ECONOMIC RISK ASSESSMENT OF DROUGHT IMPACTS ON IRRIGATED AGRICULTURE

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ABSTRACT

In this paper we present an innovative framework for an economic risk analysis of drought impacts on irrigated agriculture. It consists on the integration of three components: stochastic time series modelling for prediction of inflows and future reservoir storages at the beginning of the irrigation season; statistical regression for the evaluation of water deliveries based on projected inflows and storages; and econometric modelling for economic assessment of the production value of agriculture based on irrigation water deliveries and crop prices. Therefore, the effect of the price volatility can be isolated from the losses due to water scarcity in the assessment of the drought impacts. Monte Carlo simulations are applied to generate probability functions of inflows, which are translated into probabilities of storages, deliveries, and finally, production value of agriculture. The framework also allows the assessment of the value of mitigation measures as reduction of economic losses during droughts.

The approach was applied to the Jucar river basin, a complex system affected by multiannual severe droughts, with irrigated agriculture as the main consumptive demand. Probability distributions of deliveries and production value were obtained for each irrigation season. In the majority of the irrigation districts, drought causes a significant economic impact. The increase of crop prices can partially offset the losses

from the reduction of production due to water scarcity in some districts. Emergency wells contribute to mitigating the droughts' impacts on the Jucar river system.

Keywords: Drought, econometric modelling, risk, stochastic modelling

1. Introduction

A drought is an unpredictable extreme hydrological phenomenon, which produces a significant decrease of water resources during a long period of time (water scarcity), affecting a large area and reducing the deliveries below the target demands (CHJ, 2007). The water agencies use different indicators and thresholds together with drought monitoring systems to formally identify the periods under drought and its severity (Pedro-Monzonís et al., 2015). For example, the Jucar River Basin Authority uses a combined index that includes storages, streamflow, groundwater and precipitation (CHJ, 2007).

Severe droughts have traditionally caused considerable socio-economic losses in agriculture, both in rain-fed and irrigated lands, generating significant reductions in crop production (Ding et al. 2011). A remarkable number of studies have analyzed the impacts of droughts on irrigated agriculture (e.g., Iglesias et. al 2003; Calatrava and Garrido, 2005; Peck and Adams, 2010; Howitt et al. 2015 and Hlalele et. al 2016) and the contribution of improved irrigation management in water scarcity areas in order to reduce their vulnerability and impacts (e.g., Ward, 2014; Santos Pereira et al. 2002, Garcia-Vila et al. 2008).

Droughts can produce both direct and indirect economic impacts (Logar and van den Bergh, 2013). Indirect economic costs can be measured using input-output analysis (Pérez y Pérez and Barreiro-Hurlé, 2009), computable general equilibrium (e.g., Berrittella et al. 2007; Goodman, 2000; and Wittwer and Griffith, 2011) or non-market valuation techniques (e.g., Milne, 1991; Martin-Ortega et al., 2012). The methods used to estimate direct revenue losses in the agricultural sector are usually based on crop production functions and crop market prices. Both inputs can be embedded into basin-scale water resource management models through hydroeconomic modelling (Harou et al., 2009 and Pulido-Velazquez et al. 2008) in order to assess their economic impacts of droughts subject to the physical, environmental and institutional features of the system (e.g., Booker et al., 2005; Ward et al., 2006; Harou et al., 2010; Ward and Pulido-Velazquez, 2012). Alternatively, econometric models have been used to assess direct impacts on irrigated agriculture considering the influence of a variety of factors (e.g., water availability, crop prices). For instance, Connor et al. (2014) assessed the impacts of crop price volatility, water availability and climate conditions on the irrigation revenues at Murray-Darling river basin (Australia). Gil et al. (2010 and 2011) analyzed the impacts of crop price volatility and water availability on irrigated production value in several Spanish irrigation districts, linking agricultural productivity with water availability (based on reservoir storages) and demand.

The prediction of water deliveries to agricultural districts in each irrigation season requires the forecasting of future inflows and the system operating rules that define water allocation/distribution. Most previous studies on drought risk analysis treat water availability as a random variable, without modelling the stochastic nature of the inflows and the water balance that defines the storages. The simulation of the system operating rules allows to estimate water deliveries for irrigation. However, stochastic time series models allow for the characterization of the uncertainty of the hydrological inputs, which can be transferred into water deliveries through the simulation of the system operation.

The framework performs an economic risk analysis of drought impacts by combining stochastic projections of inflows with an explicit reproduction of the system operating rules. An econometric model is used to assess the production value in agriculture depending on water deliveries and crop prices. The work follows as: the description of the proposed framework, the characterization of the case study, and the presentation and analysis of the main results. Finally, the main conclusions and discussion of the proposed methodology and its application to the case study are presented.

2. Method

The proposed framework aims to develop a risk analysis of the drought economic impacts that can aid the managers to make decisions to deal with scarcity. It comprises of three components (see Fig. 1). The first one consists of fitting an econometric model to assess the economic drought impacts, by evaluating the changes in the production value due to water scarcity. The model should include the main explanatory variables of the irrigated production value, including the effect of water availability for irrigation as a key indicator of scarcity conditions. The choice of the independent variables and the level of aggregation of the data are conditioned by data availability. The second component consists of developing an autoregressive stochastic time series model to forecast the inflows of the system that explain the changes of storage in the main reservoirs. The third component is the simulation of the system operation, using statistical regressions among deliveries, storages and inflows.

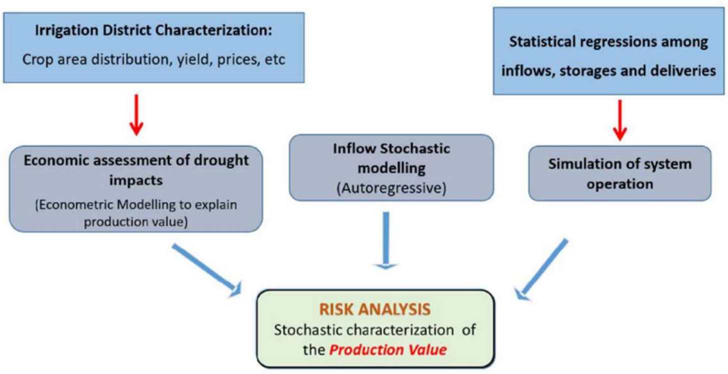

Figure 1. Risk analysis of the economic impacts of droughts

2.1 Economic assessment through econometric modelling

An econometric model is used as a basis of the risk assessment of drought impacts, employing water availability and an index of crop prices as explanatory variables of the production value of irrigated agriculture. The annual historical production value in each irrigation district "j" and year "t" is calculated as:

$$P_{v_{j,t}} = \sum_{c=1}^{n} S_{c,t} \cdot Y_{c,t} \cdot P_{c,t} \qquad [1]$$

Where "c" represents each main irrigation crop in irrigation district "j" (c=1,…,n), "$S_{c,t}$" is the crop area in irrigation district "j" in year "t" of each crop "c", "$Y_{c,t}$" is the crop yield and "$P_{c,t}$" is the annual crop price

