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Valuing drought information for irrigation farmers: potential development of a hydrological risk insurance in Spain

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Abstract

Drought events in the Mediterranean impact ecosystems and society. When meteorological drought leads to water scarcity river basin authorities and farmers are likely to be affected. The economic value of drought information and the resulting decisions that are made are of interest to these two stakeholder groups and the information providers. Here we focus on farmers' decision-making process to cope with drought consequences on crop production. The understanding of the dynamics of droughts and water scarcity is being improved continuously and new indicators are used to link science to policy actions. This paper analyses the effects of drought management plans on maize production in the Ebro river basin to compute the willingness to pay of the farmers for hypothetical hydrological risk insurance. We also compute the value of more accurate information about drought probability that would allow for better decision-making. If runoff is reduced, farmers can consider contracting hydrological risk insurance in order eliminate the risk of water scarcity. Alternately farmers can take the risk of water reduction maintaining their activities and accept a reduction of water supply reliability. The methodology and results presented are relevant to analyse climate change since drought events in the Mediterranean are likely to increase in frequency, duration and intensity. This information is also relevant for the revision of River Basin Management Plans of the Water Framework Directive (WFD) within the context of climate change.

Additional key words: economic value of drought information; farmers' decission making process; hydrological risk insurance; maize production in the Ebro basin; meteorological drought.

Resumen

Valoración económica de la información sobre sequía para los regantes: evaluación potential de un seguro de sequía hidrológica en España

La sequía en el Mediterráneo tiene gran impacto en los ecosistemas y la sociedad. Si la sequía meteorológica conduce a la escasez de agua, las autoridades de cuencas y los agricultores se verán afectados. El valor económico de la información sobre sequía es de gran interés para ambos grupos y para los proveedores de información. Este estudio se centra en el proceso de toma de decisiones de los agricultores para enfrentar las consecuencias de ésta sobre la producción agrícola. La comprensión de la dinámica de la escasez de agua mejora continuamente, usándose nuevos indicadores para vincular la ciencia y las acciones de política. Este artículo analiza los efectos de la gestión de sequía en la producción de maíz en la cuenca del Ebro, calculando la disposición a pagar de los agricultores por un seguro hipotético contra el riesgo hidrológico. También se calcula el valor de información sobre la probabilidad de sequía para tomar mejores decisiones. Si se reduce la escorrentía, los agricultores pueden considerar la contratación de un seguro con el fin de eliminar el riesgo hidrológico. Alternativamente, pueden tomar el riesgo de una reducción del abastecimiento de agua, aceptando una reducción de la fiabilidad de suministro. Este análisis es relevante para evaluar el cambio climático, dada la probabilidad de que los eventos extremos en el Mediterráneo se incrementen en frecuencia, duración e intensidad. Esta información es útil para la revisión de los planes hidrológicos de cuenca bajo la Directiva Marco del Agua (DMA) en un contexto de cambio climático.

Palabras clave adicionales: producción de maíz en la cuenca del Ebro; seguro de riesgo hidrológico; sequía meteorológica; toma de decisiones de los agricultores; valor económico de la información la sequía.

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Introduction

Under climate change, the Mediterranean region is likely to suffer increases in temperature and decreases in precipitation (Giorgi and Lionello, 2008). Apart from changing harvest patterns, these climate changes will increase the frequency and intensity of droughts and have direct impacts on the agricultural sector (Iglesias *et al.*, 2010). These changes are bound to affect agriculture through increases in uncertainty and variability that will make the importance of accurate and reliable climate information increasingly important.

Information is a factor that reduces uncertainty in decision processes. In the context of a changing climate where uncertainty is likely to increase, information will become increasingly valuable since climate change will affect farmers' decisions concerning when to plant or harvest, or which crops to produce, as well as decisions concerning investments in infrastructure or technology and insurance (Bielza and Garrido, 2009). Accurate climate information, such as that provided in climate predictions, can support and facilitate these decisions by helping farmers to increase the efficiency of agricultural management while boosting food and livelihood security (Hansen *et al.*, 2006). The value of climate information will depend on whether the information enables individuals to increase their utility relative to what it would be if that information was unavailable (Hill and Mjelde, 2002). In other words, the value of information is the expected gain in a decision outcome from using additional information.

Determining whether the information is valuable to individuals requires an analysis of decision processes which is typically undertaken with the aid of decision theory, general equilibrium modelling, game theory, and mechanism design theory (Rubas *et al.*, 2006). The insights that emerge from these analyses can greatly enhance agricultural management by shedding light on farmers' decision making processes (Hill and Mjelde, 2002). Recent studies claim that in order to be useful for farmers climate information needs to be salient, credible, and legitimate - where salience refers to the relevance of climate information, credibility refers to its technical quality, and legitimacy refers to the perception that the information has been developed for the users and not to push other agendas and interests (Cash and Buizer, 2005; Meinke *et al.*, 2006). Such information would lead to the production of "actionable knowledge" (Meinke *et al.*, 2006) that allows farmers to make informed decisions and act accordingly.

Despite great advances in climate prediction over the past twenty years, considerable challenges remain to make these predictions useful for farmers who are typically concerned with small fluctuations at the field level (Sivakumar, 2006). The fact that much climate information is provided at a scale that is irrelevant to farmers, points to a gap between the information routinely provided by climate predictions and the needs of agricultural decision makers (Hansen *et al.*, 2006). Nevertheless, recent research suggests that regional seasonal forecasts are relevant at a local scale and that the predictability of crop yield response may be more predictable than seasonal climatic means (Cane *et al.*, 1994; Gong *et al.*, 2003; Hansen and Indeje, 2004). Hansen *et al.* (2006) make use of this insight to translate seasonal climate predictions into forecasts of agricultural production, in terms of crop or forage yields, and to determine environmental quality impacts.

In Spain, water supplies decrease and irrigation demands increase under all climate change scenarios (Iglesias and Quiroga, 2007; Iglesias *et al.*, 2007, 2008). Climate change projections for the region derived from global climate model driven by socio-economic scenarios (Iglesias *et al.*, 2008) result in an increase of temperature (1.5ºC to 3.6ºC in the 2050s) and precipitation decreases in most of the territory (about 10 to 20% decreases, depending on the season). This indicates an increased likelihood of droughts (Kerr, 2005) and variability of precipitation-in time, space, and intensity-that would directly influence water resources availability and river basin management.

