Climate Services 32 (2023) 100418

Contents lists available at ScienceDirect

Climate Services

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

Managing Spring rain risks in vineyards: A user-centred approach to identify climate decision triggers in seasonal forecasts

Ilaria Vigo [a,*], Raul Marcos [a,c], Marta Terrado [a], Nube González-Reviriego [a], Albert Soret [a], Marta Teixeira [b], Natacha Fontes [b], Antonio Graça [b]

[a] Barcelona Supercomputing Center (BSC-CNS), Plaça d'Eusebi Güell 1-3, 08034 Barcelona, Spain
[b] Sogrape Vinhos SA, Rua 5 de Outubro 4527, 4430-852 Avintes, Portugal
[c] Department of Applied Physics, University of Barcelona, Av. Diagonal 647, 08028 Barcelona, Spain

A B S T R A C T

In the context of climate risk mitigation strategies seasonal forecasts have been often proposed as a potential climate risk management tool for the wine industry. However, in spite of the recent research advancements, the adoption of climate predictions in strategic decision-making remains complex. This paper aims to support decision-making in the wine sector by providing a methodology to establish the probability thresholds that can trigger a decision based on seasonal forecasts, in an illustrative setting where precipitation occurring in spring could heavily affect the effectiveness of plant protection and canopy management. The results show the probability thresholds obtained for the user involved and the specific decision under three different predicted scenarios. The advantages of this co-production methodology consist in the trust created by the engagement with the user and the high level of tailoring of the analysis performed, posing the basis for user risk profile analysis. The drawbacks lay in the use of a simplified theoretical framework and the need of engaging new users for replication.

Introduction

Practical implications

The current prospects of climate change, increasing climate variability and rising extreme events' frequency and intensity are posing a pressing need for adaptation and mitigation strategies in almost every sector of the economy. Climate predictions are one of the available tools that can support climate-dependent activities facing climate change. These predictions usually come in the form of probabilistic forecasts that estimate the evolution of climate in the upcoming seasons and years.

However, despite the recent research advancements, the application of climate predictions in strategic decision-making remains complex. The barriers are entailed both in the nature of the climate information and in the way it is applied. Climate services aim at improving the usability of this information and this study contributes to inform climate services' design to improve potential applications. In particular, we address one common barrier detected while engaging with potential users: "what is the minimum probability that makes the associated forecasted occurrence worth considering in my decision?". When looking at seasonal forecasts, this is one typical question that refrains from integrating the climate information in a real-life decision. Although the answer to this query is always user- and decision- specific, the process to obtain it is rather general. This paper illustrates this path by trying to establish which is the optimal application of probabilistic seasonal forecasts considering their potential impacts in a wine-maker decision-making workflow.

Although the approach built in this study can be extrapolated to different decisions and users from different fields, this analysis is applied to the viticultural sector which stands out due to its strong dependence on stable climate conditions. In this framework, the vineyard manager has pointed out a set of decisions that suffer from climate uncertainty and Spring rain has been identified as an indicator of primary importance to assess. The Spring Total Precipitation (SprR) is a bioclimatic indicator that has been defined according to the vineyard managers' need to adapt to the impacts of spring rain variability. More specifically, SprR is the total precipitation from 21st April to 21st June (for the Northern Hemisphere) which influences canopy management and plant protection strategies that benefit from being defined as early as January of the target year.

The close collaboration with the user continued in the entire process, allowing for co-design of the methodology for forecasts' assessment. We have economically characterised different decisions that could be adopted in each scenario, as well as the business as usual (BaU) to compare with. Finally, we have put forward a methodology to consider the minimum probability for having positive results when including

* Corresponding author.
E-mail address: ilaria.vigo@bsc.es (I. Vigo).

https://doi.org/10.1016/j.cliser.2023.100418
Received 30 May 2022; Received in revised form 19 June 2023; Accepted 19 September 2023
Available online 9 October 2023

costs, losses and benefits in each decision scenario.

These results inform the user about the minimum probability associated with predicted SprR (above normal, normal, or below normal) that should trigger earliest decisions. The advantages of this co-production methodology consist in the trust created by the engagement with the user and the high level of tailoring of the analysis performed, posing the basis for user risk profile analysis. The drawbacks lay in the use of a simplified theoretical framework and the need of engaging new users for replication. In summary, what stands out in this study is the contribution to the integration of seasonal forecasts in a real risk management workflow.

The current prospects of climate change, increasing climate variability and rising extreme events' frequency and intensity, are posing a pressing need for adaptation and mitigation strategies in almost every sector of the economy (O'Neill et al., 2022). Amidst all, the viticulture sphere stands out due to its strong dependence on stable climate conditions. In this sector climate change has been already identified to potentially impact grapevine cultivation areas, grape varieties, grapevine development and phenology, pests and diseases, grape and wine quality and yields (Cunha and Richter, 2016; Ramos et al., 2008; Fraga et al., 2014a). Climate predictions are one of the available tools that can enable grape growers and winemakers to face this challenge. These predictions usually come in the form of probabilistic forecasts that estimate the evolution of climate in the upcoming seasons and years (Terrado et al., 2018). In this context, seasonal predictions based on tercile categories have gained attention as a possible mitigation tool to face mid-range adverse events (Porras et al., 2021).

However, in spite of the recent research advancements in seasonal climate predictions targeted to the viticultural sector (Giannokopoulos et al., 2019, Santos et al., 2020, Droulia and Charalampopoulos, 2021), there is still little evidence of their adoption in current decision-making workflows. Various European-funded projects (e.g., H2020 Vineyards Integrated Smart Climate Application - VISCA, Turning climate-related information into added value for traditional Mediterranean Grape, Olive and Durum wheat food systems - MED-GOLD, and Vineyard Innovative Tool based on the Integration of Earth Observation Services and in-field Sensors - VitiGEOSS) have directed efforts to boost the uptake of such predictions by developing climate services tailored to viticulturists. In particular, the MED-GOLD project (https://www.med-gold.eu) targets the production of grapes, olives and durum wheat in the Mediterranean region and its adaptation to climate change and applies a co-production approach to the development of a climate service platform. The platform delivers readily available predictions of essential climate variables (e.g., temperature, precipitation) and sector-specific indicators (e.g., Spring Rain, Growing Degree Days) useful to inform the decisions of farmers.

In this context, the co-production of climate services is fundamental to identify the key users' challenges and create targeted forecasts and tailored products to transform climate predictions into actionable information. Precisely, the collaboration with users in climate services projects has revealed there is substantial interest in understanding how to best integrate climate information in viticulturist risk management practices. The major barriers to this adoption arise from the complexity entailed in the integration of the technical climate information into the strategic planning of each user. As a matter of fact, each user needs to overcome a *learning curve* to correctly interpret probabilistic climate information prior to reshaping any decision based on these predictions.

To undergo the learning process entails an investment of time and resources both from climate service providers and users where *trust* is a necessary condition (Hermansen et al., 2021). To facilitate this requirement, economic impact evaluations have been often used to provide simulations of the potential benefits generated using these services. These expected savings and/or gains, combined with the increasing risks posed by climate change, drive the interest in undergoing the process. Actually, climate services' evaluations are already performed in various sectors and for different forecast types (e.g., Portele et al., 2021; WMO, 2015; H2020 Subseasonal to Seasonal Climate Forecasting for Energy - S2S4E, Climate Forecast Enabled Knowledge Services - CLARA, and European Market for Climate Services - EU MACS, WMO, 2015). To this aim, some commonly applied methodologies are contingent valuation, revealed preferences, economic decision modelling, avoided costs, benefit transfer, and participatory methods (WMO, 2015; Suckall and Soares, 2020). For example, with respect to impact evaluations of climate predictions in the agri-food sector, Materia et al. (2020) use a cost–loss model approach to evaluate the impact of sub-seasonal forecasts on hazelnut agribusinesses for the prediction of Spring cold spells. Regarding the wine sector, an evaluation of seasonal forecasts has been already performed by Santos et al. (2020). This analysis suggests a positive impact for winemaking through the application of a logistic model of wine production in the Douro Valley of Portugal, based on monthly mean air temperatures and monthly total precipitation. These impact evaluation studies offer a picture of the potential benefit of climate services assuming that the climate predictions are integrated in the decision-making process and properly used. However, as we have seen, this is neither straightforward nor trivial.

