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Abstract

In Mediterranean-climate regions, irrigated agriculture is especially vulnerable to the risk of hydrological drought, and irrigators are particularly concerned about the negative effects of water supply failures. This paper proposes a new index-based drought insurance scheme to cover the risk of water supply failures in irrigated agriculture that overcomes the problems currently hindering the development of this kind of insurance, especially those related to arbitrariness in annual water allotments decision-making. Although the proposal is tailored to Spain, it can be easily adapted to other countries or regions because its main features can also be implemented worldwide. The scheme proposed is a promising instrument to help irrigators manage the risk related to hydrological droughts since it has been proved to be technically feasible. The main contribution of this paper is the innovative actuarial analysis implemented, which is aimed at calculating fair premiums. Considering that recent changes in the institutional framework (new demands, new storage capacity, and revised basin and drought management plans) make historical records unsuitable for this purpose, the actuarial analysis applied is based on a stochastic hydrological model able to simulate future hydrological situations under updated settings. Simulation results have shown that irrigated agriculture in southern Spain is expected to be more vulnerable to hydrological droughts. In fact, incidence rates are likely to increase because of the new institutional framework, leading to relatively high fair premiums. Only by implementing high ordinary deductibles can the hypothetical cost of commercial premiums be affordable for irrigators, accounting for less than 10% of their current variable costs.

Keywords: irrigation water supply; water availability; drought risk; agricultural insurance; Guadalquivir River Basin.

1. Introduction

In Mediterranean-climate agricultural regions, such as in Southern Spain, hydrological droughts are considered a major production risk in irrigated agriculture (Urquijo and De Stefano, 2016). These hydrological droughts occur when instream flows and reservoir levels are lower than average, meaning that water availability is insufficient to meet all water demands, thus leading to gaps in the water supply. Under these circumstances, irrigators cannot fully satisfy all their crop water needs, entailing negative consequences for irrigators as well as for society as a whole (OECD, 2016): losses of production and income, abandonment of the more labor-intensive crops (e.g., fruit groves), and a drop in agricultural employment. Such situations also exacerbate the problem of overexploitation of aquifers because many farmers may be tempted to illegally extract groundwater resources to cover their water needs.

Concerns about irrigation water reliability are becoming increasingly common among irrigators. The first reason for this is the growing water demand. Population growth and new economic activities (mainly irrigation and tourism) are increasing the pressure on water resources, exacerbating water scarcity in many Mediterranean regions and making them more vulnerable to drought (García-Ruiz et al., 2011). The second reason is climate change. In this sense, it is worth pointing out that future climate projections in Mediterranean-climate agricultural regions indicate a decreasing trend in rainfall (lower water availability) and an increasing trend in temperature (higher crop water needs), suggesting that irrigation water supply will become less reliable (Moatti and Thiébault, 2016; Bisselink et al., 2018).

Some studies provide consistent evidence that irrigators are willing to pay to reduce the uncertainty related to the high variability of the annual water allotments they receive (e.g., Rigby et al., 2010; Mesa-Jurado et al., 2012; Alcón et al., 2014; Guerrero-Baena et al., 2019). This shows there is an unsatisfied demand for new risk management instruments that could be implemented by irrigators to minimize the foreseen negative impacts of hydrological droughts (Garrido and Gómez-Ramos, 2009; OECD, 2016). In this sense, the development of a specific insurance scheme that would protect irrigators against losses in the event of droughts has been suggested as a potentially efficient economic instrument to manage this risk (Rey et al., 2018; Guerrero-Baena and Gómez-Limón, 2019). Furthermore, it is worth pointing out that insurance is also considered a key instrument for adapting irrigation agriculture to climate change since it improves the resilience of the irrigated farms facing climate uncertainties (Garrido et al., 2012; Varela-Ortega et al., 2016).

Although agricultural insurance is a risk management instrument that is widely used among farmers in developed countries (Bielza et al., 2008b), no specific insurance scheme aimed at covering irrigators against the risk of water supply failure is currently available. Guerrero-

Baena and Gómez-Limón (2019) explain the multiple factors hindering the development of hydrological drought insurance schemes for irrigated agriculture. Most notable among them is the fact that decisions regarding the annual water allotments are taken by a public water agency that may be influenced by irrigators' lobbying. This issue makes the risk of a water supply failures uninsurable since losses due to these failures cannot be considered entirely accidental. In order to overcome this problem, the literature has suggested the implementation of index-based insurance schemes (Bielza et al., 2008a; Jensen and Barrett, 2017). The main advantage of index-based insurance is that indemnities are calculated according to the value of an objective and non-manipulable index strongly correlated with the contingency covered (i.e., supply failure), without the need for individual loss declarations and in-field assessments. Thus, under this insurance approach, farmers do not have any capacity to influence the occurrence of damages covered by the insurance policies or the calculation of indemnities.

Only a few papers have addressed the risk of hydrological drought in irrigated agriculture by proposing an index-based insurance scheme. In this regard, the works by Zeuli and Skees (2005) and Buchholz and Musshoff (2014), proposing schemes based on rainfall indexes to be implemented in Australia and Germany, respectively, are worth citing. Also of interest are the works by Brown and Carriquiry (2007) and Leiva and Skees (2008), who proposed drought insurance schemes relying on water inflow indexes for the Philippines and Mexico, respectively. Similarly, Maestro et al. (2016b) and Guerrero-Baena and Gómez-Limón (2019) have proposed this kind of insurance scheme for Spanish irrigated agriculture, based on indexes that measure the water actually stored in reservoirs. Finally, the proposal by Maestro et al. (2016a) tailored to irrigated agriculture in California (USA), based on an index estimating water availability, is also a valuable contribution to the research.

Within this context, the first objective of this paper is to propose a new index-based hydrological drought insurance scheme specifically tailored to Spanish irrigated agriculture. In so doing, the aim is to present a useful risk management instrument that can act as a buffer against the microeconomic effects of water supply failures. This proposal further develops the guidelines set out by Guerrero-Baena and Gómez-Limón (2019) and overcomes all the factors that are currently hindering the development of this kind of insurance scheme. The second objective of the paper is to explore the financial viability of the insurance scheme proposed, using actuarial analysis to calculate fair premiums. This second objective is achieved by providing a quantitative example in the Guadalquivir River Basin (southern Spain), illustrating how the proposed index-based drought insurance scheme could be implemented in a real-world setting.

Although the proposed insurance scheme is designed for Spanish irrigation agriculture, the interest of the proposal goes beyond this national scope, since the technical features of the suggested index-based scheme overcome the factors currently hindering the implementation of this kind of insurance worldwide. In any case, the main contribution of this paper to the existing literature is the innovative actuarial analysis. Taking into account recent changes in water demands (more water rights granted), climate change (lower water availability and higher crop needs), reservoir infrastructure (increased water storage capacity), and management rules (revised basin and drought management plans), historical data is not a suitable source of information to determine fair premiums for the insurance scheme proposed. For this reason, the actuarial analysis applied in this paper is based on a stochastic hydrological model able to simulate near-future hydrological situations (i.e., short-run simulations without considering the potential impact of climate change) under updated institutional settings.

2. A case study in the Guadalquivir River Basin

The Guadalquivir River Basin (GRB), which is located in southern Spain, covers a surface area of 57,184 km^2 and is home to 4.4 million people. Most of the territory in the basin has a typical Mediterranean climate featuring relatively mild, wet winters and warm, dry summers. The average annual rainfall is 573 mm, but precipitations are irregularly distributed both spatially and temporally, with frequent drought events.

As in all Spanish river basins, water resources in the GRB are managed by a public water agency, the *Confederación Hidrográfica del Guadalquivir* (CHG), which is in charge of operating storage and conveyance infrastructures to satisfy the demand of all water right holders (3,815 Mm^3 of water every year in the basin, with the agricultural sector being the main user, accounting for 88% of total demand) and maintaining ecological streamflows. These water management operations are governed by the GRB Management Plan (CHG, 2015).

The hydrological year in the GRB begins on October 1st, at the beginning of the wet season. This wet season lasts from October (1st month) to April (7th month). During this season there is no irrigation water demand since all crops can be cultivated under rainfed conditions. This allows the CHG to store a share of natural water inflows using a well-developed reservoir network. Thus, the volume of water stored usually reaches its highest annual values by May 1st, at the beginning of the dry season. At this time, once the maximum water availability is actually known, the CHG takes decisions about the volume of water to be allocated during the dry season to irrigation water right holders. This dry season lasts from May (8th month) to September (12th month), and irrigation demand is concentrated in this period. This explains

why the volume of water stored usually reaches its lowest annual values at the beginning of the hydrological year (October 1st).

Currently, the GRB is closed to new users because of the increase in water demand over the past few decades, mainly due to the growth of irrigated areas, and the impossibility of achieving further increases in the water supply by enlarging the reservoir network (Expósito and Berbel, 2019). As a result, demand-side management has become the only tool available for managing water demands.

For operative reasons, the GRB is divided into hydrological systems, or sub-basins, which are considered by the CHG as managerial units operating their own common storage and conveyance infrastructures to meet their own water demands. The largest hydrological system in the basin is called the *Sistema de Regulación General* (SRG), currently operating a reservoir network (27 interconnected reservoirs) with a storage capacity of 5,737 Mm^3, which must satisfy annual demands from water right holders for urban and agricultural consumption (35 Mm^3 and 1,767 Mm^3, respectively). Moreover, according to the GRB Management Plan, the CHG must provide 164 Mm^3/year to maintain the minimum ecological flows that guarantee the ecological good status of water ecosystems in this sub-basin.

