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How useful are seasonal forecasts for farmers facing drought? A user-based modelling approach

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ABSTRACT

Seasonal forecasts of water availability have clear potential benefit for decisions in irrigated agriculture. This potential depends in part on how accurate the information provided is. The actual benefit, however, depends on how the information is used in the decisions, by whom, and the outcome of those decisions. In this paper we assess how useful seasonal forecasts are in supporting drought management decisions by farmers at the irrigation district level. We model the decisions irrigated farmers make on what and when to plant in the Ebro basin (Spain), and the interconnected decisions reservoir operators make on whether to apply curtailments to the water allocated to farmers. The modelled farmers are supplied from a reservoir with capacity for a single irrigation season and therefore their decisions are conditioned by the expected water availability through to the end of the season. Different farmer behaviours are considered as a function of their risk averseness and their technical capacity. The value of seasonal streamflow forecasts to inform these decisions is compared against that of current practice using extrapolated historical records, as well as against a reference forecast based on climatology. Results show that seasonal forecasts of water availability have skill, albeit limited. How salient information is to the decisions that farmers make, however, differs for each type of farmer as they take key decisions at different points in the season. As a consequence, seasonal forecast information is found to not serve the various farmer types considered equally. Our results illustrate how assessing the usefulness of information to servicing a decision can be approached from a combined technical and user-centric perspective.

Practical implications

Seasonal forecasts of water availability provide information that is useful to farmers choosing what crops to plant over the season. However, as we show in this research, how useful seasonal forecasts are depends not only on the reliability of the information itself, but also on the context within which the decisions are taken, and the various needs and preferences of the different decision makers. Though the importance of incorporating diverse user needs in the assessment of the usefulness of climate services such as those providing seasonal forecast information is widely recognised, considering these various needs in the assessment of the value of climate services to support operational water management decisions is still limited.

Here, we use a case study where we consider the cropping decisions of irrigated farmers in the Ebro basin, a drought prone Mediterranean basin. We apply a user-based model, that considers the decisions made by farmers. We identify four types of farmers, each with different attitudes to risk and technical abilities. We assess the usefulness of seasonal forecast information for these users in a comprehensive way, considering the key crop decisions they make through the season. This allows us to examine the aspects that influence the usefulness of information in supporting these decisions.

We find that the skill of the forecast, the salience of the information, and individual needs and preferences determine how useful the seasonal forecast information is for each type of farmer. Our results do show that the forecast information is useful to the decision-makers assessed, but that it is not equally useful to all. The usefulness depends on how uncertain water availability during the season is in a given year. For years that are clearly wet from the start of the season, the forecast provides little added value. Surprisingly for the more extreme drought years the forecast also

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has little added value as most farmers then choose to not grow higher value irrigated crops but opt for the safer rain-fed options. Forecast information has most value in years that transition from wet to dry, or vice versa. The usefulness of the forecast information also depends on the options that each of the groups of farmers have or are willing to choose. It is also important to consider the time of year when decisions have to be made on the available options, as the skill of the forecast that they will be able to use at the time of making the decision varies through the year. Skill is lower at the beginning of the season and improves over time. This means that the uncertainty of water availability through to the end of the season reduces, as water accumulates in the reservoir over the season and as more farmers select their crops. The latter is important, as this reduces the uncertainty of water demand, which is an important contribution to the uncertainty on whether there is sufficient water to meet demand to the end of the season. The balance between availability and demand is a key input into the decisions that the reservoir operators make, as they may apply curtailments if there is insufficient water, which in turn influences the choices farmers make.

We find that farmers that have higher technical capacity have more flexibility to design their crop pattern in a way that key decisions are taken later in the season when there is less uncertainty on seasonal water availability and information from the forecast. As a result, the information obtained from the seasonal forecast is less critical to them, but when they do use the information they benefit from the higher forecast accuracy. Farmers with lower technical capacity that do not have such flexibility, and who may be more risk averse, do get a higher added value from the forecast but, as they have to make their decisions early in the season, they need to do it using forecast information that is less accurate.

Our findings underline the influence user-related factors have on the usefulness of seasonal forecast information for operational water management decisions, and the value these forecasts have in supporting the various decisions users make. Assessment of the various needs of intended users, such as in this study, provides important insights to the tailoring of climate services such that these consider the available options and differing risk attitudes, contributing to the usefulness of these services and importantly to their use.

Introduction

Early information of water availability during the hydrological year is critical for supporting water management decisions, but difficult to predict due to the variability of the climate, as well as the uncertainty of demand through the season and from year to year. Information on expected water availability is often derived from climatology using historical observed flow data (Lopez and Haines, 2017; McMillan et al., 2017). Though this is a practical approach, it risks not capturing the full variability due to the limited length of records, or due to changes in climate and in the catchment (Hall et al., 2012).

An alternative source of information to partially overcome these issues, is to establish seasonal water availability through seasonal streamflow forecasting, though the skill with which seasonal water availability can be forecast varies (Arnal et al., 2018; Pechlivanidis et al., 2020).

Several studies have addressed the potential contribution of seasonal forecasts to inform water management decisions in a broad range of sectors including hydropower planning (Alexander et al., 2021; Beckers et al., 2016; Graham et al., 2022), food security early warning (Shukla et al., 2020), rain-fed agriculture (Winsemius et al., 2014), and irrigation planning and crop selection (Kaune et al., 2020; Steinemann, 2006). However, despite the apparent advantage of skilful seasonal forecasts demonstrated in research, the uptake by water managers and farmers faces multiple barriers (Antwi-Agyei et al., 2021; Bruno Soares and Dessai, 2016; Hansen, 2002; Lemos et al., 2012). Barriers include perceived lack of reliability, lack of relevance or awareness (Bruno Soares and Dessai, 2016), difficulty to interpret probabilistic seasonal forecasts (Crochemore et al., 2016), as well as risk perception (Kirchhoff et al., 2013). Lemos et al. (2012) classify these barriers in three categories: the user's perception of the information (e.g. accuracy, reliability, timeliness), the interplay of the information and the user's context (e.g. existing practices, technical capacity, risk aversion), and the interaction between the information producers and users.

Studies on the value of seasonal forecasts for water management tend to focus on the skill of predictions of climate variables required by decision makers, such as precipitation and streamflow. However, as a result of the barriers to the uptake and usage of seasonal forecast, it is increasingly recognised that better skill alone does not necessarily lead to added value and there is a need to consider the context in which the information is used (Findlater et al., 2021; Ritchie et al., 2004; Turner et al., 2017). Crochemore et al. (2016, 2021) set up participatory games to explore how seasonal forecasts are used to support reservoir operation decisions and assess the perceived value of this information, observing that improved seasonal forecasts led to better decisions. Golembesky et al. (2009) assess the utility of a 3-month lead-time streamflow forecast product in combination with a reservoir operation model to improve management decisions, and Kaune et al. (2020) evaluate integrating a seasonal forecast product into the complex water allocation policy in an irrigation district in Australia, finding that this allows decisions on water allocation to annual crops to be established 1–2 months earlier than when based on climatological information, which is useful to farmers.

Findlater et al. (2021) call for considering social aspects when assessing climate services, such as seasonal forecasts. Examples of such integration in climate services assessment can be found for disaster adaptation decisions, in which socio-hydrologic approaches such as agent-based models are increasingly being used to account for the behaviour of individuals or groups in decision processes (Aerts et al., 2018; Schrieks et al., 2021; Wens, 2022), and for farmer's crop decisions (Alexander and Block, 2022; Yuan et al., 2021).

Considering the behaviour of users in response to the provision of seasonal forecast information is limited among studies that assess the value of climate services that support operational water management decisions. Li et al. (2017) apply a process-based agricultural model coupled with a farmers' decision model over a period of 5 years to assess the value of different seasonal forecast products, showing that farmers attitudes to risk have an impact on the operational value of the products. Giuliani et al. (2020) explore the impact of forecast system setup and operator risk averseness on the value of seasonal forecasts for the operation of a lake with irrigation and flood control objectives, though their focus is on the behaviour of the operator in allocating water, rather than the farmers and the decisions they make, which influence demand. They suggest further research in different locations and decision contexts is required to develop general conclusions on the value of seasonal forecasts and their potential to improve decisions. These two studies do show that the attitudes users, such as farmers and reservoir operators, have to risk can have an impact on the operational value of the seasonal forecast products.

In this paper, we extend this work on assessing the potential value of climate services as a function of the behavioural response of users to seasonal forecast. We apply a user-based model of the decisions on what and when to plant in an irrigation district in a drought-prone area to assess how useful seasonal streamflow forecasts are in supporting farmers in making these decisions. The model also considers the interlinked reservoir operator decision on whether to apply curtailments to water allocations so as to preserve water and ensure supply through to the end of the season. In addition to three levels of risk averseness, our decision model considers two types of farmers, each with different levels of technical capacity. This determines whether they can plant a single or a double crop and influences the multiple paths they can follow to adapt their decision to the available information on water availability as the season evolves. This allows us to look at the role of the timing of the decision and available options, as well as how the usefulness and value of the seasonal forecasts changes during the season and from year to year.