Wilks (2001) was the first one that attempted to evaluate forecasts based on the cost loss ratio of decision makers, constructing a skill score based on economic value. However, his model does not allow for multiple decision options, which need to be considered in studies such as the one presented in this paper. In another approach, Portele et al. (2021) used the potential economic value as a direct way to achieve action recommendations based on forecast probabilities. Nevertheless, their methodology (applied to the hydro-management decision making) aims at minimising the interactions with the decision-maker and assumes no risk aversion. This makes their approach easily replicable but lacks flexibility for accommodating the multiplicity of users and needs.

In this work, we apply a user-centred methodology designed to ease forecasts' uptake while increasing the trust in the service provided. This is done by applying a transdisciplinary approach to knowledge co-production, involving climate scientists, social scientists, and users. The approach allows for knowledge exchange and helps in finding a common language, ultimately building trust (Terrado et al, in this issue). Thus, the involvement of decision-makers from a vertically integrated large wine company contextualised this study in a real-world decision workflow through the sharing of sectoral know-how ranging from farming vineyards to buying grapes from other farmers.

This paper aims to support decision-making in the wine sector by providing a methodology to establish the optimal probability thresholds that should trigger a decision based on seasonal forecasts in a setting where precipitation occurring in spring could heavily affect the outcome of plant protection and canopy management. To our best knowledge, this is the first time a user-centred methodology tries to optimise climate predictions' use in order to generate value in the wine sector. In particular, this paper aims at supporting the user in breaking one of the barriers to the uptake: **"what is the minimum probability that makes the associated forecasted occurrence worth considering in my decision?"**. This question has been consistently brought up when observing seasonal forecasts. It is important to note that this study does not intend to evaluate the climate services used nor the seasonal forecasts provided. Instead, it aims at offering an easy-to-use approach for determining the answer to the above question.

Material and methods

Demand driven co-production

The approach taken for this study is user-centred. At the basis of the methodology is the demand of the wine producer to understand how to use climate services to adapt to the variable climate. To provide a meaningful answer to this request we need to understand the wine producers' strategy and needs as well as to tailor the service for the specific decision under analysis. The methodology applied in this study builds on the user engagement started within the MED-GOLD project, which involved an exchange of knowledge among project scientists and stakeholders (Bojovic et al. 2021). This allowed a mutual understanding of the wine sector needs and the extent to which these needs could be addressed by project results. By engaging with several potential climate service users from the wine sector, we identified different solutions to better deliver actionable climate information (Marcos-Matamoros et al, 2020 & Soares et al. 2019).

Building on this knowledge, we have worked together with the leading wine producer in Portugal, SOGRAPE, to perform an in-depth analysis to co-explore the optimal application of seasonal forecasts to their decision-making. Fig. 1 summarises the co-production process which is also at the base of this study (Terrado et al., 2022 in this issue). This is a cyclical process that, for the purpose of this analysis, can be considered to have a starting point in the knowledge-exchange phase. In fact, decision-makers, scientists and social scientists have engaged in a close collaboration with the aim of generating mutual understanding of user needs, forecasting potential and risk management options. The knowledge exchange took place through meetings, interviews, working sessions, and e-mail correspondence (see Fig. 1).

The entire co-production framework is deeply discussed in Terrado et al. in this issue. In the scope of this paper, the focus is narrowed to the co-production that led to the methodology under discussion. During the last two years of the MED-GOLD project, partner companies (including SOGRAPE) and other potential users from the agri-food sector have been regularly exposed to seasonal forecasts (many have already been exposed to seasonal forecasts before). The forecasts of interest for the case study analysed in this paper are the Spring Total Precipitation which are presented in section 2.2. More specifically, Fig. 2 shows the MED-GOLD dashboard which was co-produced during the project. The prototype dashboard included different climate products that were refined by SOGRAPE and other users, by testing them and raising questions, concerns and improvement suggestions on visualisation, interpretation, and applications (including the question we are addressing in this paper). For example, Spring Total Precipitation is one of the indicators available in the dashboard because SOGRAPE was interested in applying this indicator to the vineyard management decisions described below. In this regard, the prototype dashboard is showing whether the Spring Total Precipitation is expected to be normal, above or below normal for the selected region and period. To each possible scenario there is an associated probability (see section 2.2). When and how to translate this into input information for decision-making? Answering this type of questions entails not only the understanding of the forecasts but also of the user.

Exploratory *meetings* (in person whenever possible), are especially important at the beginning of the process, because they build mutual understanding of the team members, including experts from the wine company as well as climate and social scientists. At this stage, the ambition was to have a first overview of the information and data available in the case study area (the Douro region). In fact, the vineyard manager has knowledge of the average procurement costs and grapes sales prices for the Portuguese market as well as of the best adapted vineyard management strategies in the area. After that, the user identified one decision of interest for the case study as well as its potential impacts. This allowed the identification of the most suitable bioclimatic indicator linked to the decision. Thus, the vineyard manager reported the detection of a rising uncertainty in spring rain patterns that could severely affect crop yields. This is especially important in springs with high rainfall, which favour the development of fungal diseases such as downy mildew (*Plasmopara viticola*) and can disrupt vineyard operations. Therefore, for the selected *case study*, the impacts on crop yield according to the users' adopted strategy for spraying and labour management were related to the Spring Total Precipitation indicator (SprR). Subsequently, *working sessions* served to precisely define the inputs available to perform the analysis and the expected outputs. From this point onward, different scenarios were set up based on the user's expertise on how SprR impacts the company's decision workflow. This knowledge comprised the estimation of costs and losses associated with different decision scenarios through the provision of market data and model's assumptions. The methodology was complemented with a recursive approach of feedback gathering. Reiterating questions helps to avoid biases (Elder and Miller, 1995). This process was supported by regular *meetings, interviews and email correspondence*, posing questions to

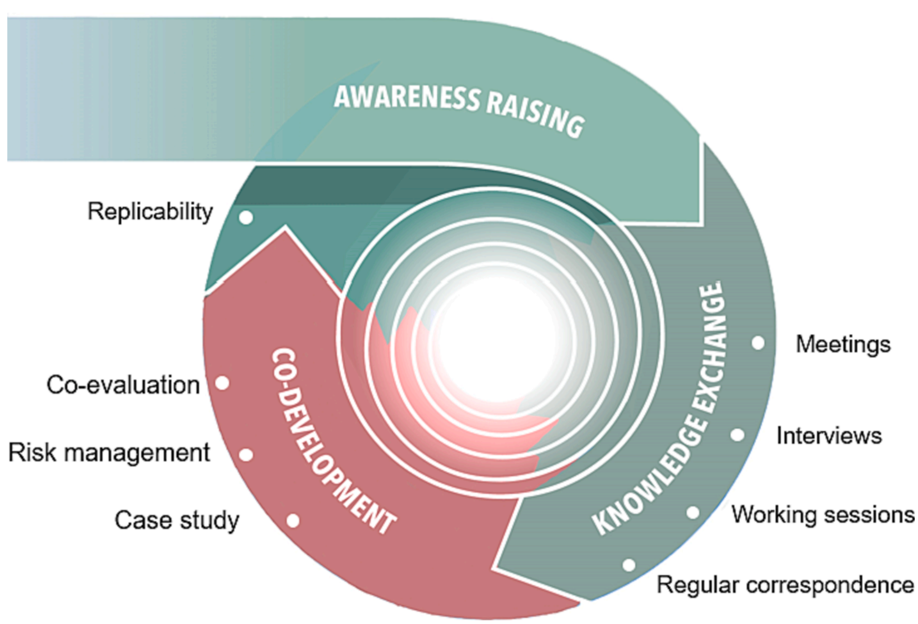

Fig. 1. Co-production framework for climate services (Terrado et al, in this issue, elaborated from Bojovic et al. 2021). The methodology of this study builds on knowledge exchange using different tools (e.g., introductory meetings, interviews, user-provider working session, regular correspondence) and contributes to the service co-development (by engaging in a co-evaluation process, building a case study and co-testing risk management with forecasts). Finally, the replicable nature of this analysis, makes it of interest for third parties that are interested in developing or uptake climate service. Therefore, awareness raising tool can be employed in the future.

