result is quite common in literature (Petrick and Kloss, 2013; Yasar et al., 2008). With regard to climate drivers, we find in general that average temperatures have a positive effect and the same for precipitation. Droughts appear to be the most important factor for external productivity shocks. This effect is crop specific and it is more important in the case of olives. This is due to the climatic conditions of this rain-fed Mediterranean crop, located basically in the southern areas which have important water availability shortages during drought.

3.2 Simulations of drought driven productivity changes

Table 4 shows the Gini coefficient for the total income, and the marginal effects of the increase of drought on the farms income distribution for the main river basins in Spain. We can observe that the most unequal distribution of incomes is presented in the Duero river basin for cereals, in the Guadiana for grapes and in the Tagus river basin for olives. We find that the increase in drought occurrence will reduce the Gini index in all the cases studied, which is it will increase the inequalities for the rural incomes. Although the effects are not large, they are mostly significant.

The estimation of these rural inequalities percentage changes allows us to project the changes in the Gini index as a response to changes in the precipitation patterns due to climate change.

Figure 3 shows the marginal effects on productivity and changes on income distribution. While the impacts on average incomes depend on the crop and the location, showing a negative or positive impact, we can observe that the changes in the Gini index values are always expected to be negative and they are lower in magnitude. That is, the expected effects on inequalities are going to get worse as a response to climate change extreme events such as drought. The magnitude depends on the crop and we can observe that olives are the one with the highest probability of having more risk and also of generating more inequalities in rural areas. We can observe that the Tagus river basin is the one where the greatest impact is noted due to droughts. These marginal effects can be used as a basis for understanding the priorities in adaptation policy. The impacts on cereals are highly dependent on the location. Since our analysis suggests

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some losses in the productivity of incomes, this will affect competitiveness in the long term. In the economic point of view, long term is not linked to a specific time scale, but it is considered when farms are able to adjust all costs, whereas in the short run farms are only able to influence prices through adjustments made to production levels. Since our model considers investment responding to the final outcome, these productivity losses can influence the investment, especially in the Tagus river basin. Since Fig. 3 suggests that different crops and regions have different expected productivity (ie. income losses), different priorities should be given for defining public support for adaptation.

The effect on income distribution seems to be low in magnitude and this can be due to some compensation through market prices. This result appears to indicate that the mitigation on agricultural losses is being compensated through consumer welfare worsening. Here we do not calculate this effect, but we find that it would be interesting to extend the effects on consumption for future research. Some results can be found in literature in terms of changes in certainty equivalent wealth for producers and based on yields ($\mathrm{t\,ha^{-1}}$) (Ciscar et al., 2011; Quiroga et al., 2009) but less attention has been placed on consumers' incomes.

3.3 Evolution of income distribution as a response to drought

From the marginal effect on income distribution we have simulated the evolution of income distribution as a response to changes in potential drought and climate variables through temperature and precipitation forecasting in the different climate change scenarios selected for the study (see Sect. 2.4). Figure 4 shows the resulting Lorenz curves (Gini index representation) to analyse how rural inequalities respond to climate change induced drought. As we have mentioned in the methodology, the Lorenz curves represent the cumulative distribution function of income distribution. The greater the difference among the line and the so called "perfect equality" or "equi-distribution" line, the more the Gini index and worse the social distribution of incomes. In Fig. 4 we show the evolution of the curve from the baseline (1990–2013) to the climate change scenarios

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for 2080 (A1B and E1 concentration pathways simulated by 4 different climate models and downscaling).

These curves show for the bottom percentage of farmers (x axis), what percentage of the total agricultural income (y axis) they have and can be considered a measure of social inequality. We can observe that the effects are not huge in terms of social distribution, but they are negative for all the crops and for the different scenarios, so climate change induced drought increase will definitely worsen rural inequalities. In addition, we can observe that the sector in which the income distribution will be more concentrated will be the olive sector followed by the cereals sector. In the case of grape production the simulated effect on social inequalities is not significant. Since drought events will be suffered by all the farmers independently of their income level, our results suggest that at least in rain-fed crops, investment, which is mostly made by farmers with higher incomes, would not be enough to compensate the expected losses, because in other case we will expect a very important effect on income distribution after drought consequences. Although the EU White paper for adaptation (COM, 2009) indicates that there is great room for adaptation in the agricultural sector, these results suggest that in the case of drought, the adaptation measures should prioritize water resource management. A limitation of this study is the fact that we do not analyze the effects on irrigated crops. The challenge for this kind of analysis is that spatial resolution for water availability data has to be linked to information at the farm level. In a further step, remote sensing methods could help to better characterize information in water use.