The Sector BXII irrigation district (SBXII) is one of the demand units served by the SRG. This irrigated area is located close to the mouth of the Guadalquivir river and occupies 14,643 hectares. Nowadays, this irrigation district is divided into 569 farms, each with an average size of 25.7 hectares.

For farmers in the SBXII, like most of the irrigators in the GRB, the supply of surface water provided by the CHG is their sole source of water (Gómez-Limón et al., 2013). Thus, there is no possibility of reducing the vulnerability of the irrigated farms to hydrological drought (water supply failures) with a portfolio of water sources (Mukherjee and Schwabe, 2014). This justifies the choice of this case study for the empirical analysis proposed here.

The CHG granted water rights for the whole district when irrigation operations started in 1980. These water rights allow the irrigators in the SBXII to use up to 6,700 m^3/ha in normal hydrological years (full water allotment), when all water rights can be satisfied with the water stored in the reservoirs operated by the SRG. In any case, the SRG sets annual water allotments depending on the water stored in the reservoir network at the beginning of the dry season (May 1st). Thus, when the volume of water stored is low, the water allotments are reduced. In fact, these annual allotments can be reduced to zero in extreme hydrological droughts.

The main crops in the SBXII district are cotton (44.5% of the total area), corn (12.9%), tomato (11.5%), sugar beet (9.4%), wheat (8.7%), and other vegetables (mostly carrots and

onions, accounting for 5.8%). A survey was administered to 60 farmers operating in this irrigation district to gather primary information about the income, variable costs, gross margin, and water needs for each of the above-mentioned crops (for further details, see Montilla-López et al., 2018). The information collected shows that all these crops are cultivated similarly throughout the study area, with a similar profit structure (i.e., variable costs and income, with the latter including product sales and coupled subsidies). Table 1 shows the average data regarding the profitability and the water needs for all these crops.

Table 1

Main crops in the SBXII irrigation district: economic variables and water needs.

	Cotton	Corn	Tomato	Sugar beet	Wheat	Other vegetables
Income (€/ha)	3,176	3,412	8,771	3,332	1,599	7,750
Variable costs (€/ha)	1,578	1,821	3,954	1,209	608	3,398
Gross margin (€/ha)	1,598	1,591	4,817	2,123	992	4,351
Variable costs May 1st (€/ha)	669	1,122	1,446	1,151	486	2,160
Water needs (m³/ha)	4,250	4,800	6,000	7,000	4,000	4,500
Water productivity (€/m³)	0.38	0.33	0.80	0.30	0.25	0.97

Note: Crop features under full water allotments.

Source: Own elaboration based on data gathered by Montilla-López et al. (2018).

It is worth noting that the survey data was obtained by asking sampled farmers about the technological itinerary followed for each crop. Thus, the farmers described in chronological order the different agricultural activities they implement over the course of the agricultural season for each crop, detailing the inputs they consume and their unit costs. This information has enabled a variable costs file to be built for each crop, recording the crop-specific variable costs generated every month. These variable cost files thus provide information about the accumulated variable costs borne by May 1st for every crop, as shown in Table 1. As will be explained in Section 3, this is key information for establishing the insurable capital and insurance indemnities in the insurance scheme proposed.

Data gathered from irrigators show heterogeneity between their farms regarding crop mixes and thus profitability. This means the capital to be insured by drought insurance (i.e., the profit obtained from irrigation water) is also heterogeneous. In order to illustrate how the drought insurance scheme proposed can be implemented in each farm in the irrigation district, a small number of representative farms were selected from the farms in the district. For this purpose, cluster analysis was applied to define homogenous groups of farms (technical details can be found in Montilla-López et al., 2018). Implementing this classification technique, three clusters of farms were identified; thus, the farm types were defined

according to the average values of the characteristic variables of the farms included in each cluster (crop mix, other features related to the farms, and farmers' characteristics). Table 2 shows the main features of these three farm types representing the heterogeneous population of farms located in the SBXII district.

The three farm types described in Table 2 are considered as the ones to be hypothetically insured against losses caused by hydrological droughts (irrigation supply failures). This pilot implementation of the drought insurance proposed here will provide relevant insights regarding the technical feasibility and the commercial viability of the index-based insurance scheme.

Table 2

Characteristic variables of farm types in the SBXII irrigation district.

	Farm type 1 "Large professional farmers"	Farm type 2 "Risk diversifying farmers"	Farm type 3 "Extensive conservative farmers"
Farm size (ha)	35.5	23.8	15.0
Cotton (ha)	11.6	14.8	8.6
Corn (ha)	0.0	2.4	0.0
Tomato (ha)	11.9	3.3	0.0
Sugar beet (ha)	9.4	1.6	5.9
Wheat (ha)	0.0	1.7	0.6
Other vegetables (ha)	2.7	0.0	0.0
Total income (€/ha)	5,433	3,877	3,175
Total variable costs (€/ha)	2,412	1,840	1,396
Total gross margin (€/ha)	3,021	2,037	1,779

Note: Crop mix under full water allotments.

Source: Own elaboration based on data gathered by Montilla-López et al. (2018).

3. The hydrological drought insurance design

3.1. Insured capital

The primary purpose of the hydrological drought insurance proposed is to protect the insured farmers against the losses suffered because of irrigation water supply shortages. Thus, the asset covered by the insurance contract (i.e., the 'insurable interest' in technical jargon) is the profit obtained from the whole set of irrigated crops grown by each farmer when full water allotments are provided by the basin authority (CHG in our case study). For operational purposes, this profit can be measured as the sum of gross margins (income minus variable costs) obtained from every irrigated crop on the farm.

Most annual crops cultivated in the Mediterranean irrigated areas are 'summer crops'; that is, crops sown in spring, grown throughout the summer, and harvested at the beginning of fall. Thus, agricultural operations usually begin in late winter, preparing the soil for sowing in spring, taking advantage of the existing soil moisture from rainfall during the wet season (fall and winter). Irrigation operations start in May, at the beginning of the dry season, once crops have consumed all the water stored in the soil through the wet season and additional irrigation water is needed. A relevant factor for the design of the hydrological drought insurance is that crop mix decisions are taken by farmers in winter. As such, these decisions are taken under uncertainty since information about water allotments for the irrigation season is not available until May 1st, when the basin authority sets annual water allotments depending on the water stored in the reservoirs. By May 1st, when water allocation decisions are taken, farmers have little leeway to cope with any water supply shortage[1]. In fact, the only options they have for dealing with the water constraints in these cases are: a) to implement deficit irrigation (irrigation doses lower than full water requirements), and b) to stop irrigating (and cultivating) a share (or the whole) of their irrigable land and leave this as fallow land. However, it is worth pointing out that the deficit irrigation strategy is most suitable for permanent crops; for herbaceous crops, this strategy is unlikely to produce a more profitable solution since the relationships between irrigation doses and herbaceous crop yields are almost linear (see, for instance, Steduto et al., 2012). This explains why the irrigators considered for the case study, who specialize exclusively in herbaceous crops (see Table 2), seldom implement deficit irrigation strategies in the event of water shortages. For this reason, stopping irrigating has been considered as the only realistic strategy to cope with water supply failures in the empirical analysis performed.

Given these circumstances, the maximum loss that a farmer may face would occur in the event of extreme hydrological drought (null water allotment), with this loss equal to the total gross margin with full annual water allotments plus the sum of all variable costs already spent on the irrigated crops by May 1st. This maximum loss that the insurer would be obliged to pay to the insured farmer is known in the technical jargon as the 'insured capital' (IC).

The insured capital can be easily estimated on a farm-by-farm basis by accounting for their crop mix and the average gross margins and variable costs for each irrigated crop within the

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[1] Farmers can implement several management strategies to cope with water scarcity, although not all of them are useful in the event of irrigation water supply failures. For instance, one alternative is changing the crop mix, replacing crops that have higher water requirements with crops that have lower water needs or even rainfed crops. However, by May 1st this is no longer an option since no rainfed or low water requirement crops can be sown then, at the beginning of the dry season. Improving irrigation efficiency at farm level could be another alternative, but this is not a solution in modern, efficient irrigation districts like the one considered as a case study.

same irrigation district. For the case of the SBXII district, combining the information provided in Tables 1 (crop mixes) and 2 (gross margins and variable costs), the insured capital for the different farm types considered can be calculated as shown in Table 3.

Table 3

Insured capital for each farm type considered.

	Farm type 1	Farm type 2	Farm type 3
Total gross margin with full irrigation allotment (€/ha)	3,021	2,037	1,779
Total variable costs May 1st (€/ha)	1,169	842	850
Insured capital (€/ha)	4,190	2,879	2,629

Source: Own elaboration based on data gathered by Montilla-López et al. (2018).

3.2. Losses: an index-based approach

The occurrence of a loss is verified when the annual water allotment set by the basin authority is lower than the full water allotment. This loss can be calculated at farm level as the difference between the total gross margin with full water allotments and the total gross margin with the reduced annual water allotments (i.e., only considering the crop area that can be actually irrigated) plus the sum of all variable costs already invested in the farm area by May 1st in the land that farmers are forced to leave as fallow (stop irrigating). All these variables can be easily calculated on a farm-by-farm basis considering tabulated values for each irrigated area, as shown above.