In the face of these changes, one possible strategy for farmers to reduce the costs associated with greater uncertainty is the hiring of insurance schemes. However, the decision to hire insurance implies a considerable economic cost for farmers. As a result, drought information will be highly valued in a context of water scarcity since it will help determine the extent to which hydrological risk insurance is a worthwhile cost for farmers. Whereas the cost of crop failure due to water

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Abbreviations used: AEMET (Spanish Meteorological Agency); C (cost of the insurance); CARA (constant absolute risk aversion); CE (certain equivalent); DR (demand-reliability); GCM (global circulation model); GDP (gross domestic product); OLS (ordinary least squares); RCP (representative concentration pathways); SPI (standardized precipitation index); SRES (special report on emissions scenarios); VIF (variance inflation factor); WAPA (water and policy analysis).

shortages occurs only in periods of unexpected drought, the cost of hiring insurance is incurred even when drought does not occur. Therefore, the value of information is given by the extent to which it can help agents allocate resources in the most efficient manner possible.

The main achievement of this paper is to present a methodology integrating agricultural, hydrological and economic models that allow the estimation of benefits from a hydrological drought insurance calculated as farmers' willingness to pay. Analytical expressions for this benefit are presented as a function of the drought impacts so the maximum risk premium that farmers will accept can be calculated once estimations about the drought losses are available. An example is presented considering a risk premium in order to illustrate how the results can be used.

In sum, the value of drought information under a changing climate is related to the extent to which it can help farmers' lower costs and risk in the long run. This paper provides an assessment of the economic value of drought information for irrigating farmers under climate change, applied to maize cultivation in the Ebro basin.

Material and methods

First, we provide an overview of climate change information about drought events in the Mediterranean. This is followed by a description of the climate change adaptation alternatives analysed in this study, an overview of the case study area as well as the Water and Policy Analysis (WAPA) Model applied. We then discuss the crop production function, the decision model and the calculation of the economic value of information (Fig. 1).

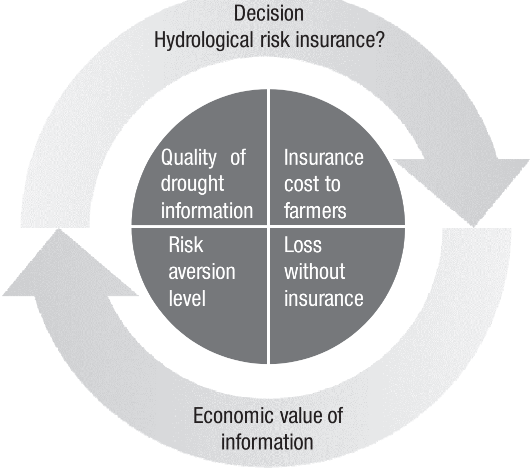

Figure 1. Steps of methodology.

Climate change information about drought events in the Mediterranean

Under normal-non drought-conditions many areas of Spain face significant problems due to the unbalanced distribution of water resources, conflicts among users, and between regions. Recurrent drought episodes in the country lead to the intensification of these problems and add to the complexity of water management. Drought events in Spain have been more frequent after 1970 (Iglesias *et al.*, 2007) with economic and social damage increasing from year to year.

Since the runoff output from the GCMs (Global Circulation Model), is not adequate for the analysis, a downscaling technique must be applied. Over the last few decades, scientists have developed techniques of regionalization or "downscaling" (dynamic and statistical) in order to translate the climatic variations into results on a regional scale (Khan *et al.*, 2006; Brekke *et al.*, 2008). Though there is extensive literature on the strengths and weaknesses of the methods of downscaling climatic variables to smaller cells, less attention has been paid to downscaling to examine the impacts of climate change on water resources systems in terms of runoff or groundwater recharge (Fowler *et al.*, 2007; Cayan *et al.*, 2008). Some research (Zhu *et al.*, 2005) employed hydrologic response ratios to translate historical streamflow in a system to streamflow under climate change conditions. Here we follow two approaches to derive the downscaled runoff for the Ebro basin.

Climate change adaptation measures

Water resources system models can be useful tools to study the effects of climate change and to identify adaptation strategies in the water sector. Climate change scenario projections for the Ebro basin imply that current agricultural water demands cannot be satisfactorily met.

In order to analyze the vulnerability of the system, we need to estimate the evolution of water demand expected in the system during the selected scenarios (period 2071-2100). Then, in order to evaluate system performance and aid in the planning and management decision process, two management options can help to analyze impact, vulnerability and potential adaptation to projected climate change. Several authors have proposed different indices to condense the results of water resources system management models. Reliability describes how likely a system is to fail (Hashimoto *et al.*, 1982a,b; El-Baroudy and Simonovic, 2004). Reservoir regulation has been one of the most important water resources management strategies in Spain in recent years and has generated significant impacts. The management of water allocation to reduce the disparity between water supply and demand has to take into account changes on water supply reliability.

Drought events are a key factor determining water supply and reliability since under drought conditions water systems reduce normal conditions and the probability of the system failing increases. Therefore, drought occurrence is an important factor to consider when designing water management plans.

In adapting to a possible reduction of water supplies in water systems, we have considered two different alternatives: the first considers maintaining water allocation for agriculture, thereby reducing supply reliability and the second considers a reduction in water allocation for agriculture, thereby increasing supply reliability. The hypotheses are described in Table 1.

Table 1. Structure of the decision making problem

Action	State of nature	
	Occurrence of extreme event (hydrological drought) (θ = 1)	No extreme event (normal conditions) (θ = 0)
Without insurance	Production loss due to the occurrence of a drought event (-*L*)	No production loss (0)
With insurance	Cost of the insurance (-*C*)	Cost of the insurance (-*C*)

Alternative 1: Without insurance

Under this alternative, the quantity of irrigation's water is assigned for river basin authorities and does not change under normal conditions. In this case the probability of failure is very small; this probability of failure is the risk that irrigators are willing to take without insurance. In the case of hydrological drought the water failure leads to crop loss; the losses are determined by the drought intensity and the probability of reduced water. In all future climate scenarios analysed the supply reliability is reduced, and irrigators may be exposed to water scarcity during drought years. In normal years (no drought), agricultural production will be maintained at the current level, and there will be no net loss. In drought years, there will be water shortages, and agricultural production will be reduced accordingly. If Y is average crop yield for current water allocation in normal years, average crop yield during drought years will be a fraction of Y, k Y, with k < 1. Under the occurrence of a drought event, farmers will take a production loss, L, equal to:

$$L = Y - kY = (1 - k)Y \qquad [1]$$

In this case, farmers cannot implement adaptation measures such as reducing the cultivated land or changing crops as possible responses to reducing the impact of water shortages. This is because under this alternative, it is assumed that water shortage cannot be anticipated and the system fails to respond to an extreme event (drought). The yield loss for Alternative 1 is therefore higher.

