Agricultural Water Management 274 (2022) 107938

Contents lists available at ScienceDirect

Agricultural Water Management

journal homepage: www.elsevier.com/locate/agwat

# Climate-sensitive hydrological drought insurance for irrigated agriculture under deep uncertainty. Insightful results from the Cega River Basin in Spain

Alberto Agudo-Domínguez [a,*], C. Dionisio Pérez-Blanco [a,b], Laura Gil-García [a], José Antonio Ortega [a], Shouro Dasgupta [b,c]

[a] Department of Economics and Economic History and Multidisciplinary Business Institute, Universidad de Salamanca, C/ Francisco Tomás y Valiente s/n, 37007 Salamanca, Spain
[b] Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC), Via della Libertà, 12, 30121 Venezia
[c] Grantham Research Institute on Climate Change and the Environment, London School of Economics and Political Science (LSE), London, UK

ARTICLE INFO

Handling Editor - Dr. B.E. Clothier

*Keywords:*
Index-based Drought insurance
Irrigation economics
Climate change
Water constraints
Deep uncertainty
GAMLSS

ABSTRACT

This paper assesses the feasibility and robustness of an index-based insurance scheme against hydrological droughts under climate change. To this end, we develop a grand ensemble that samples both modeling and scenario uncertainty in the estimation of the insurance risk premium, so to reveal potential unfavorable surprises and minimize regret in the design of the proposed insurance scheme. The grand ensemble combines four microeconomic models and seven GAMLSS models, which are run for three alternative climate change scenarios: stationary climate/no climate change, RCP 2.6, and RCP 8.5. Methods are illustrated with an application to the Cega River Sub-basin (CRS) in central Spain. Results indicate that for a conventional deductible of 30%, the proposed index-based insurance scheme would be actuarially feasible and affordable under all models for the stationary climate scenario (i.e., robust). For climate change scenarios RCP 2.6 and 8.5 and a 30% deductible, the suggested index-based insurance would be actuarially feasible under most models, albeit some outliers point towards potential unfavorable surprises. Lower deductibles decrease feasibility, particularly for deductibles <10%.

## 1. Introduction

Water scarcity and droughts, exacerbated by climate change, are an "existential threat" to societies and nature in many parts of the world (UNDRR, 2021). If we continue using water as we do now, water demand will exceed the currently available and reliable supply by 40% by 2030 (Water Resources Group, 2030, 2019), reducing GDP growth by as much as 6% in southern Mediterranean basins (i.e., continued negative growth) (World Bank, 2016). This will be aggravated by climate change, which in the Mediterranean region is expected to significantly reduce streamflow and increase its volatility (*medium-high confidence*) (IPCC, 2022). As a result, temporary water supply-demand imbalances (also known as hydrological droughts) will become more frequent and intense (IPCC, 2019).

Decision-makers are exploring several economic, engineering, and regulatory instruments to address the economic and environmental impacts of hydrological droughts. Most of these instruments focus on *damage prevention*, mainly through grey (e.g. reservoirs, canals) and green engineering (e.g. wetland restoration) solutions that expand the supply base (UN, 2018), sometimes complemented with regulations (e.g. quota-based systems) and economic instruments (e.g. water charges, voluntary agreements, market-based instruments) that modulate demand (OECD, 2015). Notwithstanding these efforts towards damage prevention, there are damages that are technically difficult to prevent, and in some cases, it may not be economically efficient to do so. This is especially true for agriculture, the largest water user, which accumulates the least valuable uses of the resource (Pérez-Blanco et al., 2021) and covers 50% of the world's habitable land (FAO, 2021). Moreover, there is a considerable level of uncertainty in water supply and demand forecasts that may result in unexpected damages that overcome prevention barriers (Marchau et al., 2019; Taleb, 2008). Accordingly, there is now a move toward innovation in *damage compensation* instruments,

* Corresponding author.
*E-mail addresses:* a.agudo99@usal.es (A. Agudo-Domínguez), dionisio.perez@usal.es (C.D. Pérez-Blanco).

https://doi.org/10.1016/j.agwat.2022.107938
Received 23 April 2022; Received in revised form 6 September 2022; Accepted 10 September 2022
Available online 24 September 2022

most notably through crop insurance mechanisms (Gómez-Limón, 2020).

Insurance is a risk-sharing strategy through which an agent (the insured) transfers part of the risk it bears to another agent (the insurer) in exchange of a payment (the risk premium). In turn, the insurer commits to compensate the insured agent if a covered risk realizes. Crop insurance policies can cover against a wide array of risks, which are often grouped in three categories (Pérez-Blanco et al., 2017): *production risks* due to extreme meteorological phenomena and other adverse events such as theft or fire; *market risks* due to price and cost variability; and the *institutional risk* associated with shifting policy choices that can affect farm's output (e.g., discretionary water reallocations during hydrological droughts), which is typically not insured. Crop insurance is most frequently delivered through yield insurance that addresses production risks, often bundling several risks together (e.g., hail, floods, fire). More sophisticated crop insurance schemes offer comprehensive income/revenue insurance packages that address both production and market risks, albeit these insurance products have significantly higher costs and lower market penetration than yield insurance (Liesivaara and Myyra, 2014; Pérez-Blanco et al., 2016). *Critically*, available insurance schemes only cover drought damages in rainfed agriculture—that is, hydrological drought damages in higher-value added (and potentially costlier to insure) irrigated agriculture are excluded (Bardají et al., 2016; Ruiz et al., 2015). As a result, hydrological drought damages in irrigated agriculture are either compensated using instruments such as state aid (Rejda and McNamara, 2014); averted through (informal) water withdrawals from buffer stocks, typically aquifers, which are often overallocated and thus transfer the burden of drought damage from the economy to the environment (Gómez and Pérez-Blanco, 2012); or absorbed by farms (economic losses).

Two major challenges have thwarted the development of hydrological drought insurance in irrigated agriculture. *First*, beyond the (probabilistic) residual risk that remains after all damage prevention instruments are considered, there are significant sources of (non-probabilistic) uncertainty that emerge from the non-mechanistic dynamics and multiple potential equilibria of complex socioecological systems (Anderies, 2015), which can lead to unfavorable surprises that significantly amplify drought damages and the costs of insurance. This is known as Knightian or deep uncertainty (Knight, 1921; Marchau et al., 2019), a situation where "experts do not know or the parties to a decision cannot agree upon (i) the external context of the system [i.e. scenario uncertainty, e.g., due to climate change or future damage prevention planning], (ii) how the system works and its boundaries [i.e. parameter and structural uncertainties within models], and/or (iii) the outcomes of interest from the system and/or their relative importance [i.e. weighting]" (Lempert et al., 2003, p. 11). While appropriate under probabilistic risk, the conventional consolidative modeling approach that has been traditionally used to make point predictions towards calculating expected compensations/indemnities and insurance premiums is no longer adequate under deep uncertainty, because it can provide more information than is warranted by available evidence and artificially reduce uncertainty—as demonstrated by recent unfavorable surprises experienced by the insurance industry, e.g. during the massive 2021 summer floods in central Europe. Deep uncertainty can be particularly harmful in the case of hydrological droughts, a systemic risk that can lead to the breakdown of entire agricultural systems (rather than the failure of individual parts, as happens with e.g. hail), which can potentially affect the stability of the insurance system and raise solvency issues (Bielza et al., 2009; Rey et al., 2019). Accordingly, insuring hydrological drought risk in irrigated agriculture under deep uncertainty calls for alternative actuarial modeling frameworks that replace consolidative modeling and point predictions by ensemble experiments that sample uncertainty and inform no-regret or low-regret *robust* solutions that prioritize the avoidance of unfavorable contingencies (Marchau et al., 2019).

*Second*, hydrological drought insurance in irrigated agriculture faces a considerable degree of institutional risk and uncertainty. Crop insurance is closely linked to existent damage prevention instruments, which often involve discretionary policy choices that condition realized damages, the extent of the compensation and the viability of the insurance scheme (Surminski et al., 2015). Notably, because water allotments during hydrological droughts are decided by the water authority, which might be subject to users' lobbying (including irrigators) (Guerrero-Baena and Gómez-Limón, 2019), the damages caused by water restrictions are not entirely owed to the vagaries of water supply and can become difficult to predict, which can further inflate uncertainty.

Regarding the *second challenge,* actuarial research has posited that institutional risk can be addressed through index-based crop insurance, a type of insurance that gives a preestablished compensation to farmers when a predetermined threshold is surpassed. In the case of index-based hydrological drought insurance, compensations/indemnities are calculated based on an external index correlated with the risk addressed instead of the realized water allocation decision by the water authority, which reduces uncertainty in the calculation of the risk premium (Gómez-Limón, 2020). External indices can be designed as a function of precipitation (Buchholz and Musshoff, 2014), accumulated discharge (Leiva and Skees, 2008; Pérez-Blanco and Gómez, 2014), stock in reservoirs (Guerrero-Baena and Gómez-Limón, 2019), or the combination thereof (Arandara et al., 2019; Gómez-Limón, 2020; Moghaddasi et al., 2014). For the case of hydrological drought insurance, (consolidative) index-based research has reported risk premiums that are either below irrigators' willingness to pay or represent a low to moderate share of their variable costs, and thus are considered affordable (Alcon et al., 2014; Gómez-Limón, 2020).

The *first challenge* remains largely unaddressed, though. Index-based and other crop insurance research and applications still rely on consolidative modeling, thus failing to account for the (non-probabilistic) modeling and scenario uncertainties that are characteristic of complex socioecological systems. The modeling frameworks used in the literature on crop insurance typically adopt a risk assessment model to provide a complete probabilistic description of the risk (i.e., scenario uncertainty is ignored), which are then used to feed an economic model—typically a mathematical programming model—to obtain a point prediction of expected compensations and risk premiums (i.e., parameter and structural uncertainties within models are also ignored). Moreover, in the case of hydrological drought risk, these point predictions rely on stationary series of hydrological variables, meaning that not only uncertainty in scenarios and modeling is not accounted for, but also that the repercussions of climate change are excluded altogether.