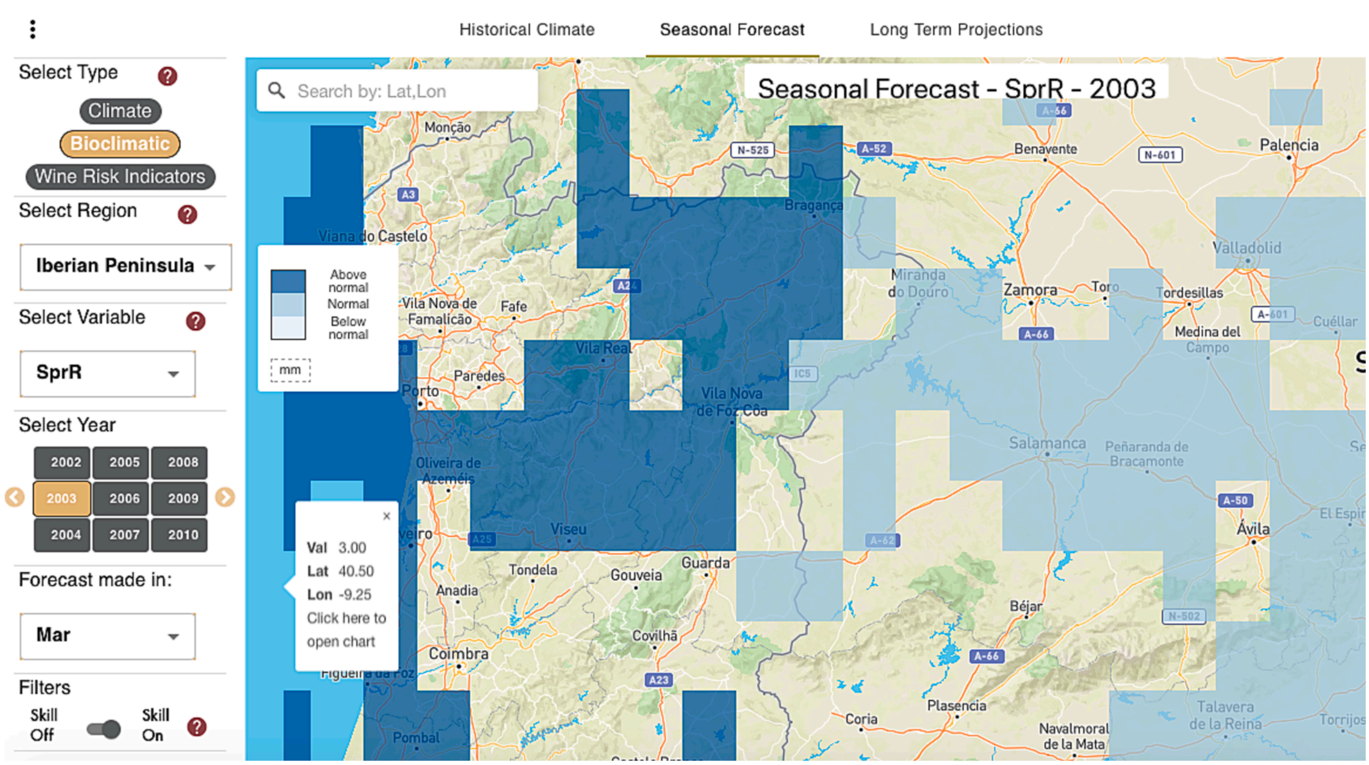

Fig. 2. MED-GOLD Dashboard displaying the Spring Total Precipitation (SprR) forecasted in March 2003. This dashboard has been developed within the MED-GOLD project to provide an easy-to-use visualization tool. It allows to access information on past climate and predictions of future climate at different time scales (seasonal forecasts and long-term projections) for the Douro Valley and the Iberian Peninsula. The user can select to display essential climate variables, bioclimatic indicators (such as the SprR) or risk indices. The user can also filter the results by displaying those with positive skill only, as shown in the figure.

the user (pre-prepared) and challenging the methodology to keep it as grounded as possible in the local reality of the case study. One of the main challenges was represented by the discussions around the probabilistic reasoning applied to the agricultural context by introducing seasonal forecasts. The user was initially firm about the impossibility of using any seasonal forecasts with a hit-rate below 70 %. This belief was probably driven by the well established threshold of two-thirds (67 %) for triggering decisions (Conradt & Roper, 2003). On the other hand, climate scientists would consider a useful information anything above 33 %, which is the climatological reference, without considering the limitations for real business risk management. The first step towards a change in approach was possible with a set of meetings (in person and virtual) where economists and social scientists also joined the conversation. During these meetings, with hours of animated debate, the team has developed the common understanding that the forecasts' acceptable hit-rate strictly depends on the decision-making application the user is envisaging. Neither 70 % nor 33 % have a concrete meaning. Finding a common ground was not trivial, but turned out to be necessary to proceed and converge to a common approach.

Beyond the specific case study presented here, this analysis aims to understand, for a given profile and a specific decision, which would be the optimal protocol to apply seasonal forecasting in the planning workflow of winemakers in the Douro valley.

User's decision-making

Data to perform this analysis has been gathered through the wine company, which provided estimates of costs and associated yields based on internal data records from several years. More specifically, the purchasing department provided unit cost data on plant protection products and labour whereas the vineyard manager combined this information with vineyard operations (spraying, canopy management, etc.) needs and vineyard yields (according to tercile scenarios). Data are combined into a single value per scenario, which results from user-specific confidential estimates.

Spring total precipitation (SprR)

The Spring Total Precipitation (SprR) is a bioclimatic indicator that has been defined according to the vineyard managers' need to adapt to the impacts of spring rain variability (Fontes et al. 2016). More specifically, SprR is the total precipitation from 21st April to 21st June (for the Northern Hemisphere). The wetness of spring represented by this indicator affects the level of sanitary risk associated with fungal disease and hence, the amount of costs linked to protective treatments and operations. The SprR indicator is defined as follows,

$$TotalPrecipitation = enddate\sum startdateprlr$$

where *prlr* is the daily total precipitation in mm. The start (end) date is the first (last) day of the period considered for the specific indicator, in this case 21st April to 21st June, corresponding with the spring period in the Northern Hemisphere.

The indicator is predicted on a tercile probability basis, that is, by giving the probability associated with the occurrence of normal, above normal and below normal precipitation. The MED-GOLD dashboard displays, on a map, the most likely of these terciles (to facilitate the information transmission to the user, see Fig. 2).

Dry springs delay vegetative growth and reduce vigour and leaf area total surface. In this scenario fungal disease pressure is often lower and, therefore, there is less need for protective and/or curative treatments (translating into lower costs). Conversely, wet springs promote greater vigour, increase the risk of fungal disease and disrupt vineyard operations, as the emergence of mud sometimes prevents machinery from entering the vineyard.

Decisions linked with SprR

Knowing the expected spring rainfall months ahead (i.e., looking at seasonal predictions of SprR) would allow users to optimise their decision-making in two areas: plant protection and canopy management. In the following paragraphs, we illustrate the impact that having this information in advance could have in the current user decision workflow in both areas.

(a) Plant protection: Each year, in January, the wine company procurement department issues an order for a fixed amount of plant protection products, needed to protect the vineyard from fungal diseases. These diseases thrive in humid conditions and, therefore, abundant rain requires the spraying of extra product quantities. Whenever this situation arises, the procurement department tries to react to it by buying more protection products, but at a risk of paying higher prices than in January, because of less economies of scale and higher demand for such products as the situation is common for all farmers in the same area. In addition, in the case of continued wet conditions affecting the whole country, the demand may become so high that, in extreme cases, suppliers may run out of stock. Thus, late purchase causes higher costs and also exposes the user to the risk of protection unavailability with potentially nefarious consequences on the diffusion of fungal diseases and inherent disruption of yields. On the other hand, in case of a dry season, less protection is needed, allowing for savings and lesser environmental impact.

In such circumstances, if the information of the seasonal predictions of SprR was available well in advance, the purchasing department could optimise the quantity of protection products to order for the upcoming spring. However, to do so the user has to be confident that using the seasonal predictions will bring a solid benefit because, otherwise, misestimating the quantity of products to purchase would cause extra costs. Indeed, often spare products cannot be carried over to the following year because they lose their protective efficacy, meaning that purchasing more than needed is a waste. On the contrary, if too little spray is purchased, the risk of running out of stock could materialise, entailing significant yield and revenue loss.

