

Value assessment and benefits of climate services

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Abstract Climate services can support decisions affected by current climate variability and longer-term climate change. However, structured methodologies to translate climate information into effective decision-making remain limited. To address this gap, this study assesses the value of climate services using a decision tree approach to a case study with Codorníu, a wine producer with vineyards in Raimat (Catalonia). Developed through a co-production methodology, the framework adopts frost-day occurrence as a proxy for spring-frost risk. Probabilistic forecasts of frost days are incorporated into a decision tree tool, StraTREEgy, which evaluates the optimal strategy between investing in a frost protection system and purchasing insurance. Results show that, for seasonal predictions, the optimal decision (to insure) is generally consistent with the user's business-as-usual practice, giving forecasts a confirmatory value for this specific location and decision. In the analysed case, decadal forecasts and climatology led to the same initial investment decision, so the practical added value of the forecast was limited. Overall, the tool's recommendation yields higher profit than non-investment scenarios based on climatology or forecasts alone. Finally, decadal predictions add value not only through profit maximisation, but also by capturing inter-annual variability, supporting more robust long-term investment decisions. These findings suggest that the value of climate services is highly dependent on the specific decision-making context in which they are applied.

I. Introduction

Throughout history, sectors such as agriculture, herding, water management, and energy have developed their practices based on experience and observed climate conditions in the past. These sectors are used to manage risks and deal with climate variability on a daily basis, often relying on a certain degree of flexibility (*Malik et al. 2010, Terrado et al. 2023*).

In recent decades, climate variability has challenged this traditional adaptive capacity. As a result, there is a growing need for climate services, understood as the provision of climate information and knowledge aimed at supporting decision-making processes related to mitigation and adaptation (*Doblas-Reyes et al. 2024*).

Climate predictions are useful tools for developing tailored climate services (*Hewitt and Moufouma-Okia 2023*). These predictions do not aim to predict specific climate conditions on a given day, but rather provide probabilistic information on whether the climate conditions for a given period are likely to be above normal, normal or below normal (e.g., warmer or colder, drier or wetter, etc.) (*MacLeod and Klassen 2019, Meehl et al. 2021*).

The main barriers to effective use of climate predictions include, first, the probabilistic nature of these predictions, which often makes them difficult for users to interpret, as they tend to require clear and decision-oriented

results. In addition, there is a disconnect between the scientific terminology used to describe climate information and the needs of users, which limits the translation of climate information into concrete actions (*Terrado et al. 2019, 2023*). Finally, the lack of methodologies to quantify the value of climate information in decision-relevant terms reduces its practical applicability (*Perrels 2020, Tall et al. 2018*).

To help overcome these challenges, a co-production approach, understood as an iterative, interactive and collaborative process between an interdisciplinary group of scientists and users, needs to be adopted (*Bojovic et al. 2021*). Co-produced climate services provide users with relevant, credible, and actionable knowledge aligned with their specific decision contexts (*Lemos et al. 2012, Vaughan and Dessai 2014*).

The value and usefulness of climate services depend on the scientific quality of the information provided. This quality is commonly assessed through the concept of skill. A forecast is considered skillful when a defined verification score is better than that of the reference forecast, usually climatology (*Murphy 1992*). This does not necessarily imply decision value, which depends on the intersection of the skill and the specific decision considered. However, the skill of a prediction is not constant and varies depending on several factors, including lead time, variable analysed, geographical region, and season (*Pérez-Zanón et al. 2024*).

Thus, the value of a climate service refers to its capacity to support action in a specific decision context, over short- or long-term horizons. It is not just about having access to skillful information but also about being able to

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use the information effectively (*Bruno Soares and Dessai 2016*). Based on this approach, the evaluation of climate services has shifted from the solely analysis of the forecast skill to the assessment of how climate information supports real-world decisions and societal impacts, recognising that forecast skill alone does not necessarily translate into practical utility or effective decision-making (*Coelho and Costa 2010*).

Different methodological approaches have been proposed to evaluate climate services, including qualitative and quantitative methods. However, there is a lack of structured approaches capable of translating climate information into valuable decisions in real operational contexts (*González-Romero et al. 2025*). Quantitative methods can include contingent valuation methods, economic decision modelling approaches that compare decisions taken with and without access to climate information, and avoided cost methodologies, which estimate the economic losses prevented through the use of weather and climate predictions (*Suckall and Bruno Soares 2020*). Qualitative and participatory methods also employ a range of approaches, such as interviews, workshops, and engagement activities, to provide a deeper understanding of the relevance of climate services for users (*González-Romero et al. 2025*).