The probability of having water shortages in any given year, P_θ, is computed with the help of a water resource system simulation model and is given by the supply reliability of agricultural demand, R:

$$R = \frac{N_a}{N_t} \qquad [2]$$

where N_a is the number of years in the simulation with acceptable water supply and N_t is the total number of years. P_θ will be: $P_\theta = 1 - R$.

Alternative 2: With insurance

Under this alternative, irrigators purchase hydrological drought insurance to cover the crop losses derived from water failure. This insurance represents a cost to the irrigators that is characterised as a function of crop loss. In this case the irrigators incur in an insurance cost both under normal and drought conditions. In this case, farmers will not be exposed to crop losses during drought years, because the insurance will be able to overcome the drought situation from the economic point of view. However, the insurance cost (C) will entail an additional production cost every year.

This loss can be expressed as a fraction γ of the loss taken under alternative one: $C = \gamma L$.

In Alternative 2, farmers are assumed to attempt to adapt to the reduced water availability, which ensures that the economic loss is less than in Alternative 1 during drought conditions. However, this economic loss is permanent and not associated to a particular extreme event.

Quantitative parameters for the decision problem can be obtained from the demand-reliability curve, which is obtained by computing the evolution of reliability as demand value is changing. For instance, Figure 2 presents an example of demand-reliability analysis in a basin for a given climate change scenario. In this paper, we use three economic scenarios, a baseline scenario, and A2 and B2 socio-economic scenarios of the Special Report on Emissions Scenarios (SRES). These scenarios represent two different world futures, both have a high economic emphasis but B2 focus on regional development patterns versus A2, which have a more global emphasis. In both scenarios, gross domestic product (GDP) increases substantially with economic convergence at differing rates and global population increases throughout the 21st century. A2 and B2 are better described in IPCC (2007). Under the control (current) scenario, the demand-reliability curve provides reliability for current water allocation in the basin, which is above the acceptable threshold. Under the climate change scenario (A2), the demand reliability curve changes. If water allocation is maintained at current level, demand reliability would be lowered to A2 reliability, below the acceptable threshold.

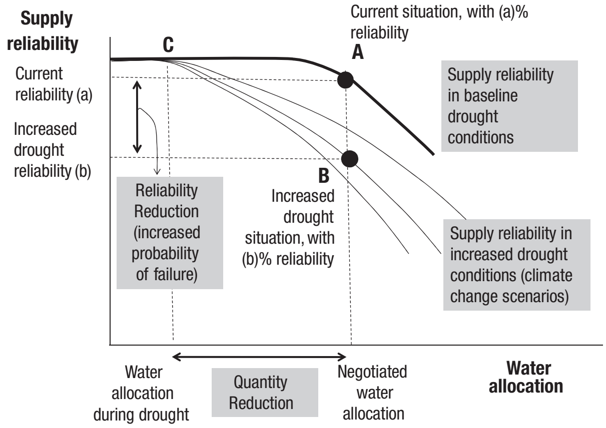

Figure 2. Framework of demand-reliability analysis in a basin for a given climate change scenario (*e.g.* under A2 socio-economic scenario).

Description of the case study

Our study focuses on the Ebro river basin. The Ebro basin, located in the northeast of the Iberian Peninsula, is the largest basin in Spain, with an area of 85,000 km^2 and a mean annual runoff of 16.92 km^3 yr^{-1}. It currently supplies water to 2.7 million people and around 800,000 ha of irrigated land. Urban supply and consumptive industrial demand is 0.96 km^3 yr^{-1} and irrigation demand is 6.32 km^3 yr^{-1}.

To illustrate the loss of production generated from differences in the management of water systems, we analyse maize (*Zea mays* L.) production in the south provinces of the Ebro river basin. Although our analysis uses maize cultivation as an example, we have not modelled water for maize production specifically but we assume that reductions of water allocation are equally distributed between different crops. Empirical data suggest that reductions are targeted to crops with lower water productivity instead. The main objective of the paper is to provide a methodology to assess the benefits of the insurance rather than assess the real level of insurance. In order to assess the real impact a farm model instead of a crop model could be used, as shown in Gómez-Limón *et al.* (2004).

Water availability and policy analysis (WAPA) model

Quantitative parameter values for the formulation of the decision problem were obtained with WAPA, a simplified water resources simulation model applied to the Ebro basin (Quiroga *et al.*, 2011).

WAPA was used to compute the demand-reliability (DR) curve, which provides a simple way to evaluate water availability under different climate change scenarios. WAPA simulates the joint operation of all reservoirs in a basin to satisfy a unique set of demands. Irrigation demands considered in the model typology are those defined in the National Hydrological Plan and the Ebro Hydrological Plan. Basic inputs to the WAPA model are the river network topology, the reservoir characteristics (monthly maximum and minimum capacity, storage-area relationship and monthly evaporation rates), the naturalized stream flow series entering different points of the river network, the environmental flow conditions downstream of reservoirs and monthly values of urban and agricultural demands for the entire basin. The model is based on the mass conservation equation, and main assumptions refer to how reservoirs are managed in the system: to supply demands any given month, water is preferentially taken from the most downstream reservoir available, since spills from upstream reservoirs can be stored in downstream ones. In each time step, the model performs the following operations: (1) satisfaction of the environmental flow requirement in every reservoir with the available inflow; environmental flows are passed to downstream reservoirs and added to their inflows; (2) computation of evaporation in every reservoir and reduction of available storage accordingly; (3) increment of storage with the remaining inflow, if any; computation of excess storage (storage above maximum capacity) in every reservoir; (4) satisfaction of demands ordered by priority, if possible; use of excess storage first, then available storage starting from higher priority reservoirs; and (5) if excess storage remains in any reservoir, computation of uncontrolled spills.

The result of the joint reservoir operation model is a set of time series of monthly volumes supplied to each demand and monthly values of stored volume, spills, environmental flows and evaporation losses in every reservoir. Reliability is computed for every demand by comparing the actual supply values during the simulation with theoretical demand values. A macro is available to repeat the computations changing values of a given demand type, which allows the computation of the demand-reliability curve.

The WAPA model was applied to the Ebro basin system composed of 34 rivers, 27 major reservoirs totalling 7.13 km^3 of reservoir storage, an urban demand of 0.96 km^3 yr^{-1} and current irrigation demand of 6.35 km^3 yr^{-1}. Naturalized monthly streamflow series are available for 47 points in the river network for the period 1940-1996. This data set was assumed to correspond to the control situation. Climate change scenarios were generated for every streamflow point in the Ebro basin by transforming the mean and coefficient of variation of the original series as suggested by the corresponding climate projection. Environmental flows were fixed at 10% of mean annual flow in every location.