(b) Canopy management: if there is a lot of rain in spring, plants grow more and, thus, leaf and shoot removal becomes necessary. In fact, too many leaves expose the grapevine to higher sanitary risks and, simultaneously, the application of the spraying products is less effective (difficult penetration). These operations require extra labour that should be contracted at the earliest convenience to anticipate widespread demand for it. Conversely, if the season is dry, cutting leaves is dangerous because there will be little or no regrowth before summer, hence there is a real risk of 'sunburnt' grape berries during the hottest months which also translate as yield and revenue loss. Consequently, miscalculation of the rainfall can lead to mistakes in canopy management practises as well as to unnecessary labour costs.

Decision workflow: Business as Usual vs. Climate predictions

When deciding whether to apply a climate service for decision-making, users need to consider that, in the case of climate predictions, the vineyard manager's decisions depend on the probability of different situations to occur. However, it is important to consider that changes in decision processes as well as deviations from the plan often entail non-negligible costs. Therefore, a change in a decision led by an unfulfilled prediction (or incorrect interpretation) can potentially cause higher damages than passively suffering the seasonal variability. This is why identifying the probability thresholds to safely trigger a decision is critical for every decision and user.

To analyse the optimal use of the SprR indicator we rely on decision theory (Rubas et al. 2006). The climate service (CS) user has to make a decision with the goal of maximising an objective (Payoff $= \prod$). Here we consider the added value of the CS to be the difference between payoffs of the decision taken with and without using the CS, as defined below (this value is decision- and user-specific, as discussed later).

$$\text{CS' Added Value} = \prod \text{cs} - \prod \text{BaU}$$

Being $\prod$BaU, payoffs from decision made without CS that we define as "Business as Usual" (as explained later in this section); and $\prod$cs, payoffs from decision with CS. If the difference is positive, using the CS benefits the decision-maker. Inversely, a negative value indicates that the information provided by the CS had a negative economic impact for the user. This may be driven by different reasons depending on the relationship between users' decisions and prediction characteristics.

To define the aforementioned payoffs, there is a need to identify the costs and benefits of the vineyard management actions related to spring rain. For simplification, costs were represented by purchase of plant protection products and labour hiring (for canopy management) and varied according to the combination of the strategy adopted and the observed rainfall. The benefits were represented by the yields and their monetary value is measured taking into account the market price of a kilogram of the type of grape of the vineyard under analysis. For this, we assumed the average price for a kg of grape yield (Y) to be 0.5 euro (refer to the Box "Grape Prices" at the end of this section for further information).

$$\text{Kg Y} = 0.5\ €$$

Regarding the payoff, it is represented by the value of the benefits minus the costs.

$$\text{Payoff}(\prod) = €\text{Y - Cpp - Ccm}$$

where Y corresponds to benefits from yield; Cpp corresponds to the costs of plant protection; and Ccm are the costs relative to canopy management.

Although yield value and costs vary substantially across companies (e.g., with different sizes and purchasing power) and even across vineyards of the same company (depending on the location, the dimension and the type of wine produced), the process for identifying the optimal threshold is always the same. Particularly, for this study we have selected a slope vineyard of 70 ha located in the Douro region.

(a) Business as Usual strategy (BaU)

The first step involves the description of the current baseline strategy. That is, to define the possible payoffs without using the climate service. In the case under analysis, the vineyard manager adopts the same strategy every year independently of the expected climate conditions. We define this strategy, characterised by not using climate information, as Business as Usual (BaU). The BaU strategy is summarised in Fig. 3.

In January, the vineyard manager communicates to the purchasing department the standard amount of protection products that is needed under normal climate conditions to treat the hectares of the field. Given the specific characteristics of the field under analysis, the costs per hectare to purchase protection products are 315€. Similarly, the vineyard manager plans canopy management assuming normal climate conditions. These costs include the labour force and amount to 495€ per hectare. If everything goes as planned, 4000 kg of grapes per hectare should be harvested - being this the expected yield -, i.e., the average yield per hectare. The expected revenue achieved with these yields, based on the sales price of 0,5€/kg, is 2000€. If the spring rain turns out to be on normal levels (N), the grape production target will be achieved (assuming no other shocks before the harvesting) at the cost envisaged at the beginning of the year.

However, if SprR deviates from the expectations there can be serious consequences. One possibility is the spring being rainier than expected (Above Normal, AN). In this case, the vineyard manager needs to

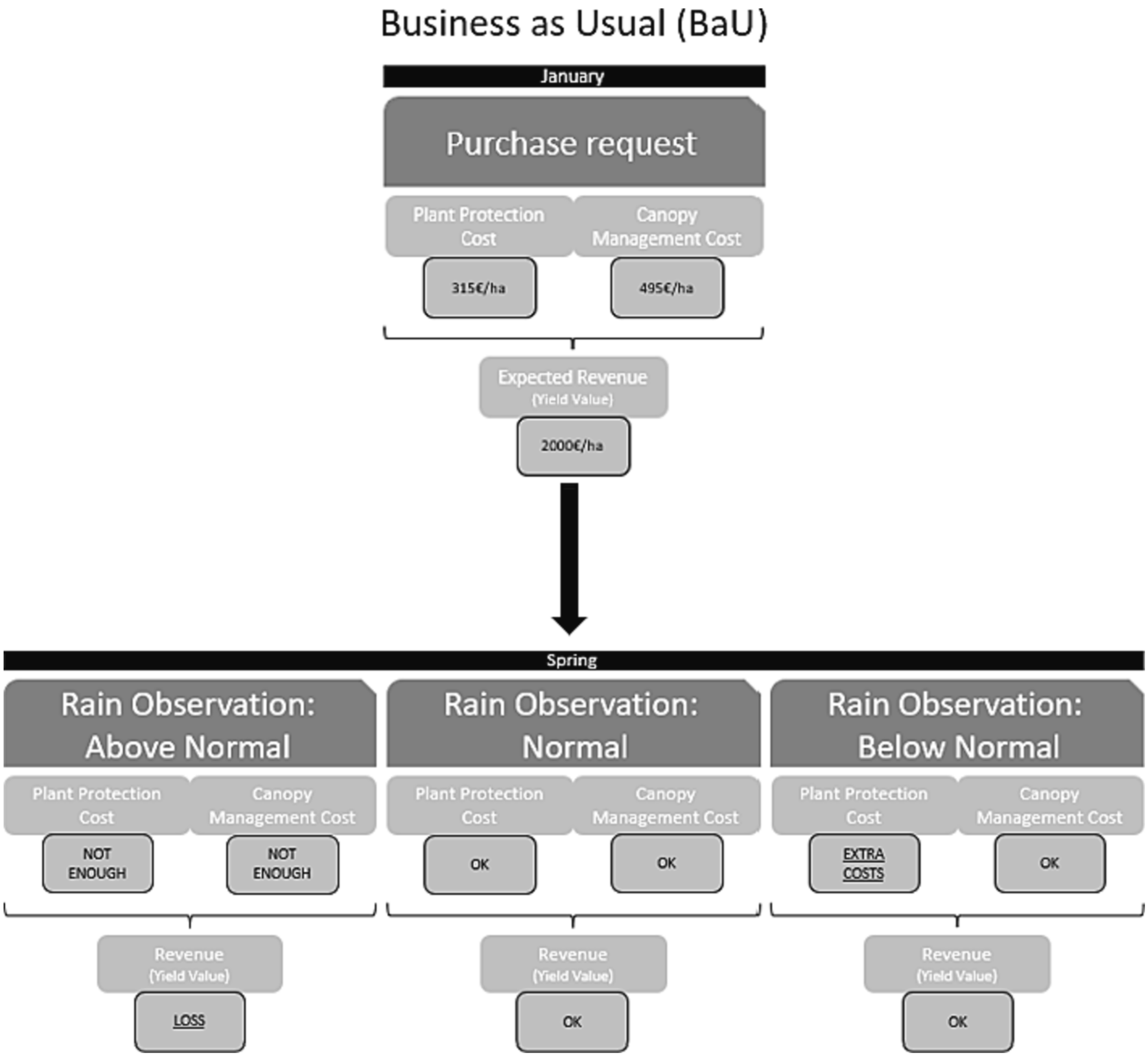

Fig. 3. Business as Usual scenarios for the spring rain-related decisions. In January, the Business as Usual strategy is applied and the outcome obtained in spring depends on the rainfall during that period. At the beginning of the year, the expenditures for plan protection and canopy management are sustained in order to obtain the maximum yields (achieving the expected revenue) under normal rain conditions. In springtime, the vineyard manager discovers if the strategy was optimal or not. In case the above normal scenario materialises, the underspending ("not enough") translates in a loss of yields. If the below normal scenario occurs, there is a waste of plant protection products because there is no need to use the whole amount purchased ("extra costs").

purchase additional spray for protecting the grapes from the increasing sanitary pressure and contract more labour force for canopy management. If the rain affects a substantial share of the country the price of spray and labour is likely to increase until there is no more supply available. This can cause huge damages to the vineyard, including the total disruption of the yield. In this exercise, based on the consultations with the vineyard manager, we assume an intermediate scenario where a supply shock occurs. This means the vineyard manager cannot purchase extra resources (the costs remain invariant), but there is a loss of 30 % of the yield (Fig. 3).