We can observe in Fig. 4 that the projected scenarios are very similar for the different models considered. That is, the results we obtain about income distribution changes are very robust in terms of the different models considered. Slightly larger differences appear among the different mitigation targets (A1B and E1). In Table 5 we have analysed these differences considering as well the quantification of uncertainty in our model. We have computed the mean-comparison test for the projected income distribution response to climate scenarios in relation to the current climate baseline. We show the t statistic and p value for the null hypothesis of having no significant dif-

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ferences among the scenarios with respect to the baseline. When p value is over 10 %, this means that the results show no statistical significant differences in inequalities. While the opposite applies when p value is less than 10 %. We can observe that only some of the scenarios considering A1B concentration pathways produce significant effects on income distribution. Although the olive crop shows a bigger effect at a glance, we can see that considering the uncertainty of the model, those impacts are not significant (this is due to a bigger standard error in the model of this crop). The scenarios for the A1B concentration pathways affect more the social distribution than those for the E1 concentration pathways, both in magnitude and confidence level. So mitigation policies can help to reduce the effects of climate change on social distribution.

Here we do not explicitly analyze rural communities, but incomes at the farm level. However, we think that a worsening in the distribution on farms' incomes will affect the social structure in these rural communities. We observe that the most important effects are expected on the olive crop in the Southern areas in Spain. The increase in income inequalities in these rural communities can be very important in terms of social conflicts since this region is mostly based on agricultural outcomes with very low development of industry. This problem we find in Spain could be the same in other Mediterranean countries where southern areas are also very much driven by the olive crop sector. Another limitation in this study is that we do not explicitly consider the role of CAP subsidies which are in fact very important particularly in this area. Further analysis could include separated incomes from market and from CAP subsidies to explicitly examine the agricultural policy effects. However, since farms incomes and their social distribution seem to be affected by climate change and drought challenges, the role of CAP seems to be revised in order to help competitiveness and incomes redistribution functions.

Here we consider the contribution of the studied crops to farmers' incomes and the effect of these losses on social disparities. However, we do not analyze cross-compensation or adaptation measures explicitly (i.e. crop rotation, change in varieties, part time non-agricultural incomes, etc). Farmers of course can take several important

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decisions to adapt to the expected losses and it would be interesting in further analyses to take into account these compensation effects on social disparities. Therefore adaptation measures should be designed considering both the economic and social aspects.

4 Discussion and conclusions

This paper focuses on the effects of drought and climate change on agricultural productivity and rural incomes distribution. We have estimated the drivers for productivity and we find that within the traditional inputs such as labour, capital and intermediate consumptions (energy, fertilizers, pesticides, etc) positively affect production as expected. However, there are also nature state variables such as drought, temperature increases, or precipitation decreases, which are not controlled by the farmers but can produce important productivity shocks. We have estimated the elasticity for these shocks and especially we have focused on drought effects on productivity losses.

The relatively complex methodology used allows us to focus on the economic aspects of climate change and drought impacts on agriculture. We estimate directly in monetary units. For this purpose we used economic information about marketable outputs (farmer incomes) and inputs (such as expenses on labour, capita, intermediate consumptions – energy, fertilizers, etc). However, there are other factors such as soil quality or farmer's effort that are not causing a marginal cost in terms of input but that have an important effect on the production. The Olley–Pakes method allows us to consider these unobservable factors and get non-biased estimations although these factors are not directly considered as explanatory variables.

According to previous literature the losses produced by drought conditions are crop specific and it depends on location and the same can be shown in this analysis. (Parry et al., 2004; Iglesias et al., 2012; Lobell et al., 2008). The climate change and drought induced losses in physical yields ($\mathrm{t\,h}^{-1}$) have been largely analyzed in literature and they are expected to be very high for some of the crops analyzed here, especially in the Southern and Eastern regions in Spain. However, the analysis of incomes has not captured so much attention. As we have mentioned in the text, the changes in income, although also crop and location specific, are not as high as those estimated in actual quantities yielded. Of course, in market economies, prices are expected to play a role adjusting the scarcity in physical goods, and this seems to be exactly the case here. Even when international agricultural goods are present, market prices seem to respond to yield losses at the local level and incomes are affected but somewhat less. This is very important because it transfers the affected community from producers to consumers.