In order to calculate this loss in a similar way for all insured farms, it is assumed that farmers behave rationally as profit maximizers when choosing which crops to stop irrigating first; that is, they abandon those with the lowest water productivity first. In our case study, as has been shown in Table 1, the first crop to be left fallow to meet irrigation water constraints is wheat, followed by sugar beet, corn, cotton, tomato, and other vegetables, in that order. Fallow land is assumed to have no rental value in the years with irrigation water supply failures.

Farmers' actual behavior when facing water supply failures could diverge from the profit-maximizing approach assumed (i.e., abandoning those crops with the lowest water productivity first), with each farmer taking different production decisions based on his/her individual utility function. However, it is worth pointing out that the actuarial analysis for any insurance scheme should rely on an 'objective' loss assessment method, providing the same results for every insured person (e.g., farmer) when insuring the same asset (e.g., profit gained from a crop mix irrigated with full water allotments), irrespective of their hypothetical different behavior when facing supply failures (i.e., the shape of their individual utility

functions). This is the reason why other, much more accurate techniques for simulating farmers' decision-making (e.g., Expected Utility Theory, EUT; Prospect Theory, PT; Positive Mathematical Programming, PMP; or Multi-Attribute Utility Theory–MAUT) have been ruled out for this purpose since all of these approaches would result in a 'subjective' loss assessment based on heterogeneous utility functions[2]. Within this context, the assumptions made regarding farmers' behavior when facing water shortages can be justified on the basis of ensuring a pragmatic, homogeneous procedure to obtain the 'objective' loss assessments required for actuarial analysis, providing sufficiently reliable results for all potentially insurable farmers. In any case, adopting alternative assumptions for the 'objective' loss assessment procedure could be worth examining in future research.

Fig. 1 shows an example of these estimations for the case of farm type 1 in SBXII. It can be seen that the loss in the year t ($Loss_t$) is a function (f) of the annual water allotment for irrigation in that year (AWA_t), with the latter variable measured as a percentage of the full water allotment: $Loss_t = f(AWA_t)$. As the reader can observe, initial reductions in the annual water allotment do not involve any loss since full water allotments are commonly slightly higher than water needs for most farms, as is the case for farm type 1 (its water needs are only 93% of the full water allotment granted).

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[2] All these simulation approaches are suitable, however, for analyzing farmers' decisions about taking out insurance policies, allowing the comparison of 'subjective' loss assessment with insurance indemnities and premiums (farmers would take out insurance policies if their expected 'subjective' losses plus the insurance premium were lower than expected insurance indemnities).
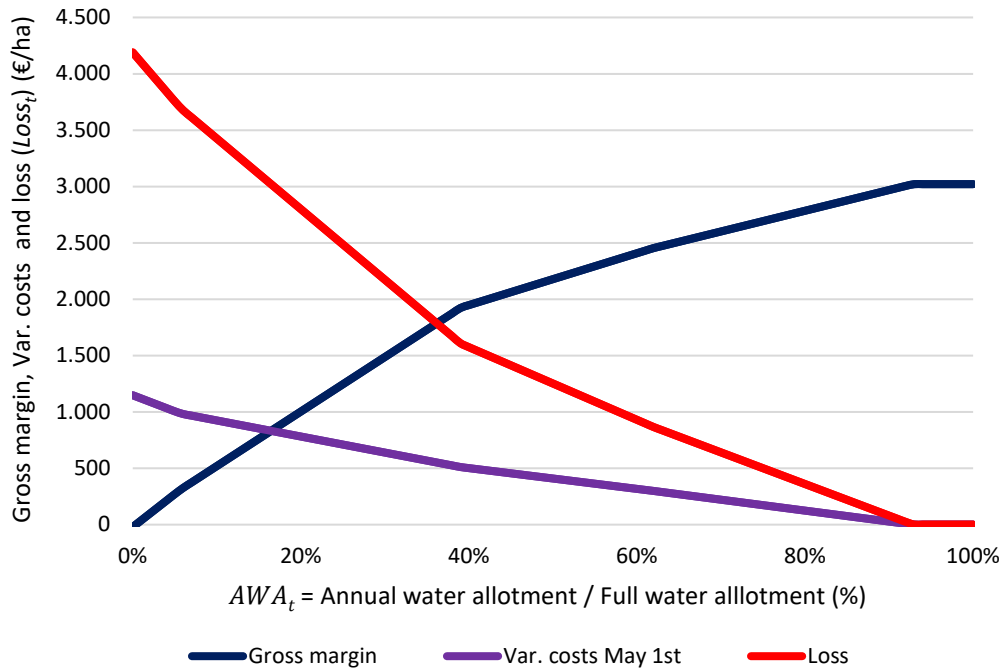
Fig. 1. Gross margins, variable costs spent by May 1st, and losses ($Loss_t$) for farm type 1 depending on the annual water allotment (AWA_t).

It is worth pointing out the fact that in Spain annual water allotments are set by river basin authorities every year as a result of an agreement with the users (i.e., irrigators) represented in the Commissions on Reservoir Water Releases (*Comisiones de Desembalse*). Although these agreements on annual water allotments depend on the water available for the irrigation season and follow the guidelines provided by Drought Management Plans (DMP), there is still some room for arbitrariness in the decisions made. Thus, irrigators' and other relevant stakeholders' representatives can influence the occurrence and the intensity of the losses caused by water supply failures. This issue makes the hydrological drought risk uninsurable if losses are directly defined as a function of actual annual water allotments, since actual losses due to allotment cuts cannot be considered as entirely accidental. As commented in the introduction section, this situation justifies the use of an index-based approach for the development of this insurance scheme.

In index-based insurance, losses (and indemnities) are calculated according to the value of an objective and non-manipulable index that is highly positively correlated with the actual loss experienced. In the case of the proposed hydrological drought insurance, the most suitable index value is the amount of water stored in the reservoir network at the beginning of the irrigation season (Guerrero-Baena and Gómez-Limón, 2019). This index is labeled WS_{8_t}, the subscript 8_t denoting that it is the water stored at the beginning of the 8th month (May 1st) in the hydrological year t, measured as a percentage of the total storage capacity of the

reservoir network. As explained below, the value of this index every year will determine whether there are losses because of irrigation water supply failures and the magnitude of any losses that occur.

In any case, it is worth pointing out that the values of WS_{8_t} to be considered when calculating index-based losses are not those that can actually be observed by May 1st. In order to avoid any possible artificial manipulation (e.g., because of anomalous decision-making regarding water releases before May 1st), it is proposed that the index should be calculated annually at the beginning of May using the following expression:

$$WS_{8_t} = WS_{1_t} + I_{1\text{-}7_t} - R_{1\text{-}7_t} - L_{1\text{-}7_t} \tag{1}$$

where WS_{8_t} is the result of the water *actually* stored into the reservoir network at the beginning of the 1st month of the hydrological year t (i.e., October 1st, WS_{1_t}) plus the *actual* water inflows into the reservoir network during the wet season of the hydrological year t (i.e., from the October 1st to April 30th, $I_{1\text{-}7_t}$), minus the *expected* water releases from the reservoir network during the wet season in the hydrological year t ($R_{1\text{-}7_t}$), and minus the volume of water *actually* lost from the reservoir network during this season in the hydrological year t because of evaporation ($L_{1\text{-}7_t}$); all these variables are measured as a percentage of the storage capacity of the reservoir network. Further details about how each of the variables included in Eq. (1) is operationally assessed for our case study (SRG) are provided in Section 4.

It is worth explaining that in order to calculate WS_{8_t} as a non-manipulable index, all the variables included in Eq. (1) also need to be non-manipulable. Although it is the case for most of these variables, since they are determined by random natural events ($I_{1\text{-}7_t}$, $R_{1\text{-}7_t}$), this requirement can be problematic for the case of the water releases variable ($R_{1\text{-}7_t}$) since it depends on the basin authority's decision-making (i.e., human-made decision sensitive to arbitrariness). This explains why all variables in Eq. (1) are incorporated using *actual* values, except water releases, which needs to be incorporated in *expected* values, taking into account the water demands to be met and the objective rules for managing the existing storage capacity, as defined in Eqs. (6) and (7)[3].

Once the value of WS_{8_t} on May 1st has been determined following Eq. (1), annual water allotments for irrigation, measured as a percentage of the full water allotment for irrigation (AWA_t), can be objectively set considering the guidance provided by the DMP for the GRB, which establishes the following four drought situations (CHG, 2018):

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[3] Nevertheless, the calculation of the WS_{8_t} index for insurance implementation in a real-world setting should be done using *actual* inflows ($I_{1,7_t}$), instead of *simulated* inflows ($\tilde{I}_{1,7_t}$) in Eqs. (6) and (7).

1) *Normality*, when water stored in the reservoir network is above 50% of its storage capacity ($WS_{8_t} > 0.5$). In these cases, water availability is high enough to meet all water demands and full water allotments are provided ($AWA_t = 1.0$). Thus, no loss is expected to occur.

2) *Pre-alert*, when WS_{8_t} is between 50% and 30% ($0.5 \geq WS_{8_t} > 0.3$), indicating moderate water scarcity. Irrigation water allotments should then be cut by between 0% and 30% relative to the full water allotments (i.e., $1.0 \leq AWA_t < 0.7$).