Water deliveries for irrigation are split into two components: surface deliveries (SW) and groundwater abstraction (GW) for two reasons: 1) the differences in efficiencies of supply depending on the water sources, and 2), that in most cases the two sources can be applied to different crops within the irrigation districts (e.g., groundwater is not used for rice). Therefore, the value of the marginal product of water is different for the 2 sources.

The effect of price change/volatility is isolated from the effect of the change in water availability by including crop prices as explanatory variable. Thus, the production value of agriculture at each irrigation district (based on Gil et al., 2011) is assessed as:

$$P_{v\,j,t} = a + b \cdot SW_{j,t} + c \cdot GW_{j,t} + d \cdot I_{P\,j,t} + u_{j,t} \qquad [2]$$

Where "j" is each irrigation district, "t" represents the year, "$SW_{j,t}$" represents the surface deliveries, "$GW_{j,t}$" are the groundwater abstractions (including both normal abstractions and the additional drought abstractions), "$I_{pj,t}$" is the crop price index and "$u_{j,t}$" is the error of the model. There will certainly be a range of other influential factors affecting the final production (rainfall, temperature, fertilization and irrigation practices, other natural hazards, etc.).

A price index for each district has been calculated to capture the shifts of the production value due to crop price volatility (Eq. 3), weighted by the contribution of each family of crops to the total production value in the district (based on Gil et al. 2011).

$$Ip_{j,t} = \sum_k \frac{Pv_{k,t} \cdot P_{k,j,t}}{Pv_{j,t}} \qquad P_{k,j,t} = \frac{\sum_c Pv_{c,k,t} \cdot P_{c,k,t}}{\sum_{ck} Pv_{k,t}} \qquad [3]$$

Where "c" is each crop, "k" represents the crop classes and "j" the crops within each crop class.

2.2 Stochastic inflow modelling and forecasting

In order to assess the uncertain future of water availability in the system, a probabilistic forecasting of the upcoming inflows is needed. Future inflows have been estimated using stochastic time series modeling. These methods try to reproduce some important statistical properties observed on the historical inflow time series (average, variance, skewness, spatial and temporal dependency and so on) for generating large sets of equally-likely inflow scenarios (Hipel and McLeod 1994; Salas et al. 1980 and 1993). The generation of future inflow projections using stochastic modeling has been widely applied in research as the basis of probabilistic assessments (Labadie 2004). Hence, the statistical distributions of the operational variables (storages, deliveries, production, etc...) can be derived using multiple time series of inflows for the influential hydrological subbasins. The methods used in stochastic modeling take advantage of the spatio-temporal dependency in the values of the inflow time series, estimating future inflows for the irrigation season based on the previous known values plus a random component. There is a variety of stochastic alternatives for modeling univariate and multivariate time series (ARMA models, ARIMA, PARMA, FARMA, Markov chains and so on). The correct choice will depend on the case study features and requirements (Hipel and McLeod 1994; Salas et al. 1980; Sveinsoon and Salas, 2017).

In the research carried out in this paper, without loss of generality, an ARMA (1,1) model with constant parameters has been used for inflow forecasting. Future inflows were estimated based on the previous ones plus some random terms, through the following equation:

$$z_t = \delta_1 \cdot z_{t-1} + \omega_0 \cdot \varepsilon_t - \omega_1 \cdot \varepsilon_{t-1} \quad [4]$$

Where z_t is the standard normally-distributed inflow forecast for time stage t; and δ_1, ω_0 and ω_1 are matrices of parameters corresponding to the previous normal standard inflows (z_{t-1}) and the random terms (ε_t and ε_{t-1}), corresponding to normally distributed and independent noise with mean zero. The model's parameters can be estimated using the procedures described in Salas et al (1980 and 1993), Hipel and McLeod (1994) and Sveinsoon and Salas (2017):

$$\delta_1 = M_2 \cdot M_1^{-1} \quad [5]$$

Where M_2 and M_1 are the autocorrelation matrices of order 1 and 2 of the time series of inflows whose forecasts are desired. The error term of order 0 can be obtained using the following iterative procedure:

$$\omega_0 \cdot \omega_0^T = F - G \cdot (\omega_0 \cdot \omega_0^T)^{-1} \cdot G^T \quad [6]$$

Where $\mathrm{F} = \mathrm{M}_0 - \delta_1 \cdot \mathrm{M}_1^{\mathrm{T}} + \mathrm{G} \cdot \delta_1^{\mathrm{T}}$; and $\mathrm{G} = \delta_1 \cdot \mathrm{M}_0 - \mathrm{M}_1$. The ω_0 term can be obtained by applying a Cholesky decomposition to $\omega_0 \cdot \omega_0^{\mathrm{T}}$. The ω_1 term can be obtained as:

$$\omega_1 = F - G \cdot (\omega_0 \cdot \omega_0^T)^{-1} \cdot G^T \quad [7]$$

Once developed, future inflows can be forecasted following the same stages:

1) Generation of residual time series (ε_t) for the given forecasting horizon L (e.g. 7 months) for each subbasin in which the forecast is desired. The number of series should be large enough to guarantee an adequate sampling of the probability distribution of the future inflows.
2) For each scenario, the forecasted inflows can be obtained by sequentially applying equation [4] from the current time stage (t) to the forecasting horizon (t+L), using the previous value of the inflows (t-1) and the residual time series computed before. The result will be a set of normally distributed inflow time series.
3) Transformation of the previous normally distributed inflow forecasts into times series of inflow preserving the main statistical properties of the historical one.

2.3 Simulation of system operations

In order to reproduce the system operation, empirical regressions based on observed decisions have been used, linking state variables (reservoir storages, inflows) and decision variables (releases, deliveries). The lead time for the forecasting for the upcoming irrigation season should be selected before carrying out this step. For the simulation of the surface deliveries the procedure includes these steps:

1) A regression model (A) is fitted to explain the storage changes during the lead time as a function of the observed initial storage and the observed inflow during the period. The storage at the beginning of the next irrigation season is then estimated as the observed initial storage at the beginning of the lead time plus the predicted changes in storage (obtained by the fitted regression model A).