With regard to incomes distribution we have estimated the marginal effects of drought on the Gini coefficient and we have observed that the effects are not large but they are negative for all the crops analysed whatever the river basin considered. The Tagus river basin is the one that shows the most important effects in both, productivity losses and incomes inequalities, and with respect to the sectors analysed, the olive sector is where the greatest impacts are noted. The results are policy relevant since adaptation policy for agricultural systems and water resource distribution could consider prioritizing the most affected basins and sectors.

When simulating climate change conditions our results show that income distribution can be expected to get worse although the effects are higher on the productivity losses than on the inequalities increase. The scenarios based on A1B concentration pathways produce higher effects on social distribution than those based on E1 concentration pathways, so mitigation policies can reduce the vulnerability of low income rural communities.

Our results are significant since although the relationship between climate change and inequalities has been identified as very important (IPCC, 2014; UNDP, 2010; López-Feldman, 2015) there are still few empirical studies quantifying the effects on incomes distribution. Here we develop a methodology that considers both sides in the economic impacts: efficiency for the incomes and distributional aspects. Most of the studies addressing distributional aspects are based on food security – yields or in-

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gested calories, poverty or development indicators. These kinds of studies are very important and pertinent to analyze the global situation where developed and non-developed countries are present. However, in the context of the EU or the OECD developed countries sometimes this kind of measures (literacy levels, access to water, ingested calories,. . .) are not adequate enough to describe the situation of a loss in income distribution. For this reason, we find that our results since they address the direct impacts considering farmers' incomes in real terms can provide a better picture for analyzing the worsening situation of farmers in developed countries. We have found that the differences in terms of income distribution are not as severe as those reported in studies that consider physical impacts which suggest an important role of market prices in stabilising farmers' outcomes. This fact is also important because it would imply that rural incomes could not suffer mostly the agriculture losses estimated for most of the studies in Spain (Iglesias et al., 2012; López-Gunn et al., 2012) but consumers' welfare is the most greatly affected.

Concerning adaptation, we have found that the Tagus river basin is the most affected region with regard to changes in the average income of farmers. This would imply that larger efforts for adaptation should be made in this region, where water resources management becomes a key element for adaptation. Also we have found that the olive sector should be considered as a priority in terms of both, farms' incomes and social equity and the role of CAP subsidies can be important to address this challenge in the future.

Appendix A: Agricultural production function simultaneous estimates: observed inputs and unobserved productivity shocks

The Olley and Pakes (1996) approach assumes that incumbent farms decide at the beginning of each period whether to continue to participate in farming activity, depending on their productivity level, which in turn depends on their production factor (it corrects the selection bias). To this end, investment (i_{it}) is considered as a proxy for the unobserved productivity shocks. Also, this method corrects the simultaneity bias arising from the fact that farms choose their level of input once they know their level of productivity.

We assume that farmers produce a homogeneous product with Cobb–Douglas technology, and that the factors underlying profitability differences among firms are neutral efficiency differences. The production function is:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_a a_{it} + \sum_j \delta_j c_{jit} + u_{it} \quad \text{(A1)}$$

$$u_{it} = \Omega_{it} + \eta_{it}$$

where y_{it} is log-output for farm i in period t; l_{it}, m_{it}, k_{it} and a_{it} are the log-values of labor, material, capital and land inputs; c_{jit} are biophysical variables (climate and river basin); Ω_{it} is the productivity shock that is observed by the farm but not by the econometrician (for example machine breakdowns, etc.); and η_{it} is an unexpected productivity shock that is unobserved by both the decision-maker and the econometrician. Thus, Ω_{it} and η_{it} are unobserved. The distinction is that Ω_{it} is a state variable in the farm's decision problem, and hence a determinant of both liquidation and input demand decisions, while η_{it} is not.

Simultaneity exists between the choice of inputs and productivity since productive farms are more likely to make capital investments to increase the future value of the farm. Then, the farm's decision to invest in further capital, i_{it}, also depends on capital stock, land and the firm's productivity shock:

$$i_{it} = I(\Omega_{it}, k_{it}, a_{it}) \quad \text{(A2)}$$

This investment decision equation implies that future productivity is increasing in the current productivity shock, so farms that experience a large positive productivity shock in period t will invest more in period $t+1$.