In the eventuality of a dry spring (Below Normal, BN) Fig. 3 may suggest that nothing occurs, because costs and yields are equal to the N case. However, this is not the optimal solution for the vineyard manager because it could have benefited from a reduction of plant protection costs (less protection was needed).

Importantly, the choice of the BaU strategy is context specific. For example, a grape grower can act based on the conditions observed in the previous few years. Therefore, the BaU would not correspond to the same category every year, it would depend on the previous year. Another user may be purchasing less spray by default every year (having a BaU focused on sustainability and spraying cost reduction). In this case "below normal" would correspond to its BaU. The approach of adapting the BaU reflects the idea that the value is not placed on the forecast but on the expected outcome of changing strategy.

(b) Climate prediction strategy

When introducing seasonal predictions based on probabilistic tercile categories, the vineyard manager can make three different decisions. This implies nine possible scenarios depending on the combinations of three possible actions and three possible outcomes of observed spring rain.

If the seasonal predicted SprR indicator suggests normal levels of spring rain (N), the actions taken by the vineyard manager, and subsequent payoffs, correspond to the BaU scenario. But if the predicted SprR suggests higher or lower rain than normal, different actions might be taken. Fig. 4 summarises the possible scenarios with their relative outcomes and payoffs.

Based on the most likely predicted SprR signal, the vineyard manager can decide to protect the vines from high expected rain by purchasing

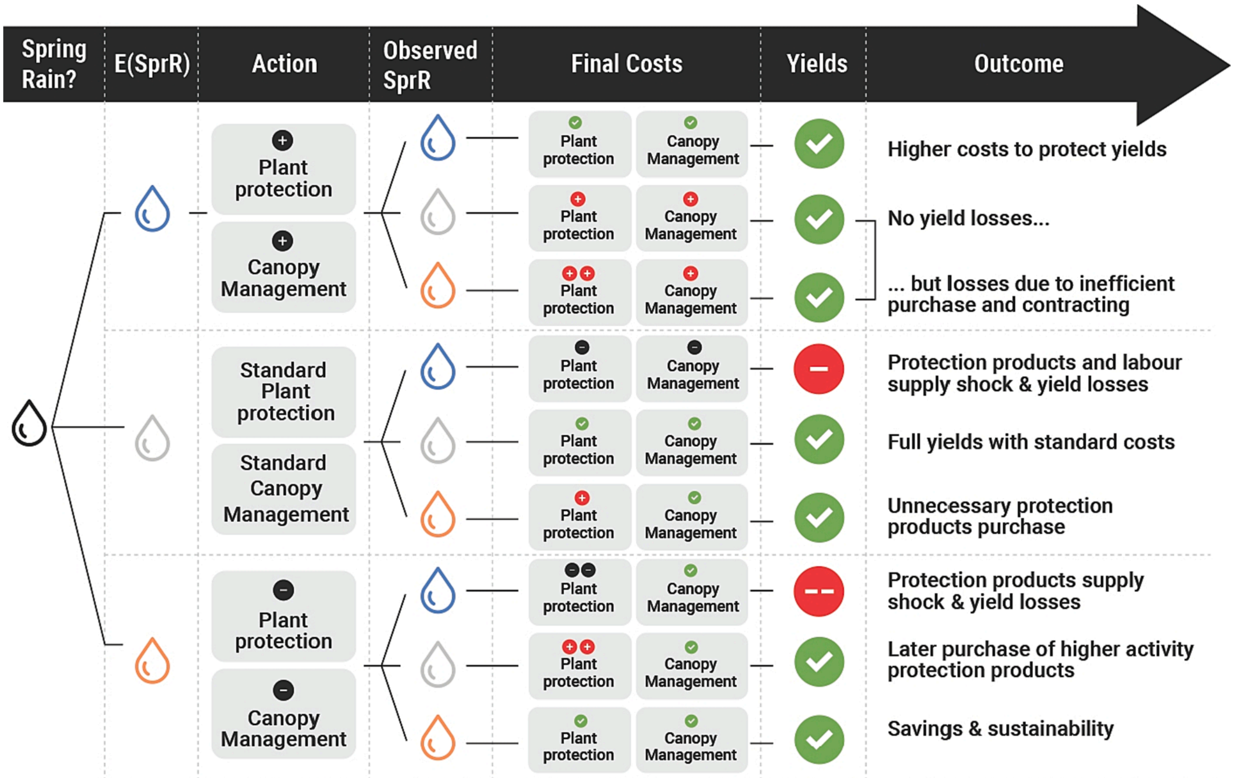

Fig. 4. Climate prediction scenarios for the spring rain-related decisions. This figure depicts the two-level decision tree representing all possible scenarios when using tercile seasonal predictions of SprR in January planning. The first level, including "Expected Spring Rain", E(SprR), and "action". E(SprR) represents the possible predicted categories in January namely: above normal (blue), normal (grey) or below normal (orange) drops. The action column indicates the decision taken and the related costs: spending more (+), less (-), or same (if nothing indicated) compared to the BaU scenario corresponding to the grey drops. The second level of the tree shows the possible outcomes (explained in the text in the last column) depending on the observed rain (observed SprRr) and the strategy adopted which is reflected in the final costs and yields. A green tick indicates that the decision was correct. The plus indicates the extra costs incurred. The minus indicates that the savings made were not appropriate to achieve the target yields. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

additional protection products and contracting extra labour force (blue drop on the first decision branch of Fig. 4. Then, if the observed rain matches the expectations (blue drop of the second decision branch of Fig. 4 the yields are almost entirely preserved from the downy mildew and the maximum payoff for these climate conditions is achieved. Nevertheless, if the spring turns out to be normal (blue drop of first branch followed by grey drop of the second decision branch of Fig. 4), there is no impact of the decision taken on yield value, but the vineyard manager would have extra costs when compared to its BaU expenses. More specifically, an additional 25 €/ha would be wasted in canopy

Table 1
Estimated outcomes of the climate predicted scenarios for spring rain-related decisions (€/ha). For each scenario (possible combination of prediction and observation) the associated costs (Cpp and Ccm) and revenue (yield value) are described along with the payoffs (∏cs) calculated as the difference between the yields and the aggregated costs. Notice that the BaU scenario is user- and decision-dependent.

Scenario (Action; Observation)	Cpp (€/ha)	Ccm (€/ha)	Revenue (€/ha)	∏cs (€/ha)
AN;AN	410	520	2000	1070
AN;N	410	520	2000	1070
AN;BN	410	520	2000	1070
N;AN (=BaU)	315	495	1400	590
N;N (=BaU)	315	495	2000	1190
N;BN (=BaU)	315	495	2000	1190
BN;AN	220	495	1000	285
BN;N	535	495	2000	970
BN;BN	220	495	2000	1285

management (see Table 1: AN;AN scenario Ccm 520 €/ha - N;AN (=BaU) Ccm 495 €/ha) and 95€/ha in plant protection (Table 1: AN;AN scenario Cpp 410 €/ha - N;AN (=BaU) Cpp 315 €/ha). Similarly, if the spring turns out to be dry (orange drop on the second decision branch of Fig. 4), there are no impact on yield benefits but the plant protection toll represent an even higher cost compared to the optimal purchase in case of a dry spring prediction (190 €/ha; obtained from Table 1 difference between AN;BN scenario Cpp 410€/ha minus Bn;BN scenario Cpp 220€/ha).