Methods

Study area

We select an irrigation district located in the northeast of the Ebro basin. The Ebro basin is a large (85,600 km^2) and highly regulated (over 7,900 hm^3 of total storage capacity) Mediterranean basin in the northeast of Spain. The basin has a long tradition of hydraulic infrastructure to store and distribute water resources for agriculture (Pinilla, 2006), with a good and accessible data record. This tradition originates from the mismatch between crop water requirements (which are high in the summer) and the seasonality of rainfall (which peaks in spring and autumn and has lows during the summer, typical of a Mediterranean climate). The issue is exacerbated by high interannual variability of rainfall, which ranges between 430 and 830 mm (CHE, 2022).

The selected irrigation district is supplied by the Aragón and Cataluña Canal (Canal de Aragón y Cataluña, CAyC, Fig. 1) and is mainly supplied from Barasona reservoir (92 hm^3), fed by the Ésera and Isábena rivers. These have a combined catchment of 1511 km^2. Supplying the irrigation district is the main use of Barasona reservoir. Groundwater use in the irrigation district is limited (CHE, 2022).

The period 1984–2016 was selected for the analysis due to data availability. This includes several drought episodes of different length (Linés et al., 2017), as well as wet years. The study area was the most affected in the basin by the drought episode in 2004–2005 (CHE, 2018).

Observed data

Streamflow. The water available for irrigation is determined by the accumulated inflow into Barasona reservoir from 1st of October (after the end of the previous irrigation season). The total inflow into the reservoir is established by summing the flow of the two tributaries. We use streamflow data from two gauging stations, Graus (Ésera River) and Capella (Isábena River), from the national gauging stations network (ROEA). The data record starts in 1931 but there are several gaps before 1984.

Precipitation. Daily precipitation data (liquid and solid) was obtained from the SAFRAN dataset over Spain (Quintana Seguí, 2015; Quintana Seguí et al., 2016; Quintana-Seguí et al., 2017), which is based on interpolated station data from the Spanish State Meteorological Agency (AEMET), combined with ERA-Interim and available for the 1979–2016 period at a resolution 5x5km.

The daily data was aggregated to monthly (sum per pixel), and spatially weighted (mean for the catchment). This dataset was also used to derive the three-month Standardised Precipitation Index (SPI-3) using the SPEI package in R (Beguería and Vicente-Serrano, 2013).

Seasonal forecasting of precipitation and streamflow

Seasonal precipitation forecasts for the 1984–2016 period are obtained from the ECWMF SEAS5 ensemble seasonal forecast model (Johnson et al., 2019), with an ensemble size of 25 and horizontal resolution of approximately 36 km (Johnson et al., 2019). Forecasts, with a 7-month lead time are initiated on the first day of each calendar month. We use these to develop an ensemble streamflow forecast for the inflow to the Barasona reservoir. Monthly forecast precipitation is spatially weighted over the catchment upstream of the reservoir, and bias corrected against the catchment averaged SAFRAN data through a parametric quantile-mapping approach (Yuan et al., 2015), using the gamma distribution for both observed and forecast precipitation (Table S1, Piani et al., 2010; Zhao et al., 2017). We assess the skill of the bias-corrected precipitation forecasts through the correlation of the ensemble mean to observed monthly precipitation and the continuous ranked probability skill score (CRPSS), using leave-one-year-out cross validation (Schepen et al., 2018). CRPSS is a statistical metric to measure the skill of the ensemble forecasts over a reference forecast and is calculated as $CRPSS = 1 - CRPS_{forecast}/CRPS_{reference}$. CRPS is the Continuous Ranked Probability Score, a metric of the distance between the forecast distribution against observations (Hersbach, 2000), averaged over all forecasts. A climatological reference forecast is obtained through randomly sampling the gamma distribution fitted to the observed precipitation for each month.

Streamflow in the basin is bi-modal, with high flows in October-December due to excess precipitation, and in spring (April-May) due

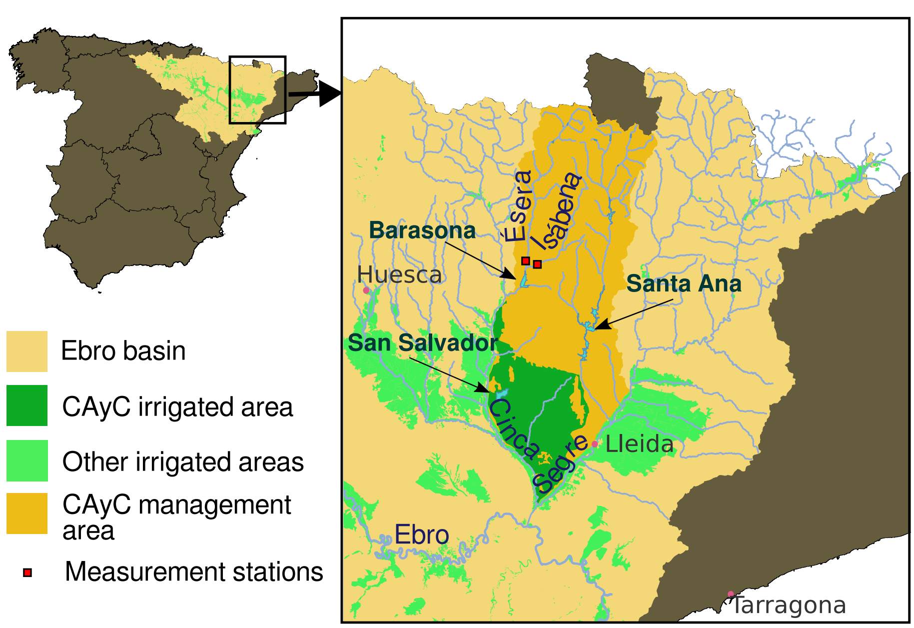

Fig. 1. Study area: Canal de Aragón y Cataluña (CAyC) irrigation district in the Ebro basin.

to precipitation and snowmelt (Supplementary material, Fig. S2). To forecast monthly inflows to the Barasona reservoir, we develop a simple stochastic model forced by the bias-corrected seasonal precipitation forecast ensemble. As baseflow has a longer memory (good autocorrelation, see Fig. S3), we separate this from the observed flow using a Lyne & Hollick baseflow separation procedure (Ladson et al., 2013; parameter alpha = 0.8). This is then transformed into the standardised form using a gamma distribution to account for seasonality (Stagge et al., 2015), and an auto-regressive time series ARIMAX model (Wilks, 2011; Mishra et al., 2007; Valipour et al., 2013) is applied to model the transformed baseflow. The three-monthly Standardised Precipitation Index (SPI-3) is used as exogenous variable. SPI-3 is calculated using observed precipitation prior to the forecast initiation date, and then forecast precipitation for each ensemble member out to the seven-month lead time. We apply the ARMAX model for each of the 25 members of the bias-corrected precipitation forecast to establish an ensemble baseflow forecast to the 7-month lead time. The shorter memory (low autocorrelation, Fig. S3) quickflow, is modelled using a simple linear regression model against precipitation. A separate regression model is established for each calendar month to account for seasonality (Supplementary material, Table S2). This regression model is then used to calculate an ensemble forecast of the quickflow, which is added to the forecast baseflow to establish a 25-member ensemble streamflow forecast. Inputs to the decision model are then derived by accumulating monthly streamflow forecasts from the forecast initiation date to the end of season for each ensemble member. Where the accumulation window is longer than seven months, flows are extrapolated for each ensemble member using the currently used forecast procedure (decision model and extrapolation approach described in next section). The skill of monthly and accumulated end-of-season forecasts is assessed using the same approach as for the precipitation forecast, again using a leave-one-year-out cross validation strategy.

Modelling the cropping decisions of the farmers

The decisions farmers in the CAyC make on which annual crop to plant in each season are modelled with a simplified version of the decision model that is described in full in Linés et al. (2018), which is based on interviews with stakeholders in the area. Decisions are made to maximise economic benefits, depending on the expected availability of water, but are also influenced by the risk each farmer is willing to take, where more risk averse farmers prioritize minimizing losses. Planting later in the season helps reduce the uncertainty of expected water availability to the end of season and therefore reduces the risk of losing the crop due to water shortage. However, the available options to the farmer reduce as the season progresses, increasing the risk of having to leave the land fallow if conditions turn out to be unfavourable, rather than planting a "safe" rain-fed crop.