The Olley and Pakes (1996) semi-parametric method accounts for these issues. Applying this method first involves using the investment decision function to control for

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the correlation between the error term and the inputs. This is based on the assumption that future productivity is strictly increasing with respect to Ω_{it}, so farms that observe a positive productivity shock in period t will invest more in that period, for any k_{it} and a_{it}. Provided that i_{it} is strictly positive, we can write the inverse function for the unobserved shock Ω_{it} as

$$\Omega_{it} = h(i_{it}, k_{it}, a_{it}) \tag{A3}$$

This function can thus be used to control for the simultaneity problem. Substituting those equations into production function yields

$$y_{it} = \beta_l l_{it} + \beta_m m_{it} + \sum_j \delta_j c_{jit} + \varphi(i_{it}, k_{it}, a_{it}) + \eta_{it} \tag{A4}$$

where

$$\varphi(i_{it}, k_{it}, a_{it}) = \beta_0 + \beta_k k_{it} + \beta_a a_{it} + h(i_{it}, k_{it}, a_{it}) \tag{A5}$$

we approximate $\varphi(.)$ with a second order polynomial series in land, capital, and investment. The partially linear equation can be estimated by ordinary least squares. The coefficient estimates for variable inputs (labour and material) will be consistent and asymptotically normal estimates of the coefficients in the linear part of the model (Andrews, 1991) because $\varphi(.)$ controls for unobserved productivity, and thus the error term is no longer correlated to the inputs. This allows us to estimate β_l and β_m without requiring identification of β_k and β_a, so more work is required to disentangle the effects of capital and age on the investment decision from their effect on output.

There is also a selection bias since farms only stay in business if the liquidation value is smaller than the anticipated future value of profits. Achieving this requires a second step to estimate survival probabilities (P_{it}), which will then allow us to control for selection bias. In our implementation, we estimate the probability of survival by fitting a probit model on $i_{i,t-1}$, $k_{i,t-1}$, $a_{i,t-1}$, as well as their squares and cross products. This

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can be viewed as a nonparametric estimator of the index function. Call the predicted probabilities from this model $\hat{P}_{\text{it}}$:

$$\Pr(\chi_{\text{it}} = 1) = \phi(i_{i,t-1}, k_{i,t-1}, a_{i,t-1}) \tag{A6}$$

In the third step, we identify the coefficient β_k, where productivity is assumed to evolve according to a first-order Markov process, we fit the following equation by nonlinear least squares in order to obtain β_k:

$$y_{\text{it}} - \widehat{\beta}_l l_{\text{it}} - \widehat{\beta}_m m_{\text{it}} - \sum_j \hat{\delta}_j c_{jit} = \beta_k k_{\text{it}} + \beta_a a_{\text{it}} + g(\hat{\varphi}_{t-1} - \beta_k k_{i,t-1} - \beta_a a_{i,t-1}, \hat{P}_{\text{it}})$$
$$\xi_{\text{it}} + \eta_{it} \tag{A7}$$

where the unknown function $g(.)$ is approximated by a second-order polynomial in $\hat{\varphi}_{t-1} - \beta_k k_{i,t-1} - \beta_a a_{i,t-1}$ and $\hat{P}_{\text{it}}$.

Finally, we use the efficient coefficients' estimates to build a measure of farm-level production for the i farm at the time t.

Appendix B: Measuring rural income distribution: a decomposition of the Gini index on equity

To characterize the inequality distribution of the agricultural output, we use the Gini coefficient decomposition proposed by Pyatt et al. (1980) and Shorrocks (1982). As developed in López-Feldman et al. (2007), 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:

$$G_{\text{tot}} = \sum_{k=1}^{K} S_k G_k R_k \tag{B1}$$

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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 with respect to total yield; G_k represents the relative Gini of source k, this part attempts 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 $R_k = \text{Cov}\{y_k F(y)\}/\text{Cov}\{y_k F(y_k)\}$, implying the question of how the income source and the distribution of total income are correlated. This decomposition of the Gini coefficient is a good measure to help us understand the determinants of inequality, and allows us to estimate the effect of small changes in a specific source of yield (income) on inequality, maintaining the other sources constant. Consequently, the decomposition of the overall Gini into specific source factor effects was derived from Lerman and Yitzhaki (1985). 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:

$$\frac{\partial G_{\text{tot}}}{\partial e_k} = S_k(G_k R_k - G_{\text{tot}})$$

In this paper, for example, we include drought as a source factor. As we mentioned before, if we consider the relationship between drought and crop yield, the interpretation of this decomposition will be the following: if drought 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 (drought) 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 crop yield distribution.