Climate change in the Ebro basin is characterised from downscaled global change scenarios obtained from the Prudence project (Christensen and Christensen, 2007; Fronzek and Carter, 2007) and from the Spanish National Adaptation Plan (MARM, 2006). Table 2 shows how downscaled scenarios were derived in this study. The socio-economic scenario used is A2 (Nakicenovic, 2000) that represent theoretically different but relatively high emissions of the representative concentration pathways (RCP) (Moss *et al.*, 2010). Since no single projection is a prediction, scenarios represent alternative futures. Here we use 11 climate change scenarios constructed as a combination of Global Climate Model (Had CM3) downscaled for Europe with 11 Regional Climate Models and downscaled for the Iberian Peninsula with one Regional Climate Model and different methods of statistical downscaling. Runoff data from climate scenarios was obtained directly from the Prudence project for the scenarios included in Table 2. These results, which vary in resolution from 50 km to 22 km, are publicly available on the web page http://prudence.dmi.dk/. The timeframe for the selected scenarios is the period 2071-2100.

Table 2. Climate change runoff projections in the Ebro basin taken from PRUDENCE project. Emission scenario A2

Scenario name	GCM model / Downscaling method[1]	Runoff change mean (%)	Runoff change Coeff. Var. (%)
DMI1-A	HadCM3/DMI	–28	–11
DMI2-A	HadCM3/DMI	–35	–28
DMI3-A	HadCM3/DMI	–39	–2
ETH-A	HadCM3/ETH	–45	+58
GKSS-A	HadCM3/GKSS	–31	+19
ICTP-A	HadCM3/ICTP	+28	+2
KNMI-A	HadCM3/KNMI	–46	+38
MPI-A	HadCM3/MPI	–42	+6
SMHI	HadCM3/SMHI	–33	+31
UCM-A	HadCM3/UCM	–36	+72
PRUD-A		–31	+18

[1] DMI: Danish Meteorological Institute, Denmark. ETH: Eidgenössische Technische Hochschule, Switzerland. GKSS: Forschungszentrum Geesthacht GmbH, Germany. ICTP: International Centre for Theoretical Physics, Italy. KNMI: Royal Netherlands Meteorological Institute, Netherlands. MPI: Max Planck Institute, Germany. SMHI: Swedish Meteorological and Hydrological Institute, Sweden. UCM: Universidad Complutense de Madrid, Spain.

A fixed value of 0.96 km^3 yr^{-1} of urban demand and a variable irrigation demand was considered in order to obtain the demand-reliability curve for irrigation demand. Priority was given to urban demand over irrigation demand. The reliability measure applied to compute the demand-reliability curve was:

$$R^k = 100\frac{N_a^k}{N_{tot}} \qquad [3]$$

where R^k is time reliability in percentage, N_a^k is the number of years with acceptable water supply (years where total supply is above a given threshold, *k)*, and N_{tot} is the total number of years. A threshold of 98% of total demand was selected as acceptable supply in any given year.

Figure 2 shows the framework of the described demand-reliability analysis in a basin for a given climate change scenario. The dot plots in Figure 2 (A, B, C) represent the different possibilities considered in the analysis. A represents the current situation corresponding to the threshold of 98% of total demand as acceptable supply; C represents the water allocation when drought conditions are given; and B represents the supply reliability loss if the water allocation is maintained in a situation of run-off reduction. Figure 2 intents to reflect the existing trade-off between water allocation and supply reliability.

Crop production functions of yield response

Statistical models of yield response have been used to estimate the water requirements and to evaluate extreme events' effects such as drought, frost or floods, at different locations for selected crops (Moss and Shonkwiler, 1993; Dixon *et al.*, 1994; Iglesias *et al.*, 2000; Chavas *et al.*, 2001; Parry *et al.*, 2004; Lobell *et al.*, 2008). Statistical models of yield response have proven useful to assess the sensitivity and adaptation to climate change (Parry *et al.*, 2004; Stanger *et al.*, 2008; Ciscar *et al.*, 2010; Iglesias *et al.*, 2010), and have shown their efficiency in the estimation of the risk associated with climate variability and their potential applications in crop insurance (Luo *et al.*, 1994; Ferreyra *et al.*, 2001; Iglesias and Quiroga, 2007); linking bio-physical and socio-economic factors introducing environmental, hydrological, technological, geographical and economic variables to characterize crop yield.

In order to determine the yield variability to the effects of drought events and water management, we estimated a multiple linear regression model using ordinary least squares (OLS) with bio-physical and socio-economic data as explanatory variables. We specifically used the usual Cobb-Douglas specification, as it allows a simple estimation and the coefficients obtained have a very intuitive interpretation in terms of elasticities. This function is not unique and varies among crops and zones.

In our model the dependent variable is ln Y_t, which is the natural logarithm of the crop yield in a site in the year *t*. Crop yield (*Y*) is computed as the ratio between production (in t) and agricultural total area (in ha). Observed annual cereals production data and agricultural total area (1976-2002) at the province level were obtained for the south provinces on the Ebro river basin, from the Statistical Division of the Spanish Ministry of Agriculture (MARM, 2010). The explanatory variables were divided in three categories: management, water and climate:

Management variables

To consider the effect of technology indicators, we have incorporated several management variables, such as, irrigated area and diverse types of fertilizers and machinery like tractors and combines (Iglesias and Quiroga, 2007; Quiroga and Iglesias, 2009). These management variables are $Irrig\_area_t$ and $Comp1\_Tech_t$. $Irrig\_area_t$ is defined as the ratio between irrigated area and total crop land, by crop type. Data were obtained from the Spanish Ministry of Environment (MARM, 2010). On the other hand, fertilizers and machinery variables came from FAO (FAOSTAT, 2010). However, all these variables are highly correlated (see Table 3) and lead to problems of multicollinearity in the regression analysis. To solve this problem we used principal components analysis and generated a new variable called $Comp1\_Tech_t$. The idea of

Table 3. Correlation matrix for technological variables

		Machinery		Fertilizers		
		Tractors	**Combines**	**Nitrogen**	**Phosphate**	**Potash**
Machinery	Tractors	1				
	Combines	0.9462	1			
Fertilisers	Nitrogen	0.7045	0.7758	1		
	Phosphate	0.6888	0.7232	0.8405	1	
	Potash	0.8958	0.8897	0.7587	0.89	1

using principal components in regression is not new (see Kendall, 1957; Jeffers, 1967). This technique 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 (Blattberg, 2008). Assuming an ($n \times k$) matrix of X of n observations on k variables with $\sum$ variance-covariance matrix, the objective of principal components analysis involves an orthogonal transformation of a set of variables ($k_1, k_2, \ldots, k_n$) into a set of components denoted by P, where P is ($n \times p$) and $p \leq k$. These components are uncorrelated with each other, even though the original variables are quite highly correlated and there are the same numbers of components as original variables, and the total variance of the variables is preserved exactly in the total variance of the new components. The first principal component (p_1) accounts for the highest proportion of the total variance, the second (p_2) reports the highest remaining, and so on (Jolliffe, 1982, 1986; Brook *et al.*, 1986; Blattberg, 2008). In this study, we only consider the first component, which explains 85% of the variability of data. However, Jolliffe (1982) showed that there is a misconception about the principal components with small eigenvalues in a regression, and demonstrated that these components can be as important as those with large variance. The alternative approach to determine the number of components to use is by using AIC, the Akaike's information criterion. In our analysis, this test verifies the importance of the first component.