The objective of this study is to explore the feasibility of a *robust* index-based insurance against hydrological droughts in irrigated agriculture that accounts for modeling and scenario uncertainty, while mainstreaming climate change impacts into the analysis. Following Pérez-Blanco and Gómez (2014, 2013) and Gómez-Limón (2020), we use the drought indices in drought management plans as a reference index for the proposed index-based insurance scheme. Regarding *scenario uncertainty*, we explore different Representative Concentration Pathway (RCP) emission scenarios for the 21st century, so to generate non-stationary hydrological inputs that account for conditions of global warming. To this end, we use a Generalized Additive Model for Location Scale and Shape (GAMLSS) (Stasinopoulos et al., 2020), a non-linear distributional regression model that elicits the parameters of the assumed distribution for the response variable (in our case the drought index in the drought management plan) using additive functions of the explanatory variables. Thus, GAMLSS makes possible to assess the impacts on both the first and second moments of the distribution of the explanatory variables, which in the case of droughts can be used to discern the effects of climate change on the drought index through projections of temperatures and precipitation under selected RCP scenarios. Regarding *modeling uncertainty*, we use an ensemble encompassing various GAMLSS with alternative model structure and parameter values to estimate the probability distribution of the drought index under alternative climate change scenarios; and a second ensemble of mathematical programming models that assesses the behavior and adaptive responses of irrigators to the water restrictions set based on the drought index. By combining the expected damage under each plausible value of the drought index (obtained with the ensemble of mathematical programming models) with the probability distribution of the drought index under each climate change scenario (obtained with the GAMLSS ensemble), we can calculate the expected damage under each climate scenario and plausible combination of models. This makes possible to sample both model and scenario uncertainty through a database of simulations that reports the economic performance of the proposed insurance scheme (including damages, compensation/indemnity and risk premium) under multiple plausible futures (where each plausible future is represented by a unique combination of models and scenarios), and to assess its feasibility and robustness. Methods are illustrated with an application to the Cega River Sub-basin in Spain.

## 2. Background to the case study: the Cega River Sub-basin in Spain

The Cega River Sub-basin (CRS) is located to the south-east of the Douro River Basin (DRB) in Spain (see Fig. 1). The average annual water supply of the CRS is estimated at 208.3 $hm^3$ (1 $hm^3$ = 1 million $m^3$), and projected to decrease by up to 11% by 2030 (MAGRAMA, 2017); while annual water demand is estimated at 76.3 $hm^3$, 80.3% of which comes from agriculture (DRBA, 2020). Of these 76.3 $hm^3$/year, 4.5 $hm^3$/year (5.9%) come from on average water abundant yet unregulated and volatile surface water bodies, while the remaining 71.8 $hm^3$/year (94.1%) are abstracted from reliable yet overallocated aquifers—mostly from the Arenales Aquifer. Due to groundwater overallocation, the Arenales Aquifer shows a poor ecological status with high levels of arsenic pollution that recurrently constrain the local population (a high priority water use claiming 4,79 $hm^3$/year) to rely on tankers for household water supply.

The CRS is managed by the Douro River Basin Authority (DRBA). The DRBA allocates surface and groundwater resources among users and operates a network of canals and other water works to distribute surface water resources (groundwater infrastructures are privately operated by users). Despite the DRBA efforts to address groundwater overallocation through quota reductions and engineering solutions for managed aquifer recharge, the piezometric levels and qualitative status of the Arenales Aquifer have shown little improvement. Quota reductions have been bypassed through irrigation modernization (which increases the consumed fraction of water abstracted while reducing return flows and infiltration to the aquifer), or straightaway violated via water theft (WWF, 2020), while supply expansion through managed aquifer recharge has fallen short of the growing demand. In this context, the DRBA is considering a ban on groundwater abstractions in an area comprising 2800 ha of the circa 4000 ha in the CRS that currently irrigate using groundwater resources, and substitute them with surface water resources. This substitution was initially planned to be supported with the construction of the Lastras de Cuéllar reservoir in the CRS (44 $hm^3$), and the Ciguiñuela (29 $hm^3$) and Carbonero reservoirs (13.2 $hm^3$) in the nearby Eresma Sub-basin (to be connected to the CRS through canals and other complementary water works). However, the construction of the Lastras de Cuéllar reservoir has been already discarded following a negative environmental assessment; while the approval of the Ciguiñuela and Carbonero reservoirs is "unlikely" (High Representative of the Douro River Basin Authority, 2022) and has been postponed, at minimum, to 2033 (DRBA, 2020). Plans to substitute groundwater with surface water resources to address aquifer overallocation problems continue, nonetheless. Accordingly, the irrigated agriculture of the CRS is expected to transition and adapt to a significantly more volatile water source, which will amplify hydrological drought risk in the area.

During hydrological droughts, the DRBA curtails water allocations based on the DRB's Drought Management Plan (DMP) (DRBA, 2017). Spanish DMPs are a damage prevention mechanism that (re)allocates scarce water resources to ensure that essential uses such as household supply or minimum environmental flows are met, while the economic damage is minimized (e.g., giving priority to industrial uses with high value-added per unit of water input over agricultural water uses). To this end, DMPs set different priorities among uses, from higher (environmental, households) to lower (irrigation). DMPs divide basins into Territorial Scarcity Units (TSU), hydrological units that typically match a sub-basin (in our case, the CRS) and share a common source of water (in the case of the CRS TSU, the Cega River and its tributaries). During hydrological droughts, each TSU assesses drought severity through a drought index, based on which available water resources are (re)allocated at the beginning of the irrigation season in April.

Since the CRS is a non-regulated catchment, the CRS TSU drought index assesses drought severity based on discharge data (instead of storage data that is typically used in highly engineered catchments) gathered at two monitoring stations at the Cega and Pirón rivers (the latter being a tributary to the Cega River—see Fig. 1). Non-regulated catchments or marginally regulated catchments (those with small dams whose capacity is significantly lower than demand) abound worldwide, including in Spain, one of the countries with most developed

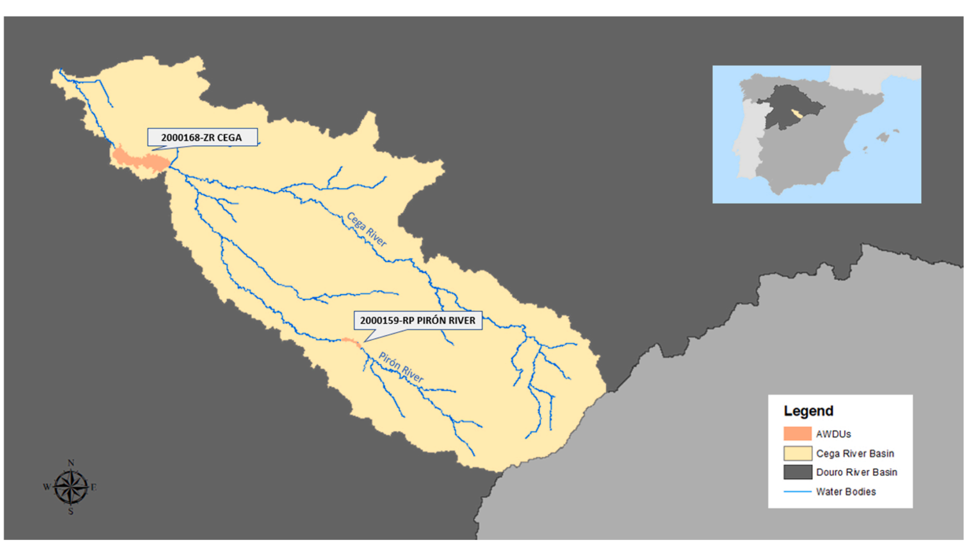


**Fig. 1.** Location of the CRS and detail of its AWDUs.

water infrastructure in the world. For example, 24% of the TSU in the DRB, 24% of the TSU in the Guadiana RB, 12% of the TSU in the Tagus RB, and 80% of the TSU in the Cantábrico RB assess drought severity based on discharge data only (CORBA, 2018; DRBA, 2017; GRBA, 2018; TRBA, 2018). Focusing on a non-regulated catchment also has the advantage of removing the uncertainty related to future water storage in reservoirs, which depends not only on natural but also on management variables (e.g. water release for hydropower generation) that are challenging to predict, particularly under climate change (ISIMIP, 2022). In fact, to circumvent this challenge, several proposed index-based insurance products for regulated catchments are designed as a function of precipitation or external discharge (Buchholz and Musshoff, 2014; Leiva and Skees, 2008). In the CRS TSU, the drought index is built as a weighted average of the six months rolling sum of discharge in the two monitoring stations at the Cega and Pirón rivers, and subsequently normalized dividing by the maximum historical value to range between 0 (absolute scarcity) and 1 (no drought). In turn, water allocation is obtained as a piecewise function of the CRS TSU drought index, as follows:

1. Normality: drought index $\in (0.5, 1]$. Water allocation for irrigation is linearly reduced between 0% (indicator equals 1) and 10% (indicator equals 0.5).
2. Pre-alert: drought index $\in (0.3, 0.5]$. Water allocation for irrigation is linearly reduced between 10% (indicator equals 0.5) and 25% (indicator equals 0.3).
3. Alert: drought index $\in (0.15, 0.3]$. Water allocation for irrigation is linearly reduced between 25% (indicator equals 0.3) and 50% (indicator equals 0.15).
4. Emergency: drought index $\in [0, 0.15]$. Water allocation for irrigation is linearly reduced between 50% (indicator equals 0.15) and 100% (indicator equals 0).

Following Gómez-Limón (2020), we use the CRS TSU hydrological drought index above as a reference to calculate damages to irrigated agriculture, which in turn give us the necessary information to calculate potential compensations/indemnities and risk premiums.

Our analysis focuses on the 2 Agricultural Water Demand Units (AWDUs) in the CRS that presently rely on surface water or are transitioning towards its adoption (Fig. 1): The Cega AWDU (AWDU2000168) and the Pirón River AWDU (AWDU 2000159). AWDUs are the basic irrigation unit in Spain, and comprise “groups of irrigators sharing a common source of water, territorial, administrative, and hydrological characteristics”. These AWDUs are one of the most productive agricultural areas in central Spain, largely irrigated with sprinklers. In the Cega AWDU, about 40% of the 832.13 ha of irrigated land in the CRS are devoted to high value-added horticultural crops such as carrot, garlic and onion, whose expected profits range between 5 430 and 16,896.5 EUR/ha (average profit: 10 906.8 EUR/ha). In the Pirón River AWDU, about 64% of the 40.3 ha of irrigated land in the CRS are devoted to high value-added horticultural crops such as onion, whose expected profits is 1 267.1 EUR/ha. Other relevant crops in the CRS include sugar beet (7% of the AWDUs combined surface), potato (13%) and alfalfa (19%) (MAGRAMA, 2020a, 2020b). AWDUs are the agents in the ensemble of mathematical programming models, meaning simulations are conducted independently for each AWDU, albeit simulation results are subsequently aggregated and presented at the district level in Section 4 (i.e., the CRS).