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Table 1. Description and descriptive statistics of the variables used in the analysis.

Type	Name	Definition	Unit	Source*	Cereals Mean	Cereals SD	Grapes Mean	Grapes SD	Olive Mean	Olive SD
Socio-economic and management factors	Y_{it}	Total crop production at farm i in year t	Thousands of 1990 EUR	SABI, INE	330.9	1470.7	263.5	766.2	181.4	375.8
	L_{it}	Total employment at farm i in year t	Number of workers	SABI, INE	8.9	29.8	7.6	29.8	9.8	14.3
	M_{it}	Materials (fertilizers, pesticides, energy, ...)	Thousands of 1990 EUR	SABI, INE	276.5	1274.4	200.3	684.3	125.7	362.1
	K_{it}	Capital assets (machineries, tractors, ...)	Thousands of 1990 EUR	SABI, INE	647.1	1480.6	707.7	1471.9	821.2	1740.0
	A_{it}	Land	Thousands of 1990 EUR	SABI, INE	196.3	1530.4	192.8	777.6	139.1	788.5
	I_{it}	Investment	Thousands of 1990 EUR	Own elaboration from SABI	93.1	608.6	115.0	444.1	108.3	617.9
	t	Time trend, $t = 1$ for 1991, $t = 23$ for 2013	Year sequence	Own elaboration						
Biophysical factors	$T_{son_{it}}$	Average seasonal temperature at site i in the year t (Sep–Nov)	°C	AEMET	16.9	2.7	16.3	2.6	17.9	2.0
	T_djf_{it}	Average seasonal temperature at site i in the year t (Dec–Feb)	°C	AEMET	8.5	3.0	7.9	2.8	9.5	2.3
	T_mam_{it}	Average seasonal temperature at site i in the year t (Mar–May)	°C	AEMET	15.0	2.5	14.1	2.3	15.8	1.9
	Prec_son_{it}	Total seasonal precipitation at site in the year t (Sep–Nov)	mm	AEMET	154.2	78.4	171.8	103.9	167.8	85.3
	Prec_def_{it}	Total seasonal precipitation at site in the year t (Dec–Feb)	mm	AEMET	139.2	124.8	129.0	118.4	175.9	149.3
	Prec_mam_{it}	Total seasonal precipitation at site in the year t (Mar–May)	mm	AEMET	131.8	60.3	143.5	79.6	147.1	72.4
	Prec_jja_{it}	Total precipitation at a site in the year t (Jun–Aug)	mm	AEMET	37.6	39.8	56.2	49.4	26.3	35.9
	Drought_{it}	Dummy variable (1 for dry years, 0 in other case)	1 or 0 as a function of SPI index	Own elaboration from AEMET	55.0 %		49.0 %		54.1 %	
	River_basin_{i}	Dummy variables for river basin selection: (1) Duero, (2) Ebro, (3) Guadalquivir, (4) Guadiana and (5) Tajo	1 or 0 as a function of the area	Own elaboration from SABI	5.8 % 12.8 % 23.8 % 5.1 % 26.6 %		7.1 % 14.1 % 7.9 % 1.6 % 24.6 %		0.6 % 2.1 % 55.1 % 3.1 % 16.8 %	

* Iberian Balance sheet Analysis System (SABI); Spanish National Statistics Bureau (INE), Spanish Meteorological Agency (AEMET).

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Table 2. Climate change scenarios: average values for medium temperature and total precipitation under the selected climate change scenarios for the period 2070–2100.

Emission Scenario	GCMmodel/ Downscalling	Prec_son (mm)	Prec_djf (mm)	Prec_mam (mm)	Prec_jja (mm)	T_son (°C)	T_djf (°C)	T_mam (°C)	T_jja (°C)
A1B	BCM2_1	−73.3	−41.0	−83.4	−40.5	2.3	1.9	3.0	3.3
A1B	CNCM3_1	−77.3	−54.8	−105.5	−77.0	3.5	2.1	3.5	4.9
A1B	DMIEH5_4	−81.9	−88.0	−92.4	−149.9	4.1	2.3	3.1	5.2
A1B	EGMAM_1	−13.5	10.2	−100.1	−68.9	3.2	2.7	2.8	3.7
E1	BCM2_1	−58.2	−47.2	−24.6	−11.1	1.1	1.0	0.9	1.5
E1	CNCM3_1	−56.7	−8.9	−70.7	1.9	1.3	0.8	1.0	1.4
E1	DMIEH5_4	−11.9	17.5	−11.9	−0.2	1.3	1.6	1.4	1.6
E1	EGMAM_1	4.7	−6.1	−31.8	−58.8	1.7	1.2	1.2	1.6

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Table 3. Olley–Pakes estimates for the factors elasticities of the statistical function of income response for cereal, grape and olive sectors (baseline: 1991–2013).