Fig. 2 shows the different decision paths farmers can follow when deciding on what crop to grow on each plot of land. In reality farmers in the Ebro Basin may well have multiple plots at their disposal and may take different decisions on what crop to grow on each, including a mix of annual and perennial crops. However, for the sake of simplicity we consider here a farmer to be the farmer of a single plot on which only one crop can be grown at any one time. We consider two types of farmers with different technical capabilities: farmers who can only plant a single crop each season (T1) and farmers who have the technical capacity to plant a second crop after the first one is harvested (T2). This double-crop is invariably short-cycle rainfed barley (SCB) during the winter, followed by a short-cycle irrigated maize (SCM) crop planted in May if water availability is considered sufficient. If availability is considered insufficient in May, the land is left fallow. Short-cycle maize is less productive than long-cycle maize and therefore requires more efficient techniques to make it worth the investment, particularly in relation to irrigation methods such as drip irrigation. The option of planting two crops is therefore considered only by farmers who avail of these technical capabilities.

For the single crop farmers there are different options, depending on the level of risk the farmer is willing to take. Three levels of risk tolerance are considered: low (RL), medium (RM) and high (RH). The single crop can be either long-cycle rainfed barley (LCB) planted in November, short-cycle rainfed barley (SCB) planted in February, or long-cycle irrigated maize (LCM) planted in April. Maize is more productive than barley and therefore preferred, but it is more expensive to plant and can result in higher losses if the crop is lost due to drought conditions and subsequent shortage of water. LCB is more productive than SCB but needs to be planted earlier in the season. This poses a lock-in as the decision to plant barley prevents the farmer to plant the more productive

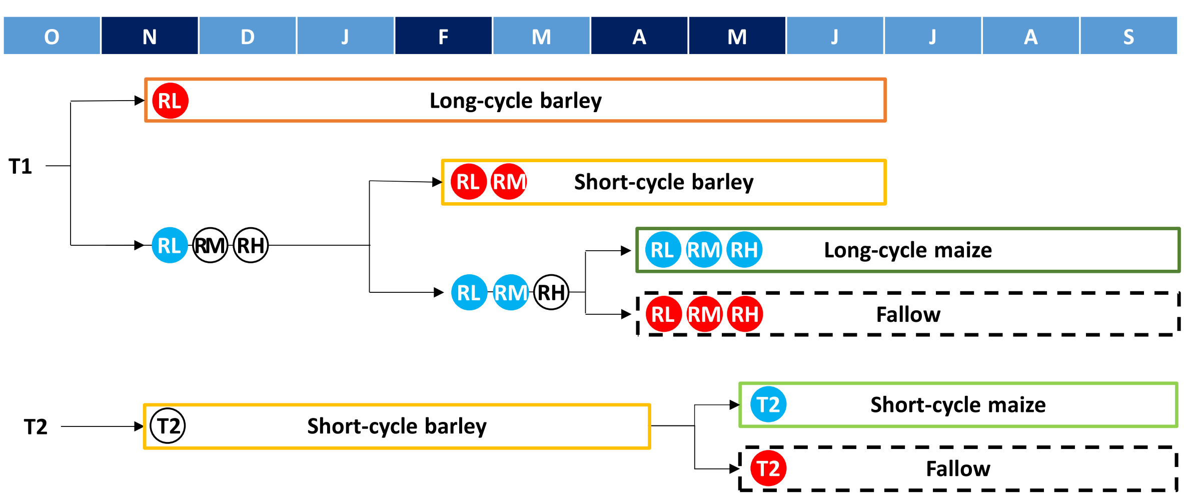

Fig. 2. Crop options for the different types of farmers: single-crop farmers (T1) and double-crop farmers (T2). For single-crop farmers three levels of risk tolerance are considered: low (RL), medium (RM) and high (RH). The arrows mark the decision path each type of farmer follows, which depends on the expected water balance at the end of the season. Blue (red) circles indicate the path that is followed if a positive (negative) balance at the end of the season is expected. White circles indicate that the path is followed irrespective of water availability. Decision months are highlighted in dark blue, with the decision assumed to take place at the beginning of the month.

maize crop if conditions improve. Risk averse farmers prefer to secure a crop, even if it is less profitable, rather than waiting to see if conditions improve and risking having to leave the land fallow if the expected water availability is not enough to irrigate the maize crop. More risk averse farmers (RL) therefore go for the safe option and plant LCB in November if the expected availability is not good at that time. Medium risk averse farmers (RM) in contrast wait until February to decide and then plant SCB if expected water availability is insufficient to support the preferred LCM crop. The least risk averse farmers (RH) wait until April and then choose either to plant LCM or leave the land fallow. If during the irrigating season water is considered insufficient to support the demand of the irrigated crops planted following decisions made, allocated water is curtailed by the operator, with all irrigated annual crops receiving the same reduction.

Table 1 presents the proportions for each type of farmer in the area, with 35 % of the farmers planting one crop per season (T1), and 65 % two crops (T2) (based on Lloveras Vilamanyà et al., 2014). Three levels of risk aversion are considered for T1 farmers. Annual crops cover a third of the total area, while the other two thirds are predominantly covered in equal parts by two permanent irrigated crops, alfalfa and peaches. These permanent crops have priority to be irrigated over maize when water is scarce (Linés et al., 2018).

Farmers base their decision on their perception of sufficient water availability during the season to grow irrigated maize, which is calculated as the balance between the expected availability of water and the expected demand of irrigated crops through to the end of the season if the options for good water availability are selected. The information on expected water availability is provided by the reservoir operators who also use the balance between supply and demand to decide whether to apply curtailments to water allocations, in this case we use perfect information of demand when establishing the balance for the reservoir operator to focus on the decision of farmers and the availability of information. Farmer decisions that occur before the start of the irrigation season (November, February and April, see Fig. 2) consider the total demand if LCM and SCM are planted by T1 and T2 farmers respectively (D1 demand, i.e. demand resulting from all farmers planting the good water availability options in all the decisions that remain), while decisions made in May, consider the total demand since the start of the irrigation season plus the additional demand if SCM is then planted by T2 farmers (D2 demand). Both D1 and D2 include the demand of the permanent crops (alfalfa and peach). A positive balance indicates the expected availability is enough to plant the maize crop. We consider four scenarios to inform expected availability to the end of the season:

- Historic extrapolation (HE): Water availability to the end of season is based on percentiles of the historic record. The climatological percentile of the observed inflow accumulated up to the decision moment is determined, and this is then used to extrapolate the total inflow to the end of the season by taking the value of total accumulated inflow at the end of the season corresponding to that climatological percentile. This is the current approach used by the reservoir operator.
- Seasonal streamflow forecast (F#): Water availability to the end of season is based on the accumulated ensemble streamflow forecast. The numeral indicates the non-exceedance decile of the ensemble (F10-F90), or the ensemble mean (FM).
- Perfect streamflow forecast (Fp): Water availability to the end of season is based on streamflow model driven by observed precipitation from SAFRAN. This scenario serves to check the relative contribution to the error by the hydrological model used for the streamflow forecast.
- Perfect information (P): Water availability to the end of season is based on the observed streamflow, thus assuming that reservoir operators and farmers have perfect knowledge of how much water is available.

Table 1
Model parameters.

Parameter	Value
Proportion farmer types	0.35 (T1), 0.65 (T2)
Proportion risk aversion levels	1/3 (RL), 1/3 (RM), 1/3 (RH)
Proportion crops	1/3 (alfalfa), 1/3 (fruit), 1/3 (variable: barley and maize)

As the available conservation storage in the reservoir is expected to be depleted during each irrigation season, the annual availability of water is determined by the variable inflow to the reservoir during the hydrological year.

Perfect information of crop water requirements over the season is used in all scenarios, so the differences come from the estimation of the future availability alone. Yield estimations and monthly water requirements of the crops planted are obtained through simulation with the AquaCrop-OS (Foster et al., 2017) and Cropwat 8.0 (FAO, 2000) models. Default parameters for each of the crops are used, adapted to the Ebro basin calendar and the two different types of maize considered (Foster et al., 2017). The monthly water requirement values obtained are assigned to the first day of each month in the decision model.

In the decision model, the yield obtained from the crop models is multiplied by the number of hectares planted. Curtailments are applied in the decision model when the expected water availability until the end of the season is estimated to not be sufficient to fulfil the demand of all irrigated crops. Curtailments are then applied as a reduction of the irrigated areas of the variable (irrigated) crops. Crops in areas no longer irrigated are considered to be lost. The reduction in the irrigated crop area is determined proportional to the availability such that the conservation storage of the reservoir is depleted after considering the water requirements of all crops.

Evaluating the benefit of decisions

Selected forecast verification scores are calculated to evaluate the outcomes of the decision model informed by each of the scenarios (HE, Fp, F#). The scores considered are summarised in Table 3 and are calculated through a confusion matrix, comparing the outcome (i.e. the crop selected) of the crop model in each of the scenarios against the outcome of the decisions made using the perfect information scenario. The decisions made under perfect information are either planting maize (LCM for T1 farmers or SCM for T2 farmers), if there is sufficient water to irrigate during the season, or selecting the preferred non-irrigated option in the case of insufficient water. The preferred non-irrigated option corresponds to LCB for RL, SCB for RM farmers, and leaving the land fallow for RH and T2 farmers. As summarised in Table 2, if the outcome in the tested scenario matches the outcome in the perfect information scenario, then we classify the result as a true-positive if the farmers opt to plant maize, as this is the preferred option, or a true-negative if they opt for the preferred non-irrigated option. Otherwise, if the outcome in

Table 2
Possible outcomes of the comparison between the crop selected using the perfect information (PI) scenario and the crop selected for each of the tested information scenarios. Note that the option to leave the land fallow is also considered as a (non-irrigated) crop option in scoring.