## 3. Methodology

Our methods nest two ensembles to create an ensemble of ensembles, or ‘grand ensemble’ capable of sampling scenario and modeling uncertainty. In the first layer of the grand ensemble, there is a GAMLSS ensemble encompassing various econometric models with alternative structure and parameter values, which are used to estimate the probability distribution of the drought index with and without climate change. In the second layer of the grand ensemble, there is a microeconomic ensemble of mathematical programming models to assess the adaptive responses of irrigators to the water restrictions set based on the drought index, and estimate damages under drought events of different intensity (emergency, alert, pre-alert, normality). Next, we combine each model within the GAMLSS ensemble with each model within the microeconomic ensemble and each climate change scenario; and run a simulation to estimate the expected drought damage. Thus, we create a database of simulations that reports the economic performance of the proposed insurance scheme under multiple plausible futures, where each plausible future is represented by a unique combination of models and scenarios. A graphical workflow of our methods is presented in Fig. 2.

### 3.1. GAMLSS to simulate drought indices under climate change

The GAMLSS is a statistical model designed to overcome the limitations associated with conventional generalized linear models (GLMs) and generalized additive models (GAMs). The critical innovation of GAMLSS is that, instead of predicting the response of the mean of the distribution, it makes possible to assess how the different independent variables in the model affect the second, third and fourth moments of the distribution of the independent variable (variance, asymmetry, kurtosis). In our case, this potential is used to explore the effect of changes in temperatures and precipitation on the expected value and variance of the drought index. A typical GAMLSS is defined as follows (Stasinopoulos et al., 2020):

$$\boldsymbol{Y} \sim^{ind} \boldsymbol{D}(\boldsymbol{\mu}, \boldsymbol{\sigma}, \boldsymbol{\nu}, \boldsymbol{\tau}) \tag{1}$$

$$\boldsymbol{\eta}_1 = \boldsymbol{g}_1(\boldsymbol{\mu}) = \boldsymbol{X}_1\boldsymbol{\beta}_1 + \boldsymbol{s}_{11}(\boldsymbol{x}_{11}) + \ldots + \boldsymbol{s}_{1J_1}(\boldsymbol{x}_{1 \quad J_1}) \tag{2}$$

$$\boldsymbol{\eta}_2 = \boldsymbol{g}_2(\boldsymbol{\sigma}) = \boldsymbol{X}_2\boldsymbol{\beta}_2 + \boldsymbol{s}_{21}(\boldsymbol{x}_{21}) + \ldots + \boldsymbol{s}_{2J_2}(\boldsymbol{x}_{2 \quad J_2}) \tag{3}$$

$$\boldsymbol{\eta}_3 = \boldsymbol{g}_3(\boldsymbol{\nu}) = \boldsymbol{X}_3\boldsymbol{\beta}_3 + \boldsymbol{s}_{31}(\boldsymbol{x}_{31}) + \ldots + \boldsymbol{s}_{3J_3}(\boldsymbol{x}_{3 \quad J_3}) \tag{4}$$

$$\boldsymbol{\eta}_4 = \boldsymbol{g}_4(\boldsymbol{\tau}) = \boldsymbol{X}_4\boldsymbol{\beta}_4 + \boldsymbol{s}_{41}(\boldsymbol{x}_{41}) + \ldots + \boldsymbol{s}_{4J_4}(\boldsymbol{x}_{4 \quad J_4}) \tag{5}$$

where $\mathbf{Y}= (y_1,.,y_n)^\top$ is the vector with the dependent variable observations, which are independently distributed and have a distribution D, which is defined by its four moments: μ, σ, ν and τ (some distributions, as the Normal or the Beta distribution only need to model the first two moments/two parameters instead of four). The predictors $\eta_i$ explain the moments of the distribution through a function that depends on the chosen probability distribution. $X_i$ is a $n_i \times p_i$ matrix ($p_i = r_i + 1$) containing the r covariate columns chosen for the ith predictor, plus a column of ones (if a constant is required), and $\beta_i$ is the vector of coefficients for the variables selected in the equation of the ith predictor. Finally, $s_{ij}$ is a nonparametric smoothing function applied to the covariate $x_{ij}$ of the ith predictor, for $j_i = 1,.,J_i$ smoothed variables—i.e., the function that establishes the non-linear effects on the parameters of the distribution. In GAMLSS, the effect of the independent variables on the parameters of the distribution is allowed to be non-linear, thus letting data determine the relationship between the predictor, e.g., $\eta_1 = g(\mu)$ and the explanatory variables, rather than enforcing a linear (or polynomial) relationship. The methods used to define these relationships are known as supervised machine learning, since the algorithm iteratively models the relationship making predictions about the data and is corrected on a recurring basis during this process. The estimation procedure stops when the algorithm has converged, that is, when it reaches a pre-determined level of performance which might be modified.

In our application to the Cega TSU, we use the drought index in April as the dependent variable, which is calculated using historical discharge data from the Cega and Pirón monitoring stations. This data is available at several separate webpages in the CEDEX (2021) database and was downloaded using a web scraping script coded in R. On the other hand,

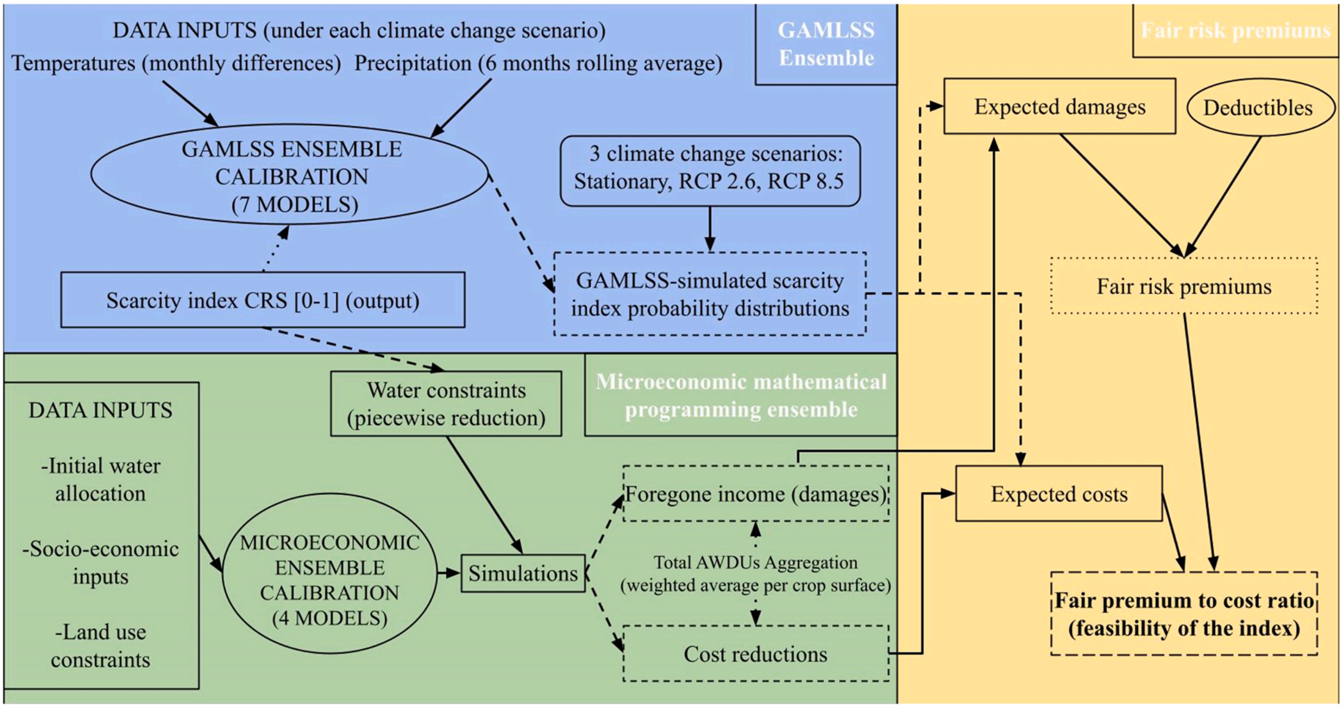


**Fig. 2.** Graphical abstract on the methodological workflow.

the independent variables are the weighted average of the six-month rolling sum of precipitation, and the weighted average of monthly differences of temperatures between April and March in the observed year, which is obtained from historical meteorological data measured in the two discharge monitoring stations at the Cega and Pirón rivers, available at Copernicus Climate Change Service (C3S) Climate Data Store (CS3, 2022). Precipitation and temperature are the two key forces used in multi-model ensemble experiments to predict impacts on discharge, as well as on other key hydrological variables (ISIMIP, 2022; CMIP6, 2022). Accordingly, forecasts of these two variables are available for long periods into the future—a key piece of information that we will use to mainstream climate change in our model. The database with the dependent and independent variables used to run GAMLSS is available in Annex I of the online supplementary material.

Since the drought index is standardized between 0 and 1, we use Beta as the reference distribution (which is continuous, and ranges from 0 to 1). We also explore alternative models that use other distributions, such as the LogisticNormal (LOGITNO) or the Generalized Beta Type 1 (GB1). From this set of distributions, we generate 17 models by adjusting the degrees of freedom and using alternative smoothing functions (all 17 models and the coding used to obtain them in R are available in Annex II of the online supplementary material). The models intertwine the smoothing functions between variables, which is performed in order to model various levels of complexity and find different ways of fitting the drought index to both precipitation and temperatures. Among the 17 models generated using this approach, we choose the top seven that show a satisfactory predictive performance according to the AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) criteria (i.e., AIC lower than −41.5 and BIC lower than −37.5). AIC allows more complex models (e.g., using smoothing functions for some variables), whereas BIC tends to penalize complexity and chooses more parsimonious models. As seen by the population distribution of the models, only the Beta distribution models satisfy the aforementioned requirements. Each of the seven GAMLSS models used in the ensemble is described in the Table 1.

As seen in the table above, model 11 is the one which performs best under the BIC. On the other hand, model 15 is the best under the AIC.