2) Another regression model (B) is also fitted to explain the surface water deliveries (SW) depending on the storage at the beginning of the irrigation season coming from step 1
3) The stochastic inflow forecasting (section 2.2) is combined with the regression models (A) and (B) to obtain the stochastic surface water deliveries $\widetilde{SW_{j,t+1}}$

2.4 Risk analysis of the economic impact of the drought

The forecasted value of the production $\widetilde{Pv}_{j,t+1}$ for the season t+1 has been calculated as:

$$\widetilde{P_{v\,j,t+1}} = a + b \cdot \widetilde{SW_{j,t+1}} + c \cdot GW_{j,t+1} + d \cdot \overline{I_{P\,j,t+1}} + u_{j,t+1} \quad [8]$$

Where "t+1" is the starting of the upcoming irrigation season, and "$\overline{I_{P\,j,t+1}}$" is the forecasted crop price index evaluated as the average of the last two years.

$\widetilde{SW_{j,t+1}}$ represents the stochastic surface water deliveries, derived from the stochastic inflow modelling. The groundwater deliveries (GW) have been estimated as a function of the observed total demand and surface deliveries.

3. Case study

The Jucar river basin is a complex water resource system located in Eastern Spain (Fig. 2). The system is strongly regulated and with a high share of water used for crop irrigation (about 83%). Water scarcity, irregular hydrology and groundwater overdraft cause droughts to have significant economic, social and environmental consequences. The total water demand has been estimated at 1,397 Mm^3/year, while the average water resources availability is 1,517 Mm^3/year (data from 1940/41 to 2011/12) (CHJ, 2015). The main surface reservoirs are Alarcon (1,112 Mm^3 of capacity), Contreras (463 Mm^3 of useful capacity) and Tous (378 Mm^3). This river basin has suffered several severe droughts in the last 60 years with significant socio-economic impacts (CHJ, 2007). The latest drought periods (1991/92 to 1994/95; 1997/98 to 1999/00 and 2004/05 to 2008/09) were classified as extreme drought periods using the SPI index (McKee et al., 1993). Drought frequency and severity in the basin is expected to increase in the future due to climate change (Marcos-Garcia and Pulido-Velazquez, 2017).

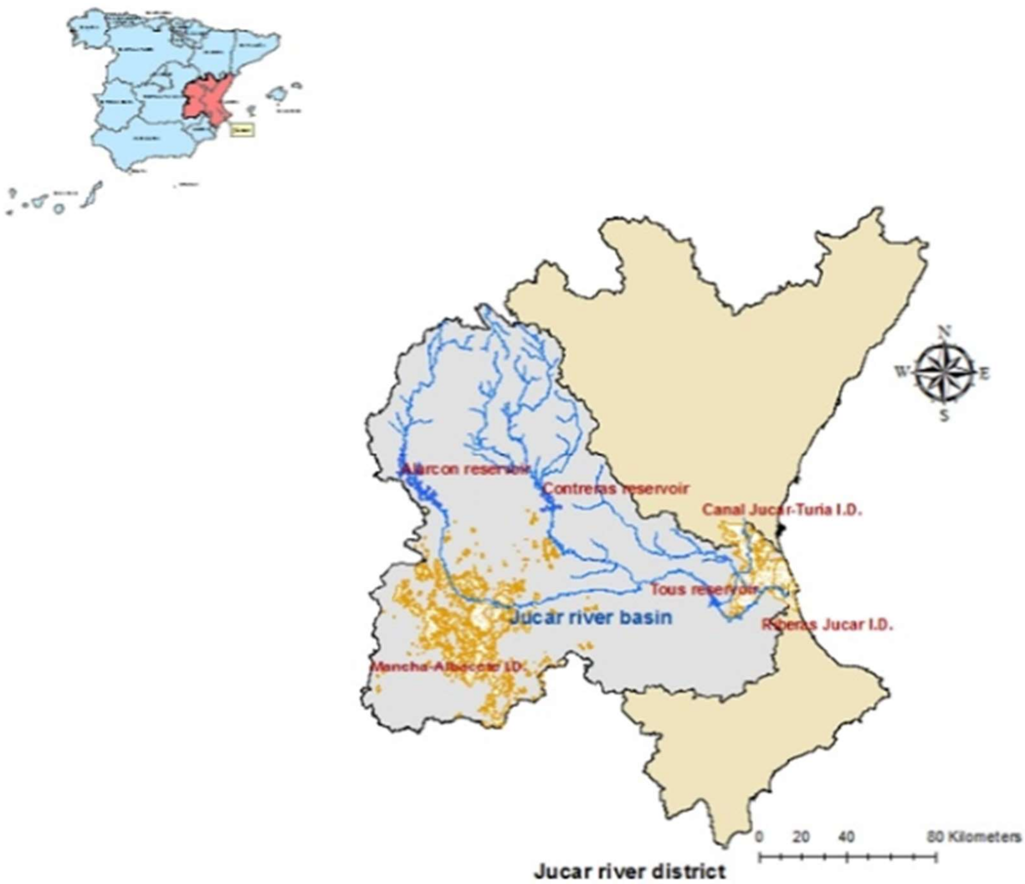

Figure 2. Jucar river district / Jucar river basin

The agricultural demand of water is divided into 3 major irrigation districts (Mancha-Albacete, Canal Jucar-Turia and Riberas del Jucar) (Fig. 2). In Mancha-Albacete the main crop types are cereals, legumes, tubers, green vegetables, and fodder crops (20 crops); while in both, Canal Jucar-Turia and Riberas del Jucar, the main crops are rice and citrus (mainly orange, mandarin, and persimmon). The observed production value and the price index have been calculated using the available data of crop yield, prices and surface distribution at the yearly technical reports and inventories of the Ministry of Agriculture of Spain (e.g., MAPAMA, 2010a,b,c) from 2000 to 2013. Figure 3 shows the evolution of the observed production value in the Riberas del Jucar from 2002 to 2008. (Table 1 of supplementary material shows the observed production value and crop price index for the 3 irrigation districts)