The principal components methodology has been used here to capture the marginal effect of technology on crop yields. Other approaches for crop production functions do not take into consideration the technological factor explicitly but include a trend to make the time series stationary (Gil *et al.*, 2010, 2011). This is an alternative assuming an average increase in yields across time. In our approach, the marginal effects can be interpreted and give additional information about the growth patterns. This approach has been widely used for global analysis (Parry *et al.,* 2004; Lobell *et al.*, 2006), for European projections (Iglesias *et al.*, 2007, 2011) and more specifically in Spain (Iglesias and Quiroga, 2007; Quiroga and Iglesias, 2009; Quiroga *et al.*, 2011). Table 4 shows the correlation matrix of variables and components, with the purpose of a better interpretation of this variable in the regression analysis.

Water variables

In this category, we consider precipitation and water for irrigation, these are $Prec_{it}$ and $Irrig_{it}$, respectively. $Prec_{it}$ is the total precipitation in mm in the i^{th} month or 3-month period in year t, It was taken from the Spanish Meteorological Agency (AEMET, 2010). To build a proxy variable for irrigation ($Irrig_{it}$), we used data on net crop water requirements from the Ebro basin management authority (CHEBRO, 2004). It is a good approximation given that currently there are no explicit restrictions on the irrigated area in the Ebro basin. We assume that water requirements of crops are being met. These variables are at the province level. Precipitation data was obtained from the main station of the province. When more than one principal station is located in one province, AEMET aggregated them to obtain a province level data. The variable $Irrig_{it}$, is considered for each of the crops also at the province level.

Climate variables

Data of monthly maximum temperatures (T_Max_{it}), mean temperatures (T_Mean_{it}) in degree Celsius (ºC), and number of days below 0ºC (Fr_{it}) were taken from AEMET (2010). In this case the subscript i^{th} refers to periods of 1 or 3 months in year t. Also, it is known that in the Ebro basin exists a very high variability in precipitation and it is common to observe that recurrent drought periods affect agricultural production. Nowadays, drought characterization is difficult because of

Table 4. Principal components analysis: correlation matrix of variables and components

	Comp1	Comp2	Comp3	Comp4	Comp5
Tractors	0.9216	–0.3592	0.0204	0.1381	0.0466
Combines	0.9425	–0.2671	0.1210	–0.1586	0.0228
Nitrogen fertilisers	0.8820	0.3308	0.3314	0.0400	–0.0367
Phosphate fertilisers	0.8972	0.3762	–0.2166	–0.0157	0.0792
Potash fertilisers	0.9638	–0.0482	–0.2395	0.0011	–0.1070

their spatial and temporal properties and the lack of a universally accepted definition (Bradford, 2000; Keyantash and Dracup, 2002; Hayes, 2002; Tsakiris *et al.*, 2007). Given that, we chose for the commonly used Standardized Precipitation Index (SPI, McKee *et al.*, 1993). The SPI calculates the difference of accumulated precipitation between a selected aggregation period and the average precipitation for that same period and for any location. For its calculation it is necessary a long-term precipitation record. This precipitation record is normalized so that all precipitation values vary around 0, then areas with different climates can be relatively compared (McKee *et al.*, 1993; Steinmann *et al.*, 2005). In this paper, we have selected 12 months as the aggregated period for calculation and defined the threshold of drought as values of SPI < –1, following previous detailed work in Spain (Garrote *et al.*, 2007; Iglesias *et al.*, 2007). Then Dro_t, a dummy variable = 1 if the year *t* is a drought year (with SPI < –1) and = 0 in other cases, has been constructed. All the variables are summarized in Table 5.

The specified model has this general form:

$$\begin{aligned}\ln Y_t &= \alpha_0 + \alpha_1 Comp1\_Tech_t + \alpha_2 Irrig\_area_t + \alpha_3 \ln Irrig_{it} \\ &+ \alpha_4 \Pr ec_{it} + \alpha_5 T\_Max_{it} + \alpha_6 T\_Mean_{it} + \alpha_7 Fr_{it} + \alpha_8 Dro_t + \varepsilon_t\end{aligned} \quad [4]$$

As we said above, we used OLS to estimate the coefficients from the observed time series (1984-2002). In order to improve particular model estimation for each crop, the coefficients were estimated assuming normality of the residuals, and significant relations were considered into the estimated model. In order to avoid multicollinearity problems, we calculated the variance inflation factor (VIF) for each of the explanatory variables. Akaike (1973) and Schwarz (1978) criteria and adjusted R^2 criteria have been used to assist in the selection of suitable models. The Ljung-Box Q test, based on the autocorrelation plot, was used to test the absence of autocorrelation in the residuals. White's general test (White, 1980) was used to test conditional heteroscedasticity.

When the parameters α_i are estimated, the marginal effect of a change in the explanatory variables is given by:

$$\frac{\partial E[\ln Y \;\; \ln X_i]}{\partial X_i} = \alpha_i$$

The signs and magnitude of the marginal effects indicate the effect of a particular input variable X_i over the crop yield. Given that the model presents a semi-logarithmic transformation, the coefficients have to be interpreted as semi-elasticities, so the interpretation is the percent increase of yields produced given a unit change in the input variable.