3) *Alert*, when WS_{8_t} is between 30% and 15% ($0.3 \geq WS_{8_t} > 0.15$), indicating severe water scarcity. If such cases, the supply of water for irrigation should be further reduced, with these cuts ranging from 30% to 80% (i.e., $0.7 \leq AWA_t < 0.2$).

4) *Emergency*, when WS_{8_t} is below 15% but above 10% ($0.15 \geq WS_{8_t} > 0.1$), highlighting extreme water scarcity. Under these circumstances, irrigation water allotments should be further reduced (i.e., $0.2 \leq AWA_t < 0.0$). When WS_{8_t} is equal to or lower than 10%, no irrigation water is supplied (i.e., $AWA_t = 0.0$).

This guidance for decision-making is plotted in Fig. 2, showing how annual water allotments for irrigation can be determined as a function of the water stored on May 1st: $AWA_t = g(WS_{8_t})$.
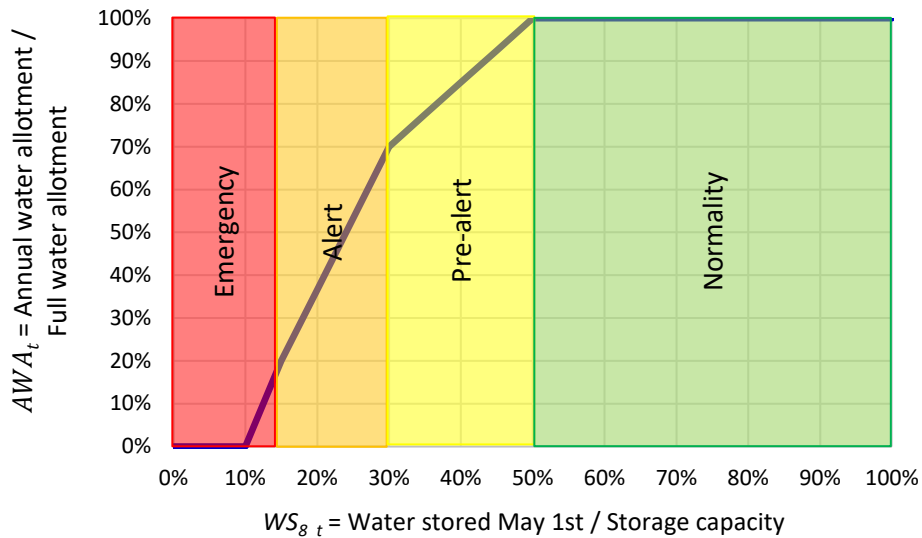

Fig. 2. Guidelines for setting annual water allotments for irrigation ($AWA_t \ vs. \ WS_{8_t}$) (CHG, 2018).

Considering these objective allocation rules, losses caused by hydrological drought can be estimated for insurance purposes as a function of the water stored on May 1st:

$$Loss_t = f(AWA_t) = f[g(WS_{8_t})] = h(WS_{8_t}) \tag{2}$$

Note that function f depends on the individual farm (or farm type) considered, while function g is the same for every farm (or farm type) within the same hydrological system (SRG in our case study). Functions f and g can be used to calculate losses for each farm type ($Loss_t = h(WS_{8_t})$), as depicted in Fig. 3. This example shows how, under the proposed index-based approach, the declaration of losses and also the indemnity assessment could be easily carried out at the beginning of the irrigation season (May 1st), once the value of the WS_{8_t} index has been calculated, using tabulated data only and without any need for in-field damage evaluations.
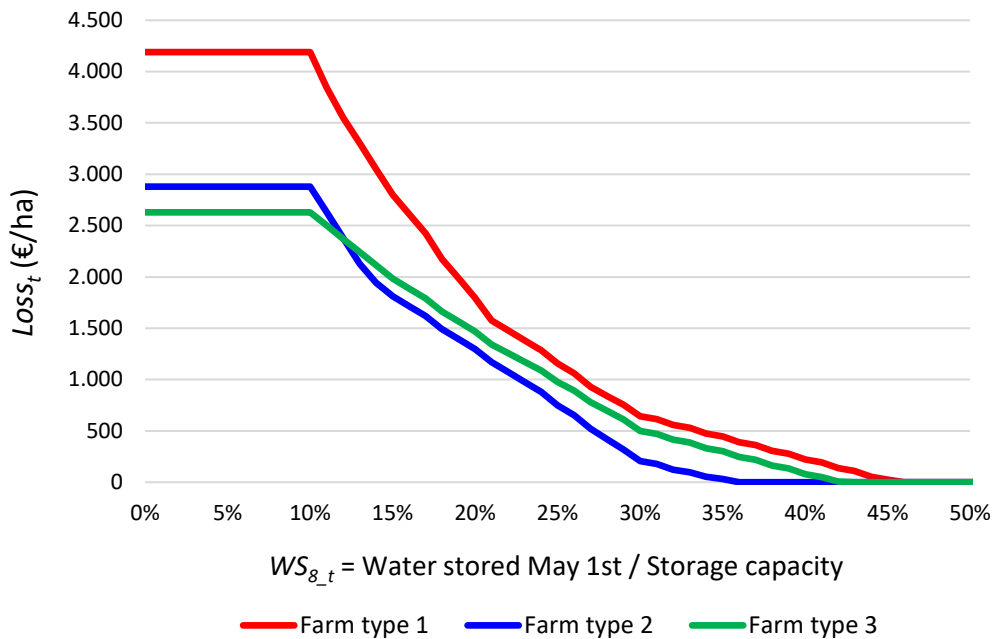

Fig. 3. Loss assessment ($Loss_t$) by farm types depending on the water stored on May 1st (WS_{8_t}).

3.3. Indemnities and premiums

The *indemnity* (I_t) is the cash amount that the insurance company pays insured farmers, which is equivalent to the value of the loss minus the *deductible* (DED) agreed in the policy (i.e., the percentage of the insured capital that the farmer is responsible for covering). In the case of the index-based insurance scheme proposed here, the indemnity can be easily calculated after determining the value of the WS_{8_t} index, using the following formula:

$$
I_t = \begin{cases} 0 & \text{if} & 0 < h\!\left(WS_{8_t}\right) < DED \times IC & \text{(non-indemnified loss)} \\ h\!\left(WS_{8_t}\right) - DED \times IC & \text{if} & DED \times IC \le h\!\left(WS_{8_t}\right) < IC & \text{('partial' loss)} \\ IC \times (1 - DED) & \text{if} & h\!\left(WS_{8_t}\right) = IC & \text{('total' loss)} \end{cases} \tag{3}
$$

For analytical purposes, to assess the fair premium, a range for the ordinary deductible (DED) has been considered: 10%, 20%, and 30%.

The *commercial insurance premium* is the money paid by the insured farmers for the coverage included in the insurance policy. This price is set by insurance firms based on the *fair premium* (P), equal to the expected value of the indemnities to be paid by the insurer ($P = E[I_t]$). The expected indemnity can also be defined in percentage terms as the fair premium rate (PR), calculated as P/IC. Fair premiums are calculated by means of actuarial analysis, as is done in this paper. Once these fair premiums have been determined, insurance firms set their commercial insurance premiums by adding loadings to the fair premium. These loadings cover the management, administrative and re-insurance costs of the insurance company, and ensure the profit level required by the firm for the capital used and the risk assumed.

3.4. Contract term and intertemporal adverse selection

The proposed hydrological drought insurance is based on annual policies with an annual premium. These policies should be formalized by paying the premium during a pre-established contracting period throughout the entire month of September every year. These contracts are valid from the purchase of the policy to May 1st the following year, when the WS_{8_t} index is calculated and, if losses have occurred, indemnities can be claimed. The policy could be extendable for subsequent annuities.

However, it is worth pointing out that during the contracting period both the policyholder and the insurer have information about the volume of water stored in the reservoir network at the beginning of the hydrological year t (October 1st, WS_{1_t}), potentially leading to some intertemporal adverse selection. That is, it is reasonable to suppose that potential insured farmers could be more (less) inclined to purchase the insurance product when the WS_{1_t} is low (high) since the WS_{8_t} index is also likely to be low (high). As a measure to minimize this problem jeopardizing the viability of the insurance scheme, if a pre-alert, alert or emergency situation is declared during the contracting period (September), the insurance firms will underwrite policy renewals only for those who purchased the insurance in the previous year. The inclusion of new insured farmers would only be possible during the contracting period under normal hydrological conditions ($WS_{1_t} > 0.5$). Furthermore, farmers who wish to take out a policy would also be required to sign a commitment that they will renew their policies for the next five years.

4. Stochastic simulation approach

The actuarial analysis to be performed is aimed at assessing the fair premium and the fair premium rate of the proposed insurance scheme. One possible approach for this purpose is to take historical data covering a long enough period regarding the water actually stored in the reservoir network at the beginning of the irrigation season (May 1st) and the annual water allotments actually granted by the basin authority, and use this data to estimate annual losses and the resulting indemnities.