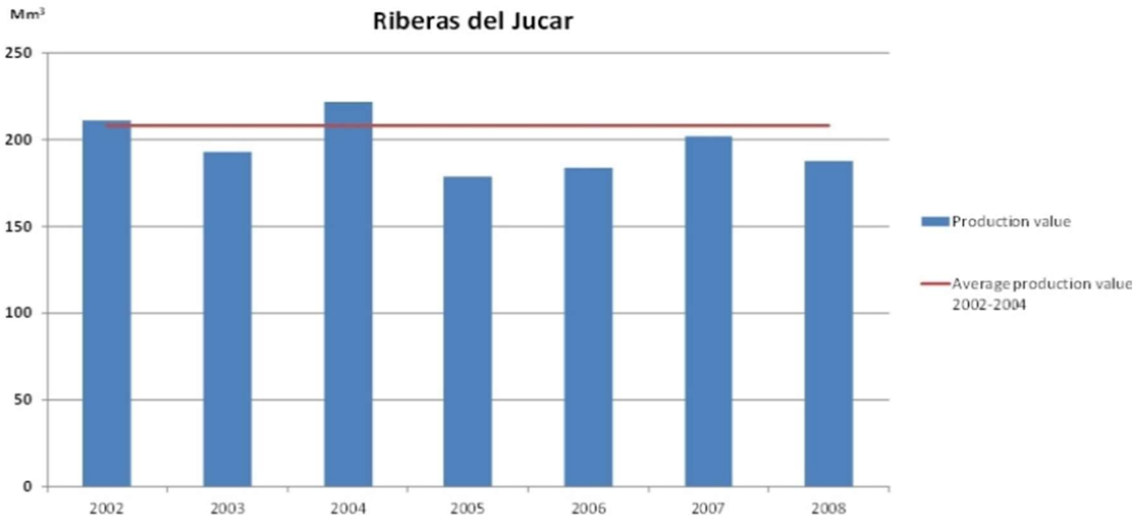

Figure 3. Observed production value in Riberas del Jucar

With respect to water resources, the historical time series of surface (SW) and groundwater (GW) deliveries (Fig. 4) are sourced from the Jucar river basin agency and the Provincial Technical Agronomic Institute of Albacete (ITAP) databases. During the drought period from 2005 to 2008 the surface deliveries for the 3 irrigation districts decreased up to 40% in respect to the previous normal years, while groundwater abstractions increased as a result of the use of drought emergency wells in the Riberas del Jucar irrigation district. In Mancha-Albacete, the authorities established some pumping restrictions from 2006 to 2008.

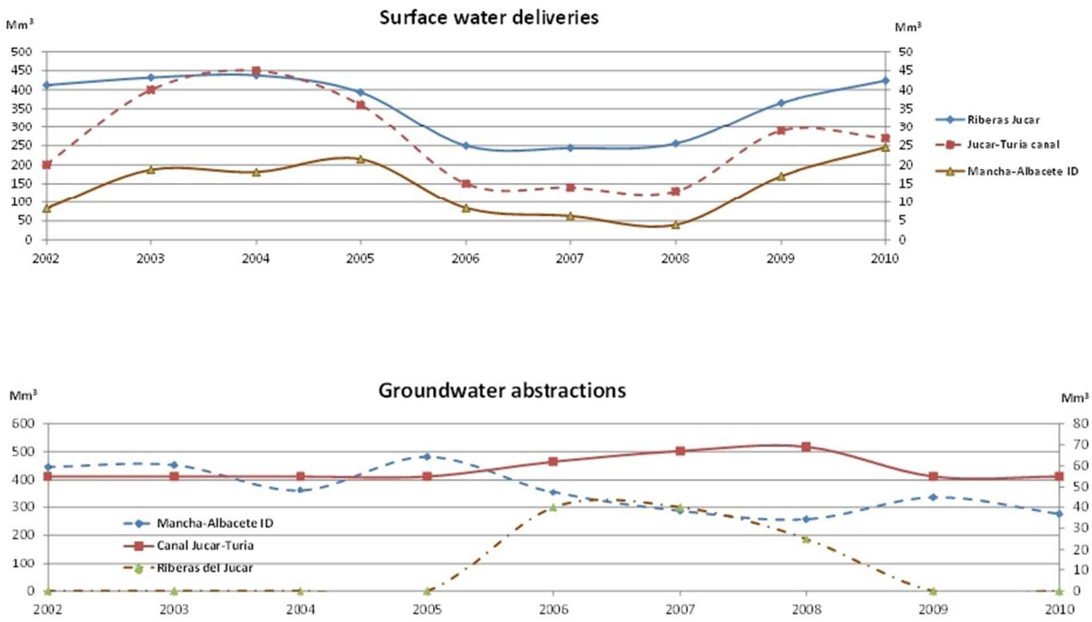

Figure 4. Surface and groundwater deliveries

4. Results

4.1 Econometric assessment

Table 1 shows the summary of the fitted econometric models according to Eq. [2] for the 3 irrigation districts. High values of the adjusted coefficient of determination are obtained in all cases (R^2 greater than 70%). Both surface delivery and crop price variables are significant in the case of the Riberas del Jucar I.D, which is consistent with the fact that these districts only use groundwater during drought periods (drought emergency wells). Fig 1 in the supplementary material shows the plot of the observed vs simulation values of the production value. We have also tested the existence of anomalous observations by analysing the time series of studentized residuals. These residuals measure how many standard deviations each observed value of "Pv" deviates from the adjusted model using all data except from that observation. No anomalous observations were found in any of the 3 districts.

In order to verify that the impact of price volatility can be isolated from the impact of water resources availability, a test of multicollinearity was carried out. Multicollinearity reveals the existence of a perfect relationship among some or all the explanatory variables (Gujarati, 2004). For that purpose, the variance-inflating factor (VIF) have been calculated (Gujarati, 2004).The maximum VIF value in excess of 10 is frequently taken as an indicator that multicollinearity may be unduly influencing the least squares estimates (Kutner et al. 2004). Our results demonstrate that multicollinearity is not significant in any of the regressions, proving that the impacts of crop prices volatility and water resources availability are independent (Table 1).

Table 1. Regression results of the production value of irrigated agriculture

		SW		GW		Ip	
	R^2	**Coefficient**	**VIF**	**Coefficient**	**VIF**	**Coefficient**	**VIF**
Mancha-Albacete I.D.	0.71	-3109.14*	1.52	-477.38*	1.41	-69718.80	2.01
Canal Jucar-Turia I.D.	0.79	-279.40	1.88	1012.54*	2.28	552470*	1.58
Riberas del Jucar I.D.	0.81	253.58*	4.9	1125.56	4.81	458995*	1.07

*P<0.05

VIF>10 shows multicollinearity problems

These results point out that the set of selected explanatory variables (surface and groundwater resources availability and crop price index) does explain accurately the observed changes on the production value of the irrigated districts during droughts.