Option selected in PI scenario	Option selected in test scenario	Result
Preferred irrigated crop	Same option	True-positive (tp)
Preferred non-irrigated crop	Same option	True-negative (tn)
Preferred irrigated crop	Alternative option	False-negative (fn)
Preferred non-irrigated crop	Alternative option	False-positive (fp)

Table 3
Definition and formula for the scores selected to evaluate the outcomes of the decision model.

Score	Formula*
Accuracy: fraction of the years in which the crop planted using imperfect information corresponded to the crop planted using perfect information.	$\frac{tp+tn}{n}$
Precision: fraction of the years in which the preferred crop was planted when using imperfect information that corresponded to the preferred crop being planted using perfect information. Same as 1-*false alarm rate.*	$\frac{tp}{tp+fp}$
Recall: fraction of the years in which the preferred crop was planted when using perfect information that corresponded to the preferred crop being planted using imperfect information. Also referred to as the *hit rate*.	$\frac{tp}{tp+fn}$
F1-score: harmonic mean of precision and recall, indicating balance between these two. F-score is zero when either precision or recall are zero, and one when both underlying scores are one (perfect prediction).	$\frac{2tp}{2tp+fn+fp}$

* *tp*: true positive; *tn*: true negative; *fp*: false positive; *fn*: true negative; *n*: number of years.

the perfect information scenario is maize and in the selected scenario it is not, then we classify the result as a false-negative, while if the outcome in the perfect information scenario is the preferred non-irrigated option and in the other scenario it is something else, then the result is classified as a false-positive.

The scores above do not consider the application of curtailments, but only evaluate the decision made as a function of the information scenario used. If curtailments are applied, then these may reduce the yield and consequent profits due to the crop options selected. We determine the relative economic value (Zhu et al., 2002) of the decisions made as the total benefit obtained from the crops with decision based on each of the scenarios (F#) for forecasting water availability to the end of season, compared to the benefit obtained using the current (HE) forecast applying a skill score function (Stanksi et al., 1989):

$$\mathrm{RV} = \frac{Benefit_F - benefit_{HE}}{Benefit_P - benefit_{HE}} \quad (1)$$

The relative economic value (RV) ranges between $-\infty$ and 1. $\mathrm{RV}=1$ corresponds to perfect information. $\mathrm{RV}=0$ means that the information does not contribute to improving the decisions made over the reference (HE), while a negative RV implies that it is of more value to base decisions on the reference (HE).

We establish the economic benefit of decisions made using a selling price of 200 euro/1000 kg for barley and 225 euro/1000 kg for maize (Fig. S9). The costs of planting are 400 euro/ha for barley and 1400 euro/ha for maize. Both of these parameters are kept constant for simplicity but, their impact is assessed through a sensitivity test. Note that while the selling price for barley and maize are comparable, the yield per hectare is higher for maize, thus explaining the preference for that crop. Crop yields vary with the actual weather conditions, and the ranges obtained in the crop model for each of the crops are 16,77–18,64 kg/ha for LCM, 14,21–15,97 kg/ha for SCM, 2.47–5.68 kg/ha for LCB and 1.45–2.49 kg/ha for SCB (Table S3). This ranges are considered representative for the region (Gobierno de Aragon, 2021, 2024).

Results

Seasonal forecast of water availability to end of season

The model was run for each information scenario for the period 01/10/1984 to 30/09/2016 with the farmer proportions indicated in Table 1. Fig. 3 illustrates the water balance to the end of season at each decision month (Fig. 2). Light blue bars indicate the expected accumulated inflow to the end of the season as derived from historic data (HE), while black dots and whiskers show the ensemble median (FM) and the 10 and 90 percentiles (F10 and F90) of expected water availability based on the streamflow forecast. Dashed lines indicate the expected demand (D1 for the November, February and April decisions, and D2 for the May decisions). If the expected accumulated inflow at the end of the season (30th September, labelled O in Fig. 3) is greater than the expected demand, water availability is considered sufficient for an irrigated maize crop (i.e. the option marked in blue in Fig. 2 is selected). If the accumulated inflow to the end of season is less than expected demand, availability is considered poor as curtailments may then be necessary, and the options commensurate with poor availability are selected (marked in red in Fig. 2).

The observed accumulated inflow at each step is shown by the dark blue bars for comparison. This shows that the skill of the predicted availability is low in November, with accumulated inflow to the end of season derived from the seasonal streamflow forecast (SF, black dot and whiskers in Fig. 3) showing little improvement to predictions based on historic extrapolation (HE, light blue column in Fig. 3) when compared to observed availability (OBS, dark blue column in October in Fig. 3). Selected years do, however, show the added value of including the indication of uncertainty (e.g. 1988, 2004), though in the more extreme drought years (e.g. 2005) the final availability is well below this range. Predicted water availability for both methods improves markedly by February, with both SF and HE providing a better estimate for the observed accumulated inflow at the end of the season.

Comparison of decisions made under the different information scenarios

Fig. 4 shows the expected water balance to the end of season at each decision point, depending on the information used. Red squares indicate a negative water balance (availability < demand) and blue squares a positive water balance. These balances are used to determine the decision path followed (corresponding to red and blue circles in Fig. 2) and consequently the crops planted by each farmer type. The figure also shows whether water curtailments are applied by the operator because of available water being deemed insufficient to meet demand. This is indicated by a cross or a circle for curtailments applied to LCM or SCM respectively. The size of the symbol represents the proportion of the planted crop that cannot be irrigated. For decisions made using the ensemble streamflow forecast, the ensemble mean (FM) is explored as well as five non-exceedance deciles (10 %, 30 %, 50 %, 70 %, 90 %, labelled F10 to F90). A non-exceedance of 10 % (90 %) represents a conservative (confident) expectation of water availability.

As expected, the streamflow forecast based on perfect rainfall information (Fp) produces a decision pattern that resembles that of the perfect streamflow information (P) most, as the uncertainty derives only from errors of the streamflow model.

Curtailments are applied mostly when the higher deciles of the forecast are used (F70, F90), which is also expected as these are overconfident in predicting the availability of water, particularly for dry years (1989, 1991, 1995, 2002, 2011). Crop choices commensurate to good water availability are then too often made, leading to expected shortfalls. Interestingly, for the more extreme drought years (1990, 2005, 2006, 2015, 2016) few curtailments are applied for all scenarios (except for the most overconfident F90 forecast). This is due to the expected availability being low from the start in these years, with farmers then taking the non-irrigated options related to poor water availability, resulting in low demand. 2011 is the year in which curtailments are applied most as all scenarios except perfect information fail to predict the exceptionally dry summer, with the start to the hydrological year looking normal (Fig. 3). Curtailments for the HE scenario tend to happen when there is a wet start to the hydrological year that ends to be average (1994) or very dry (1995, 2011).

The final economic benefit obtained for the harvested crops each year depending on the information used and the type of year (wet, normal or dry) is shown in Fig. 5. For most years, the decision made