However, given recent changes in water demands (new water rights granted), reservoir infrastructure (increased water storage capacity), and water management rules in the GRB because of the revised Basin Management Plan (CHG, 2015) and the DMP (CHG, 2018), the former approach is not a suitable way to assess future hydrological situations. Therefore, an approach based on a stochastic hydrological simulation model is used to estimate the feasible future probability distributions of the WS_{8_t} index and the annual water allotment for irrigation (AWA_t) considering the new institutional framework. Once the distributions of both variables have been obtained, it will also be possible to estimate within a stochastic framework the probability distribution of losses caused by hydrological droughts ($Loss_t$) and the distribution of the corresponding indemnities (I_t). This section explains how these probability distributions have been obtained.

The hydrological model built to assess the distribution of the WS_{8_t} index and AWA_t relies on two water balance equations, representing the volumes of water stored in the reservoir network that is the focus of our case study (SRG) at the beginning of the dry and the wet seasons (May 1st and October 1st, respectively):

$$WS_{8_t} = WS_{1_t} + \tilde{I}_{1\text{-}7_t} - R_{1\text{-}7_t} - L_{1\text{-}7_t} \tag{4}$$

$$WS_{1_{t+1}} = WS_{8_t} + \tilde{I}_{8\text{-}12_t} - R_{8\text{-}12_t} - L_{8\text{-}12_t} \tag{5}$$

where WS_{8_t} is the water stored on May 1st of the hydrological year *t*, and $WS_{1_{t+1}}$ is the water stored on October 1st of the hydrological year *t*+1. Both variables depend on the water stored in the previous periods (WS_{1_t} and WS_{8_t}), the water inflows into the reservoir network during the wet and the dry seasons ($\tilde{I}_{1\text{-}7_t}$ and $\tilde{I}_{8\text{-}12_t}$), the water releases from the reservoirs during these two periods ($R_{1\text{-}7_t}$ and $R_{8\text{-}12_t}$), and the losses by evaporation during these two seasons ($L_{1\text{-}7_t}$ and $L_{8\text{-}12_t}$). All these variables are measured as a percentage of the storage capacity of the whole reservoir network.

4.1. The water stored on May 1st of the hydrological year t (WS_{8_t})

The explanation of the variables included in Eq. (4) is the same as that for the WS_{8_t} index given above. The only difference from the explanation provided for expression (1) is that the variables included in (4) are to be simulated within a stochastic framework.

$\tilde{I}_{1\text{-}7_t}$ is a stochastic variable measuring the water inflows into the reservoir network during the wet season of the hydrological year *t*, which ultimately depends on the rainfall throughout this season and other climatic variables. In order to assess how this variable is statistically distributed we have taken actual data for the period 1980-2019 regarding inflows into the SRG reservoir network between October and April, and have run @Risk 7.6 software (Palisade Corporation, 2015) to choose which statistical distribution fits best. Considering the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), the distribution that best fits $\tilde{I}_{1\text{-}7_t}$ is the Inverse Gaussian distribution (AIC=-14.86 and BIC=-11.81) with the parameters μ = 0.338 and λ = 0.369. Moreover, this fit is shown to be sufficiently accurate by calculating the Kolmogorov-Smirnov (K-S=0.11, p-value=0.38) and the Anderson-Darling (A-D=0.46, p-value=0.33) statistics.

Taking into account the fact that the objective of water managers working at the basin authority is to store as much water as possible during the wet season, water releases during this period ($R_{1\text{-}7_t}$) are only permitted to meet urban demand and maintain ecological flows, or when releases are needed for reservoir management (e.g., when inflows are expected to exceed storage capacity). This variable mainly depends on the volume of water stored at the beginning of the hydrological year (WS_{1_t}) and the water inflows during the wet season ($\tilde{I}_{1\text{-}7_t}$). Regressing the data observed in the last 40 years (the period 1980-2019), water release during the wet season according to historical data (variable $\hat{R}_{1\text{-}7_t}$) can be obtained using the following linear model:

$$\hat{R}_{1\text{-}7_t} = -0.09777 + 0.15853\, WS_{1_t} + 0.45145\, \tilde{I}_{1\text{-}7_t} + 0.72310\, EX_{1\text{-}7_t} \tag{6}$$

where $EX_{1\text{-}7_t}$ is the volume of water inflows during the wet season in excess of the storage capacity, measured as a percentage of the total storage capacity. This is calculated as $WS_{1_t} + \tilde{I}_{1\text{-}7_t} - 1$ when $WS_{1_t} + \tilde{I}_{1\text{-}7_t}$ is larger than 1. When $WS_{1_t} + \tilde{I}_{1\text{-}7_t}$ is lower than or equal to 1, $EX_{1\text{-}7_t} = 0$.

The above-mentioned linear model is highly explanatory (adjusted R²=0.93). However, to model water releases under new management rules as realistically as possible, $R_{1\text{-}7_t}$ (simulated water release during the wet season under the current management rules) has been forced to reach a minimum value every year equaling current urban demand plus the

volume of water needed to maintain ecological flows during the wet season ($UD_{1\text{-}7}$ and $ENV_{1\text{-}7}$, respectively). These two water uses can be taken as parameters since their values remain the same every wet year, accounting for 2.3% of the storage capacity of the SRG reservoir network (CHG, 2015). Thus, this variable has been calculated as follows:

$$R_{1\text{-}7_t} = \text{Max}\big[\hat{R}_{1\text{-}7_t}, UD_{1\text{-}7} + ENV_{1\text{-}7}\big] = \text{Max}\big[\hat{R}_{1\text{-}7_t}, 2.3\%\big] \qquad (7)$$

Finally, losses by evaporation during the wet season in the hydrological year t ($L_{1\text{-}7_t}$) have been calculated using the data provided by the GRB authority about local climatic conditions and the geometry of the reservoirs in the SRG (CHG, 2015). Data regarding the former (local climatic conditions) reveal the average evaporation rates recorded for each reservoir, measured in millimeters of water during the period from October to April; these rates have been considered as constants (i.e., the same every year). Data regarding the latter (geometry of the reservoirs) provide information about the surface area of water (i.e., the surface area evaporating water) for each reservoir depending on the volume of water stored. Thus, losses for months 1-7 in the year t have been estimated for each reservoir by multiplying local evaporation rates by the surface area of water according to the average volume of water stored in this year (($WS_{1_t} + WS_{8_t}$)/2). Finally, $L_{1\text{-}7_t}$ has been calculated simply by adding individual losses in year t for every reservoir in the SRG.

4.2. The water stored on October 1st of the hydrological year t+1 ($WS_{1_{t+1}}$)

The second water balance equation considered for the simulation model (Eq. (5)) follows the same pattern explained for Eq. (4). Thus, $WS_{1_{t+1}}$ has been simulated as the result of the water stored in the reservoir network at the beginning of the 8th month of the hydrological year t (i.e., May 1st, WS_{8_t}) plus the water inflows into the reservoir network during the dry season of the hydrological year t (i.e., from May 1st to September 30th, $\tilde{I}_{8\text{-}12_t}$), minus the water released from the SRG reservoir network during the dry season in the hydrological year t ($R_{8\text{-}12_t}$), and minus the volume of water evaporated (lost) from the SRG reservoirs during this season in the hydrological year t ($L_{8\text{-}12_t}$). All these variables are also measured as a percentage of the storage capacity of the reservoir network.

$\tilde{I}_{8\text{-}12_t}$ is also a stochastic variable depending on annual climatic conditions. Using @Risk 7.6 software it has been shown that the statistical distribution that best fits actual data for this variable in the period 1980-2018 is the Gamma distribution with α=4.675 and β= 0.017 (AIC=-146.86 and BIC=-143.86). Furthermore, the hypothesis that the actual data do not fit this distribution has been rejected (K-S=0.08, p-value=0.72 and A-D=0.29, p-value=0.65).

It is worth pointing out that $\tilde{I}_{1\text{-}7_t}$ and $\tilde{I}_{8\text{-}12_t}$ are highly correlated (Spearman coefficient=0.787). This relationship can be explained by the fact that water inflows during the wet season are correlated with soil condition (soil moisture level) and snow availability (snowpack storage level) at the end of this season since all these variables ultimately depend on the annual rainfall. Furthermore, the latter two variables (soil condition and snow availability at the end of the wet season) affect water inflows during the dry season since they both influence the share of rainfall that becomes water inflows during this season. Moreover, it has been observed that the relationship between $\tilde{I}_{1\text{-}7_t}$ and $\tilde{I}_{8\text{-}12_t}$ does not follow an elliptical Gaussian pattern, showing nonlinear dependencies in the tails of the distributions. Accordingly, the joint simulation of these two variables is better achieved by using a copula[4]. Also using @Risk 7.6 software, it has been shown that the copula function that best fits the joint simulation of $\tilde{I}_{1\text{-}7_t}$ and $\tilde{I}_{1\text{-}7_t}$ is the Gumbel copula reflected about both axes (GumbelR) with parameter θ equal to 2.423.

According to the GRB Management Plan, the aim is for water releases during the dry season ($R_{8\text{-}12_t}$) to meet all existing water demands: urban demand ($UD_{8\text{-}12}$), ecological flows ($ENV_{8\text{-}12}$), and irrigation demand under full water allotments ($IR_t = IR_{full}$). Thus, in hydrological years where water availability does not constrain releases ($WS_{8_t} > 50\%$), water releases during this season can be as obtained as follows:

$$R_{8\text{-}12_{t\_full}} = UD_{8\text{-}12} + ENV_{8\text{-}12} + IR_{full} \tag{8}$$

Under these circumstances, urban and ecological demands are served with a volume of water equivalent to 1.3% of the storage capacity ($UD_{8\text{-}12} + ENV_{8\text{-}12} = 1.3\%$), and full irrigation water rights are supplied accounting for 32.4% of the storage capacity ($IR_{full} = 32.4\%$) (CHG, 2015). That is, $R_{8\text{-}12_{t\_full}} = 33.7\%$.