4.2 Projection of water inflows

As referred in section 2.2, an ARMA (1,1) stochastic model with constant parameters (Salas et al, 1980) was selected because of the strong temporal dependency (high autocorrelation) observed in the inflow time series. The historical streamflow time series in the Jucar river basin from 1980 to 2012 were used in the determination of the model parameters. The ARMA (1,1) model was tested and validated analysing the residuals, assumed to be normally distributed with mean zero, uncorrelated and independent (Salas et al, 1980).

After its validation, the ARMA (1,1) model was used to generate 10,000 synthetic time series of inflow for each lead time considered in the analysis. The lead time spans from October to April (before the irrigation season), and the observed inflows from the previous September were used as the starting value z_0 for the simulations for each inflow scenario. Figure 5 shows the cumulative distribution function for the inflow upstream the Tous reservoir at both the beginning of the drought period (2004-2005) and the rest of the drought period (2006-2007), illustrating the drought effect on the water input to the system.

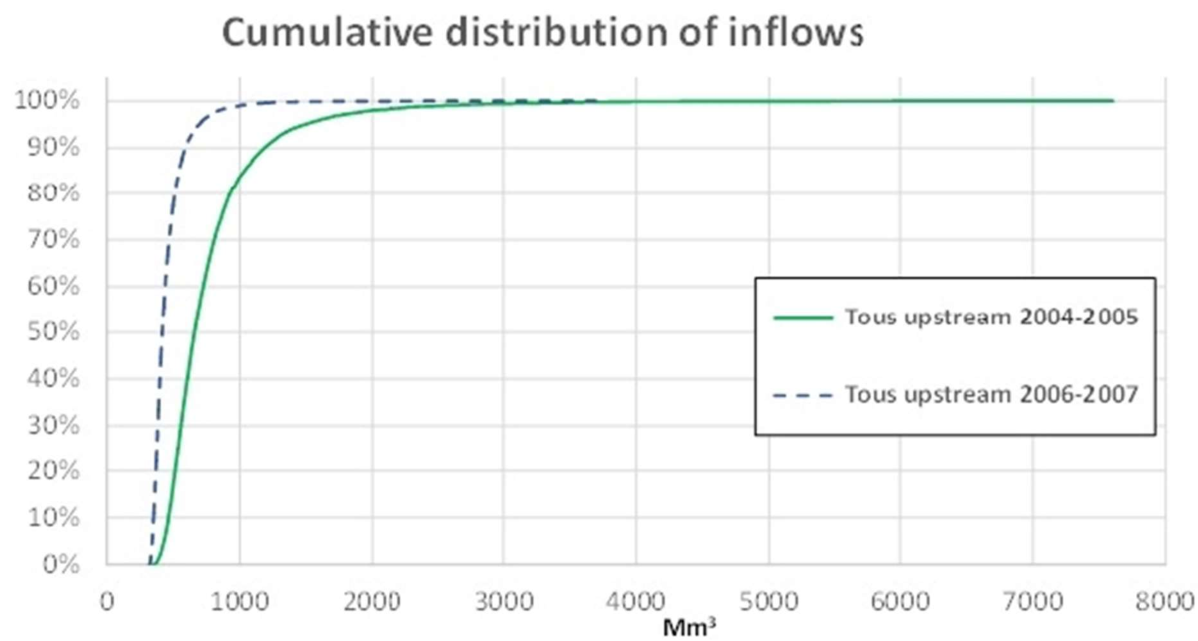

Figure 5. Cumulative distribution of inflows to Tous reservoirs

4.3 Simulation of the operation of the system

In order to simulate the water deliveries to the irrigation districts under different conditions of water availability, the system's operating rules were represented by statistical regressions. The linear regressions shown in Eq. 9 and 10 represent the relations among inflows, storages and deliveries during the lead time (from October, t, to May, t+1, within each hydrological year). Table 2 shows the goodness-of-fit for the three irrigation districts, with R^2 greater than 0.9 in all cases (see figures 2 and 3 in supplementary material).

$$\nabla \mathrm{Vol}_{t,t+1} = a \cdot Vol_{\,t} + b \cdot Inflow_{t,t+1} + u \qquad [9]$$

$$SW_{t+1} = a \cdot Vol_{\,t+1} + u \qquad [10]$$

Table 2. Statistical parameters of the regressions of the system's operating rules

Storage Changes		**a**	**b**
	R²	***Estimation***	***Estimation***
Alarcon, Contreras & Tous reservoirs	0.97	-0.41935*	0.68031*
Alarcon reservoir	0.97	-0.373626*	0.906147*
Deliveries		**a**	
	R²	***Estimation***	
Riberas del Jucar I.D.	0.95	0.6171*	
Canal Jucar-Turia I.D.	0.92	0.0435*	
Mancha-Albacete I.D.	0.97	0.0541*	

*P<0.05

For the assessment of the storage changes for Canal Jucar-Turia and Riberas del Jucar districts, all inflows upstream Tous reservoir have been considered. For the Mancha-Albacete case, the regression only considers the inflows to its main reservoir, Alarcon. All the explanatory variables were found to be statistically significant (Table 2). Figure

6 shows observed vssimulated surface deliveries from 2001 to 2010 for the 3 irrigated districts.