In this work, the methodology draws on some of these approaches, applying a decision tree tool that supports decision-making, while also incorporating participatory elements with the user, which shape both its design and the interpretation of results.

Objectives

This study aims to understand how decisions that users make can be supported through information provided by climate services. The climate service considered has been developed in the framework of the ASPECT project, an EU-funded Horizon Europe initiative that aims to develop climate information at seasonal and decadal timescales to support climate adaptation decisions (*ASPECT Project 2026*).

The thesis follows a co-production approach in collaboration with users, to identify their needs, decision-making processes, and operational limitations. This approach allows to better understand the utility and value of climate predictions compared to traditional climatological information. Particularly, this study assesses the added value of a climate service developed with Codorníu, one of the oldest wine producers in Spain, operating vineyards in Catalonia, in the regions of Raïmat (Lleida) and the Penedès. The company faces increasing climate-related challenges affecting grape and wine production (*Torralba et al. 2025*). Following user's preferences, two management decisions are incorporated into the decision tree tool: investing in a frost protection system, a long-term decision that may be supported by decadal predictions, and purchasing insurance, an annual decision that may be informed by both seasonal and decadal information.

The specific objectives of this thesis are, first, to assess the value of seasonal and decadal climate services for user's decision-making; second, to identify the conditions under which climate services add value compared to using climatological information alone; and third to explore how co-production with users contributes to a better understanding of their decision context and to the identification of qualitative values of the climate service.

II. Methodology

In this section, we provide a description of the climate service delivered to Codorníu through a regular bulletin directed to support crop protection and water management decisions. Then, we describe in detail the climate data and information contained in the bulletin, including variables, indicators and temporal scales. Finally, we introduce the decision tree tool, a model designed to identify the optimal strategic decision path for users.

A. Climate services delivery

To address the needs of wine sector users, ASPECT provides a bulletin (Figure 1) designed through a collaborative process to support decision-making and the better understanding of climate information. The bulletin is tailored to ensure that its delivery mode (type of content, visualisations used and delivery timing and frequency) is aligned with user needs.

A description of the ASPECT climate bulletin is provided in the ASPECT Deliverable D4.2 (*Torralba et al. 2025*).

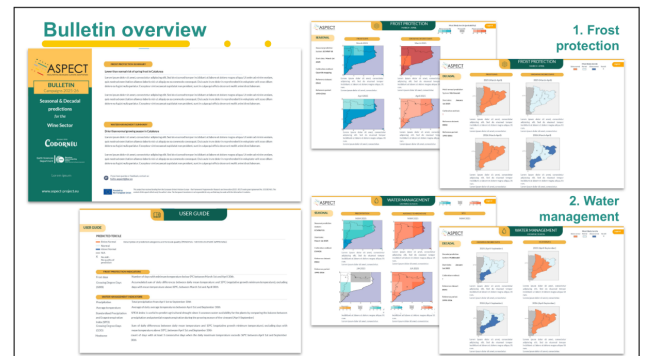


Figure 1: Overview of the first version of the bulletin co-designed with Codorníu for the April-September season in 2025. For a better visualisation, see the ASPECT Deliverable D4.2 (*Torralba et al. 2025*)

The bulletin provides probabilistic seasonal climate predictions (for the next months and seasons) and decadal predictions (multi-year, up to 10 years) expressed in tercile categories: below normal, normal, and above normal. The idea behind including these two different periods is that planning across different time scales ensures that short-term actions align with long-term objectives, hence preventing future maladaptation (*Finucane et al. 2020*).

The bulletin also combines regional-scale maps with local information for specific areas. This combined spatial representation is considered particularly useful by users, as it allows not only the assessment of local conditions but also the comparison with other strategic regions where they have activities and/or interests. To achieve this, decadal and seasonal predictions have been post-processed with statistical downscaling techniques that increase the spatial resolution of the climate information (Maraun *et al.* 2010). Customized outputs are provided for Catalonia and also for the Raïmat region, where the vineyards in the case study are located. All detailed climate data are compiled in the Appendix Table I.