However, this is not always the case since drought events mean reduced water availability in reservoirs at the beginning of the dry season and make meeting all demands infeasible. In such situations of scarcity, the DMP for the GRB establishes priority-based allocation rules. In this regard, the first demand to be met is urban consumption. The next priority is meeting minimum ecological flows. Irrigation demand has the lowest priority and is met only when urban and ecological demands are fully satisfied. Considering that $UD_{8\text{-}12}$ and $ENV_{8\text{-}12}$ in the SRG are only 10% of total demand (IR=90% of total demand), both demands are virtually

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[4] A copula is a function that describes how univariate marginal distributions are 'coupled' together to form a multivariate distribution (Nelsen, 2006). Copulas are especially well-suited for capturing the complex dependencies that exist among random variables analyzed in actuarial (McNeil et al., 2005) and hydrological (Chen and Guo, 2019) models.

guaranteed every year. For this reason, in our simulation approach, $UD_{8\text{-}12}$ and $ENV_{8\text{-}12}$ have been considered constant, with their values accounting for 1.3% of the storage capacity for all hydrological years. Water scarcity impacts only on irrigation demand, for which annual allotments are progressively cut depending on the volume of water stored at the beginning of the dry season (WS_{8_t}); as a result, IR_t becomes a variable depending on the water availability ($IR_t = AWA_t \times IR$):

$$R_{8\text{-}12_t} = UD_{8\text{-}12} + ENV_{8\text{-}12} + IR_t = 1.3\% + \left[AWA_t \times IR_{full}\right] \qquad (9)$$

Considering the allocation rules established in the DMP explained in Section 3.2, AWA_t can be defined as follows:

$$AWA_t = \begin{cases} = 100\% & \text{if} \quad WS_{8_t} > 50\% & \text{(Normality)} \\[2mm] = \dfrac{(WS_{8_t} - 50\%)(70\% - 100\%)}{(30\% - 50\%)} + 100\% & \text{if} \quad 50\% \geq WS_{8_t} > 30\% & \text{(Pre-alert)} \\[2mm] = \dfrac{(WS_{8_t} - 30\%)(20\% - 70\%)}{(15\% - 30\%)} + 70\% & \text{if} \quad 30\% \geq WS_{8_t} > 15\% & \text{(Alert)} \\[2mm] = \dfrac{(WS_{8_t} - 15\%)(0\% - 20\%)}{(10\% - 15\%)} + 20\% & \text{if} \quad 15\% \geq WS_{8_t} > 10\% & \text{(Emergency)} \\[2mm] = 0\% & \text{if} \quad 10\% \geq WS_{8_t} & \text{(Emergency)} \end{cases} \qquad (10)$$

Water losses during the dry season ($L_{8\text{-}12_n}$) have been calculated similarly to losses in the wet season, as a function of local climatic conditions and the geometry of every reservoir in the SRG and the average volume of water stored during this period each hydrological year.

4.3. The water stored on October 1st of the hydrological year t (WS_{1_t})

Finally, it is worth noting that the simulations of the distributions of the WS_{8_t} index and the annual water allotment for irrigation (AWA_t) using Eqs. (4) and (5) are conditional on the value considered for the water stored on October 1st of the hydrological year t (WS_{1_t}). In order to avoid the use of conditional distributions (as used in Maestro et al., 2016a), we have built a simulation model considering a period of 100 hydrological years (from t=1 to t=100), including the Eqs, (4) and (5) 100 times. The seed values for $\widetilde{WS}_{1_{t=1}}$ were simulated from a Beta distribution with the parameters α_1= 1.989, α_2= 1.6401, minimum=0, and maximum=1, which proved to be the distribution that best fits historical data (1980-2019) for this variable. Using @Risk 7.6 software, this model has been simulated for 100,000 iterations implementing Latin Hypercube sampling techniques for the three stochastic variables considered ($\tilde{I}_{1\text{-}7_t}$, $\tilde{I}_{8\text{-}12_t}$ and $\widetilde{WS}_{1_{t=1}}$). We thus obtained a probability distribution for WS_{8_t} and AWA_t with 100,000 simulated observations for every year t, from t=1 to t=100.

Analyzing the simulated probability distributions of WS_{8_t} and AWA_t for the first years (t=1, t=2,…), we checked that the seed values for $\widetilde{WS}_{1_{t=1}}$ drawn from the Beta distribution fitted with the historical data bias of the results obtained for these years. This can be seen in Fig. 4, where distributions of the WS_{8_t} index for t=1, t=2, and t=3 are plotted. It can be clearly observed that the distributions are different (K-S test confirms the rejection of the null hypothesis that distributions are the same with p<0.001) and the average of this variable progressively shifts downward. This means that the new institutional framework has changed the hydrological balances, and the volume of water stored in the reservoir network will tend to be lower than in the past. New demands for irrigation and more stringent requirements for ecological flows approved under the new Management Plan (2015) and the new DPM (2018) can explain this decrease in the volume of water stored.
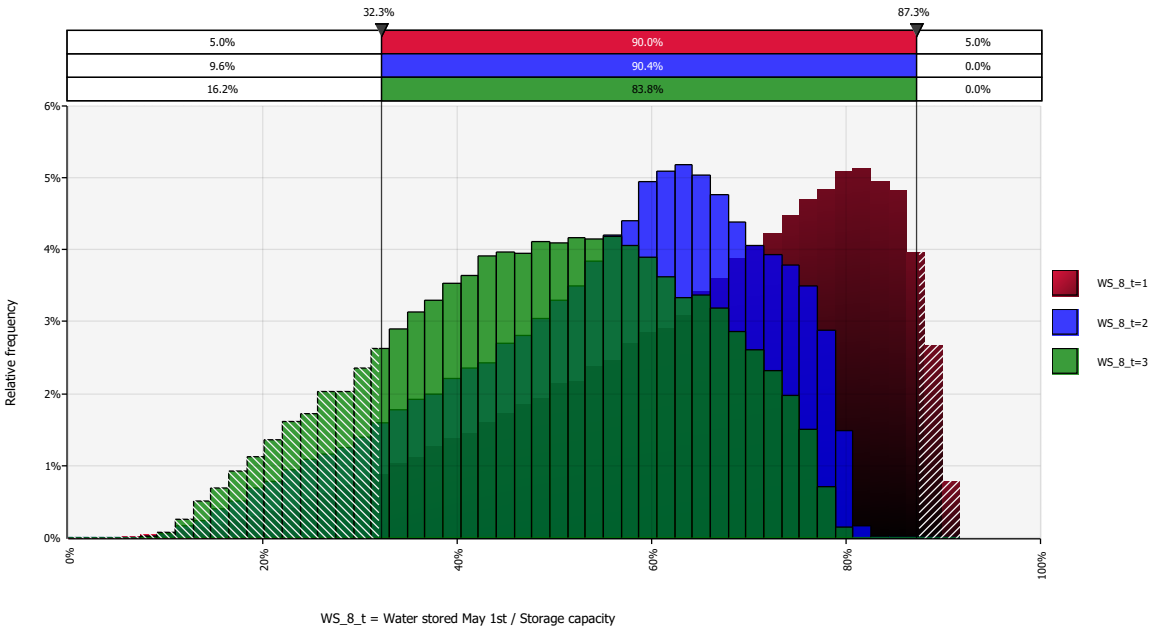

Fig. 4. Distribution of the WS_{8_t} index for years t=1, t=2, and t=3.

However, it has been observed that WS_{8_t} and AWA_t distributions quickly converge to stable solutions (stationary distributions). In fact, for t>5 the K-S test confirms the null hypothesis that distributions for both variables are the same, indicating that the impact of the seed values of WS_{1_t} is negligible 5 years after implementing new management rules. These stationary distributions reached for WS_{8_t} and AWA_t when t>5 have been considered when simulating the distributions of losses and indemnities under the new regulatory framework. In fact, distributions obtained for t=100 have been taken for simulation purposes. Thus, considering each of the 100,000 simulated observations for WS_{8_t} and AWA_t, 100,000 simulated observations have been obtained for $Loss_t$ using the empirical function explained

in Section 3.2, and for I_t applying Eq. (3), in both cases for each of the three farm types and the three ordinary deductibles (DED) considered.