Decision model and risk aversion

Our decision making problem has the same structure of the more general cost-loss ratio situation problem also widely known as the "umbrella problem". The cost-loss ratio situation is a decision-making problem widely analyzed in the literature in assessing the economic value of weather forecast (*e.g.,* Murphy *et al.*, 1985; Murphy and Ehrendorfer, 1987; Katz, 1993; Palmer, 2002; Katz and Ehrendorfer, 2006). The model involves two possible actions, protect, and not protect, and two possible events, adverse weather, and no ad-

Table 5. Summarized description of the variables

Type of variable	Name	Unit	Source of data
Economic	Y_t	t ha^{-1}	MARM (2010)
Water	$Irrig_{it}$	m month^{-1}	CHEBRO (2004)
	$Prec_{it}$	mm month^{-1}	AEMET (2010)
Management	$Comp1\_Tech_t$	Standardized units	Own elaboration from FAO data (2010)
	$Irrig\_area_t$	Per unit of crop land	MARM (2010)
Climate	T_Max_{it}	° Celsius	AEMET (2010)
	T_Mean_{it}	° Celsius	AEMET (2010)
	Fr_{it}	Number of days below 0°C	AEMET (2010)
	Dro_t	Dro = 1 when drought occurrence and Dro = 0 in other case (based on SPI critical values)	SPI calculated from AEMET precipitation data (2010)

verse weather. The decision maker is assumed to incur a cost C if protective action is taken, and a loss L if protective action is not taken and adverse weather occurs, and no cost or loss otherwise. An expected value approach has been commonly used.

However, results highly depend on agents' behaviour with respect to risk. Most of the studies consider that agents are neutral to the risk, but there is evidence of risk aversion under most situations. In Cerdá and Quiroga (2011) a model is proposed to evaluate the information considering the risk aversion level. The role of risk aversion is analyzed here by considering that the manager decides between Alternative 1 (more risk) and Alternative 2 (less risk) and calculating how much money is willing to pay for having less risk. We assume that farmer preferences can be represented by the expected utility with the utility function $U(–)$, the CARA (constant absolute risk aversion) function (Mas-Colell *et al.*, 1995) being:

$$U(x) = -\exp\left\{-\rho x\right\} \qquad [5]$$

where x is the monetary gain and $\rho > 0$ is the Arrow-Pratt coefficient of absolute risk aversion, which is constant for this function.

The Arrow-Pratt absolute risk aversion coefficient can be interpreted as the percentage change in marginal utility caused by each monetary unit of a gain or loss (Raskin and Cochran, 1986). If the Arrow-Pratt absolute risk aversion coefficient does not change across the monetary level, the decision-maker exhibits CARA, which implies that the level of the argument of the utility function does not affect his or her decisions under uncertainty. This is suitable for the farmer's decision problem if the risk aversion remains independent on the harvest value. Gomez-Limón *et al.* (2003) present extended discussion on the analysis of agricultural risk aversion. As in Quiroga *et al.* (2011), we consider the incorporation of several scenarios to the model that generate several information systems with different probabilities associated to the extreme event (hydrological drought). Table 6 summarizes the variables introduced in the model and the source of information for the case study considered.

Computing farmers willingness to pay for the insurance

In order to achieve a monetary value unchanging with linear utility transformations to compute the amount of money that farmers will pay for the insurance, we have considered the certainty equivalence approach. The certain equivalent (*CE*) can be defined as the amount of money for which the farmer is indifferent between the gamble and the certain amount *CE* (Mas-Colell *et al.*, 1995) that is the amount of money producing the same utility without uncertainty as the expected utility when the risk exists.

The *CE* allows us to define a value of information in monetary terms. The optimal policy for the decision

Table 6. Description of the variables included in the decision making model

Name	Variable	Source of information
θ	Extreme event variable $\theta = 1$, "drought event"; $\theta = 0$, "no drought event"	SPI calculation
K	Reduction coefficient for production during drought years	Crop production functions
$L = Y - (K \cdot Y) = (1 - K)Y$	Production loss during dry years in the case of a reduced guarantee	Crop production functions
β	Reduction coefficient for water demand	WAPA simulations
α	Yield elasticity to irrigation water availability	Crop production functions
C	Loss when the water for irrigation is reduced. % of the loss when the guaranty is reduced: $C = Y - (\alpha\beta Y) = (1 - \alpha\beta)\, Y = \gamma L$	WAPA simulations and crop production functions
ρ	Arrow-Prat absolute risk aversion coefficient	Calibration based on Gómez-Limón *et al.* (2003)
P_θ	Climate information: $\Pr[\theta = 1]$	WAPA simulations
q	Forecast quality: *Corr* (θ, Z), where Z represents imperfect forecast variable; $Z = 1$, "adverse weather"; $Z = 0$, "non adverse weather"	Sensitivity analysis

Source: Quiroga *et al.* (2011).

making problem with risk defined in Table 1, was analysed in Cerdá and Quiroga (2011). The optimal farmer decision considering the maximization of the expected utility criterion is:

(i) Alternative 1 if $A > P_\theta$, and in this case the expected utility is $EU(0) = -P_\theta \exp\left\{\rho L\right\} + P_\theta - 1$.

(ii) Alternative 2 if $A < P_\theta$, and the expected utility is $EU(1) = -\exp\left\{\rho\gamma L\right\}$.

(iii) Indifference between both alternatives if $A = P_\theta$

where $A = \dfrac{1-\exp\left\{\rho\gamma L\right\}}{1-\exp\left\{\rho L\right\}}$.

Considering this optimal policy we can compute the farmer's willingness to pay for the insurance (C) as the monetary amount that make the farmer prefer the insurance option. That occurs if and only if:

$$\frac{1-\exp\left\{\rho\gamma L\right\}}{1-\exp\left\{\rho L\right\}} < P_\theta \Leftrightarrow \exp\left\{\rho\gamma L\right\} < 1 - P_\theta\left(1-\exp\left\{\rho L\right\}\right) \quad [6]$$

So we have that the maximum willingness to pay for the insurance can be computed as:

$$C = \gamma L < \frac{\ln\left[1 - P_\theta\left(1-\exp\left\{\rho L\right\}\right)\right]}{\rho} \quad [7]$$

If the cost of insurance (C) exceeds this amount, farmers will prefer the Alternative 1 (without insurance). This threshold increases with the absolute risk aversion coefficient of Arrow-Pratt ρ. So, as expected, with a more risk adverse agent the willingness to pay increases. Although individuals' risk tolerance varies, we assume that $\rho = 0.5$ represents the risk aversion coefficient. Palacios-Huerta (2003) suggested that ρ typically ranges from 0.3 to 0.7, centred on 0.5. So, using the WAPA simulations and the production functions results, we have calculated the monetary gains or economic value of the extremes information systems.