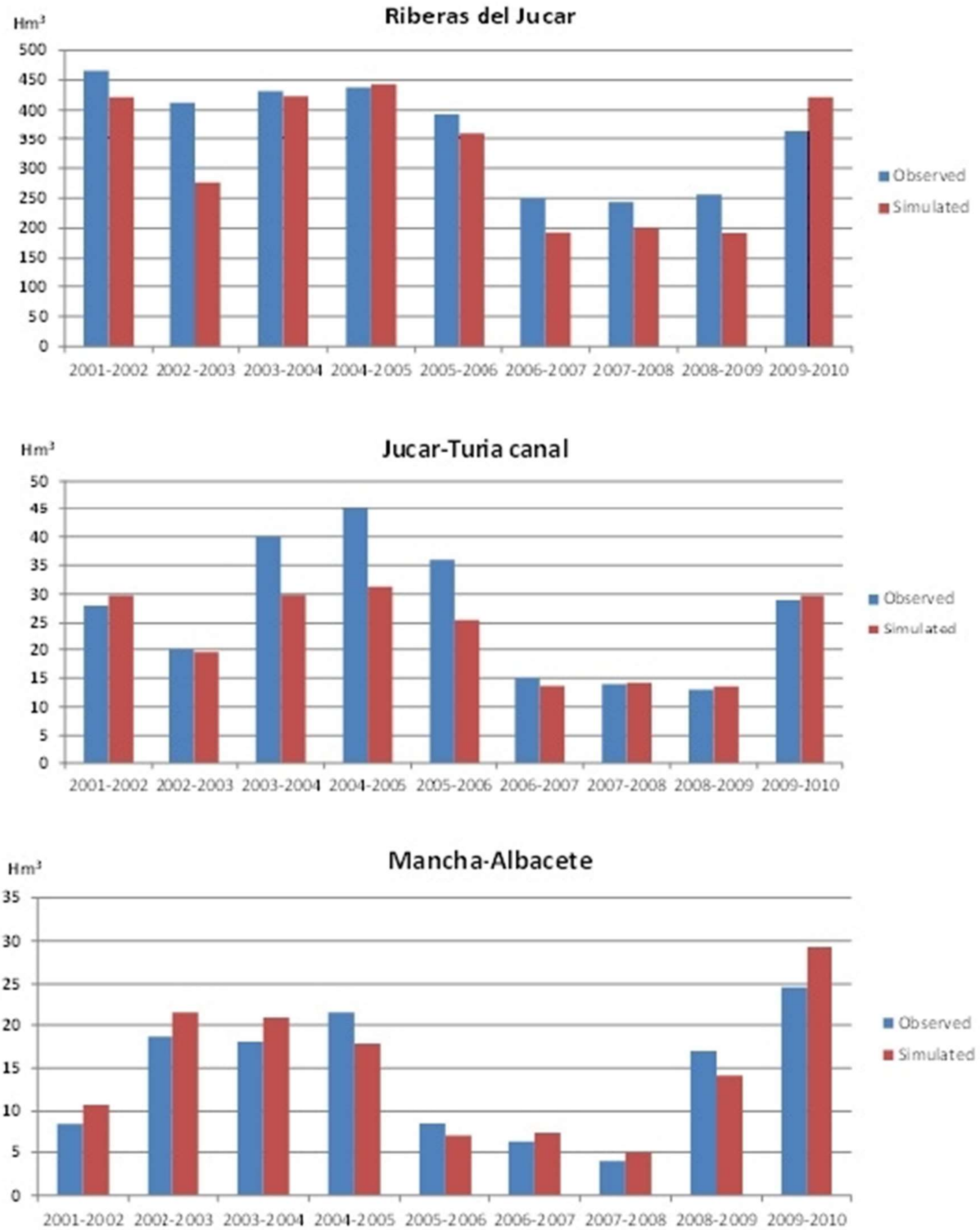

Figure 6. Observed vs. simulated surface water deliveries

By the combination of the probability distributions of the future inflows (stochastic time series model) with the simulation of the operation of the system (statistical regressions), we derive the probability of the amount of water delivered to the different irrigation systems for each irrigation season. Figure 7 shows the probability of water deliveries for the Riberas del Jucar in a normal year (without official declaration of meteorological or hydrological drought by CHJ) and in a dry year (please see figure 4 in supplementary material for the Canal Jucar-Turia and Mancha-Albacete irrigation districts).

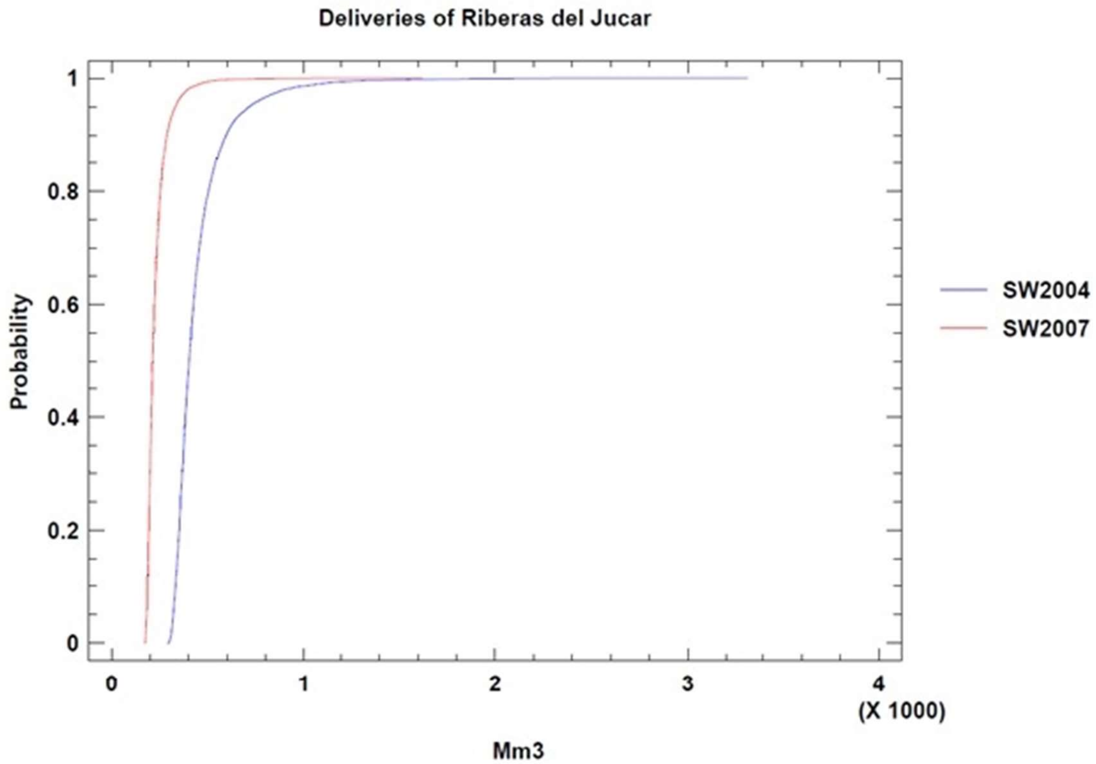

Figure 7. Cumulative distribution of surface deliveries for Riberas del Jucar

4.4 Risk analysis

The econometric model presented in section 4.1 has been applied to convert the probabilities of water deliveries into production values at the different irrigation districts. The band plot (Fig. 8) shows the forecast of the production value from October to the upcoming irrigation season (lead time) for each year (from 2002 to 2008, including the 2005-2008 drought). The 1st and 99th percentiles are used respectively as the lower and upper limits of the plot. Most of the observed values fall within the confidence intervals, except for a few outliers caused by the uncertainty regarding inflow prediction.