B. Data and climate information

The tercile categories mentioned in subsection II A are derived from the climatology, defined as the long-term statistical distribution of a climate variable based on past observations. Each variable’s historical distribution is divided into three equiprobable intervals using the 33rd and 66th percentiles, so that each category contains exactly 33.3% of the historical observations under baseline conditions; these define the reference thresholds to generate the forecast (Pérez-Zanón *et al.* 2024, Torralba *et al.* 2025).

Forecasts are generated from an ensemble of prediction system simulations, with each member classified into a tercile category according to these thresholds. The probability of each category is calculated as the proportion of members falling within it, and the tercile with the highest probability is taken as the most likely outcome, while the others represent alternative scenarios (Pérez-Zanón *et al.* 2024). Each prediction is then compared with the observation for the same year; if the number of years in which observations coincide with the most likely tercile is higher than the years when they coincide with climatology, the forecast is considered skillful and thus better than climatology.

Indicators

Climate indicators are tailored to the specific risks of the sector and its management practices, and are directly linked to user-relevant decisions.

The indicators provided in the bulletin for Codorníu include frost days, defined as days with $T_{\min} < 0^{\circ}\text{C}$, used here as a meteorological proxy for spring frost damage; Growing Degree Days (GDD), which measure heat accumulation relevant for plant growth; total precipitation; average temperature; heatwaves, representing prolonged periods of high temperatures; and the Standardised Precipitation Evapotranspiration Index (SPEI), used to assess drought conditions through the balance between precipitation and atmospheric water demand (Torralba *et al.* 2025).

In this work, we focus on the frost days indicator. This indicator is selected due to its relevance in assessing spring frost damage during the growing season, which is

one of the most vulnerable periods for grapevines and highly relevant for the user. Spring frost occurs when temperatures drop below freezing after bud burst, damaging young shoots and buds that are sensitive to cold conditions. Such events can lead to significant yield losses and, consequently, economic impacts (Roncoroni and Athanasiadis 2026, Saa-Requejo *et al.* 2022).

For this indicator, two thresholds (0 and 1) were used to define the next tercile categories: below normal (0 frost days), normal (1 frost day), and above normal (more than 1 frost day) (Torralba *et al.* 2025). Although these thresholds are usually defined according to the terciles based on the historical climatological distribution, in this study we adapt them to the criteria that are meaningful for users (e.g., the occurrence of at least one frost day, $P(\text{frost} \geq 1) = P(N) + P(AN)$). This represents a shift from a purely statistical categorisation towards a more decision-oriented framework, tailored to each specific situation.

Seasonal prediction framework

The seasonal prediction system used for this work is the ECMWF SEAS5 (Johnson *et al.* 2019). Predictions are calibrated using quantile mapping to remove model biases (Berg *et al.* 2024) and evaluated against the ERA5-Land reference data set, a high-resolution historical reference. The reference period for calibration and verification is 1993–2016 (Hersbach *et al.* 2020).

Figure 2 shows a seasonal forecast issued on February 1st, 2026, for March 2026, indicating probabilities of frost days in Catalonia and in Raïmat (Torralba *et al.* 2025).

Black crosses on the map (Figure 2a) indicate regions where the prediction lacks skill, meaning the model does not improve upon the climatology reference. Skill is assessed using metrics such as the Ranked Probability Skill Score (RPSS). The RPSS is computed as a squared distance between the cumulative probabilities of a categorical forecast and a reference forecast - in this case, climatology (Torralba *et al.* 2017). An RPSS of zero or below indicates no predictive skill. In tercile barplots (Figure 2b), forecasts without skill are shown with transparency and labelled “no quality”, alerting users that climatology may be more reliable in that case (Pérez-Zanón *et al.* 2024).

Decadal prediction framework

Decadal predictions provide information on climate conditions up to ten years in advance, allowing the estimation of long-term trends. The probability of frost days during the last decades (Figure 3) is based on a multi-model ensemble. This multi-model ensemble is built from 17 decadal forecast systems, following the framework of the Decadal Climate Prediction Project (DCPP) within the Coupled Model Intercomparison Project (CMIP6) (Delgado-Torres *et al.* 2026).