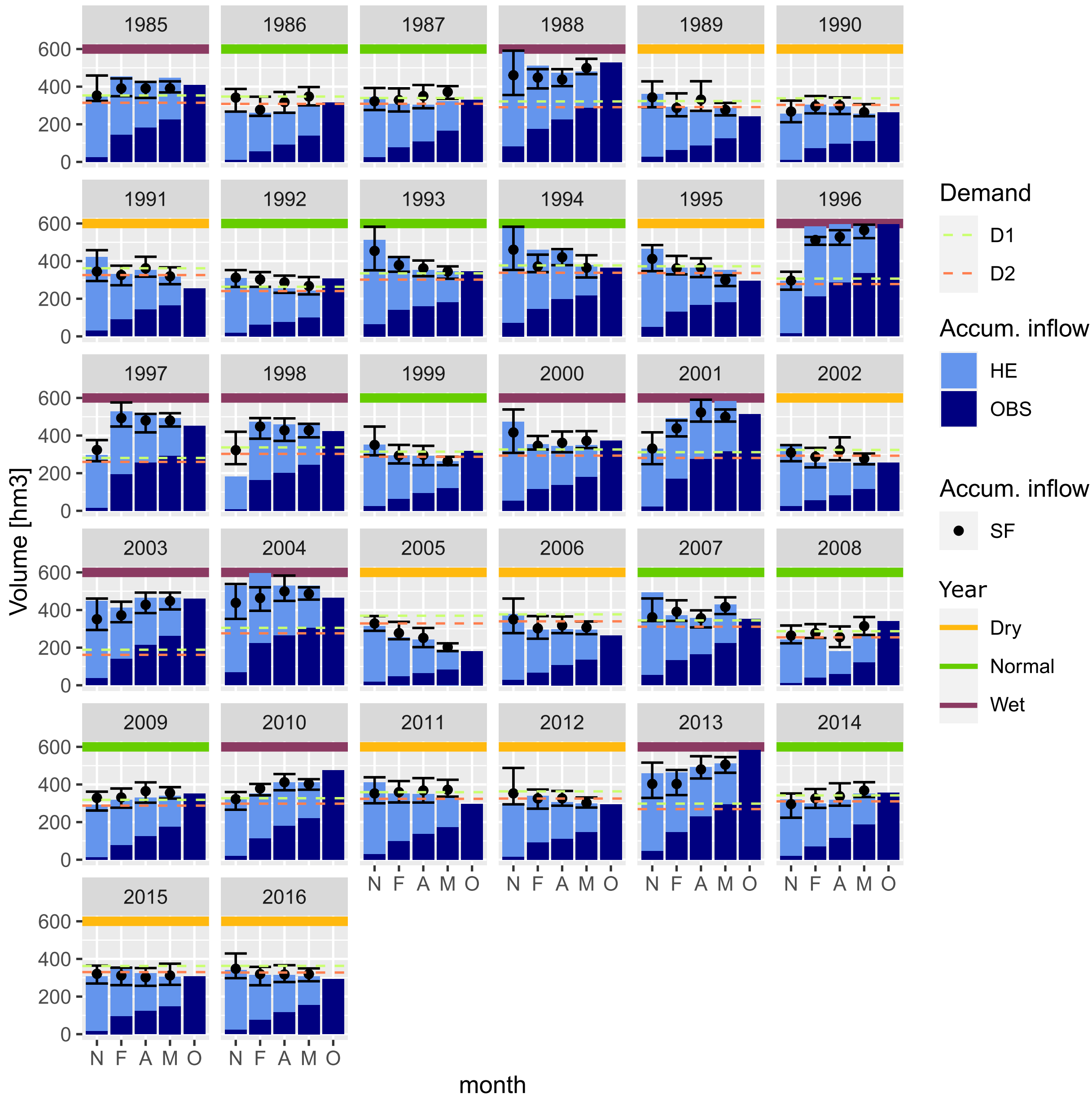

Fig. 3. Accumulated inflow to the end of season estimated at each of the decision points in November (N), February (F), April (A), May (M) and observed at the end of the season on 30th September (O). Light blue bars indicate the expected accumulated inflow to the end of the season as derived from historic data (HE), while dark blue bars show the observed accumulated inflow at each step (OBS). The black dots and whiskers show the ensemble median and the 10 and 90 percentiles (F10 and F90) of expected water availability based on the streamflow forecast (SF). The dashed green horizontal line corresponds to D1 demand; the dashed red horizontal line corresponds to D2 demand. Years are marked as wet (purple), normal (green) or dry (yellow) based on the terciles of accumulated observed inflow to the end of season.

using the forecast mean (FM) tends to provide a similar benefit than when using the current (HE) scenario. When they differ, the benefits of using the forecast mean are generally higher in years with a positive balance (1986, 1992), but so are the losses in the years with a negative balance (1989, 2011). Informing the decisions using the higher deciles (F70, F90) sometimes results in significant curtailments (1989, 1991, 1995, 2002, 2011, 2015, 2016). Losses in 2011 are particularly high as curtailments affect both types of crops (LCM and SCM). Curtailments of smaller proportion only result in a small loss of value (1986, 1987, 1994).

For wet years, the information used does not make a difference to the benefits achieved. These are years in which there is plenty of water (e.g. 1988, 2003, 2004, 2013). Similarly, differences are small when water is abundant after a relatively dry start of the season (low accumulated inflow values in November, e.g. 1996, 1997, 1998, 2001, 2010), and for clearly dry years (marked in yellow in Fig. 5), although some of the scenarios can result in significative losses (e.g. 1991, 1995).

Influence of farmer type on forecast value

Fig. 6 shows the verification scores based on the outcomes of the decision model for all farmer types and information scenarios considered. For all scores, the outcomes of the decision model established with perfect knowledge is used as the reference. For the risk averse farmers (RL), recall is low for the conservative scenarios (F10 to F30). This is due to them readily making the choice for the safer LCB crop, despite water availability in many years being sufficient for the more desirable LCM crop. Precision is high, however, as when the LCM crop is selected, it is indeed a good choice. For the more confident scenarios, recall increases while precision drops, as the more desirable crop is selected more often though it is not always the correct choice. As a consequence, the F1-score, the geometric mean of precision and recall, is low for all scenarios for the RL farmers (with the exception of the forecast based on perfect precipitation as this is close to perfect information given the relatively small contribution of the error in the hydrological model). The overall accuracy, which considers the correspondence of all outcomes for the selected information scenario to those found using perfect information, is also low. For the less risk averse RM and RH farmers, a broadly similar pattern is found, though all scores are marginally better, with improved F1-score and accuracy. This is likely due to these farmers taking decisions later in the season, when forecast skill improves. The scores for T2 farmers, who take the decision on the second crop only in May, are almost perfect, with only the most conservative or most confident scenarios showing lower performance. Though the scores of the different farmer types may be modulated due to the different number of possible outcomes, the results suggest that the T2 farmers can rely most on the information provided being accurate for the decision they make, while this is least so for the RL farmers. Moreover, the latter are more sensitive to forecast uncertainty, as selection of the crop to be planted based on a different non-exceedance probability (F#) influences the outcomes more than it does for the T2 farmers.

Fig. 7 shows the total benefit each type of farmer obtains over the period analysed (1985–2016). To calculate the benefit, we consider that all single crop farmers (T1, Fig. 2) have the same benefit when making decisions based on scenarios P irrespective of their level of risk aversion, as they would all select the same crops if they knew from the start of the season how water availability would evolve. They would then either plant LCM later in the season, if there is sufficient water, or LCB early in the season if there is not. For all other scenarios, benefits are calculated for each farmer type depending on the crops chosen.

Risk averse farmers (R1) have the highest overall benefit as they rarely end up leaving the land fallow (this only happens in 1992 for F10 and F30, 1993 for F30, 2007 for F50 and Fp and 2008 for F70 and Fp). Together with R2 farmers, they then get the least curtailments, and