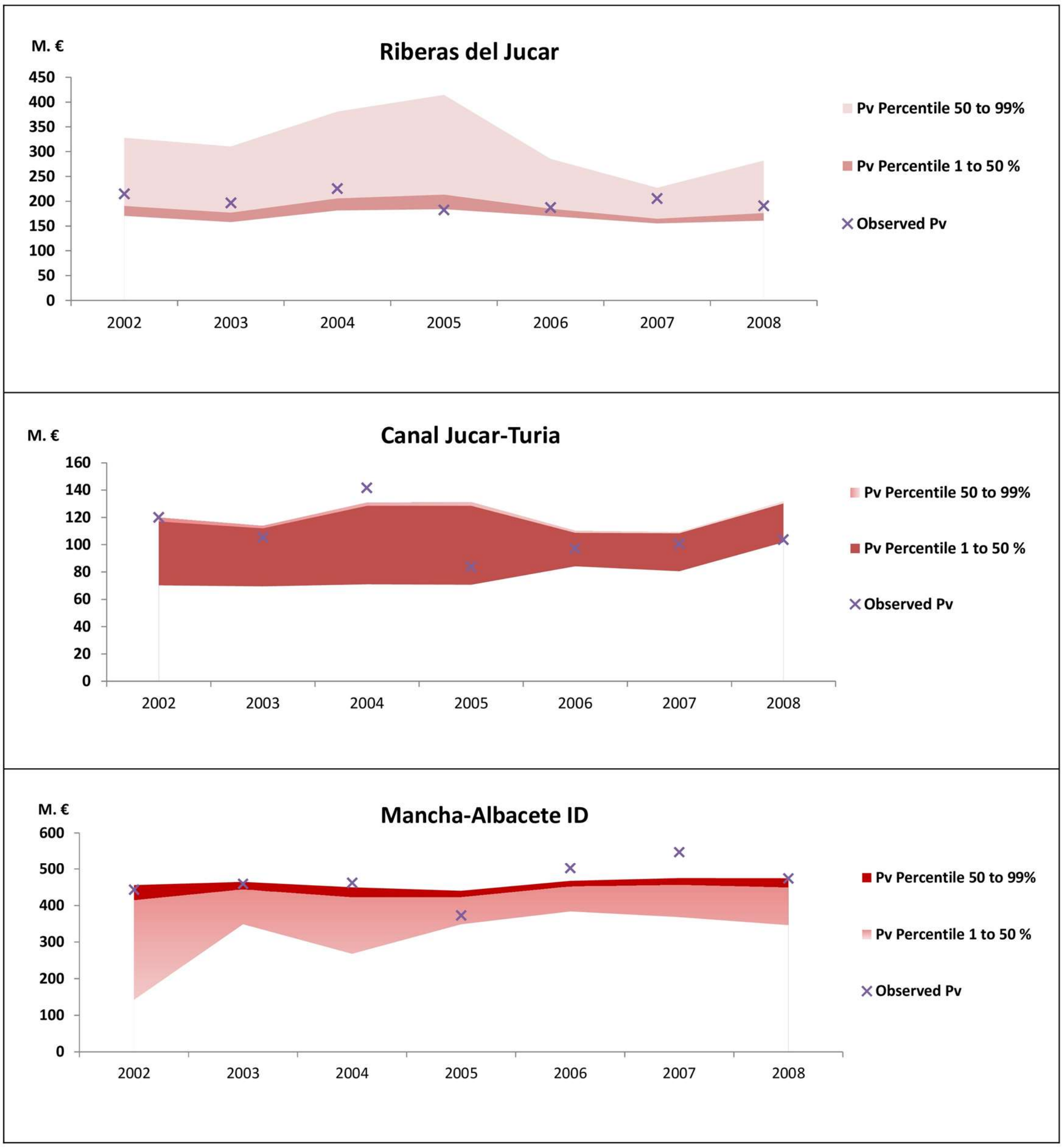

Figure 8. Band plot of the production value.

Droughts induce high economic losses in both, Riberas del Jucar and Canal Jucar-Turia districts (mainly from 2006 to 2008). In the case of the Riberas del Jucar, the 99th percentile of the predicted production value of year 2007 decreases 40 % with respect to

2004 (about 153 M€). However, during the beginning of the hydrological drought in 2005, the production value did not decrease, since any storage hedging/water supply restrictions were imposed due to the large storage in the main reservoirs. The Jucar river basin authority activated drought emergency wells in the Riberas del Jucar from 2006 to 2008 to partially compensate the economic losses due to the reduced surface water deliveries. The total pumped groundwater was 40, 40 and 25 Mm^3 during the years of 2006, 2007 and 2008 respectively (CHJ, 2010), from which we estimated a reduction of the potential economic losses at 56, 56 and 28 M€. In the Canal Jucar-Turia, the 99^{th} percentile of the projected production in 2006 dropped 18 % as compared to the value in 2004 (23 M€ losses). During the beginning of the drought period (2005) the production value experienced only a slight decrease. In Mancha-Albacete district the production value does not decrease during the drought period due to the high increase of the crop prices (crop price index during drought years is higher than the one of the previous normal year, up to 20%). Moreover, Mancha-Albacete is not strongly subject to surface water scarcity as 8% of the total supply comes from the surface water and groundwater is barely restricted.

We have compared the cumulative distribution of the forecast production value from the worst year in terms of predicted production value for the Riberas del Jucar and Canal Jucar-Turia irrigation districts (2007 and 2006 respectively, according to figure 8) with the observed value of production from year 2004 (the year prior to the beginning of the drought period) (Fig.9). Thus, it is possible to evaluate the forecasted economic losses with respect to a normal year. The variability of the expected losses is higher for the Riberas del Jucar than for the Canal Jucar-Turia.