Decadal predictions are calibrated using the variance

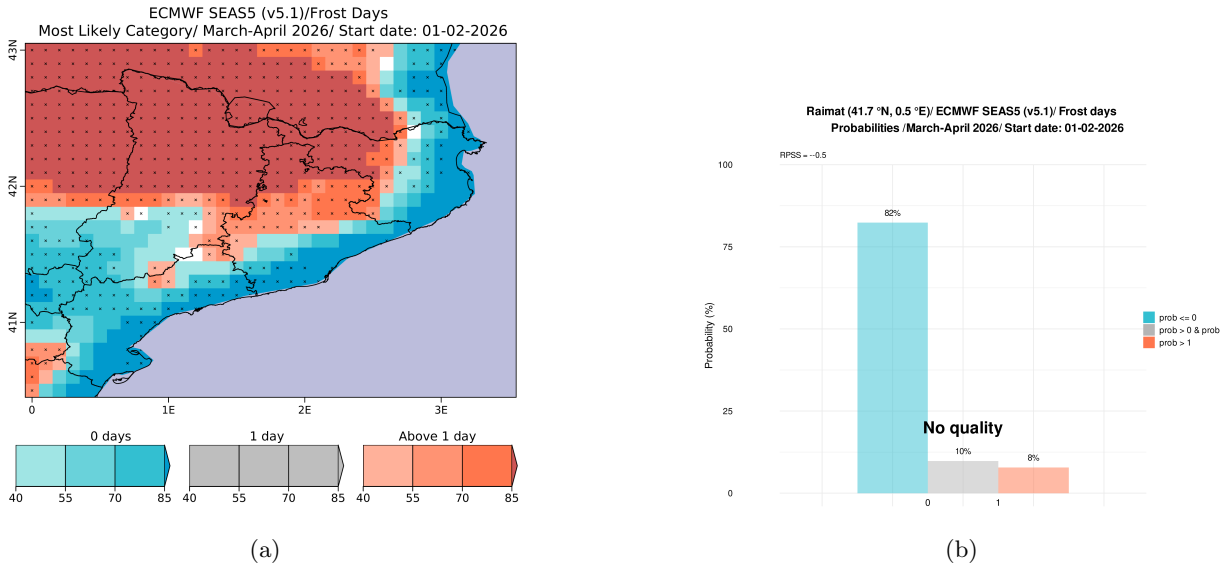


Figure 2: Most likely tercile predictions for March-April 2026 frost days. Seasonal forecast initialised the 1st of February 2026 for Catalunya (left) and Raïmat (right). (a) Dark blue indicates a high probability of below-normal frost-days, whereas dark red indicates a high probability of above normal frost-days. Black crosses mark areas with no forecast skill. (b) Bar plot for Raïmat showing tercile probabilities (82% below normal, 10% normal, 8% above normal). Faded colors with a "No quality" label indicate a lack of forecast skill. RPSS = -0.5.

inflation method to address recurring systematic errors *Doblas-Reyes et al. (2005)*. As with the seasonal predictions, decadal predictions are also verified against the ERA5-Land data set and the forecast quality is quantitatively assessed using the RPSS (*Torrallba et al. 2017*).

Each column in the figure represents one year. A prediction is considered successful when the black dot (observation) falls within the most intensely colored square (highest predicted probability); otherwise, the model failed to anticipate that year's conditions. This visualisation illustrates how well the model reproduces the observed variability of frost days at the Raïmat station over the past six decades.

C. Decision tree tool

Climate data are fed into a decision tree tool that translates probabilistic forecasts into operational decisions. The tool, called StraTREEgy, evaluates the optimal decision a user could take based on available climate predictions (*Saklani, S 2026*). This is done by computing the expected payoff of each decision based on user-defined actions and forecast probabilities to determine the most profitable strategy path. Using the tool with both climate prediction and climatology probabilities allows a comparison between forecast-based and climatology-based decisions.

The tool consists of two main sections. The first section contains the model configuration parameters, shown in Figure 4. The number of periods, with a maximum of five to avoid excessive complexity, is defined first; each period allows the user to introduce a set of actions, rep-

resenting decisions with different time horizons. After defining the actions for each period, the model establishes the different decision paths across all periods. Finally, the predicted probabilities for each tercile (below normal, normal, above normal) are entered.

Investing in frost protection and purchasing insurance are two actions considered by Codornú. Putting in place a frost protection system entails a significant investment and requires long-term planning and an overview of future predictions. This action is considered only in the decadal analysis, because seasonal information cannot support such a long-term decision. Conversely, insurance is purchased annually and is a decision that may be informed by both seasonal and decadal information. Additionally, insurance not only covers the vineyards against frost, but it also protects the plant against other threats.