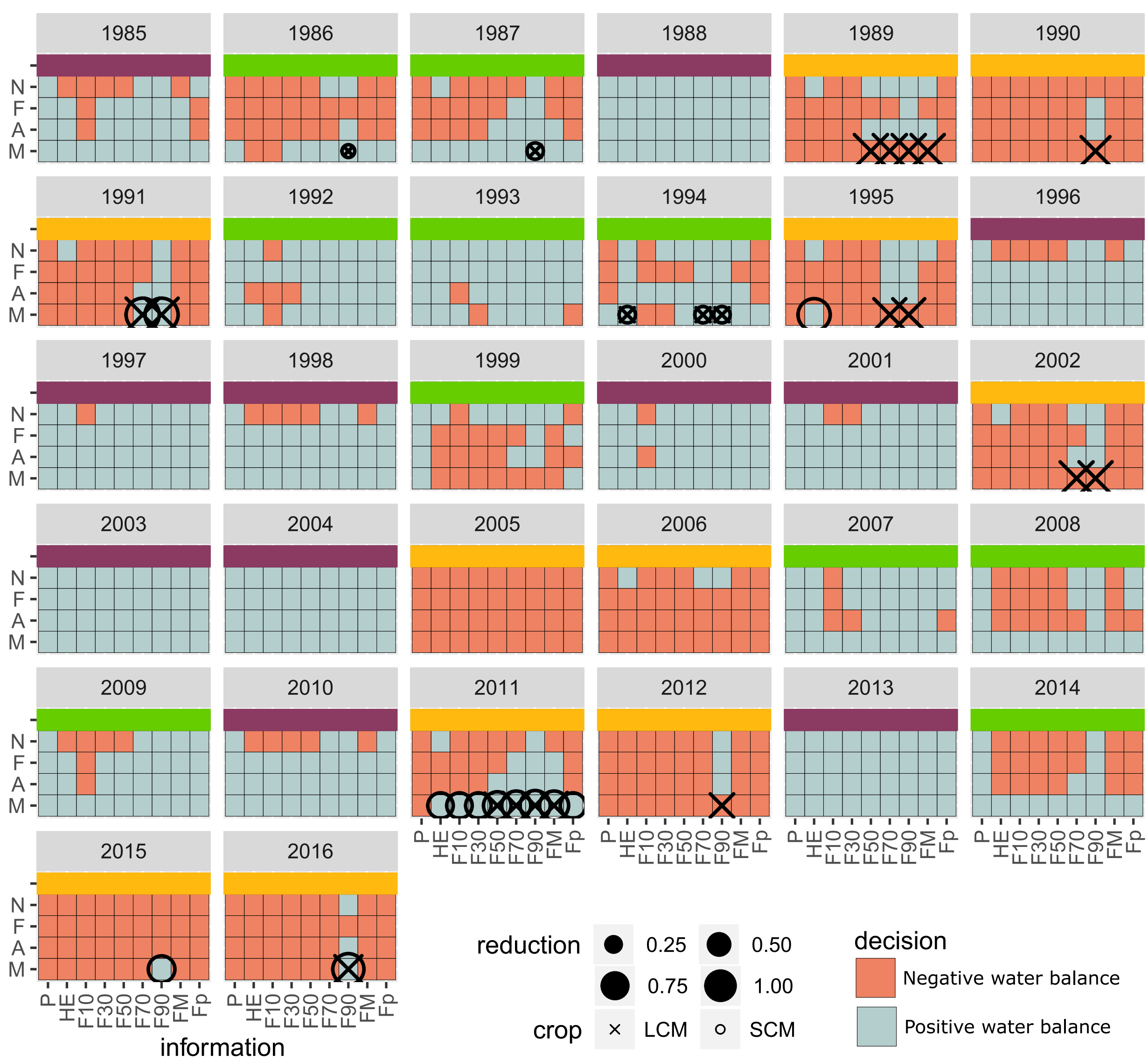

Fig. 4. Decisions taken at each decision month based on the expected water balance to end of season. Blue (red) squares indicate positive (negative) water balance at the end of season if the preferred option is selected for each decision point (vertical axis) and information source (horizontal axis; information scenarios defined in Section 2.3). Circles in the lower row indicate the need for curtailments for SCM (black circle) and LCM (crosses). The size represents the proportion of the crop that cannot be irrigated. Years are marked as wet (purple), normal (green) or dry (yellow) based on the terciles of accumulated observed inflow to the end of season.

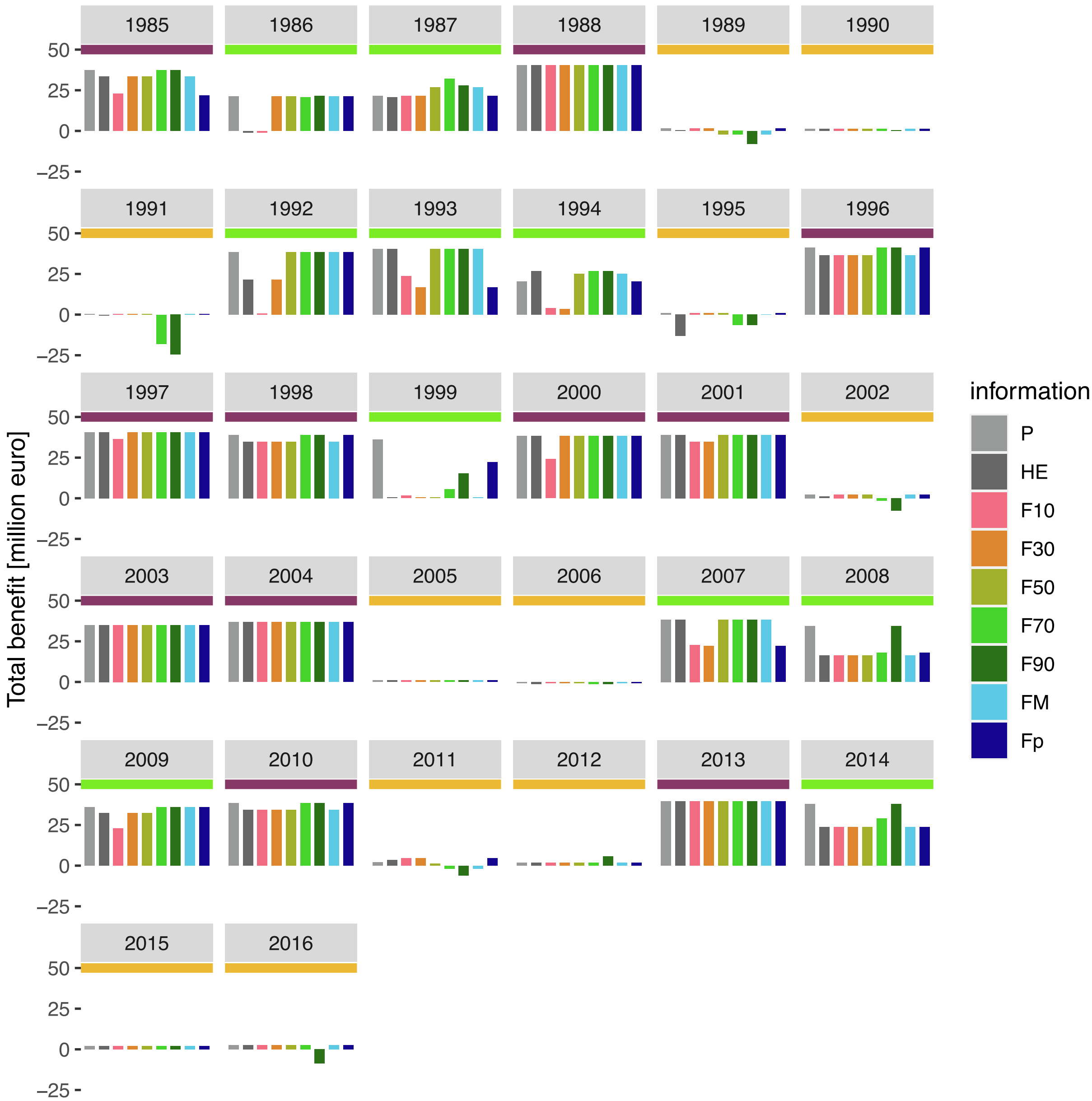

Fig. 5. Benefit obtained each year from the variable crops depending on the information used to decide what to plant. Years are marked as wet (purple), normal (green) or dry (yellow) based on the terciles of accumulated observed inflow to the end of season.

especially because they have the more productive alternative option (LCB) for years with limited water availability. Despite the potential higher gain obtained from planting a double crop, T2 farmers have a lower overall benefit per hectare than R1 farmers. This is due to the losses of leaving the land fallow in some years not being compensated by the higher gain from SCM in the good years in the long run. Single-crop farmers obtain a higher benefit from overconfident scenarios (F70, F90), as they then more often tend to choose the more productive LCM, though

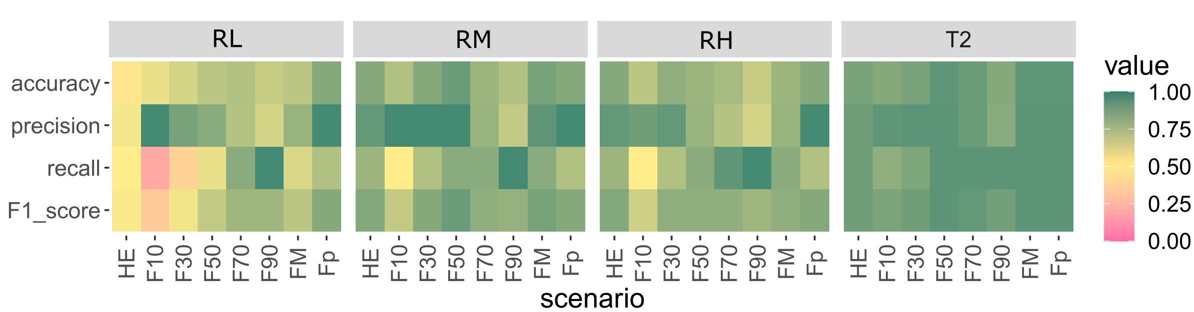

Fig. 6. Scores for the outcomes of the decision model as a function of information scenario used, separated per farmer type.

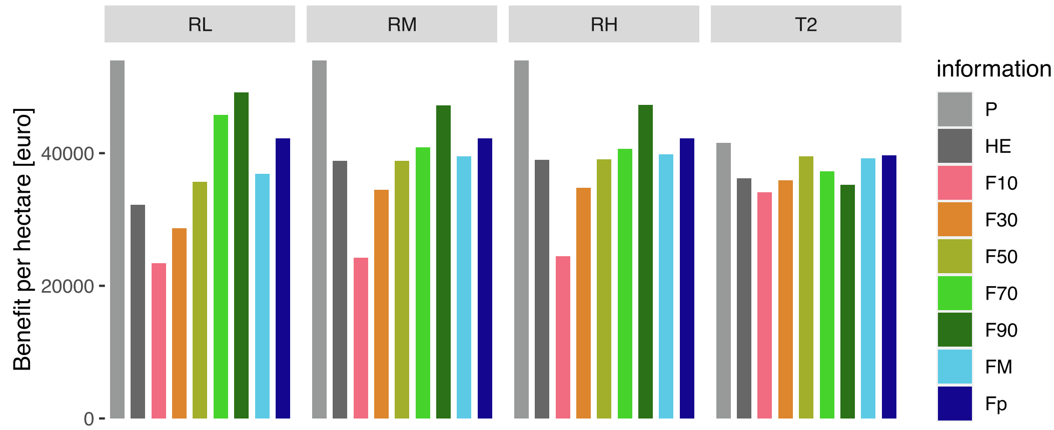

Fig. 7. Benefit per hectare over the whole period by farmer types, with RL the most risk averse single crop farmers, RH the least risk averse single crop farmers and T2 the double crop farmers.