Results

Water allocation reductions and water reliability trade-off

The results obtained are presented in Figure 3 and in Table 7. Figure 3 presents the demand-reliability curves of irrigation demand, once urban demand has been satisfied, for current conditions and for average projections. Desired reliability (98%) is represented as a horizontal dashed line. Intersections of this line with the demand reliability curves in climate change projections correspond to the maximum irrigation demand values that are allowed to maintain the desired reliability. Current demand (6.32 km^3 yr^{-1}) is represented as a vertical line. Intersections of this line with the demand reliability curves in climate change projections correspond with the reliabilities that would be obtained if irrigation demand was left unchanged. Numerical values for all projections are presented in Table 7.

Water effects on irrigated agricultural production

Table 8 shows the result of the statistical function of yield response to water. The coefficients of the model can be interpreted as direct elasticities since the model presents a logarithmic transformation except for the drought effects. So, the estimated coefficients represent the proportional changes on the dependent variable, when a 1% change is produced on the explanatory variable associated to this coefficient. Drought variable coefficient can be interpreted as semi-elasticity, and represents the percent variation of yield when drought occurs. Due to the presence of heteroskedasticity, we used the White test (1980) to obtain robust estimates. Technological change, represented by farm machinery, results in yield increases for crop production. This variable is the main driver of the productivity. Then, irrigation has also a

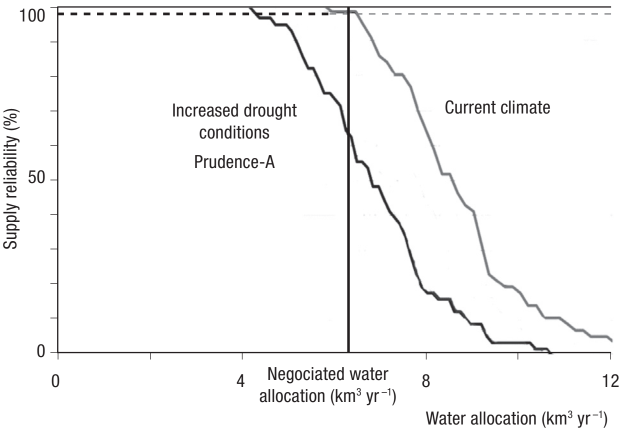

Figure 3. Demand reliability curves for current conditions and for climate projection PRU-A average of Prudence models for A2 scenario. Source: Quiroga *et al.* (2011).

Table 7. Summary of results from the WAPA model

Projection	Mean annual runoff ($km^3\ yr^{-1}$)	Change in mean annual runoff (%)	Change in coef.var. annual runoff (%)	Irrigation demand for 98% reliability ($km^3\ yr^{-1}$)	Required reduction of irrigation demand β	Reliability for current irrigation demand (%)	Probability of water shortage for current irrigation demand P_0
DMI1-A	12.18	–28	–11	5.50	0.13	80	0.20
DMI2-A	11.00	–35	–28	5.42	0.14	70	0.30
DMI3-A	10.32	–39	–2	4.61	0.27	54	0.46
ETH-A	9.31	–45	58	2.67	0.58	43	0.57
GKSS-A	11.68	–31	19	4.41	0.30	64	0.36
ICTP-A	21.66	28	2	7.70	0.00	100	0.00
KNMI-A	9.14	–46	38	3.15	0.50	41	0.59
MPI-A	9.81	–42	6	4.14	0.34	48	0.52
SMHI-A	11.34	–33	31	3.80	0.40	59	0.41
UCM-A	10.83	–36	72	2.72	0.57	54	0.46
PRU-A	11.68	–31	18	4.41	0.30	64	0.36

Source: Quiroga *et al.* (2011).

positive impact, so reductions in water availability for irrigation will result in a decrease of yields. The water output elasticity is 0.10, which indicates that a decrease of 1% in the water for irrigation will lead to a decrease of more than 10% in the crop yield. This reduction is not so high, but it is important to notice that during drought events, a reduction of more than 14% have to be added (since elasticity of drought is 0.14). The Ebro Basin is located in the Northeast of the Iberian Peninsula with a primarily Continental Mediterranean climate, characterized by hot-dry summers and cold-wet winters. By now there are no explicit restrictions on the irrigation area in the Ebro basin. However, in a climate change context with more drought events and the water framework directive environmental restrictions, the scene can be very different.

Computing farmers optimal decision making

The payoff matrix for each of the scenarios considered was calculated from the WAPA simulations and the crop production functions. Table 9 shows an example of the decision making problem under the Prudence-A scenario. Alternative 2 (with insurance) acts as a non risk option, since the farmers know by how much is going to pay for the insurance. This reduction takes place independently of the existence of drought. On the other hand, under Alternative 2 (without insurance) farmers do not pay the insurance cost, but if hydrological drought occurs higher losses are expected. If drought does not occur, the system will not fail and farmers will not suffer water shortages, in which case no losses are incurred and they saved the insurance cost.

Table 8. Estimated coefficients of the crop production function for maize production

Dependent variable: logarithm of maize yield				
Variable	**Coeff.**	***p*-value**	**[95% confidence interval]**	
$Comp1\_Tech_t$	0.1424	0.0000	0.1091	0.1756
ln_Irrig_{it}	0.1922	0.0000	0.1324	0.2520
$Prec_{jja}$	0.0015	0.0050	0.0005	0.0025
T_Mean_{year}	–0.1582	0.0000	–0.2428	–0.0735
Constant	4.0150	0.0000	2.7363	5.2937
Observations	226			
Adj R^2	0.5559			
White test *p*-value	0.0000			

Table 9. Payoff matrix reduction of maize yield for Prudence-A scenario

Action	State of nature	
	Occurrence of extreme event (drought years) ($\theta = 1$)	**No extreme event (non-drought years) ($\theta = 0$)**
Insurance	Cost of hydrological drought insurance –3%	Cost of hydrological drought insurance –3%
No insurance	Production loss due to the occurrence of hydrological drought –13.58%	No production loss 0%

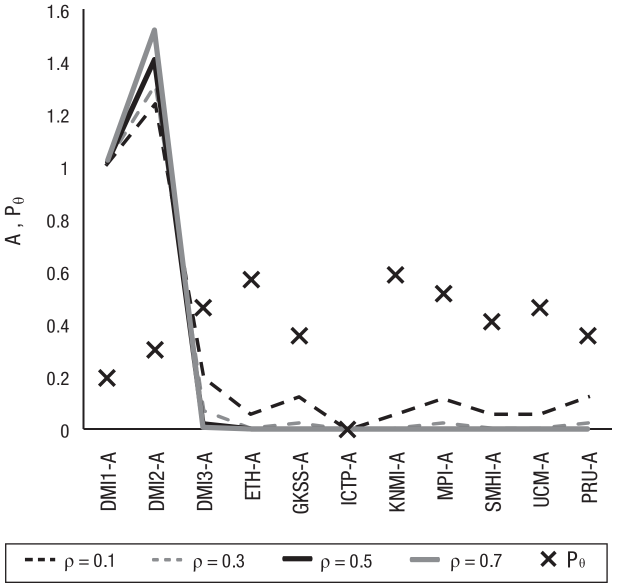

Figure 4. Optimal policy for different levels of risk aversion considering an insurance cost of 3% of crop yield.