The second section of the model configuration consists of a payoff table (Figure 5). This table has three columns corresponding to the three probability categories—above normal, normal, and below normal— while each row represents a possible combination of the actions described above.

A payoff is the outcome resulting from a specific action. In this study, and according to user preferences, payoffs are expressed as *Revenue*, *Profit*, and *Net Present Value* (NPV).

Revenue is defined as the expected monetary income; the main objective of the user is to maximise it, whether framed as cost minimisation or profit maximisation. Revenue in the below-normal (BN) state of nature is taken as

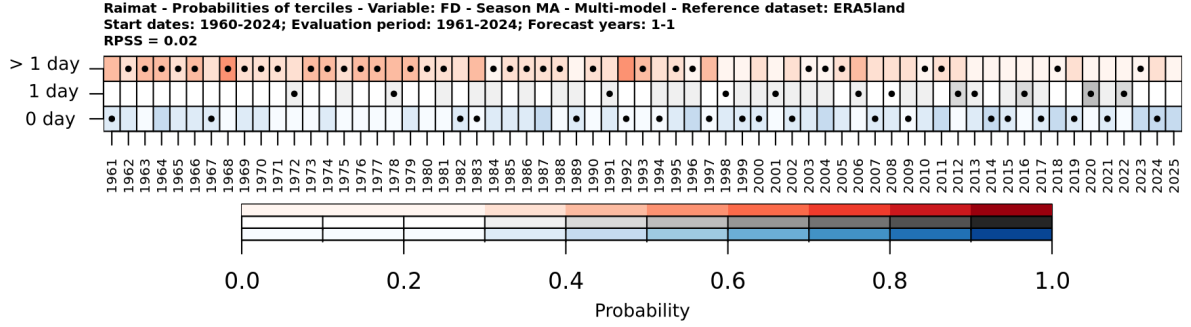


Figure 3: Predicted probability in each tercile category for Frost Days (March–April) at the Raïmat station, 1961–2025. Color intensity indicates the model’s assigned probability (red: above normal; grey: normal; blue: below normal), with lighter color indicating low probabilities and darker colors higher probabilities. Black dots mark the tercile in which the actual observation fell each year. Source: [Delgado-Torres et al. \(2024\)](#).

Figure 4: Decision tree configuration. Two actions are considered for frost protection: investing in a frost protection system (invest, –invest), and insuring the crop (insure, –insure). Three types of predictions are compared: climatological (equal tercile probabilities, 33.3% each), seasonal, and decadal predictions (with specific yearly probabilities). A forecast skill of 1 is assumed. Source: [Saklani, S \(2026\)](#)

the baseline, normalised to 1, since the absence of frost days does not affect benefits; all other matrix entries are expressed relative to this baseline. From this matrix, costs, losses, and avoided losses (costs of inaction) can be derived for each scenario. Revenue values (Appendix A1) were agreed with the user and based on experiential knowledge.

Profit is defined as the difference between revenue and costs for each period t (where $t = 0, \dots, n - 1$). In our case, $n=32$, since our seasonal forecast includes data from 1993 to 2024.

$$P_t = \text{Revenue}_t - C_{\text{insurance},t} - C_{\text{frost protection},t} \quad (1)$$

The *Net Present Value* (NPV) determines the current value of future cash flows generated by an investment, discounting future costs (e.g., maintenance) using a spe-

cific rate of return (cost of capital) to evaluate long-term profitability. The baseline data used in the analysis are detailed below.

Following discussions with the user, baseline revenue (without considering costs) for a standard year is set at 4000 € ha⁻¹ yr⁻¹, over a total estate area of 600 ha. The fixed installation cost of the frost protection system is approximately 6000 € ha⁻¹, and the annual insurance premium is approximately 100 € ha⁻¹ yr⁻¹. All matrix entries are normalised relative to baseline revenue, giving a normalised frost protection cost of $C_{fp} = 6000/4000 = 1.5$ and a normalised insurance cost of $C_{in} = 100/4000 = 0.025$ (see Appendix A1).

The following equation defines NPV:

$$NPV = \sum_{t=0}^{m-1} \frac{P_t}{(1+r)^t} - I_0 \quad (2)$$

Where P_t represents the profit generated in a specific time period t . At period $t = 0$, the profit corresponds to revenue minus the cost of the frost protection system and the cost of insurance. The normalised cost of frost protection is fixed at $C_{\text{frost protection},0} = 1.5$, representing the initial installation. For all subsequent periods ($t = 1, \dots, 31$), based on user confirmation, the cost of frost protection transitions to an annual maintenance fee equivalent to 5% of the original installation cost. A fixed discount rate of $r = 3\%$ is applied, yielding a discount factor of $(1+r)^t = (1.03)^t$. The initial investment cost (I_0) in the formula is set to zero, as initial setup costs are integrated directly into the profit (P_0).