**Table 1**
Description of each GAMLSS model and its performance under the AIC and BIC criteria. Pb() and S() are the smoothing (non-linear) functions of the variables. Note: The Model IDs are showed as a reference for the reader who wants to revise the code used in developing the 17 original models (available in Annex II of the online supplementary material).

| Model ID | Distribution | AIC | BIC | Explanatory variables of mu | Explanatory variables of sigma |
|---|---|---|---|---|---|
| 3 | Beta | -42.94 | -38.93 | Pb (temperatures) Precipitation | Temperatures Precipitation |
| 5 | Beta | -42.94 | -38.93 | Pb (temperatures) Pb (precipitation) | Temperatures Precipitation |
| 9 | Beta | -42.94 | -38.93 | Pb (temperatures) Precipitation | Pb (temperatures) Precipitation |
| 11 | Beta | -41.83 | -38.98 | Pb (temperatures) Precipitation | Constant |
| 12 | Beta | -41.63 | -38.82 | S (temperatures) Precipitation | Constant |
| 14 | Beta | -42.57 | -38.59 | S (temperatures) Precipitation | Temperatures Precipitation |
| 15 | Beta | -43.24 | -37.82 | S (temperatures) Precipitations Interaction between both | Temperatures Precipitation |

One option at this point is to apply performance tests to choose one of the two models. Nevertheless, that would attribute all the predictive capacity to a single model and would not allow for sampling modeling uncertainty, which is a key objective of this research. Thus, we use all seven models in our research through an ensemble of GAMLSS models. Fig. 3 shows the centiles plot of the effect of each independent variable

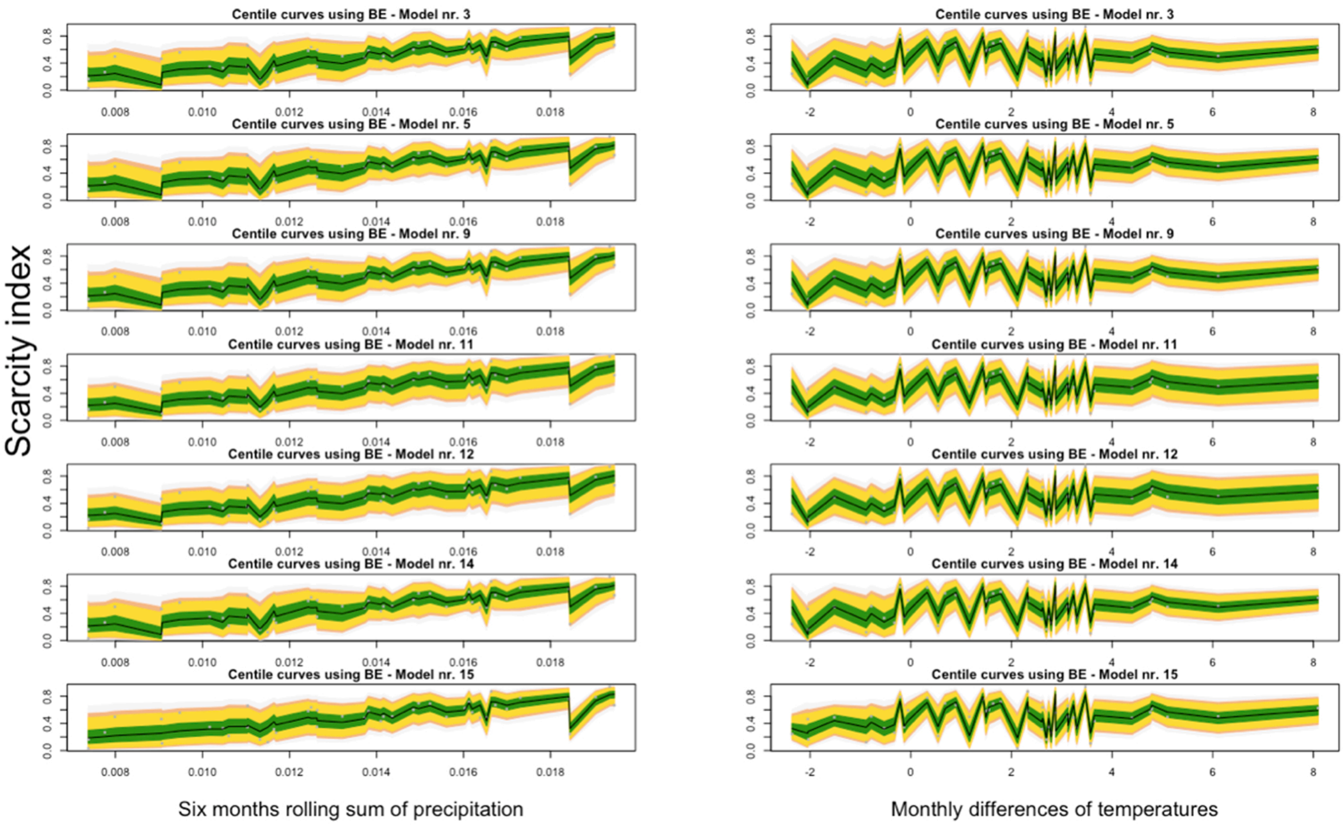


**Fig. 3.** Centile curves of the scarcity index against explanatory variables. The grey/orange/yellow/green band shows the upper and lower bounds of the 99%/95%/90%/50% confidence interval of the corresponding distribution (i.e., Beta) and how the values of the drought index vary depending on the six months rolling sum of precipitation or the monthly differences of temperatures. The width of the interval informs on the variance of the drought index for that specific model, while the black line (which is the median percentile) informs on its mean.

(precipitation and temperatures) on the distribution of all models.

Once the ensemble of seven GAMLSS models is calibrated, we gather data from EURO-CORDEX predictions on future precipitation and temperatures in the CRS for the period 2017 (last year with historical data available) to 2100 to account for climate change (EURO-CORDEX, 2022). These forecasts are obtained for two climate change scenarios for the 21st century: RCP 2.6 and 8.5. While other scenarios such as RCP 4.5 or RCP 6 can be considered, our main objective here is to provide worst-case and best-case climate change scenarios as compared to stationary climate. Next, each model in the GAMLSS ensemble uses the EURO-CORDEX forecasts as an input data to predict the drought index throughout the 2017–2100 series. In other words, we use the already trained GAMLSS ensemble (trained with the past observations) to transform the future values of precipitation and temperatures into predictions of the drought index. This is the approach that we have used to allow for climate change: using precipitation and temperature forecasts in EURO-CORDEX for two key climate change scenarios and, given these as an input, predicting the future values of the CRS TSU drought index. Once we have the predictions of both mu and sigma of the drought index per year, we can estimate the parameters of the population distribution by averaging mu and sigma for each RCP scenario. In this way, we have estimated the parameters of the drought index distribution under each climate change scenario. Finally, we simulate the underlying population distribution of the model (e.g., Beta) using the parameters obtained with the 2017–2100 forecasts (mean of future values), reaching eventually two probability density functions for each model; out of which we can extract the probabilities of each drought situation (normality, pre-alert, alert and emergency). This information is then combined with the drought damage simulations run with the ensemble of mathematical programming models to obtain an expected compensation/indemnity and insurance premium for each combination of scenarios and models.

### 3.2. *Mathematical programming models to simulate irrigators' responses to water reallocations*

This section presents a multi-model ensemble comprising several microeconomic mathematical programming models, which are used to sample modeling (structural and parameter) uncertainty in the representation of human responses to water allocation restrictions under drought (Pérez-Blanco et al., 2021; Sapino et al., 2020). The ensemble includes two Positive Multi-attribute Utility Programming (PMAUP) and two Positive Mathematical Programming (PMP) models. In all four models, the agent (an irrigator) aims to maximize its utility $\boldsymbol{U}(\boldsymbol{X})$ within a domain $\boldsymbol{F}$, as follows:

$$\boldsymbol{Max} \quad U(\boldsymbol{X}) = (f(z_1(\boldsymbol{X}), \quad z_2(\boldsymbol{X}), \quad \dots, \quad z_m(\boldsymbol{X})) \tag{6}$$

Subject to:

$$\boldsymbol{x_i} \geq \boldsymbol{0} \tag{7}$$

$$\sum_{i=1}^{n} \boldsymbol{x_i} = \boldsymbol{1} \tag{8}$$

$$\boldsymbol{X} \in \boldsymbol{F} \tag{9}$$

$$\boldsymbol{X} \in \mathbb{R}^n \tag{10}$$

$$z_1(\boldsymbol{X}), \quad z_2(\boldsymbol{X}), \quad \dots, \quad z_m(\boldsymbol{X}) = \boldsymbol{Z}(\boldsymbol{X}) \in \mathbb{R}^m \tag{11}$$

Where $\boldsymbol{U}(\boldsymbol{X})$ is a monotonically increasing utility function, i.e., increasing the provision of any utility-relevant attribute $z_1(\boldsymbol{X}), \quad z_2(\boldsymbol{X}),$

…, $z_m(X)$ increases the utility for the agent. Thus, all attributes are defined so that "more-is-better", meaning "less-is-better" attributes are transformed accordingly (e.g., risk is measured as risk avoidance). We explore the relevance of five attributes in our microeconomic ensemble: profit ($z_1$), measured as the expected gross margin, the only relevant attribute for PMP models (and a relevant attribute for PMAUP models as well) and a critical variable to estimate drought damage and the risk premium; risk avoidance ($z_2$); and management complexity avoidance, measured through three proxies: total labor avoidance ($z_3$), hired labor avoidance ($z_4$), and direct costs avoidance ($z_5$). A comprehensive description and mathematical formulation of each attribute, as well as a database including all the input data used to quantify attributes provision in the AWDUs (including source and reference year), is available in Annex I of the online supplementary material.

$\boldsymbol{X}$ is the decision variable or crop portfolio, a vector indicating the share of land allotted to each crop $x_i$ (in %), which is revised on a yearly basis (at the beginning of the irrigation campaign in April). We consider both irrigated and rainfed crops in the portfolio for simulation purposes (to allow for super-extensive margin adaptations/crop switching towards rainfed crops). Each crop $\boldsymbol{x_i}$ delivers a unique combination of utility-relevant attributes $\boldsymbol{Z}(\boldsymbol{X})$. $\boldsymbol{F}$ represents the set of constraints that conform the domain, including the water allocation constraint, of relevance for our research since it is the variable directly affected by the DMP:

$$\sum_{i=1}^{n} w_i \quad x_i \leq W \tag{12}$$

where $w_i$ represents the water needs by crop $\boldsymbol{x_i}$, and $\boldsymbol{W}$ represents the water allocation, on a per hectare basis. The other constraints conforming the domain $\boldsymbol{F}$ are presented in Annex III of the online supplementary material.

The PMP and PMAUP models included in the ensemble of mathematical programming models use the same data inputs and share a common specification of the domain; but differ in the form of the utility function $\boldsymbol{U}(\boldsymbol{x})$ and calibration method used. PMP models adopt a single-attribute quadratic utility function where the only utility-relevant attribute is profit ($z_1$). PMP models are calibrated in three steps: "(i) an additional area constraint that bounds the model calibration results to observed choices is introduced in the domain and the dual values associated to the constraint for each crop obtained; (ii) these dual values are used to add a non-linear component to the utility function (typically a quadratic cost function, or shadow cost); and (iii) the utility non-linear function obtained in (ii) is maximized subject to a similar set of constraints to those considered in the original problem, which perfectly reproduces the observed agent's behavior" (Heckelei et al., 2012). The two PMP models used in our ensemble are the classical PMP model developed by Howitt (1995), and a variation of this model developed by Júdez et al. (2002), which skips the first step in the calibration procedure above.