In fact, according to the assumptions set for BN conditions (Fig. 4), the yield is not affected by a drier than normal spring and, additionally, less plant protection products are needed due to the climate conditions, unfavourable for the development of fungal diseases. As a result, in the BN category prediction 220 €/ha (Table 1 BN;BN scenario) of protection would be enough to guarantee the safety of the yield. Knowing this in January would allow for timely communication to the purchasing department and 95€/ha of savings compared to BaU (see Table 1: BN;AN scenario Cpp 220 €/ha minus N;BN (=BaU) scenario - Cpp 315 €/ha). On top of that, the application of less protection products is beneficial for the environment (however, this positive externality is not quantified among the impacts for the farmer in this model). On the other hand, purchasing savings on plant protection exposes the vineyard to a huge risk in case the predicted SprR turns out to be different than expected. If a normal rain scenario arises (orange drop of first decision branch and grey drop on the second decision branch of Fig. 4), additional plant protection has to be purchased at the last minute at a higher price (getting to a total expenditure for Cpp of + 535 €/ha, Table 1 BN;N scenario) to ensure no crop disruption is faced. Even worse would be if the above rain scenario materialises (orange drop of first decision branch and blue drop on the second decision branch of Fig. 4) causing the loss of 30 % of the yield, being too late to purchase any extra spray (see Table 1: BN;AN scenario Revenue).

The scenarios resulting from this co-production process served as the base for the calculations of the potential impact of the climate service and the decision triggering thresholds for the modelled user's decision strategy.

Grape Prices

In the context of the Douro region, changes in farmers' revenues are mostly associated with variations in grapes' quantity rather than in prices. Actually, the user has not detected significant grape price fluctuations despite changes in production in the area. More specifically, in the Douro two appellations coexist: Port (for liqueur wines) and Douro (for still wines). Both appellations can be produced from the same grapevines in the whole region, the choice lies with the farmer. However, the appellation system establishes a maximum amount of Port that can be produced by each farmer, that is established around June / July every year as a function of existing stocks, forecast sales and expected production. Douro can be made from whatever amount is left provided production won't exceed the maximum allowed production per hectare (considering production of grapes for both appellations)

, something that very rarely occurs.

Considering the price of Port to be 0.9 €/L and Douro 0.37 €/L (equivalent respectively to 1.23 and 0.50 €/kg)

, no significant difference in price has been reported between years characterised by huge differences in production. The farmers' revenue changes have been caused by the changing weight of each appellation in the total production and not because of a change in offer. The appellation system of rating vineyards for Port was created to improve the stability in income for farmers, protecting them from speculation, and has been the reason why the average transaction price for both Port and Douro grapes in the region has not changed much in the past 20 years.

In summary, according to this information, using fixed prices for grapes is an acceptable approximation, and analysing Douro grape is particularly relevant since these are the ones suffering more fluctuations in production

(because the allowance for Port ensures that in the majority of situations, grapes will be used to produce Port first, Douro to be produced with whatever grapes are left).

Results

Climate service potential added value

In this section, we show the results of the estimated value of the climate service for the user to support predicted SprR-related decisions. As explained in the methodology, this value can be computed as the difference in payoffs between the decision taken using the climate predictions (∏cs) and without using any climate information (∏BaU). Table 2 shows the payoffs and CS value for each scenario previously defined in Table 1.

Table 2
Estimated annual added value of the climate service in support of SprR-related decisions for this user (€/ha). For each scenario (possible combination of prediction and observation) the payoffs of using the climate service (∏cs) and the BaU (∏BaU) are indicated along with the added value, obtained as the difference between payoffs. Notice that ∏BaU is always the same for a given observation (590€/ha for AN, 1190€/ha for N and for BN) since the action remains constant.

Scenario (Action; Observation)	**∏cs (€/ha)**	**∏BaU (€/ha)**	**Climate Service Added Value ∏ cs -∏ BaU (€/ha)**
AN;AN	1070	590	**480**
AN;N	1070	1190	**−120**
AN;BN	1070	1190	**−120**
N;AN (=BaU)	590	590	**0**
N;N (=BaU)	1190	1190	**0**
N;BN (=BaU)	1190	1190	**0**
BN;AN	285	590	**−305**
BN;N	970	1190	**−220**
BN;BN	1285	1190	**95**

Changes in decisions based on seasonal predictions of above or below normal rain generate benefits whenever prediction and observation match (as shown in Table 2 and 'hits' in Fig. 5). However, it is also clear that a shift from BaU generates losses in those cases when the observation turns out to be different from the expectations. From Fig. 5, we can also infer that the benefits of a match are much larger in case of correctly predicted high rainfall (when yields can be preserved, amounting to 480 €/ha), compared to the benefits given by plant protection savings in case of a well-predicted drought (95 €/ha). Contrarily, the costs associated with a decisional mistake are high in case of drought, and relatively low in case of rainy spring, especially if compared to the potential benefits.

So far, we have identified the potential value each scenario brings. However, when it comes to the real use of the forecasts, vineyard managers are interested in knowing what is the minimum probability threshold for a scenario to occur in order to shift their strategy from a business as usual to one using the climate service.

Decision-triggering thresholds

In the climate service field, we consider the predictions to be of enough quality when the users can rely on the benefits of including them in their decision workflows. Thus, once the CS annual added value per hectare has been established (third column of Table 3), we can focus on linking CS-based decisions and the probability threshold that could safely trigger them. In our case, considering we have three tercile categories in which the user could be interested - above normal (AN), normal (NN) and below normal (BN) -, there are 3 groups of 3 possible value scenarios each (depending on the possible combinations of prediction-observation, Table 3 s column).

On the basis of this information, we can develop a general approach on how to perform the computation of the decision-triggering thresholds for each scenario. It is worth noting we consider each potential decision to be tercile category independent, that is to say, there are no decisions that simultaneously depend on the prediction of two categories, such as, AN and BN. This is the reason why our exploration of the probability thresholds is independent for every tercile category. Table 3 shows the needed information for this calculation.

For obtaining the thresholds there are two conditions that have to be fulfilled:

(i) the sum of all the fractions is equal to 100 (eq. 1), because D1, D2 and D3 are, respectively, the fraction of times that AN, NN and BN categories have been observed out of the total of times TRC has been predicted.

$$D_1 + D_2 + D_3 = 100$$

(ii) the sum of the products obtained from multiplying each fraction by the corresponding CS added value is equal or higher than zero (eq. 2) because we would like to avoid that the user has losses after using the CS information.

$$D_1\ x\ +\ D_2\ y\ +\ D_3\ z \geqslant 0$$

These two equations link CS annual added value per hectare and the historical counts for each prediction-observation pair, independently of the category considered. As we can see, we have three degrees of freedom (D_1, D_2 and D_3) for two equations. Hence, not only will we have multiple possible solutions, but we would need specific boundary conditions to be able to solve them. These constraints could be either inferred from the magnitude of each CS added value scenario or directly stated by the user. Hereafter we will proceed to compute these thresholds with the Climate Service added value data gathered in Table 2 (third column) for every tercile prediction.

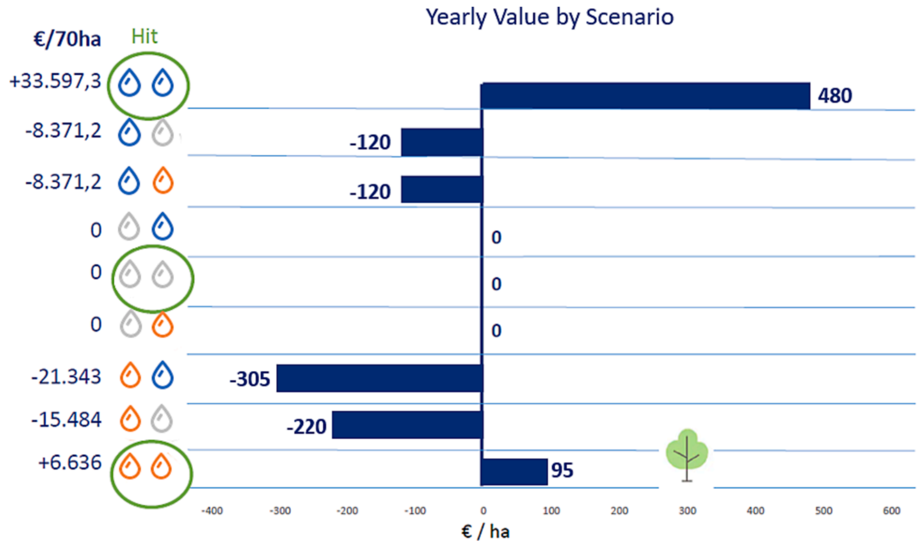

Fig. 5. Summary of the seasonal climate service added value per year and scenario (€/ha). Each scenario possibility is represented by pairs of drops (first drop corresponds to the prediction and second drop to the observation). The bars show the benefits (on the right, positive values) / losses (on the left, negative values) generated per hectare. The added value for the entire vineyard (70 ha) is reported on the left of the figure. The green circle (hit) identifies scenarios when prediction and observation match. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Fraction (%) refers to the percentage of times each scenario has been observed (D_1, D_2 and D_3) from the total number of times TRC it has been predicted. Scenario shows the prediction (TRC) followed by the actual observation (AN, NN or BN). CS Added Value, (∏ cs -∏ BaU) is the economic impact of using the CS in each of these scenarios compared to BaU (x, y and z).