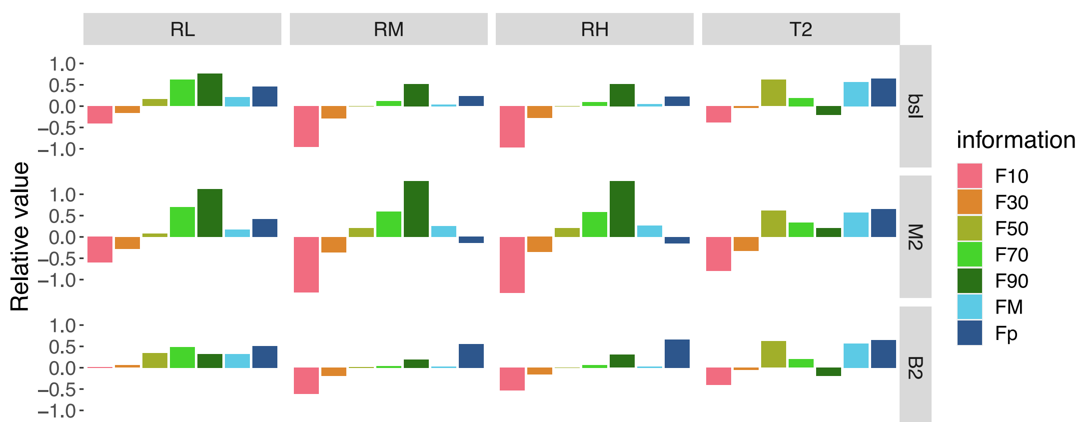

Fig. 8. Relative value (RV) of information over the period of study for each farmer type and information scenario. Upper row shows RV using baseline (bsl) profits for each crop. Middle row shows RV when profits for Maize are doubled (M2), while lower row shows RV when profits for Barley are doubled (B2).

selection of a such an overconfident scenario may contradict risk tolerance levels, particularly of RL farmers. Conversely, for the T2 farmers benefits for the ensemble mean (FM) and F50 scenarios are the highest, balancing between the more conservative F10 scenario where the land is left fallow in more years than necessary, and the F70 and F90 scenarios where SCM is planted in dry years (e.g. 1991, 2002, 2011, 2015, 2016), thus increasing demand and requiring curtailments to be applied, leading to losses.

In Fig. 8, we explore the relative value of each information scenario for the different types of farmers. We also assess the sensitivity of the value of information to the ratio of the profits obtained from each of the two crops (Maize and Barley). The relative value of information for each type of farmer (upper row in Fig. 8) is calculated by scaling the values between the benefit obtained when using perfect information (P) and the benefits obtained for the reference hydrological extrapolation (HE) scenarios, which is current practice. This shows if there is value in adopting the seasonal forecast to inform crop decisions over current practice. The results using baseline profits for each of the crops show that the forecast based on perfect rainfall information (Fp), which has the closest decision pattern to that of the scenario using perfect information in Fig. 4, performs relatively well for all types of farmers. For other information scenarios, there is a difference between single-crop farmers, who favour more confident estimate of water availability (high relative value obtained with F70-F90 scenarios). The relative value of these more confident scenarios is greater for the RL farmers, as these would allow them to more often choose for the maize crop, though RL farmers may be less inclined to follow these scenarios, given their lower risk tolerance. The risk of curtailments is higher for T2 farmers as they represent a larger total area in the irrigation district and therefore require more water, given that in the model they all follow the same behaviour. This results in a higher risk of losses, which makes being overconfident a less profitable option than for the single-crop farmers.

However, the benefits obtained by each type of farmer and therefore the relative values of the different information scenarios in our results depend on the ratio of profits obtained from each of the two crops considered, though the pattern of performance of the different information scenarios for each type of farmer remains relatively unchanged. When the ratio is altered by for example doubling the profits obtained for maize (M2, middle row in Fig. 8) or doubling the profits of barley (B2, lower row) the picture changes for some scenarios. With a higher benefit for maize, more confident scenarios improve in relative value for all types of farmers, as this leads to the planting of maize more frequently, and the increased profit of maize weighs up against the lower profits of barley, despite more frequent losses due to curtailments when maize is planted in years with poor water availability. The sensitivity analysis does show that as the ratio of profits is skewed more towards the maize crop (M2), the simplified decision model is stretched beyond its initial assumptions. The decision model does consider maize as the preferred option, but does allow for the choice of barley when water availability is poor. As the profits for maize increase, always planting maize would lead to higher benefits despite curtailments during years with poor water availability. This results to relative values greater than 1 or less than -1 (M2, middle row Fig. 8), which are not realistic. The limits of the model would similarly be stretched if profits for barley would be greater than those of maize.

Changes in the profit ratio of the two crops have less impact on the relative value of information for T2 farmers as they always plant SCB, and the only decision modelled is whether they plant SCM afterwards. With a higher value for maize, overconfident scenarios again do improve in relative value as the opportunity cost of leaving the land fallow is compensated by the higher gain obtained from maize in good years, compared to the lower losses incurred due to curtailments imposed in the not so good years.

Discussion

Is the forecast information good enough to be useful?

Quality, or skill, of a forecast in predicting the variables of interest to decision makers is an important aspect to credibility (Bojovic et al., 2022; Peñuela et al., 2020), and pre-requisite to usefulness (see e.g. Bennett et al., 2016; Shukla et al., 2020; Winsemius et al., 2014; Anghileri et al., 2016). Our assessment of the skill of the bias corrected precipitation seasonal forecasts over the Barasona catchment, shows that though correlation of the ensemble mean is positive for all forecast lead times (see Supplementary material, Fig. S5), skill reduces substantially beyond the one-month lead-time. CRPSS also shows positive skill compared to the climatological reference for one-month lead time but decreases to zero or marginally negative skill at longer lead times. This reflects the poor seasonal predictability of precipitation in this region of Europe (Crespi et al., 2021). Although a more elaborate bias correction method may result in a slightly increased skill, this is expected to be minor given the positive correlation of the ensemble mean to the observed precipitation at all lead times (Zhao et al., 2017). For streamflow, forecast skill is better than for precipitation (Fig. S6), with a correlation of $>$ 0.6 of the ensemble-mean to observed flows. This is attributed primarily to the skill in predicting the longer memory baseflow component, with the skill of the fast response (quickflow) component poor. We also assess skill of the accumulated streamflow forecasts to end of season (Fig. S7), as this is the variable that is used in the decision. This indicates good correlation for most months, except in November and in the spring snowmelt season, where the simple regression-based quickflow model performs worst due to the absence of snow accumulation and melt. The low CRPSS values, with the forecast being reliable for most months (except November), tested using the Probability Integral Transform (Zhao et al., 2017) (Fig. S8) suggests that the ensemble spread is too wide (underconfident). The strong correlation of the streamflow forecast model forced with perfect precipitation indicates that loss of skill with lead time can primarily be attributed to the uncertainty in the forecast precipitation, as well as the poor performance of the quickflow model. The skill of the streamflow forecasts we find compare to those found by Pechlivanidis et al. (2020) in the Northeastern part of the Iberian Peninsula using a conceptual hydrological model, which includes snow accumulation and melt. Though a more complex model could improve skill here, the good skill of the baseflow forecast, which accounts for 73 % of the annual flow suggests this may only provide marginal improvement to the skill of the forecast of the volumetric decision variable.

In what context is the forecast information useful?

Although there is (limited) skill in the streamflow forecasts, whether the information provided is useful depends on the context in which the forecast is used as well as on the users themselves (White et al., 2022). To be of value, information not only needs to be credible through being scientifically sound, but also salient to the decision in which it is intended to be used (Bremer et al., 2022; Cash et al., 2003) so that users can act on it (Hansen, 2002; Macauley, 2006). The decision model we develop here for the different types of farmers of annual crops in the selected irrigation district in the Ebro basin, maps out the decision points they make. This is, however, clearly a simplification of the true diversity of farmers in the region and their behavioural choices. Indeed, the model used here is simplified compared to the more elaborate model used to evaluate farmer decisions in the same irrigation district in Linés et al. (2018). The model could be further expanded to include the permanent crop farmers, to represent whether the curtailments to the annual crops are indeed achieving their aim of avoiding the losses in those permanent crops. Despite its simplicity, the decision points identified through the cropping season are the points when farmers may act on seasonal forecasts of water availability through their crop choice. Similar approaches to mapping out decision points of corn farmers in the US (Haigh et al., 2015) and Argentina (Bert et al., 2006), or livelihood calendars for maize farmers in Malawi (Calvel et al., 2020) have been used to support a qualitative assessment of the usefulness of climate information. Here we extend these through a quantitative modelling of the interconnected decisions of irrigated farmers and reservoir operators. This shows that information is more relevant at the beginning of the season when water availability is more uncertain, though this is primarily so for the T1 type farmers who need to take a decision early in the cropping season, in particular the more risk averse farmers (RL). However, higher uncertainty early in the season results in a lower overall accuracy of the forecasts to the RL farmers, as well as lower precision and recall when compared to decision made using perfect forecast information. For farmers that have the option of two crops (T2), the uncertain early season information is less relevant than the forecast information in May, when most of the seasonal accumulated inflows are already in the reservoir, though the streamflow forecast in May is also uncertain due to the poor snowmelt prediction of the model used. The forecast then supports T2 farmers' choice between cropping an irrigated crop or leaving the land fallow in dry years, which is the action taken when considering the more conservative inflow scenario.