5. Results and discussion

5.1. The distributions of the WS_{8_t} index and the annual water allotment for irrigation

The distributions of the 100,000 simulated observations for WS_{8_t} and AWA_t are shown in Figs. 5 and 6. The main descriptive statistics of both distributions are reported in Table 4.
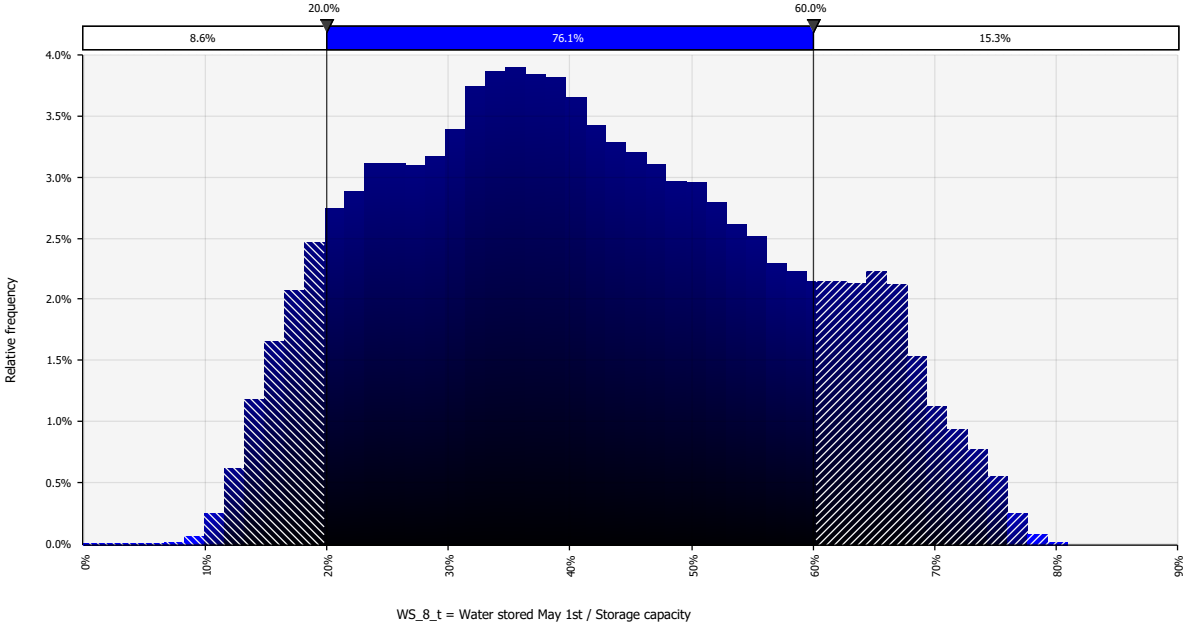

Fig. 5. Distribution of the WS_{8_t} index.

The distribution simulated for WS_{8_t} clearly shows that the new institutional framework considering new irrigation demands and the changes included in the GRB Management Plan and in the DPM (namely higher ecological flows) will reduce the water availability at the beginning of the irrigation season (May 1st). In fact, while the historical average (period 1980-2019) of the water stored in the reservoir network of the SRG on May 1st is 54.5% of total storage capacity, the anticipated average for the future is just 41.4%. In any case, it is also true that the stochastic values for WS_{8_t} are expected to be less dispersed; historical standard deviation is 23.9%, while the simulated value for the future is 15.7%.

Table 4

Summary statistics for the WS_{8_t} index and annual water allotment for irrigation (AWA_t).

Statistics	WS_{8_t}	AWA_t	Percentile	WS_{8_t}	AWA_t
Minimum	0.00%	0.00%	10%	20.83%	39.43%
Mean	41.40%	79.55%	20%	26.36%	57.86%
Median	40.19%	87.73%	30%	31.48%	76.85%
Maximum	80.77%	100.00%	40%	35.82%	82.27%
			50%	40.19%	87.73%
Std. deviation	15.69%	24.00%	60%	44.96%	93.69%
Variance	0.02461	0.05761	70%	50.40%	100.00%
Skewness	0.19195	-1.18993	80%	56.60%	100.00%
Kurtosis	2.13282	3.38322	90%	64.10%	100.00%

Source: Own elaboration.

This decrease in water availability under the new institutional framework will also negatively impact annual water allotment for irrigation. In this sense, it is worth pointing out that the historical mean of AWA_t for the period 1980-2019 is 90.3%, but this is expected to drop to 79.6% (see the average of AWA_t in Table 4). Moreover, the standard deviation of this variable is expected to increase from a historical value of 11.7% to 24.0% (see Table 4). Obviously, these changes will lead to a less reliable irrigation water supply, with more frequent and intense water supply failures, as shown in Fig. 6. In fact, it is expected that irrigation water allotments will be lower than 70% of full irrigation water rights for 26.8% of the irrigation seasons, and lower than 50% of full irrigation water rights for 15.7% of the irrigation seasons. These figures confirm the increasing vulnerability of the irrigation sector to droughts.
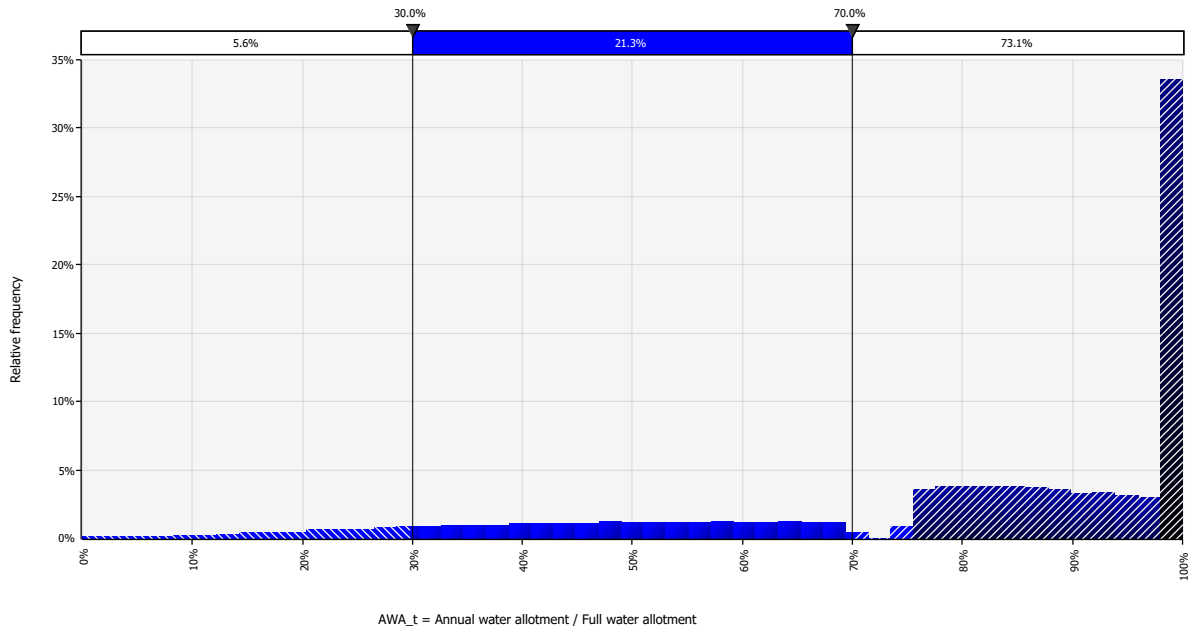
Fig. 6. Distribution of the annual water allotment for irrigation (AWA_t).

5.2. The distribution of indemnities and fair premiums

For each simulated observation of AWA_t, the related indemnities (I_t) for the three farm types and the three alternative ordinary deductible options (DED=10%, 20%, and 30%) considered have also been simulated using Eq. (3). This has allowed us to obtain distributions with 100,000 simulated indemnity observations, as shown in Fig. 7 for the case of farm type 2 with an ordinary deductible of 20%. Descriptive statistics of the 9 distributions (3 farm types × 3 deductible levels) are reported in Table 5.

Table 5

Summary statistics for the distributions of the indemnities depending on the farm type and the level of the ordinary deductible (DED).

| Statistics	Farm type1			Farm type2			Farm type3		
	DED=10%	*DED*=20%	*DED*=30%	*DED*=10%	*DED*=20%	*DED*=30%	*DED*=10%	*DED*=20%	*DED*=30%
Minimum (€/ha)	0	0	0	0	0	0	0	0	0
Mean = Fair premium (€/ha)	313	202	122	200	135	84	264	191	129
Maximum (€/ha)	3,771	3,352	2,933	2,591	2,304	2,016	2,366	2,103	1,840
Mode (€/ha)	≈0	≈0	≈0	≈0	≈0	≈0	≈0	≈0	≈0
Median (€/ha)	0	0	0	0	0	0	0	0	0
Std Dev (€/ha)	644	508	388	435	340	253	500	405	317
Skewness (dimensionless)	2.42	3.06	3.86	2.38	2.92	3.72	1.91	2.27	2.76
Kurtosis (dimensionless)	8.74	12.71	18.84	8.32	11.90	18.51	5.71	7.47	10.25
Prob. [Indemnity = 0 €/ha]	67.8%	77.1%	84.5%	74.3%	79.4%	84.5%	66.0%	73.8%	78.8%
Prob. [0 €/ha < Indem. ≤ 1,000 €/ha]	19.5%	14.9%	10.3%	17.3%	16.0%	13.6%	22.4%	18.8%	17.0%
Prob. [Indemnity > 1,000 €/ha]	12.7%	8.0%	5.2%	8.4%	4.6%	1.9%	11.6%	7.4%	4.2%