On the other hand, PMAUP models use a multi-attribute utility function that in our case includes profit, risk avoidance and management complexity avoidance. PMAUP replaces the dual variables added to the utility function in PMP models with agent's preference parameters represented as shares of a utility function, the arguments of which are competing attributes (e.g., profits v. risk avoidance). The two PMAUP models included in the ensemble differ on the functional form and calibration method used: building on work by Gutiérrez-Martín and Gómez (2011), Gómez-Limón et al. (2016) adopt a non-linear Cobb--Douglas utility function that is calibrated using a projection method (conventional PMAUP); while Montilla-López et al. (2018) adopt a linear utility function that is calibrated using a weighted goals programming method (WGP PMAUP) à-là-Sumpsi et al. (1997).

PMAUP and PMP models are calibrated for the year 2017, which is also the last year in the data series used in the GAMLSS ensemble. Calibration results and calibration errors for the PMAUP models are available in Annex IV in the online supplementary material. Calibration results for PMP models are not reported since they perfectly calibrate to the observed decision/crop portfolio, so the error is always null, and the only relevant attribute is profit. As per the metrics for performance assessment of PMAUP models in Essenfelder et al. (2018), all AWDUs have a very low calibration error (average error <10%) in the conventional PMAUP model, while in the WGP PMAUP model 2 AWDUs have a very low calibration error and 2 of them have a moderate calibration error (average error in the range of 10–15%).

## 4. Results and discussion

The sub-sections below present the i) losses and ii) fair risk premium estimations obtained through the application of our methods to the CRS. As noted in Section 2 and elsewhere in the paper, modeling is performed at an AWDU level, and afterwards aggregated to the level of a representative farm for the whole CRS. Hence, even though results are robust at an AWDU and sub-basin level, the performance of the insurance on individual farms would show heterogeneity depending on the individual crop-mix and economic preferences (i.e., robust performance of the drought insurance scheme for the average CRS agent does not ensure robust performance for every single farmer over the sub-basin).

### *4.1. Simulation results: drought damages*

We first run a series of simulations with the ensemble of mathematical programming models to assess irrigators' responses to alternative water allocations under normality (100% or full water allocation to 90%), pre-alert (90–75%), alert (75–50%) and emergency (50–0%). To this end, we progressively strengthen the water allocation constraint from 100% to 0% at 1% point intervals, and estimate the corresponding expected damages in each of the 100 simulation runs (measured through changes in profit, $z_1$, under different water restrictions as compared to the situation with a full water allocation). Second, we estimate the probability distribution of the drought index for each of the seven models in the GAMLSS ensemble, under three alternative climate change scenarios (no climate change, RCP 2.6 and RCP8.5). Finally, we combine the expected damage under each plausible value of the drought index (obtained with the ensemble of mathematical programming models) with the probability distribution of the drought index under each climate change scenario (obtained with the GAMLSS ensemble) to calculate the expected damage under each climate scenario and combination of models. The resultant ensemble of ensembles, or 'grand ensemble', yields 84 alternative predictions/ensemble elements (7 GAMLSS models times 4 mathematical programming models times 3 climate change scenarios) that assess modeling and scenario uncertainty. The range of foregone profit forecasts under each climate scenario is shown in Fig. 4.

Our results show two clusters of predictions/ensemble elements. The first cluster in the upper part of the figure comprises the grand ensemble

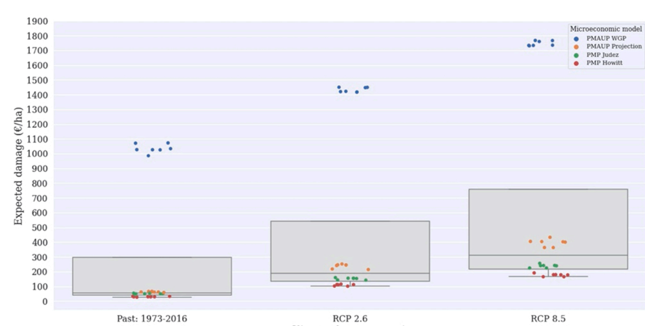


**Fig. 4.** Expected damage/foregone profit under each climate change scenario. Note: Each simulation result is represented by a point.

elements that result from the combination of the WGP model in the microeconomic ensemble with the models in the GAMLSS ensemble and predicts damages in the range of 985.6–1767.6 €/ha. The second cluster in the lower part of the figure comprises the grand ensemble elements resulting from the combination of every other microeconomic model with the models in the GAMLSS ensemble and predict drought damages in the range of 26.9 – 433.2 €/ha. The non-trivial differences observed between the two clusters in the grand ensemble are primarily owed to the drought damages estimated in the WGP model, which differ significantly from the estimations of other models in the microeconomic ensemble (see Fig. 5).

When an emergency drought is declared (drought index value of 0.15) and water allocation is reduced by 50%, the WGP microeconomic model estimates an expected profit of 1381 €/ha, while the other three models estimate an expected profit in the range of 3524–3688.6 €/ha (more than twice as much), meaning the WGP overestimates drought damage under emergency as compared to the other three models in the microeconomic ensemble. The WGP also overestimates drought damage as compared to the other three microeconomic models under alert (and most of the pre-alert values). On the other hand, the WGP underestimates drought damage under normality, which partly but not fully offsets the higher damages under pre-alert, alert and emergency when combining the drought damage estimated using the microeconomic model with the probability distribution of the drought index estimated using GAMLSS.

What explains these differences? It should be noted that the WGP PMAUP is the only microeconomic model in the ensemble of mathematical programming models that has a linear utility function. Linear models have been often criticized in the academic literature because of their tendency to yield over-specialized or even corner solutions: the irrigator chooses the crop with the highest utility at the maximum level (i.e., maximum possible land allocated to that crop), until a constraint becomes binding and prevents the agent from further specialization (for a review of these models see e.g., Graveline, 2016). This results in a "jumpy behavior" and simulated crop portfolio choices that seem "too far from reality, at least in the short term" (Graveline, 2016). To illustrate the responses of irrigators in linear v. non-linear models, Fig. 6 shows the crop portfolio responses (the decision variable in the ensemble of microeconomic models, $X$) predicted by the four models in the microeconomic ensemble under emergency, alert, pre-alert and normality drought index thresholds.

Fig. 6 shows how irrigators' responses differ significantly between the WGP PMAUP and the other three models in the microeconomic ensemble, whose crop portfolio simulations are also closer to observed irrigators' choices. As a result, the WGP PMAUP has significantly higher calibration errors than the other three models (see Annex IV in the online supplementary material). With this in mind, we could employ model selection techniques to compare and choose among the models in the ensemble those that perform better in terms of calibration errors, which would lead to the exclusion of the WGP PMAUP. On the other hand, calibration errors cannot be directly compared among all the mathematical programming models in the ensemble, since these errors are independent (Cloke et al., 2013). Moreover, while we can assess the capacity of microeconomic models to reproduce observed behavior through realized crop portfolio choices and calibration errors, data on irrigators' responses to water allocation reductions is limited to drought years since 2007 (the year DMPs were first approved), meaning that we do not have sufficient data to evaluate the predictive performance and prediction errors of the models in the microeconomic ensemble. Assessing the predictive performance of models is a critical step in model selection (Konishi and Kitagawa, 2008), which can be also used towards improving model calibration (notably through the use of machine learning techniques, as it is done in GAMLSS). Without this information, we cannot conclude that the WGP PMAUP predicts worse than the other models in the ensemble just because it has relatively high calibration errors. On the contrary, it may occur that a model with a relatively high calibration error is a better predictor for non-observed data than other alternative models with relatively low calibration errors (Pindyck, 2015).

It can be argued that the higher calibration error of the WGP PMAUP is a valuable piece of information to improve our analysis, e.g., by allotting different weights to the models in the microeconomic ensemble. Yet, this is challenging due to the subjectivity involved in defining prior assumptions about the accuracy and weight attributable to each model (Tebaldi and Knutti, 2007). Besides, ensemble experiments that assign weights to models typically do so based on the predictive performance of the model (Taner et al., 2019), which cannot be assessed due to the above-mentioned data constraint.

Accordingly, rather than excluding models with high calibration errors or using a weighting approach, we consider all the models in the microeconomic ensemble (including the WGP PMAUP) and adopt an unweighted approach[1]. This allows us to more thoroughly sample modeling uncertainty, identify a larger number of potential surprises (as compared to ensembles excluding specific models and related predictions/ensemble elements), and minimize potential regret—thus contributing to a more robust analysis on the feasibility of the proposed index-based drought insurance scheme.

### 4.2. *Fair premium estimations*

Next, we use the predictions on expected damages (see Fig. 4) to calculate the corresponding fair risk premiums under each climate change scenario. The fair risk premium is a critical variable to assess the feasibility of insurance and can be interpreted as the minimum long-term annuity cost for the proposed drought insurance scheme to be supplied by a competitive and risk-neutral insurance firm. The fair risk premium is obtained as the ratio of the expected compensation to the insured asset. In our case, the insured asset equals the expected profit under full (100%) water allocation (in constant prices); while the expected compensation (or indemnity) is obtained as a function of the expected damage under each climate scenario reported in Fig. 4 and the deductible applied by the insurance industry. The deductible is a mandatory out-of-pocket expense by the insured that is typically required before any compensation is paid, represented as the fraction of the potential economic damage that is not covered by the insurance company. In Spanish crop insurance schemes, the deductible is typically set at 30% (Ruiz et al., 2015). If the deductible is 0%, the company compensates the irrigator for all drought damages; on the other hand, when there is a deductible, the company only compensates the irrigator if damages are higher than the deductible multiplied by the value of the insured asset, and the compensation paid amounts to the damages in excess of the deductible. For example, if the deductible is 30% and a drought causes damages equaling 32% of the value of the insured asset, the company would compensate the irrigator with an amount equaling 2% of the value of the insured asset (damage in excess of the deductible). For any damage of 30%, or lower, there would be no compensation. Deductibles are a key instrument to address moral hazard behavior: without deductibles, irrigators would have no incentives to reduce their drought exposure (and drought damages) because they do not bear the cost of that risk. Thus, deductibles are typically applied to crop insurance schemes worldwide (Pérez-Blanco et al., 2017). By reducing the share of damages to be compensated, deductibles also reduce the fair risk premium and make insurance policies more affordable to farmers. Fig. 7 reports the range of the fair risk premium (in %) under each climate change scenario for deductibles of 1%, 5%,10% and 30%.

[1] It has been argued that when "probabilistic information is not considered, each potential vulnerability is equally important on the overall robustness, which can also be interpreted as an implicitly equal weighting" (Taner et al., 2019). Yet, in our case we cannot claim that each model has an equal weight, because these weights are essentially unknown.