Codornú indicated that the lifetime of a frost protection system ranges between 20 and 50 years. Given that the study spans a total horizon of $n = 32$ periods (1993–2024), we decided the system’s lifetime to also span $m = 32$ years (this is one of the assumptions de-

scribed in the next sub-section), so that the NPV is calculated to complete a full investment cycle coinciding with the total study horizon. This approach simplifies the case scenario and eliminates the need to make further decisions based on the tool's outputs prior to this period.

Assumptions

Three key assumptions are integrated into the model. The first assumption simplifies the tool's operability throughout the study, while the other two specifically simplify the NPV calculation:

- **Assumption 1 (Forecast skill):** When a forecast shows negative or very low skill, users find it difficult to trust and use it. Rather than reacting to small differences in skill scores, users tend to trust or distrust a forecast as a whole, a pattern consistent with heuristic-based decision-making under bounded rationality ([Kahneman and Tversky 1974](#), [Simon 1955](#)). Since forecasts delivered to users should ideally add value relative to climatology, in this work skill is assumed to be 1 or sufficiently high for users to trust the prediction, allowing the decision tree model to work directly from the comparison of probabilities and decisions.
- **Assumption 2 (Insurance decision):** While for seasonal predictions the insurance decision is assumed to be made annually, the analysis for decadal predictions focuses mainly on the investment decision. Accordingly, the insurance decision is assumed to be made once, at $t = 0$, and to remain constant for all subsequent periods. This assumption reflects the tendency for insurance contracts to be passively renewed each year rather than actively reconsidered, due to their relatively minor cost, which often leads to status quo bias and consumer inertia in insurance purchasing ([Handel 2013](#), [Samuelson and Zeckhauser 1988](#)).
- **Assumption 3 (Frost protection decision):** The frost protection decision is made at $t = 0$ and revisited every m years, matching the system's assumed lifespan. Once the investment option is selected by the user, it is not reconsidered within this m period. More frequent revision would turn the problem into a multi-stage one: the user would need to form expectations over future forecasts, solve those future decisions first, and work backward to evaluate the present decision.

With these values, Profit and NPV can be estimated to complete the payoff table (Figure 5). This information is entered into StraTREEgy to determine the optimal decision-making strategy.

As shown in the illustrative example of Figure 6, the tool indicates the sequence of decisions required to maximise the expected payoff. The optimal path starting

Payoffs		
Above Normal	Normal	Below Normal
Invest → Insure 17.475	Invest → Insure 17.475	Invest → Insure 17.475
~Invest → Insure 13.125	~Invest → Insure 13.125	~Invest → Insure 20.475
Invest → ~Insure 15.900	Invest → ~Insure 15.900	Invest → ~Insure 18.000
~Invest → ~Insure 6.300	~Invest → ~Insure 6.300	~Invest → ~Insure 21.000
Generate Decision Tree		

Figure 5: Payoffs under each possible scenario derived from the contingency matrix and calculation of NPV.

Source: [Saklani, S \(2026\)](#)

in the second period reflects the best decision going forward, assuming the first-period decision has already been made. Each path displays the resulting payoff for every possible state of nature considered in the table: below normal (BN), normal (N), and above normal (AN). The expected payoff under the optimal strategy (EP_{optimal}) is calculated as the probability-weighted average of the payoffs across all climate states and is used to select the strategy with the highest expected value.

Using the tool, actions are evaluated over the 32-year period from 1993 to 2024. To understand when the tool can be trusted, the results will be assessed and, if so, whether climatology or forecast-based information should be used.

III. Results and discussion

The outcomes of the tool are analysed separately for each time scale, since different decisions are being considered at each one.

For seasonal predictions, the interpretation is simpler because the only decision is whether to insure or not to insure. We already know that the user would choose to insure as a preestablished option, regardless of the forecast information. As shown in Figure 7, the tool always recommends purchasing insurance. Therefore, in this timescale, the seasonal climate service mainly serves to confirm the decision already being made, rather than to change behaviour on the user decision. This means that the added value of the seasonal prediction is limited in most cases, since it usually does not alter the user's action.