Whether information provided is salient to the decisions farmers make also depends on water availability. In wet years, when there is plenty of water, the seasonal climate information does not make a difference, as all information scenarios indicate sufficient water to support the crops. Similar results by Kaune et al. (2020), show that seasonal forecast information is most relevant when it provides resolution to the decision being made. This is also found by (Golembesky et al., 2009), who conclude that when the reservoir capacity is much larger than the maximum potential seasonal demand, then information on water availability is of lesser value. Interestingly our results also show that information is less useful in the more extreme dry years. This insight is gained through the modelling of the interlinked decisions of the farmers in their choice of crop, and of the reservoir operators in applying curtailments when demand due to the farmer decisions exceeds available water. Our results suggest that in years with more extreme droughts (e.g. 2005, 2006, 2015, 2016), water scarcity to irrigated agriculture may be less an issue if most farmers choose to leave the land fallow or choose the rain-fed crop to avoid the losses as assumed in the model, thus reducing demand for irrigated water.

To whom is the information useful?

The decision analysed shows that information provided by the seasonal forecast is not equally useful to all types of farmers at each of the decision points. The four types of farmers we consider here, have different options available to them. The options available, and as described in the previous section, the timing associated with each of those options, play a key role both in the benefit they obtain, and the usefulness of the information provided by the forecast. Farmers who have the option to make their crop choices later in the season can rely more on information being more accurate. This is the case for the T2 farmers who only use the forecast in May to select whether to plant a second crop. The decisions made at this stage in the season are also less sensitive to the uncertainty in the forecast, though this also means that the seasonal forecast is less salient than to farmers who are taking the highest risk, such as RM and RH as for them selecting the wrong option has a higher cost. The results therefore imply that the farmers with a higher technical capacity (T2), whose available options are less affected by the uncertainty of the forecast, benefit from the forecast being more accurate when they need it. This raises questions on the equity of climate services provision (Greene and Ferguson, 2023), as the more advantaged farmers stand to benefit most. The more risk averse RL farmers are also more sensitive to uncertainty in the forecast and so may be less inclined to using the information provided to their benefit.

The different types of farmers favour different information scenarios depending on their options and their attitude to risk. When the benefits are considered over a multiyear period, T1 farmers benefit from overconfident scenarios, as the higher benefit obtained in years with good water availability compensates the losses incurred by curtailments in other years. T2 farmers, instead, benefit from more balanced scenarios. Being a larger group, T2 farmers have a higher risk of curtailments when they all plant an irrigated crop and therefore, they do not benefit as much from the overconfident scenarios. These preferences depend, however, on the cost-benefit ratio between the different options and changes when these ratios change. The decision model applied here uses the assumptions that maize has better value than barley and that the value for both crops over the whole period is constant. In reality, prices change every year, even varying from week to week, and may also be subject to (European) subsidies (Gil et al., 2013; Linés et al., 2018). This adds uncertainty and complexity to the actual decision of farmers. The simple decision used here also includes other assumptions, with a limited and fixed number of options for each type of farmer, the same cost of planting for both types of farmers, a constant proportion of farmers in each group, and all farmers of a given type or risk aversion level making the same decisions. The latter has some impact on the results as when the water availability is not enough for all of them to plant an irrigated crop, they will all choose the alternative option, despite water availability being sufficient for some to plant the irrigated crop. Allowing for more heterogenous decisions per farmer type may then result in a higher value for the group. We also assume that all farmers have the same access to information and capacity to understand it, which are also factors that influence the use of information and may introduce inequalities (Lemos et al., 2010). Additionally, we assume that attitude to risk is constant, which in reality may change in time and experience with forecasts.

Developing a full agent based model, with agents formed by groups of farmers and their behaviour defined by decision rules (Helbing, 2012; Huber et al., 2018) would allow for more individual and heterogenous behaviour, and agent-based models have previously been applied to understand drought adaptation behaviours (Schrieks et al., 2021; Wens et al., 2019), seasonal forecast uptake by farmers (Alexander and Block, 2022) and farmer's crop choices (Yuan et al., 2021). Although the model we use here has some characteristics of an agent-based model, more simple models or game scenarios (see also Giuliani et al. (2020) and Crochemore et al. (2021)) are helpful to isolate the impacts on the usefulness of the information provided to the four types of user considered, and contribute to increase the understanding of different decision maker's needs. This can inform the design of climate services to meet those needs, thus improving usability (Lemos, 2015).

Conclusions

This paper aims to bridge the gap between technical evaluations of the usefulness of seasonal forecasts, and human-centred approaches that evaluate how useful forecasts are to actual decisions users make. We assess the usefulness of seasonal forecasting in supporting decisions in irrigated agriculture in the Ebro Basin in Spain through a user-based model of farmer decisions on what and when to plant, which is conditioned by water availability and the interrelated decision of water managers on when to apply curtailments should shortages occur during droughts. We consider two types of farmers with different available options depending on their technical capabilities, as well as differing levels of risk aversity. This allows the usefulness of information to be illustrated through three key angles:

- Credibility: We show that seasonal forecasts of water availability to the end of the season have positive skill, even using a simple streamflow prediction model. Though seasonal precipitation forecasts have only limited skill, the memory of the baseflow response contributes to improved skill of streamflow predictions. Accuracy of the information on which decisions are based is important to this being considered credible by users.
- Salience: How useful the seasonal forecast information is, depends on how relevant it is to the decisions informed. The different types of farmers considered take key decisions at different times in the season, depending on their options. Forecasts are most relevant to the farmers that are more risk averse and have fewer technical capacities, as these need to take decisions early in the season, when water availability to the end of season is most uncertain. The relevance of the seasonal forecasts also varies between years and is low for years that are clearly wet from the outset. Interestingly, we find that forecasts are also less relevant in years that are clearly dry from the start, as then demand for irrigation is lower due to farmers opting choosing a rainfed option. Seasonal forecasts are most relevant in years that are changeable, such as those starting wet and then following a drier path, or vice versa.
- Equity: The results also show that how useful the forecast is to a user depends on their individual behaviour. This means forecast information does not serve all the farmers equally. Farmers with higher technical capacity have more flexibility to design their crop pattern in a way that decisions are made later in the season when there is less uncertainty on seasonal water availability and information from the forecast. Although the added value of the forecast is not high to them, it is useful when they do as accuracy is then high. More risk averse farmers with less options available stand to obtain a higher added value from using the forecast. However, as they need to make key decisions earlier in the season due to their limited technical capacities, they also then make use of forecast information that is less accurate.

Overall, we show that seasonal streamflow forecasts are useful and there is benefit over the currently used approach in using seasonal forecast information to support the decisions farmers in the Ebro basin make. However, how useful forecast information is, depends very much on the context in which decisions are made, by whom, and the options they have available to them. This also means that the usefulness of forecast information is not equal among different users, highlighting the importance of not only considering usefulness of information provided through a service such as a seasonal forecast from the perspective of the information itself, but also from the perspectives of the various users, and the decisions they make.

CRediT authorship contribution statement

Clara Linés: Writing – original draft, Software, Formal analysis, Visualization, Methodology, Conceptualization. **Micha Werner:** Writing – review & editing, Methodology, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cliser.2025.100595.

Data availability

Seasonal forecast data from ECMWF SEAS5 is available from the ECMWF MARS archive (https://www.ecmwf.int/). Seasonal forecast data (raw and bias corrected) sampled to the catchment available at https://github.com/lnscl/P3/tree/main/input_files/seasonal%20forecast.

SAFRAN data is published under DOI 10.14768/MISTRALS-HYMEX.1388. See https://www.obsebre.es/en/en-safran for additional information.

Streamflow data from the Spanish national gauging station network (ROEA) is openly available at https://sig.mapama.gob.es/redes-seguimiento/index.html?herramienta=Aforos. See https://www.saihduero.es/. Metadata: https://www.mapama.gob.es/ide/metadatos/srv/spa/catalog.search#/metadata/d4ec156a-f733-4ab2-8a2c-a84f07247ff1.

AquacropOS input files (used for barley and maize simulation) containing the crop model parameters available at https://github.com/lnscl/P3/tree/main/input_files/crop_model_files. For Cropwat the default parameter files for alfalfa and peach were used.

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