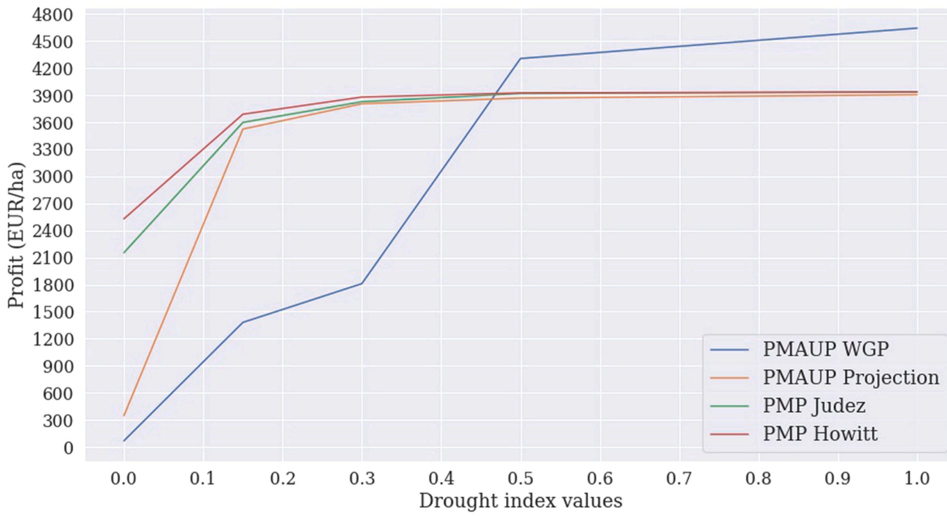


**Fig. 5.** Expected profit under each plausible value of the CRS TSU drought index for the four models in the ensemble of microeconomic mathematical programming models.

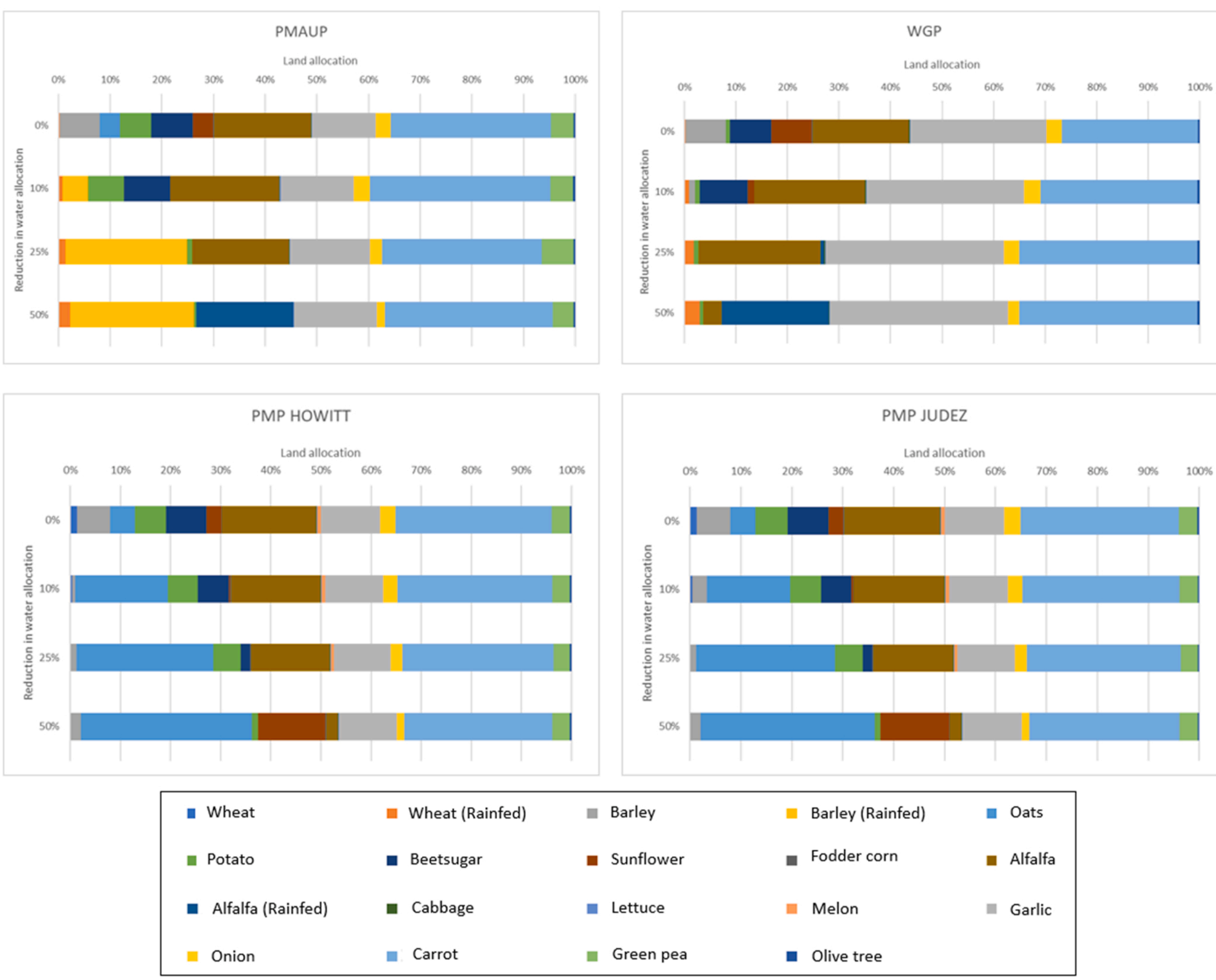


**Fig. 6.** Crop portfolio choices in the four mathematical programming models in the microeconomic ensemble.

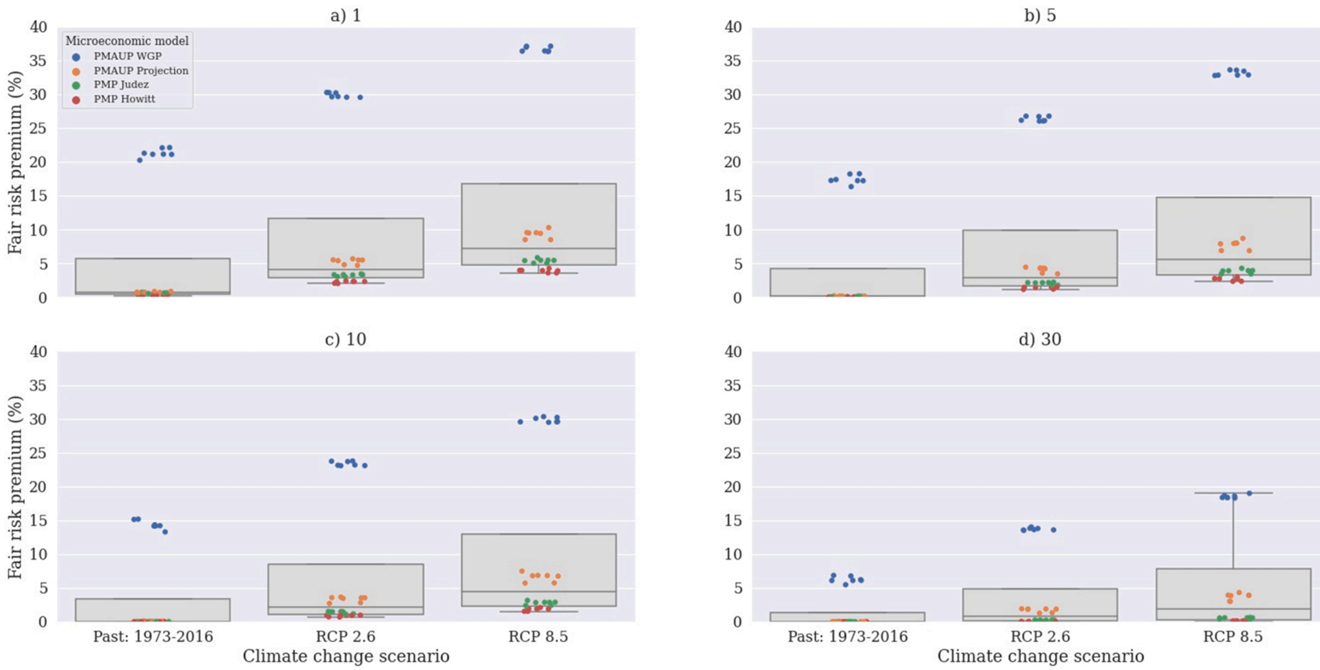


**Fig. 7.** Fair risk premiums under each climate change scenario for a deductible of 1% (a), 5% (b), 10% (c) and 30% (d).

In the scenario with stationary climate (no climate change), the fair risk premium ranges between 0.2% and 22% of the insured asset for a 1% deductible; between 0.01% and 18.2% for a 5% deductible; between 0% and 15% for a 10% deductible; and between 0% and 6.8% for a 30% deductible. In the RCP 2.6 scenario, the fair risk premium ranges between 2% and 30.3% of the insured asset for a 1% deductible; between 1.1% and 26.8% for a 5% deductible; between 0% and 23.8% for a 10% deductible; and between 0% and 14% for a 30% deductible. In the RCP8.5 scenario, the fair risk premium ranges between 3.6% and 37.1% of the insured asset for a 1% deductible; between 2.3% and 33.6% for a 5% deductible; between 1.5% and 30.3% for a 10% deductible; and between 0.1% and 19% for a 30% deductible. It is important noting that the cost of the insurance policy depends, on top of the fair risk premium, on the commercial premium (administration, commercialization); albeit for index-based insurance schemes with low administration and commercialization costs, commercial premiums are minor and typically increase fair risk premiums by 10–20% (Bielza et al., 2009; Guerrero-Baena and Gómez-Limón, 2019). Accounting for this additional margin has no impact on our results in Table 2; thus for the sake of simplicity we treat insurance costs and fair risk premium as synonyms.