Looking at the tercile probabilities of forecasts for the analysed years, a higher probability of Below Normal (BN), meaning a lower risk of frost days, is associated with higher expected payoffs. This happens because, as the probability of frost risk decreases, the expected benefit of insurance, becomes smaller relative to its fixed cost (the premium). Eventually, when the probability of frost is low enough, the cost of insurance is no longer justified by the risk it covers, and not insuring becomes the

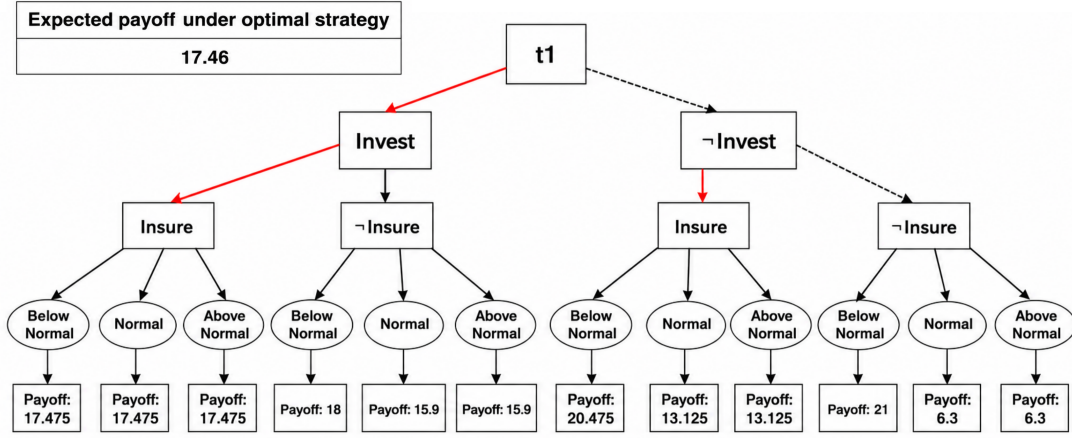


Figure 6: Decision tree illustrating the optimal strategy path, showing the optimal choice at each decision node. In this specific case, the optimal path consists of investing and insuring, with a normalised expected payoff (Net Present Value) of 17.46. Adapted from: [Saklani, S \(2026\)](#)

optimal choice.

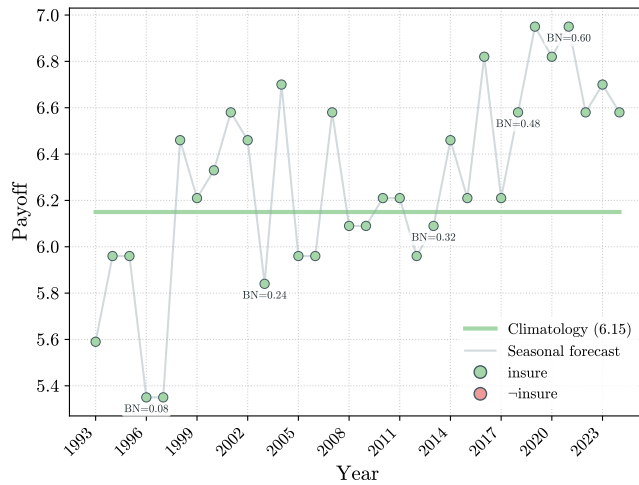


Figure 7: Evolution of profit (payoffs) under the seasonal forecast. Insurance is the only action selected as optimal across all years. The climatology-based payoff remains constant at 6.15, while forecast-based payoffs show an increasing trend, as the probability of below-normal conditions increases through the years.

According to the calculations, the tool only changes its recommendation from insure to not insure when the probability of BN is extremely high, around 94%. Therefore, only under very favourable conditions would the seasonal forecast lead to a different decision.

For the decadal forecast, the optimal expected path is identified based on the Net Present Value (NPV). Figure 8 shows the tool recommendation for each year. Following Assumption 3 (Section II C), if investing in a frost protection system is recommended in the first year and

the user follows this decision, this decision is not considered for the following 32 years, since the system will be in place. Once this path is defined, profits are used to compare the outcomes of following versus not following the tool's recommendation in 1993.

Using both climatology and the climate service, the tool recommends the same option of investing and insuring in 1993 (Figure 8), the only remaining cost in subsequent years is the annual insurance.