Scenario distribution for each specific tercile prediction (TRC)		
Fraction (%)	**Scenario**	**CS Added Value ∏ cs -∏ BaU**
D1	TRC;AN	x
D2	TRC;N	y
D3	TRC;BN	z

Probability threshold for AN predicted conditions

Supposing we are mostly interested in D_1 (when the prediction-observation pairs match, also known as 'hits') we could look at the minimum percentage of hits needed to achieve a positive outcome:

$$D_1\,x + D_2\,y + D_3\,z = 0$$

And constrain D_2 and D_3 to obtain the percentage of hits needed to reach the desired positive result. Hence:

$$D_1 = -\frac{D_2\,y + D_3\,z}{x}$$

In this category,

$$y = z = -120/hax = 480/ha$$

So D_1 equation becomes,

$$D_1 = -\frac{y}{x}\,(D_2 + D_3)$$

If we develop it further (taking advantage that y = z),

$$D_1 = -\frac{-120}{480}\,(D_2 + D_3)D_2 + D_3 = 100 - D_1$$

$$D_1 = \frac{25}{1.25} = 20\%$$

Now we can work out the minimum value of D_1,

$$D_1 \geqslant 20\,\%$$

Therefore, assuming the model is reliable, the 'climatic' observed D_1 fraction also equates to the predicted probability. Thus, whenever the probability for AN prediction lies equal or above 20 %, the user will be safe triggering the decision corresponding to this category.

Probability threshold for N predicted conditions

In this case, since the N conditions are assumed to be what drive the BaU, there is no benefit nor loss in using them (see Table 2).

$$x = y = z = 0$$

Probability threshold for BN predicted conditions

Finally, in the BN category, if we need to work with hits, we would need to isolate D_3 (see Table 2 and 3).

$$D_3 = -\frac{D_1\,x + D_2\,y}{z}$$

Where, in this case,

$$x = -305\,€/ha\ ;\ y = -220\,€/ha\ ;\ x = 95\,€/ha$$

Then,

$$D_3 = -\frac{(-305\,D_1 - 220\,D_2)}{95} = 3.21\,D_1 + 2.32\,D_2$$

However, even though we use the equation,

$$D_1 + D_2 + D_3 = 100$$

In this scenario we still have two equations for three variables, so we will need to introduce another constraint. To do so we can explore the 'best' and 'worst' settings. The 'best' would be when $D_1 = 0$, so we would only have D_2 and D_1 events (every time the model 'fails' causes the lower prejudice). In that situation,

$$D_2 = \frac{1}{2.32}\,D_3$$

So,

$$D_3 = \frac{100}{1.43}\ 70\%$$

$D_3 \geqslant 70\%$

It is important to note there would be a 'theoretical' better scenario if the model was perfect (so D_1 and D_2 were 0). In that case, whenever the model predicted any category it would signal it with 100 % probability and always would be correct. However, this would convert our prediction into deterministic and, consequently, there would be no probabilistic threshold to be determined.

Conversely, the worst case scenario would be when $D_2 = 0$ (every time the model 'fails' causes the maximum prejudice). In that case,

$$D_1 = \frac{1}{3.21} D_3$$

And,

$$D_3 = \frac{100}{1.31} 76.3\%$$

$D_3 \geqslant 76.3\%$

n a real working scenario, neither D_1 or D_2 will be 0. One option to achieve a more proper threshold would be to apply the mean on both. However, although D_1 and D_2 are climatologically equivalent, their relative impact is not,

$$\frac{x}{y} 1.38$$

Thus, to achieve the probability threshold in this case we need to use a weighted mean.

$$D_3 \geqslant \frac{1.38 \cdot 76.3 + 70}{2.38} = 73.7\%$$

Here again, assuming the model is reliable, the 'climatic' observed D_3 fraction also equates to the predicted probability. Thus, whenever the probability for BN prediction lies equal or above 73.7 %, the user will be safe triggering the decision corresponding to this category.

Discussion

In the three examples considered above, we have seen that the probability thresholds that can reassure the user on its actions are deeply dependent on the predicted categories and their link with the cost / loss / benefits compared to BaU strategy. More specifically, we have obtained the following thresholds:

- AN: 20 %
- NN: it is the assumed BaU (no gain possible by using the climate service)
- BN: 73.7 %

In the BN prediction, for example, we need a very confident model to be able to see any benefit from anticipated actions (probabilities above 73.7 %). This is logical, because of the negative consequences on the yield when purchasing less plant protection than needed.

The AN case, on the other hand, is interesting because the percentage is quite low (20 %). This means that even the straightforward SprR climatology (~33 % probability for each category, AN, N and BN) would offer value to the user even if always applying the AN actions. Actually, if we look at the expected CS value in the event, we always assumed the AN scenario (having 33 % of 'climate' hits), we would see that we would have 79.47 €/ha of benefits (see Table 4). It seems that always purchasing extra plant protection and contracting extra labour force implies less costs than allowing any damages caused by potential yield losses.

However, as explained in the methodology, this approach accounts solely for climate related information of the decision process. Actually, wine companies have to deal with broader risks beyond the sanitary ones: heat-related (dehydrated, sunburnt grapes, water stress), all sorts of pests - insects, birds, even wild boars, hail and others (Wallace & Moss, 2005). These risks may impact their own grape production, but they also impact the grape production of their grape supply base, i.e. farmers growing grapes and selling them to winemaking companies. As a result, the strategy and budgeting are set at company level and, hence, vineyard managers optimise the grape growing strategy within certain boundaries according to these guidelines. This means that although converting the AN strategy into the BaU seems to produce better results on average the risk associated with the occurrence of a different scenario may still be too high in the overall strategic framework of the company. Nevertheless, the methodology proposed remains a valid tool to highlight when a climate service based on seasonal forecasts could be used to inform decisions for optimising plant protection management in viticulture, factoring in the costs of both plant protection and canopy management together with the value of grapes, which are different from region to region and, for the latter, within the same region, often also from grape variety to grape variety.

Table 4
Aggregated climate service value using climatological probabilities (in the AN prediction scenario).

Scenario	**Climate Service Added Value ∏cs-∏BaU (€/ha)**	Climate probability (observed)	Weighted Climate service Value (€/ha)	Aggregated Climate Service Value (€/ha)
AN;AN	**480**	0,33	158.4	
AN;N	**−120**	0,33	−39.6	78,8
AN;BN	**−120**	0,33	−39.6	

Behavioural components also importantly affect decision-making. For example, an analysis of users' risk aversion is likely to shift upwards the acceptable probability thresholds (the first MED-GOLD workshop collected evidence in this respect). As previously mentioned, the methodology does not attempt to perform an evaluation of the Climate Service. Instead, it should serve as a methodological tool for users to quickly find the probability threshold that indicates when the forecast is appropriate for application in a given context. However, it is worth highlighting that once the user uptakes a forecast, this will not directly translate into a real-life decision. It will contribute to shaping it together with non-climate variables and with the influence of behavioural components. In any case, further co/production is needed to extend the methodology into more complex considerations for multiple outcomes of both concurrent and synergic decisions so as to increasingly facilitate the forecasts' uptake.