**Table 2**
Statistical summary of the fair risk premium to variable costs ratios for an insurance scheme with a 1%, 5%, 10% and 30% deductible.

| Scenario | Deductible | Maximum | Minimum | Mean | Median |
|---|---|---|---|---|---|
| **Past: 1973 – 2016** | **1%** | 63.6% | 0.3% | 15.1% | 1.4% |
| **RCP 2.6** | **1%** | 87.8% | 3.7% | 25.4% | 8.0% |
| **RCP 8.5** | **1%** | 107.8% | 6.6% | 33.9% | 14.1% |
| **Past: 1973 – 2016** | **5%** | 52.4% | 0.0% | 11.8% | 0.2% |
| **RCP 2.6** | **5%** | 77.7% | 2.1% | 21.4% | 5.6% |
| **RCP 8.5** | **5%** | 97.6% | 4.3% | 29.4% | 11.0% |
| **Past: 1973 – 2016** | **10%** | 43.6% | 0.0% | 9.7% | 0.1% |
| **RCP 2.6** | **10%** | 69.1% | 1.3% | 18.5% | 4.2% |
| **RCP 8.5** | **10%** | 88.1% | 2.8% | 25.7% | 8.7% |
| **Past: 1973 – 2016** | **30%** | 19.7% | 0.0% | 4.2% | 0.0% |
| **RCP 2.6** | **30%** | 40.7% | 0.0% | 10.2% | 1.5% |
| **RCP 8.5** | **30%** | 55.2% | 0.1% | 14.7% | 3.6% |

The feasibility of drought risk in irrigated agriculture depends on the affordability of the estimated fair risk premiums, which calls for additional information on irrigators willingness and/or ability to pay for the proposed drought insurance scheme. Estimating the willingness to pay for crop insurance requires ad-hoc fieldwork/interviews and modeling through revealed preference (Pérez-Blanco et al., 2016) or stated preference methods (e.g., contingent valuation) (Liesivaara and Myyra, 2014), a task that is out of the scope of this paper. On the other hand, the ability to pay of economic agents is often assessed in the literature by comparing the risk premium to the other variable costs already paid by the agent. For example, Gómez-Limón (2020) assesses the affordability of an hypothetical drought insurance scheme through the ratio of the fair risk premium (in absolute instead of relative terms) to variable costs (which we weight by the probabilities of each water constraint, so as to determine the simulated cost). According to this author, if the fair risk premium represents less than 20% of the variable costs, the insurance policy can be considered affordable; albeit the preferred threshold is 10%. Table 2 shows the fair risk premium to variable costs ratios for different deductibles in the CRS.

For a conventional deductible of 30%, the proposed index-based insurance would be actuarially feasible (fair risk premium to variable costs ratio <20%) under all models for the current (stationary) climate (i.e., robust); and under all models except for the WGP PMAUP (which overestimates drought damage as compared to the other three models in the microeconomic ensemble) for the RCP2.6 and RCP8.5 climate change scenarios. Based on the median estimate, which is more robust to the WGP outlier, the proposed index-based insurance scheme would be actuarially feasible under all models and scenarios, as well as all deductibles. If we consider the mean estimate, the proposed index-based insurance scheme would be unfeasible under RCP2.6 and RCP8.5 scenarios unless a deductible of 30% (10% in the case of RCP2.6) is applied.

It is worth noting that the information on the WGP PMAUP outliers warns us about potential unfavorable surprises, which can trigger massive damages and threaten the feasibility of the proposed index-based insurance. To prevent these damages from realizing, and particularly in the case of systemic risks such as droughts, insurers often hire re-insurance instruments to hedge against potentially massive damages without the need to immobilize large amounts of money (Rejda and McNamara, 2014). The exploration of these outliers can thus provide valuable information for insurers assessing the development of hydrological insurance and the acquisition of re-insurance instruments.

## 5. Conclusions

This paper assesses the feasibility and robustness of an index-based insurance scheme against droughts in irrigated agriculture under climate change. To this end, we develop a grand ensemble that samples both modeling and scenario uncertainty in the estimation of the insurance risk premium. The grand ensemble combines four microeconomic models and seven GAMLSS models, which are run for three alternative climate change scenarios. Methods allow us to reveal potential unfavorable surprises and minimize regret in the design and development of the proposed drought insurance scheme. Methods are illustrated with an application to the CRS in Spain, where we find that, for a conventional deductible of 30%, the proposed index-based insurance is actuarially feasible under all models for the current (stationary) climate (i.e., robust). Under climate change (RCP2.6 and 8.5), all models considered, with the exception of the PMAUP WGP, show that the risk premium is affordable (all deductibles).

We envision several ways in which further research can improve the methods presented here. First, ad-hoc studies on the willingness to pay for drought insurance in irrigated agriculture are necessary to obtain more conclusive results on the feasibility of the proposed insurance scheme. Second, our analysis has been applied considering the current approach to water resources management in the CRS. If water resources management in the area changes (e.g. new infrastructures are built, such as reservoirs, and/or TSU drought indices are revised), our assessment will have to be updated to account for these changes and reassess the feasibility of index-based hydrological drought insurance in the area. Third, assessments on the costs of re-insurance policies and its impact on risk premiums are necessary to assess the feasibility of the proposed index-based hydrological drought insurance Fourth, crop insurance may trigger moral hazard, because the insured agent has an incentive to increase its exposure to risk given it does not bear the full costs of that risk. Recent research has suggested that moral hazard tends to negatively affect autonomous climate change adaptation efforts by farmers through a reduction in self-protection behavior, such as the adoption of drought-resistant crops with a lower expected profit and risk (Miao, 2020; Müller et al., 2017). Moral hazard has been traditionally addressed through insurance deductibles, albeit new approaches have suggested that risk-based pricing can play a relevant role in reducing moral hazard while also encouraging self-protection behavior (Surminski et al., 2015). Further research should also explore the impact of risk-based pricing and other incentives supporting autonomous adaptation on the performance and affordability of hydrological drought insurance. Fifth, in line with conventional mathematical programming modeling, the decision variable used in the microeconomic ensemble refers exclusively to crop portfolio choices/land allocation. While this allows for extensive (land reallocations towards less water intensive crops) and super-extensive (land reallocations from irrigated to rainfed agriculture) margin adjustments, it excludes intensive margin adjustments through deficit irrigation, an increasingly relevant adaptation option to irrigators in water stressed areas—albeit still of marginal relevance in the CRS (Graveline and Mérel, 2014). As the new generation of mathematical programming models allows for intensive margin adjustments, and an ensemble of such models can be conformed, we expect the microeconomic ensemble to become more realistic—and potentially more accurate—in the predictions of irrigators' responses. Finally, additional relevant scenarios and systems could be incorporated into the analysis to more thoroughly sample uncertainty. Critically, our methodology combines the impact of future climatic variables on water availability with microeconomic simulations using historical and climate stationary agricultural data on water need, crop yield, crop prices and farming costs—all of which will be likely affected by climate change (AgMIP, 2022). This limitation should be explored in further research, e.g. by expanding our GAMLSS modeling to predict changes in these variables, or by explicitly incorporating additional systems and their models (e.g., macroeconomic modeling to assess price fluctuations).

## Data availability

The data and code used to reproduce the article can be found at the Zenodo link in the Online Supplementary Material.


## Acknowledgments

The research leading to these results has been developed with the support of the PRIMA Foundation's TALANOA-WATER Project (Talanoa Water Dialogue for Transformational Adaptation to Water Scarcity under Climate Change), of the Spanish Ministry for the Ecological Transition and Demographic Challenge through Fundación Biodiversidad (ATACC Project - Adaptación Transformativa al Cambio Climático en el Regadío) and of the Ministry of Science and Innovation's IRENE Project (Integrated socioeconomic and environmental modeling using remote sensing data for the management of unauthorized water abstractions).


## Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agwat.2022.107938.

## References


2030 Water Resources Group, 2019. The 2030 Water Resources Group Annual Report (Report No. 2019). World Bank, Washington D.C. (US).

AgMIP, 2022, Agricultural Model Intercomparison and Improvement Project [WWW Document]. agmiporg. URL ⟨https://agmip.org/⟩ (accessed 5.26.22).

Alcon, F., Tapsuwan, S., Brouwer, R., de Miguel, M.D., 2014. Adoption of irrigation water policies to guarantee water supply: A choice experiment. Environ. Sci. Policy 44, 226–236. https://doi.org/10.1016/j.envsci.2014.08.012.

Anderies, J.M., 2015. Managing variance: Key policy challenges for the Anthropocene. Proc. Natl. Acad. Sci. 112, 14402–14403. https://doi.org/10.1073/pnas.1519071112.

Arandara, R., Gunasekera, S., Mookerjee, A., 2019. Index Insurance: A Viable Solution for Irrigated Farming? The World Bank,, Washington D.C. (US) doi: .1596/1813-9450-9055.

Bardají, I., Garrido, A., Blanco, I., Felis, A., Sumpsi, J.M., García-Azcárate, T., 2016. State of Play of Risk Management Tools implemented by member states during the period 2014-2020: national and european frameworks (Research for Agri-Committee No. Final Report). European Parliament,, Brussels (Belgium).

Bielza, M., Conte, C., Gallego, F., Stroblmair, J., Catenaro, R., Dittman, C., 2009. Risk Management and Agricultural Insurance Schemes in Europe (JRC Reference Reports No. EUR 23943 EN). Joint Research Centre, Ispra (Italy).

Buchholz, M., Musshoff, O., 2014. The role of weather derivatives and portfolio effects in agricultural water management. Agric. Water Manag. 146, 34–44. https://doi.org/10.1016/j.agwat.2014.07.011.

C3S, 2022, Climate Data Store [WWW Document]. Database. URL ⟨https://cds.climate.copernicus.eu/#!/home⟩ (accessed 3.18.22).

CEDEX, 2021, Centro de Estudios y Experimentación de Obras Públicas: Anuario de Aforos 2013 - 2021 [WWW Document]. Anu. Aforos. URL ⟨http://ceh-flumen64.cedex.es/anuarioaforos/default.asp⟩.

Cloke, H.L., Pappenberger, F., van Andel, S.J., Schaake, J., Thielen, J., Ramos, M.H., 2013. Hydrological ensemble prediction systems. Hydrol. Process. 27, 1–4. https://doi.org/10.1002/hyp.9679.

CMIP6, 2022, Detailed and up-to-date description of the CMIP6 experiments protocol [WWW Document]. ES-DOC. URL ⟨https://search.es-doc.org/?project=cmip6&⟩ (accessed 12.9.21).

CORBA, 2018. Plan Especial de Sequía (Report). Cantábrico Occidental River Basin Authority.

DRBA, 2017. Plan Especial de Sequía (Report). Duero River Basin Authority.

DRBA, 2020. Esquema de temas importantes en materia de gestión de las aguas del Plan Hidrológico 2022-2027 (River Basin Management Plan). Duero River Basin Authority,, Valladolid (Spain).

Essenfelder, A.H., Pérez-Blanco, C.D., Mayer, A.S., 2018. Rationalizing Systems Analysis for the Evaluation of Adaptation Strategies in Complex Human-Water Systems. Earths Future 6, 1181–1206. https://doi.org/10.1029/2018EF000826.

EURO-CORDEX, 2022, EURO-CORDEX Data [WWW Document]. EURO-CORDEX Database. URL ⟨https://www.euro-cordex.net/060378/index.php.en⟩ (accessed 3.18.22).