	Cereals		Grapes		Olives	
	Coef	Std.Err.	Coef	Std.Err.	Coef	Std.Err.
Land	−0.0452	(0.036)	0.1237	(0.142)	−0.0285	(0.077)
Capital	−0.0497	(0.020) [b]	0.0381	(0.086)	0.0521	(0.086)
Labour	0.2935	(0.017) [c]	0.3814	(0.032) [c]	0.2827	(0.032) [c]
Material	0.7805	(0.015) [c]	0.6440	(0.033) [c]	0.6743	(0.044) [c]
T	−0.0012	(0.002)	−0.0069	(0.005)	−0.0113	(0.008)
T_son					0.0406	(0.017) [b]
T_djf			−0.0243	(0.013) [a]	−0.0551	(0.016) [c]
T_mam	−0.0189	(0.008) [b]				
Prec_son	−0.0001	(0.000)	0.0002	(0.000)	−0.0002	(0.000)
Prec_def	−0.0001	(0.000) [b]	−0.0003	(0.000)	0.0000	(0.000)
Prec_mam	0.0002	(0.000)	0.0002	(0.000)	0.0004	(0.000)
Prec_jja	0.0006	(0.000) [a]	0.0008	(0.000) [c]	−0.0006	(0.001)
Drought	−0.0309	(0.019) [a]	−0.0178	(0.029)	−0.0860	(0.051) [a]
Duero	0.0767	(0.052)	−0.0175	(0.114)	−1.3191	(0.602) [b]
Ebro	0.1224	(0.045) [c]	0.0173	(0.078)	0.2656	(0.129) [b]
Guadalquivir	0.0434	(0.035)	0.0156	(0.116)	0.0605	(0.083)
Guadiana	0.0225	(0.059)	0.4534	(0.150) [c]	0.1171	(0.198)
Tajo	−0.2184	(0.048) [c]	−0.0776	(0.073)	−0.2626	(0.101) [c]
Obs	17 157		3488		3028	
Farms	2250		503		401	

Note: Standard errors in OP model are bootstrapped using 50 replications.
[a] Significant at the 10 % level.
[b] Significant at the 5 % level.
[c] Significant at the 1 % level.

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Table 4. Gini decomposition for drought by crop and river basin.

Crop	River Basin	G	$S_{k=\text{Drought}}$	$G_{k=\text{Drought}}$	$R_{k=\text{Drought}}$	% Change	[95 % Conf. Interval]
Cereals	Duero	0.561	0.003	0.413	−0.051	−0.32	[−0.35 −0.28]
	Ebro	0.704	0.002	0.424	−0.022	−0.21	[−0.23 −0.18]
	Guadalquivir	0.729	0.002	0.398	−0.039	−0.17	[−0.19 −0.16]
	Guadiana	0.664	0.002	0.412	−0.009	−0.18	[−0.21 −0.16]
	Tajo	0.714	0.003	0.466	−0.056	−0.27	[−0.32 −0.21]
Grapes	Duero	0.651	0.002	0.399	−0.054	−0.23	[−0.29 −0.19]
	Ebro	0.642	0.002	0.408	−0.028	−0.23	[−0.27 −0.18]
	Guadalquivir	0.769	0.001	0.444	0.025	−0.10	[−0.17 −0.08]
	Guadiana	0.364	0.004	0.395	0.303	−0.27	[−0.44 −0.15]
	Tajo	0.644	0.003	0.522	0.045	−0.28	[−0.34 −0.23]
Olives	Duero	0.694	0.008	0.500	−0.167	−0.91	[−0.79 −0.32]
	Ebro	0.720	0.002	0.539	0.077	−0.18	[−0.32 −0.09]
	Guadalquivir	0.609	0.003	0.426	−0.009	−0.35	[−0.39 −0.31]
	Guadiana	0.550	0.004	0.403	−0.011	−0.46	[−0.64 −0.23]
	Tajo	0.485	0.005	0.412	−0.029	−0.50	[−0.61 −0.42]

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Table 5. Mean-comparison test (*t* statistic and *p* value for H0: mean differences = 0) for the incomes distribution responding to the different climate change scenarios with respect to the current climate baseline.