In Spain, hydrological drought insurance is being considered as an option but still not in practice. Drought insurance for cereals can have an additional cost of approximately 3%. For example, a farmer with a harvest of 2700 kg ha^{-1} of barley in Segarra county has to pay a risk premium of 5.51% for the drought insurance, while the normal conditions insurance (without considering drought) is about 2.26%. As an illustrative example, we have computed the optimal policy for the hydrological risk insurance in the case of a cost of 3% of crop yield. The loss has been computed with the statistical function of yield response for the Prudence-A scenario.

The optimal policy is calculated as described in the methodology. Figure 4 shows the optimal policy regions for the considered scenarios. The Arrow-Pratt's risk aversion coefficient (ρ) ranges between 0.1 and 0.7. The bigger the value for ρ, the higher the risk aversion considered. The X dots represent the probability of drought events (P_θ). The lines are the thresholds bellow which the farmer should take Alternative 1. They depend on the risk aversion coefficient. For the scenarios in which the X dot is over the lines, Alternative 2 (contract insurance) is the optimal decision for the farmer, independently of the risk aversion coefficient considered. On the other hand, for the scenarios in which the X dot is below the lines, Alternative 1 (not to contract insurance and take the risk of hydrological drought) is the optimal decision. Therefore, the different lines represent the threshold above which, the decision makers take an alternative or another for different levels of risk aversion. In our study, we can observe that for DMI1_A and DMI2_A scenarios, farmers will not contract a hydrological drought's insurance whichever the risk aversion level. In most of the remaining cases, farmers will prefer Alternative 2 (take the insurance). ICTP-A is not significant because under this scenario the probably of drought is equal to zero, so this implies no risk of hydrological drought and the decision is not relevant. The results show that there is no optimal policy response and that this is highly dependent on the scenario considered. This is indicative of the importance and relevance of the climate change information.

Willingness to pay for drought insurance

In Figure 5 we present the economic cost that a farmer could accept for hypothetical hydrological risk insurance. In other words, this graph represents the willingness to pay of the farmers for drought insurance as a percentage of the crop yield, for the different climate change scenarios. The thresholds have been computed as reported on the methods section.

Each climate change scenario is associated with a different estimated probability of drought (P_θ) and a different runoff reduction in the case of hydrological drought, and as we have seen above, this determines the optimal farmer decision.

Based on our analysis in the Ebro River Basin, we observe that the willingness to pay for a hypothetical

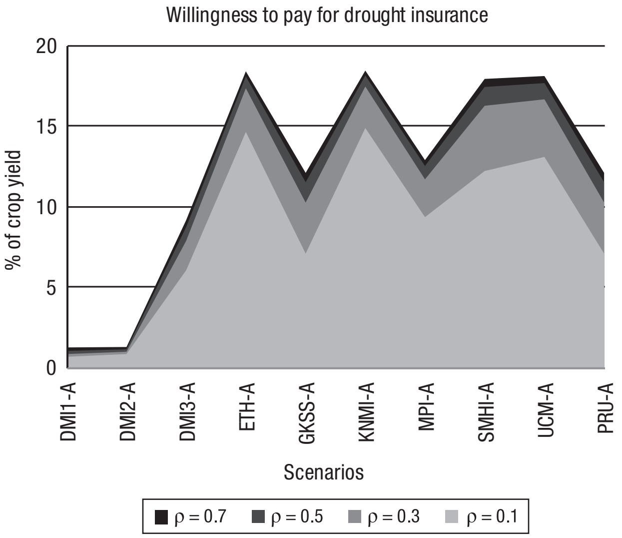

Figure 5. Willingness to pay for hydrological drought insurance (% of crop yield loss).

hydrological risk insurance depending of the information on streamflow forecasts and the risk aversion of the farmer could reach almost 20% of crop yield. For example, in the scenario BMI3-A, a person with low risk aversion would be willing to give between 5 and 10% depending on the level of aversion. In some scenarios, as ETH-A, KNMI-A, SMHI-A and UCM-A, this willingness to pay exceeds 15% of their crop yields. As might be expected, the different scenarios show that farmers are willing to pay more when the probability of drought is higher. Of course, the risk aversion of the farmer plays an essential role, but sometimes the variability associated to the climate change scenario uncertainty is much determinant. The avoided losses have been estimated for maize production. An interesting extension of the study would be to estimate the impacts on other crops in the basin to see if there are important differences in the avoided losses.

Discussion

Here we present a methodology to estimate the maximum willingness to pay for hydrological risk insurance depending on risk aversion and climate information. We derive the analytical expression of the risk premium given the risk aversion coefficient of farmers adopting the insurance. This methodology is then applied to the Ebro basin as an example to calculate the importance of climate projections on the design of an insurance scheme. The Ebro Basin is the largest basin in the Iberian Peninsula and it is located in the Northeast side with a primarily Continental Mediterranean climate, characterized by hot-dry summers and cold-wet winters and great heterogeneity in temperature across the basin (CHEBRO, 2004). Nowadays, there are no explicit restrictions on the irrigation area in the Ebro basin. However, in a climate change context with more drought events and the water framework directive environmental restrictions, the scene can be very different. The results allow defining if the farmer has incentives to use hydrological insurance as risk management mechanism. Therefore this information may be useful to define the cost of insurance, although this definition is beyond the scope of this paper.

The availability of drought information has a significant impact on farmers' decisions concerning the hiring of hydrological risk insurance schemes. Although these schemes are not yet existent in Spain, this paper shows how they might be evaluated by farmers when accurate climate information is available. The results do not indicate a single optimal policy option; instead the most appropriate policy option depends on the climate information provided by the different scenarios. Although the risk aversion preferences of each farmer are clearly an important component in the decision process, it can also be observed that the uncertainty associated with a changing climate may also impact the decisions that farmers make.

On a more general level, the importance of information that this paper also indicates the need for making climate information available and comprehensible for a wide array of stakeholders-including farmers, policy makers, and managers. Further research might shed light on the extent to which different kinds of climate information affect farmer decisions for different crops and explore the ways in which information can be presented in ways that are most useful for agricultural users. Also, futures studies could be the estimation of realistic risk premium which is a very complex and interesting issue.

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