FAO, 2021, FaoStat [WWW Document]. Food Agric. Organ. U. N. URL ⟨http://faostat.fao.org/⟩ (accessed 2.10.21).

Gómez, C.M., Pérez-Blanco, C.D., 2012. Do drought management plans reduce drought risk? A risk assessment model for a Mediterranean river basin. Ecol. Econ. 76, 42–48. https://doi.org/10.1016/j.ecolecon.2012.01.008.

Gómez-Limón, J.A., 2020. Hydrological drought insurance for irrigated agriculture in southern Spain. Agric. Water Manag. 240, 106271 https://doi.org/10.1016/j.agwat.2020.106271.

Gómez-Limón, J.A., Gutiérrez-Martín, C., Riesgo, L., 2016. Modeling at farm level: Positive Multi-Attribute Utility Programming. Omega 65, 17–27. https://doi.org/10.1016/j.omega.2015.12.004.

Graveline, N., 2016. Economic calibrated models for water allocation in agricultural production: A review. Environ. Model. Softw. 81, 12–25. https://doi.org/10.1016/j.envsoft.2016.03.004.

Graveline, N., Mérel, P., 2014. Intensive and extensive margin adjustments to water scarcity in France's Cereal Belt. Eur. Rev. Agric. Econ. 41, 707–743. https://doi.org/10.1093/erae/jbt039.

GRBA, 2018. Plan Especial de Sequía (Report). Guadiana River Basin Authority.

Guerrero-Baena, M.D., Gómez-Limón, J.A., 2019. Insuring water supply in irrigated agriculture: a proposal for hydrological drought index-based insurance in Spain. Water 11, 686. https://doi.org/10.3390/w11040686.

Gutiérrez-Martín, C., Gómez, C.M., 2011. Assessing irrigation efficiency improvements by using a preference revelation model. Span. J. Agric. Res. 9, 1009–1020. https://doi.org/10.5424/sjar/20110904-514-10.

Heckelei, T., Britz, W., Zhang, Y., 2012. Positive Mathematical Programming Approaches - Recent Developments in Literature and Applied Modelling. Bio-Based Appl. Econ. J. 1, 109–124.

High Representative of the Douro River Basin Authority, personal communication, 2022. Personal Communication. TALANOA-WATER Project Local Workshop,.

Howitt, R.E., 1995. Positive mathematical programming. Am. J. Agric. Econ. 77, 329–342. https://doi.org/10.2307/1243543.

IPCC, 2019. Special Report on Climate Change and Land. Intergovernmental Panel on Climate Change, Geneva (Switzerland).

IPCC, 2022. AR6 Climate Change 2022: Impacts, Adaptation and Vulnerability — IPCC (Assessment Report No. AR6). IPCC, Geneva (Switzerland).

ISIMIP, 2022, The Inter-Sectoral Impact Model Intercomparison Project [WWW Document]. Inter-Sect. Impact Model Intercomp. Proj. URL ⟨https://www.isimip.org/gettingstarted/data-access/⟩ (accessed 12.3.21).

Júdez, L., de Miguel, J.M., Mas, J., Bru, R., 2002. Modeling crop regional production using positive mathematical programming. Math. Comput. Model. 35, 77–86. https://doi.org/10.1016/S0895-7177(01)00150-9.

Knight, F.H., 1921. Risk Uncertainty and Profit. Martino Fine Books.

Konishi, S., Kitagawa, G., 2008. Information Criteria and Statistical Modeling. Springer Series in Statistics. Springer-Verlag, New York.

Leiva, A.J., Skees, J.R., 2008. Using Irrigation Insurance to Improve Water Usage of the Rio Mayo Irrigation System in Northwestern Mexico. World Dev., Spec. Sect.: Soc. Mov. Dyn. Rural Dev. Lat. Am. (pp. 2874-2952) 36, 2663–2678. https://doi.org/10.1016/j.worlddev.2007.12.004.

Lempert, R.J., Popper, S.W., Bankes, S.C., 2003. Shaping the Next One Hundred Years (Product Page). RAND Santa Monica,.

Liesivaara, P., Myyra, S., 2014. Willingness to pay for agricultural crop insurance in the northern EU. Agric. Financ. Rev. 74, 539–554.

MAGRAMA, 2017. Evaluación del impacto del cambio climático en los recursos hídricos y sequías en España (Report). Ministerio de Agricultura y Pesca, Alimentación y Medio Ambiente,, Madrid (Spain).

MAGRAMA, 2020a. Anuario de Estadística Agraria (Agricultural Statistics Yearbook) (Report). Ministerio de Agricultura, Alimentación y Medio Ambiente,, Madrid (Spain).

MAGRAMA, 2020b. Resultados técnico-económicos de explotaciones agrarias (Database). Ministerio de Agricultura, Alimentación y Medio Ambiente,, Madrid (Spain).

Marchau, V.A.W.J., Walker, W.E., Bloemen, P., Popper, S.W., 2019. Decision Making under Deep Uncertainty: From Theory to Practice, 2019th ed..,. Springer,, Cham, Switzerland.

Miao, R., 2020. Climate, insurance and innovation: the case of drought and innovations in drought-tolerant traits in US agriculture. Eur. Rev. Agric. Econ. 47, 1826–1860. https://doi.org/10.1093/erae/jbaa010.

Moghaddasi, R., Eghbali, A., Lakhaye Rizi, P., 2014. Analysis and Forecasting of Drought by Developing a Fuzzy-Based Hybrid Index in Iran (Working Paper). MPRA,.

Montilla-López, N.M., Gómez-Limón, J.A., Gutiérrez-Martín, C., 2018. Sharing a river: Potential performance of a water bank for reallocating irrigation water. Agric. Water Manag. 200, 47–59. https://doi.org/10.1016/j.agwat.2017.12.025.

Müller, B., Johnson, L., Kreuer, D., 2017. Maladaptive outcomes of climate insurance in agriculture. Glob. Environ. Change 46, 23–33. https://doi.org/10.1016/j.gloenvcha.2017.06.010.

OECD, 2015. Water Resources Allocation: Sharing risks and opportunities. OECD Studies on Water. OECD Publishing,.

Pérez-Blanco, C.D., Gómez, C.M., 2013. Designing optimum insurance schemes to reduce water overexploitation during drought events: a case study of La Campiña, Guadalquivir River Basin, Spain. J. Environ. Econ. Policy 2, 1–15. https://doi.org/10.1080/21606544.2012.745232.

Pérez-Blanco, C.D., Gómez, C.M., 2014. Insuring water: a practical risk management option in water-scarce and drought-prone regions. Water Policy 16, 244–263. https://doi.org/10.2166/wp.2013.131.

Pérez-Blanco, C.D., Delacámara, G., Gómez, C.M., 2016. Revealing the willingness to pay for income insurance in agriculture. J. Risk Res. 19, 873–893. https://doi.org/10.1080/13669877.2015.1042505.

Pérez-Blanco, C.D., Delacámara, G., Gómez, C.M., 2017. Crop insurance in drought conditions. In: Eslamian, S., Eslamian, F. (Eds.), Handbook of Drought, Environmental Impacts and Analysis of Drought and Water Scarcity. CRC Press, Taylor & Francis, Boca Raton (US).

Pérez-Blanco, C.D., Gutiérrez-Martín, C., Gil-García, L., Montilla-López, N.M., 2021. Microeconomic ensemble modeling to inform robust adaptation to water scarcity in irrigated agriculture. J. Water Resour. Plan. Manag. 147, 04021038, 10.1061/(ASCE)WR.1943-5452.0001385.

Pindyck, R.S., 2015. The Use and Misuse of Models for Climate Policy (Working Paper No. 21097). National Bureau of Economic Research,.

Rejda, G.E., McNamara, M.J., 2014. Principles of Risk Management and Insurance, 12th ed..,. Pearson Education.

Rey, D., Pérez-Blanco, C.D., Escriva-Bou, A., Girard, C., Veldkamp, T.I.E., 2019. Role of economic instruments in water allocation reform: lessons from Europe. Int. J. Water Resour. Dev. 35, 206–239. https://doi.org/10.1080/07900627.2017.1422702.

Ruiz, J., Bielza, M., Garrido, A., Iglesias, A., 2015. Dealing with drought in irrigated agriculture through insurance schemes: an application to an irrigation district in Southern Spain. Span. J. Agric. Res. 13, 0106.

Sapino, F., Pérez-Blanco, C.D., Gutiérrez-Martín, C., Frontuto, V., 2020. An ensemble experiment of mathematical programming models to assess socio-economic effects of agricultural water pricing reform in the Piedmont Region, Italy. J. Environ. Manag. 267, 110645 https://doi.org/10.1016/j.jenvman.2020.110645.

Stasinopoulos, M.D., Rigby, R.A., Heller, G.Z., Voudouris, V., Bastiani, F.D., 2020, Flexible Regression and Smoothing: Using GAMLSS in R. S.l.

Sumpsi, J., Amador, F., Romero, C., 1997. On farmers' objectives: A multi-criteria approach. Eur. J. Oper. Res. 96, 64–71. https://doi.org/10.1016/0377-2217(95)00338-X.

Surminski, S., Aerts, J.C.J.H., Botzen, W.J.W., Hudson, P., Mysiak, J., Pérez-Blanco, C.D., 2015. Reflections on the current debate on how to link flood insurance and disaster risk reduction in the European Union. Nat. Hazards 79, 1451–1479. https://doi.org/10.1007/s11069-015-1832-5.

Taleb, N.N., 2008. The Black Swan: The Impact of the Highly Improbable. Edición: Trade Paperback. ed. Penguin,, London.

Taner, M.Ü., Ray, P., Brown, C., 2019. Incorporating multidimensional probabilistic information into robustness-based water systems planning. Water Resour. Res. 55, 3659–3679. https://doi.org/10.1029/2018WR022909.

Tebaldi, C., Knutti, R., 2007. The use of the multi-model ensemble in probabilistic climate projections. Philos. Trans. R. Soc. Math. Phys. Eng. Sci. 365, 2053–2075. https://doi.org/10.1098/rsta.2007.2076.

TRBA, 2018. Plan Especial de Sequía (Report). Tagus River Basin Authority.

UN, 2018. The United Nations World Water Development Report 2018 (Report). United Nations.

UNDRR, 2021. GAR Special Report on Drought 2021 - World (Special Report on Drought). United Nations Office for Disaster Risk Reduction,, Geneva (Switzerland).

World Bank, 2016. High and Dry: Climate Change, Water, and the Economy (Report). Water Global Practice. World Bank,, Washington D.C. (US).

WWF, 2020. El robo del agua: Cuatro ejemplos flagrantes del saqueo hídrico en España (Report). WWF,, Madrid (Spain).