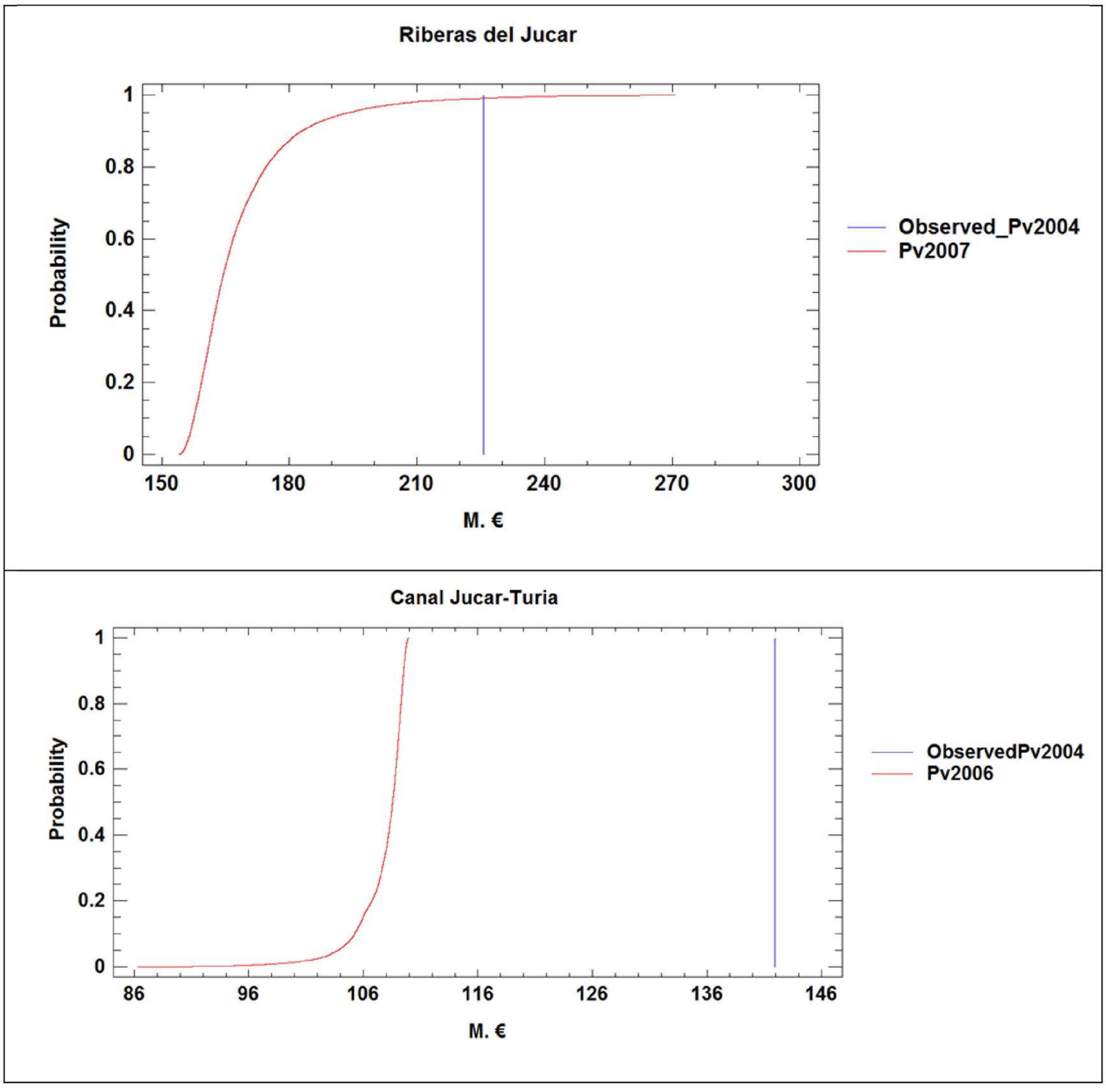

Figure 9. Prediction of production value in drought conditions vs observed production in a previous normal year

5. Discussion and conclusions

An integrated framework for predictingdirect economic impacts of droughts on irrigated agriculture has been presented, considering the uncertainty on water resources availability and the crop price volatility. This approach relies on a combination of econometric assessment, stochastic projection of inflows, and simulation of the system's operation.

The econometric approach can be an accurate way to simulate the direct economic impacts of droughts (in the case study, $R^2 > 0.7$). Our results indicate the importance of considering the price volatility in the assessment of the production value on irrigated agriculture, as it is a statistically significant variable in the 3 irrigation districts. The framework allows evaluating the forecasted production losses due to scarce water deliveries, by comparing the cumulative distribution for the upcoming season with the value of a normal year. Thus, it can contribute making management decisions in advance, from October to the upcoming irrigation season, in order to reduce the potential economic impacts of droughts. Moreover, the results demonstrate the suitability of the method of combining the stochastic inflows, storages and deliveries with the prediction of the production value (high values of the R-squared coefficient).

The drought losses might be offset by an increase in crop prices, as in the Mancha-Albacete district, and/or by the use of groundwater, a more reliable source than surface deliveries. These results illustrate the importance of the conjunctive use of surface and groundwater resources to buffer drought losses in agriculture. We have also tested the potential economic impact of applying drought emergency wells to complement the deliveries, showing that they can significantly reduce economic losses. Other mitigation measures could also be evaluated with the proposed framework.

The methods adopted in the three main parts of the developed framework (inflow projections, simulation of system operation, and economic risk assessment) could be addressed using other approaches. The inflow projections can also be obtained, for example, from weather forecasts combined with hydrological simulation (Faber and Stedinger 2001; Ficchì et al. 2015; Roulin 2007), ANNs (Mundher Yaseen et al. 2016) or fuzzy regression (Macian-Sorribes and Pulido-Velazquez 2017). The system operation could also be simulated using water resources simulation models, or through heuristic approaches such as ANNs (Cancelliere et al. 2002; Raman and Chandramouli 1996) or fuzzy logic (Macian-Sorribes and Pulido-Velazquez 2017; Panigrahi and Mujumdar 2000). The fact that different modelling alternatives can be accommodated within the same proposed framework increases its generality, flexibility, and robustness.

The economic risk assessment was performed using a simple forecasting method for crop price: just considering the crop price as the average of the last two years. More detailed risk assessment on prices could be tested. Prices depend on both physical (crop yields, yields of competitors) and economic features (local, regional and even global crop demand and supply). Nonetheless, taking into account all these features would require considerable amounts of information regarding variables whose measurement is difficult or not available.

The proposed framework can be implemented in other agricultural irrigation districts to evaluate potential economic losses derived from drought risk In future research, it could be interesting to extend the study to consider the indirect economic losses of droughts, other sources of uncertainty, and different risk management strategies (crop insurances, option contracts in water markets, etc).

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