Emission Scenario	GCMmodel/ Downscalling	Cereals *t* stat	Cereals *p* value	Grapes *t* stat	Grapes *p* value	Olives *t* stat	Olives *p* value
A1B	BCM2_1	**1.91**	**0.06**	1.41	0.15	0.00	0.99
A1B	CNCM3_1	**2.71**	**0.01**	**1.92**	**0.06**	−1.00	0.31
A1B	DMIEH5_4	**3.36**	**0.00**	**2.71**	**0.01**	**−2.12**	**0.03**
A1B	EGMAM_1	**2.72**	**0.00**	**2.16**	**0.03**	0.22	0.82
E1	BCM2_1	0.33	0.74	0.52	0.60	0.02	0.97
E1	CNCM3_1	0.58	0.56	0.56	0.57	0.14	0.89
E1	DMIEH5_4	0.65	0.51	0.71	0.47	0.65	0.51
E1	EGMAM_1	1.52	0.12	1.20	0.23	−0.42	0.67

Note: Standard shaped values indicate no significant differences. Bold values indicate significant differences at the 10 % level.

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Climate change and drought effects on rural income distribution in the Mediterranean

S. Quiroga and C. Suárez

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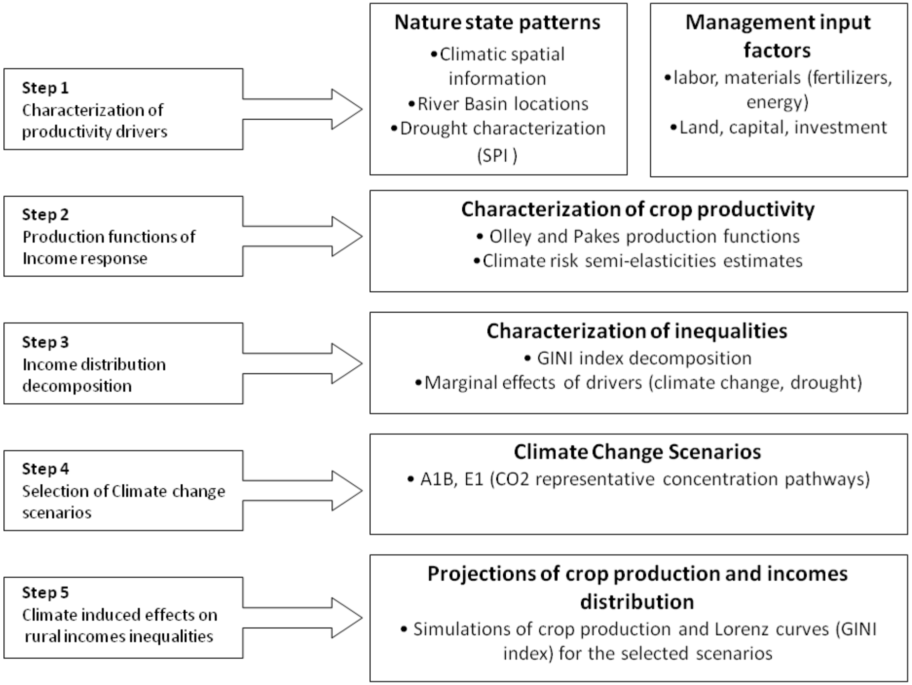

Figure 1. Steps of methodology.

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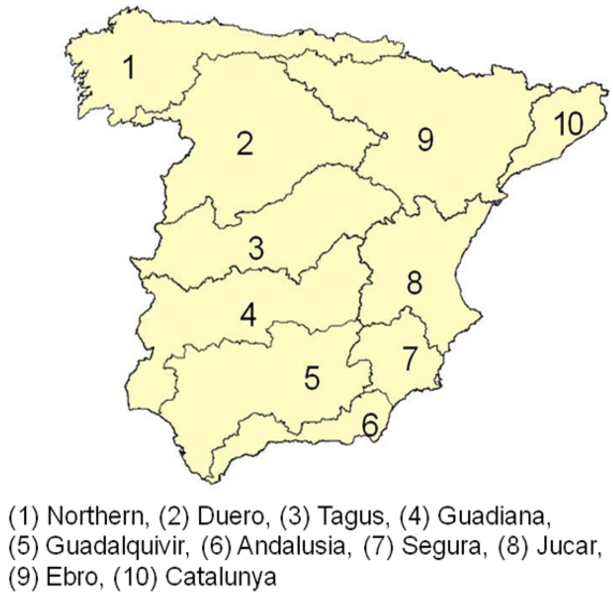

Figure 2. Spanish river basins.