Conclusions

In this study we have illustrated a methodological approach to characterise the probability thresholds that a vineyard manager could apply to trigger a likely profitable decision based on tercile categories. The vineyard manager needs to answer the following question: "what is the minimum probability that makes the associated forecasted occurrence worth considering in my decision?". The short answer is: "It depends on users' characteristics and on the decision to be addressed". This paper proposes a simple methodology that can be applied to identify the potential decision-triggering probability thresholds, and shows an application with a case study. The case study proposed has been based on spring rainfall, a critical component in the wine producing workflow.

In a co-production approach with a large wine company, we have firstly identified the bioclimatic indicator that could account for the aforementioned spring variable, Douro SprR. Afterwards, we have economically characterised different decisions that could be adopted in each tercile scenario, as well as the BaU to compare with. Finally, we have put forward a methodology to consider the minimum probability for having positive results when including costs, losses and benefits in each decision scenario. The advantages of this co-production methodology consist in the trust created by the engagement with the user and the high level of tailoring of the analysis performed, posing the basis for user risk profile analysis. The drawbacks lay in the use of a simplified theoretical framework and the need of engaging new users for replication.

The results obtained under the specific technical, climatic and economic situation of a significantly large vineyard in the Douro Valley of Portugal, point towards the adoption of AN as a better BaU. Actually, the expected payoffs suggest that acting to prevent above normal rainfall is the best default strategy because a forecasted probability of 20 % of above normal rain is already sufficient to take action against the risk and see benefits. On the other hand, a high probability, 73.7 %, of dry conditions should be signalled by the forecasts for the user to act accordingly. However, in the real world the user is not subject to a single decision and climate is not the only variable affecting them. Moreover, risk preferences play an important role. Future co-production can address the integration of non-climate variables and risk preferences in the analysis.

A potential caveat of this approach, and a topic for future research, is that we have assumed perfect reliability of the climate models. That is to say, the forecasted probabilities are the ones that would be observed climatologically if we had enough predictions with the same forecast probability to do the computation. This seldom happens with climate models and so one further step needed to be able to bridge the gap between seasonal forecast climate services and users' adoption, is to include this uncertainty in the computation of any probability thresholds aimed to work as 'decision-triggers'.

Finally, the method followed in this case-study can be easily applied to different cases as long as it is tailored to the user's costs and benefits. It's worth noting that the thresholds elicited in this case study are only for methodological purposes, because different users and decisions may require other threshold values. Another topic for future research could be to generalise the computation of the probability triggers, e.g., through an indicator, to offer a flexible framework where the user could obtain the thresholds based on information that they could provide by themselves.

CRediT authorship contribution statement

Ilaria Vigo: Conceptualization, Investigation, Methodology, Formal analysis. **Raul Marcos:** Conceptualization, Investigation, Methodology, Formal analysis, Funding acquisition. **Marta Terrado:** Writing – review & editing. **Nube González-Reviriego:** Conceptualization, Supervision, Funding acquisition. **Albert Soret:** Supervision. **Marta Teixeira:** . **Natacha Fontes:** Funding acquisition. **Antonio Graça:** Conceptualization, Investigation, Supervision, Funding acquisition.

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.

Data availability

The data that has been used is confidential.

Acknowledgements

The research leading to these results has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 776467 (MED-GOLD).

References

Bojovic, D., St. Clair, A.L., Christel, I., Terrado, M., Stanzel, P., Gonzalez, P., Palin, E.J., 2021. Engagement, involvement and empowerment: Three realms of a coproduction framework for climate services. Glob. Environ. Chang. 68, 102271.

Conradt, L., Roper, T.J., 2003. Group decision-making in animals. Nature 421 (6919), 155–158. https://doi.org/10.1038/nature01294.

Cunha, M., Richter, C., 2016. The impact of climate change on the winegrape vineyards of the Portuguese Douro region. Clim. Change 138 (1–2), 239–251. https://doi.org/10.1007/s10584-016-1719-9.

Droulia, F., Charalampopoulos, I., 2021. Future Climate Change Impacts on European Viticulture: A Review on Recent Scientific Advances. Atmos. 12 (4), 495.

Elder, N.C., Miller, W.L., 1995. Reading and evaluating qualitative research studies. Studies 2, 5.

Fraga, H., Malheiro, A.C., Moutinho-Pereira, J., Santos, J.A., 2014a. Climate factors driving wine production in the Portuguese Minho region. Agric. For. Meteorol. 185, 26–36. https://doi.org/10.1016/j.agrformet.2013.11.003.

Giannokopoulos C., Varotsos K., Graça, A., Del Aquilla, A., Marcos-Matamoros, R., González-Reviriego, N., Kumar, P. 2019. Assessment of quality of seasonal forecasts and climate projections. https://www.med-gold.eu/documents-deliverables/ (accessed 06 May 2022).

Hermansen, E.A.T., Silmann, J., Vigo, I., Whittlesey, S., 2021. The EU needs demand-driven innovation policy for climate services. Clim. Serv. 24, 100270 https://doi.org/10.1016/j.cliser.2021.100270.

Marcos-Matamoros, R., González-Reviriego, N., Graça, A., Del Aquilla, A., Vigo, I., Silva, S., Sanderson, M., 2020. Second feedback report from users on wine pilot service development. https://www.med-gold.eu/documents-deliverables/ (accessed 03 May 2022).

Materia, S., Muñoz, A.G., Álvarez-Castro, M.C., Mason, S.J., Vitart, F., Gualdi, S., 2020. Multimodal Subseasonal Forecast of Spring Cold Spells: Potential Value for the Hazelnut Agribusiness. J. Am. Meteorol. Soc. 35, 237–254. https://doi.org/10.1175/WAF-D-19-0086.1.

O'Neill, B., M. van Aalst, Z. Zaiton Ibrahim, L. Berrang Ford, S. Bhadwal, H. Buhaug, D. Diaz, K. Frieler, M. Garschagen, A. Magnan, G. Midgley, A. Mirzabaev, A. Thomas, and R. Warren, 2022. Key Risks Across Sectors and Regions. In: Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. Cambridge University Press. In Press.

Porras, I., Solé, J.M., Marcos, R., Arasa, R., 2021. Meteorological and Climate Modelling Services Tailored to Viticulturists. Atmosph. Climate Sci. 11 (01), 148. https://doi.org/10.4236/acs.2021.111010.

Portele, T.C., Lorenz, C., Dibrani, B., Laux, P., Bliefernicht, J., Kunstmann, H., 2021. Seasonal forecasts offer economic benefit for hydrological decision making in semi-arid regions. Sci. Rep. 11, 10581. https://doi.org/10.1038/s41598-021-89564-y.

Ramos, M.C., Jones, G.V., Martínez-Casasnovas, J.A., 2008. Structure and trends in climate parameters affecting winegrape production in northeast Spain. Climate Res. 38 (1), 1–15. https://www.jstor.org/stable/24870393.

Santos, J.A., Ceglar, A., Toreti, A., Prodhomme, C., 2020. Performance of seasonal forecasts of Douro and Port wine production. Agric. For. Meteorol. 291, 108095 https://doi.org/10.1016/j.agrformet.2020.108095.

Soares,M.B., Marcos, R., Teixeira,M., Fontes N., & Graça, A. 2019. First feedback report from users on wine pilot service development. MED-GOLD H2020. https://www.med-gold.eu/documents-deliverables/ (accessed 03 May 2022).

Suckall N., and Soares M.B., 2020. Valuing climate services: Socio-Economic Benefit studies of weather and climate services https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/business/international/arrcc_mop_wp4_seb_evaluation_guidance-final.pdf.

Terrado, M., Christel, I., Bojovic, D., Soret, A., & Doblas-Reyes, F. J. 2018. Climate change communication and user engagement: a tool to anticipate climate change. Handbook of Climate Change Communication, 3, 285-302, Springer, Cham. 10.1007/978-3-319-70479-1_18.

Wallace, M.T., Moss, J.E., 2005. Farmer Decision-Making with Conflicting Goals: A Recursive Strategic Programming Analysis. J. Agric. Econ. 53, 82–100. https://doi.org/10.1111/j.1477-9552.2002.tb00007.x.

Wilks, D.S., 2001. A skill score based on economic value for probability forecasts. Meteorol. Appl. 8, 209–219. https://doi.org/10.1017/S1350482701002092.

Wmo, 2015. Valuing Weather and Climate: Economic Assessment of Meteorological and Hydrological Services. WMO N°1153.