Source: Own elaboration.
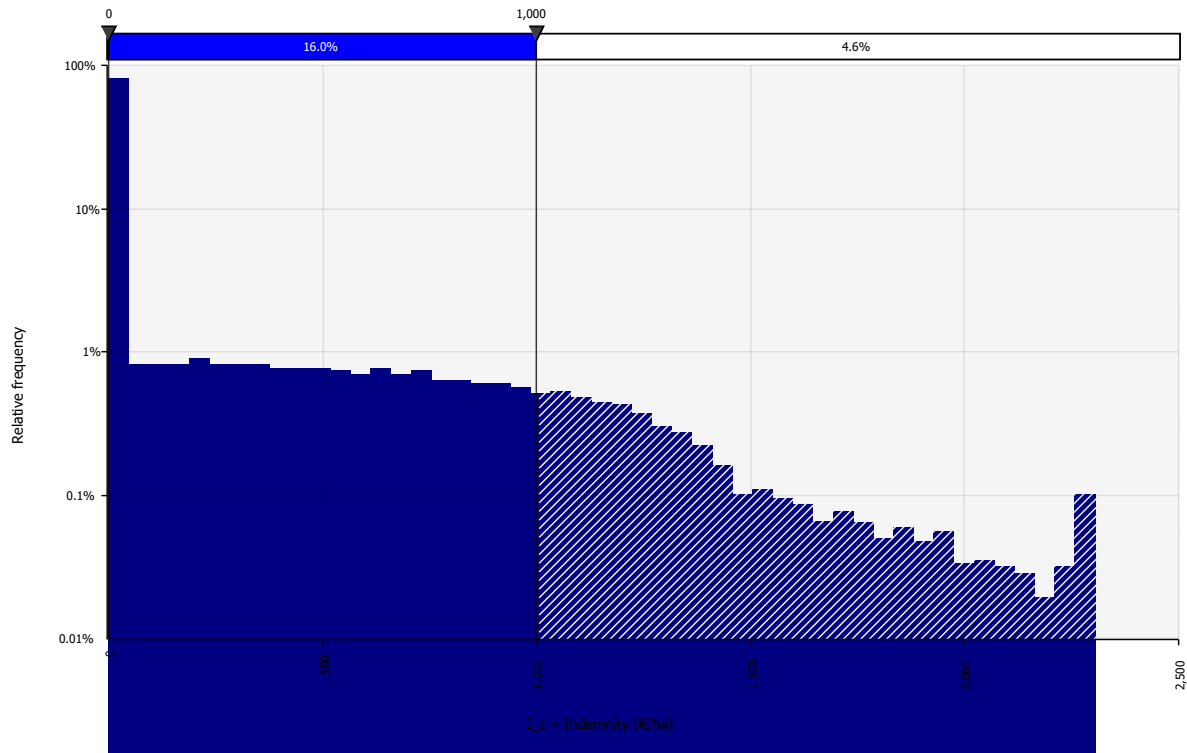
Fig. 7. Distribution of the indemnities (I_t) for farm type 2 with an ordinary deductible of 20%.

As expected, results show that the higher the deductible the lower the average indemnity and the higher the probability of null indemnity. However, it is worth pointing out that the probability of non-zero indemnity is rather high, ranging from 15.5% in the case of an ordinary deductible of 30% for farm types 1 and 2 to 34.0% for an ordinary deductible of 10% in the case of farm type 3. These relatively high probabilities are just the consequence of the volatility of the annual water allotment for irrigation under the new management rules explained above.

As a result of these high incidence rates, the fair premiums (expected or average value of the indemnities, $P = E[I_t]$) reach high values, ranging from 83 €/ha for farm type 2 with an ordinary deductible of 30% to 313 €/ha for farm type 1 with an ordinary deductible of 10%.

The expected indemnity can also be defined in percentage terms calculating the fair premium rate (PR) as the ratio P/IC. This fair premium rate has also been calculated for each farm type and each ordinary deductible option considered as shown in Table 6. These relatively high percentages, ranging from 2.9% to 10.0%, confirm the above-mentioned high incidence rates.

Table 6

Fair premium, fair premium rates, and estimated commercial premium for each farm type and each deductible option.

	Farm type1			Farm type2			Farm type3		
	DED=10%	*DED*=20%	*DED*=30%	*DED*=10%	*DED*=20%	*DED*=30%	*DED*=10%	*DED*=20%	*DED*=30%
Fair premium ($P = E[I_t]$) (€/ha)	313	202	122	200	135	84	264	191	129
Fair premium rate (P/IC) (%)	7.5%	4.8%	2.9%	7.0%	4.7%	2.9%	10.0%	7.3%	4.9%
Estimated commercial premium ($CP = P\,(1 + 37.3\%)$) (€/ha)	429	278	168	275	185	115	362	262	177
Fair premium over total variable costs (P/VC) (%)	13.0%	8.4%	5.1%	10.9%	7.3%	4.6%	18.9%	13.7%	9.2%
Estimated commercial premium over total variable costs (CP/VC) (%)	17.8%	11.5%	7.0%	14.9%	10.1%	6.3%	26.0%	18.8%	12.7%

Source: Own elaboration.

The commercial insurance premium is the money paid by the insured farmers for the coverage included in an insurance policy. This price is fixed by insurance firms charging loadings on the fair premium for acquisition effort, administrative expense, risk-bearing (i.e., reinsurance costs), and profit allocation. Although these loadings vary among insurance firms, the average loading in Spain for agricultural insurance is 37.3% of the fair premium (Machetti, 2015). Assuming the same loadings could be applied to the fair premiums obtained to underwrite the policies of the proposed drought insurance (see estimations in Table 6), it is worth noting that the money that irrigators would have to pay for these policies could significantly increase their variable costs. These increases could range from 6.3% (farm type 2 with an ordinary deductible of 30%) to 26.0% (farm type 3 with an ordinary deductible of 10%). These figures show that buying these insurance policies would involve substantially higher costs for these farmers. However, the proposed insurance scheme could presumably also benefit from public subsidies similar to those applied to other agricultural insurance schemes, where the premiums actually paid by farmers are currently reduced by 39.2% (Agroseguro, 2019), making these policies more affordable.

Finally, it is also worth mentioning a limitation of the estimations carried out; namely, that the actuarial analysis implemented has ignored the possible effects of climate change on the distributions of water inflows feeding the reservoirs ($\tilde{I}_{1,7_t}$ and $\tilde{I}_{8,12_t}$ have been simulated based on historical records) and on the irrigation water needs (IR_{full}). The high degree of uncertainty about future changes in these variables justifies this omission (Pérez-Blanco et al., 2017). In any case, sound climate models generally predict an ongoing reduction in the average volume of water available for irrigation and an increase in its variance, changes that would raise the fair premium. This issue is usually solved by adding an additional 'ambiguity load' to the fair premium to calculate the commercial premium (Collier et al., 2009). Thus, it should be assumed that the cost to be borne by irrigators willing to purchase this kind of insurance policy would be about 5-10% higher than the ones estimated above. This situation further emphasizes the potentially high costs that farmers would face if using this instrument to hedge against drought risk.

A more accurate approach to incorporate climate change into the analysis is to feed the actuarial models with the outputs from the hydrologic and agronomic modeling. In this sense, it is worth commenting that there are sound hydrological models (e.g., HEC-HMS, MIKE-SHE, or SWAT+) that could provide new distributions of water inflows ($\tilde{I}_{1,7_t}$ and $\tilde{I}_{8,12_t}$) adapted to different climate change scenarios (Srinivasa Raju and Nagesh Kumar, 2018). Similarly, distributions of irrigation water needs (IR_{full}) adapted to the same climate scenarios could also be obtained using simulated climatic data as an input of agronomic models (e.g., FAO

AquaCrop) (Foster et al., 2017). However, this is a challenging task that is far beyond the scope of this paper. In any case, further multidisciplinary research in this regard, combining the expertise of hydrologists, agronomists, and actuaries, is a potentially effective way of providing sounder fair premium estimations.

6. Conclusions

This paper has proposed a new index-based drought insurance scheme to cover the risk of water supply failures in irrigated agriculture that overcomes the problems currently hindering the development of this kind of insurance, especially those related to arbitrariness in annual water allotments decision-making. The scheme proposed is a promising instrument to help irrigators manage the risk related to hydrological droughts, since it has been proved to be technically feasible. Although the insurance proposal has been tailored to the Spanish irrigation sector, its main features can also be implemented worldwide.

The most challenging issue tackled in this work is how to implement the actuarial analysis to calculate the fair premium, taking into account the fact that recent changes in the institutional framework (new demands, new storage capacity and revised basin, and drought management plans) mean historical records are not suitable for this purpose. This work has shown that under these circumstances, actuarial analysis based on stochastic hydrological models simulating the current institutional framework can yield fruitful outcomes.

Simulation results have shown that irrigated agriculture in southern Spain is expected to become more vulnerable to hydrological droughts. In fact, incidence rates are likely to increase because of the new institutional framework, involving relatively high fair premiums. Only by implementing high ordinary deductibles (e.g., 30%, as is standard in agricultural insurance schemes in Spain) can the hypothetical cost of commercial premiums be affordable for farmers, accounting for less than 10% of their current variable costs.

In any case, further research is needed to assess whether the proposed scheme is commercially viable in a real-life setting. In this sense, additional studies from a demand-side perspective are called for in order to determine the potential acceptance of this risk management instrument in terms of willingness to pay, as has been done by Pérez-Blanco et al. (2015). Similarly, supply-side studies aiming at assessing the cost of this insurance scheme for insurance firms should be refined by considering climate change predictions regarding both water inflows feeding the reservoirs and irrigation demand. These avenues for research would be valuable for assessing the role of insurance as a policy aimed at facilitating adaptation to climate change.

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