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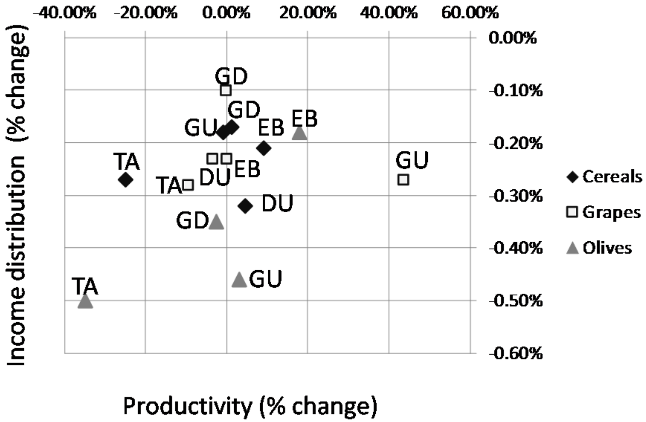

Figure 3. Marginal effects of drought events on crop productivity and income distribution for the selected crops in the main river basins in Spain.

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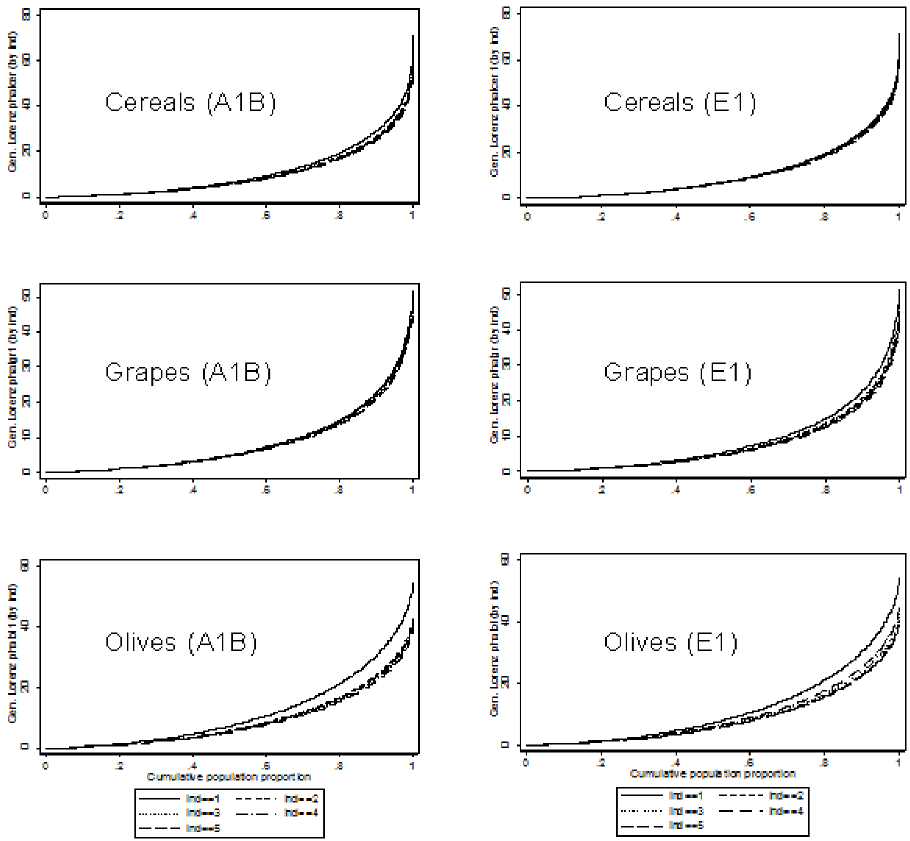

Figure 4. Lorenz curves (Gini index) for the selected crops under the baseline (1990–2013) and climate change scenarios (A1B, E1).

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