Using Equation 1, and knowing that the frost protection system cost of 1.5 is only incurred in the first year of the 32-year period, for the remaining years only the insurance cost applies (0.025). The total (dimensionless, normalised) profit is:

$$(1 - 1.5 - 0.025) + 31 \times (1 - 0.025) = 29.7 \quad (3)$$

By contrast, if the user does not follow the tool recommendation, the expected annual profit under climatology is given by the climatological probabilities of the non-below-normal and below-normal terciles (0.67 and 0.33, respectively) weighted by their corresponding payoffs (0.65 and 1, A1), and subtracting the insurance cost. Resulting in a total profit over the 32-year period of:

$$(0.67 \times 0.65 + 0.33 \times 1 - 0.025) \times 32 \approx 23.68 \quad (4)$$

Using the climate service, and considering forecast probabilities predicted for each year:

$$\sum_{t=0}^{n-1} [Pr(AN + N)_t \times 0.65 + Pr(BN)_t \times 1 - 0.025] = 25.20 \quad (5)$$

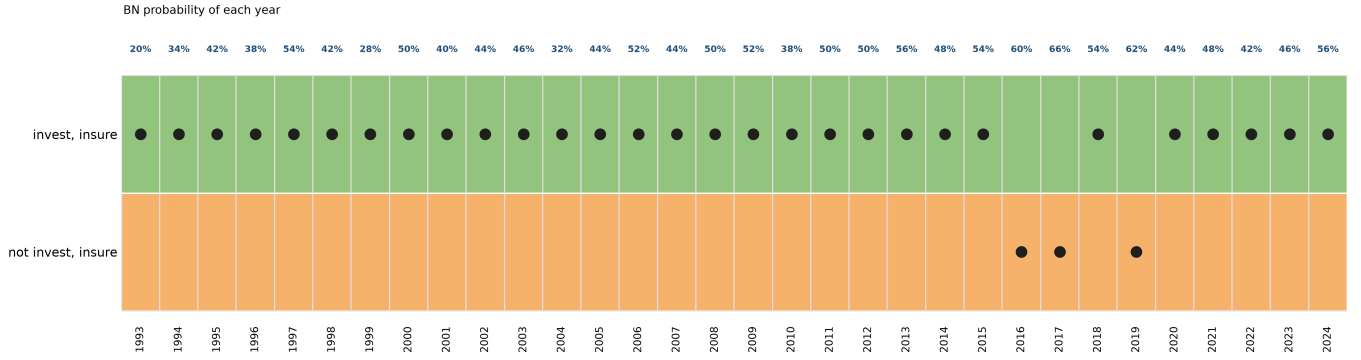


Figure 8: Outputs of the tool for decadal forecast. In green, the option of investing and insuring; in orange, the option of not investing but insuring. Black dots mark the optimal path selected by the tool based on the given probabilities. Above each year, the probability of the Below Normal tercile is shown in dark blue.

These results indicate that, for the case analysed here, following the tool’s recommendation to invest and insure in 1993 yields a higher total profit over the long term (29.7, Equation 3), with an additional gain of 6.02 relative to climatology without investment (23.68, Equation 4) and of 4.5 relative to climate services without investment (25.20, Equation 5). Although using the climate service without investment improves the expected profit relative to climatology (25.20 vs. 23.68), the improvement is not enough to outweigh the profit associated with following the tool’s recommendation of investing (29.7).

A sensitivity analysis shows that the recommendation to invest would only switch to not investing if $\text{Pr}(\text{BN})$ exceeded approximately 60%. Since the observed value in 1993 was considerably low (20%), both information sources (i.e., climatological vs. forecast-based) led to the same initial decision to invest that year. Consequently, the practical added value of the forecast for this specific investment decision is limited in this case.

The analysis shows that the main added value of decadal predictions does not lie in profit maximisation, since climatology also leads to the optimal decision, but in their ability to capture the inter-annual climate variability that climatology cannot represent. This is a relevant finding, showing that the benefit of investing in a frost protection system depends on the persistence of frost risk over a sufficiently long period to justify the initial cost. In this case, the observed inter-annual variability was not large enough to make non-investment more profitable than investing.

An additional added value of the tool, identified during interactions with the user, is the possibility of presenting the two timescales together in the same climate service. This has allowed the user to compare decisions across timescales and recognise that a strategy which appears suboptimal in the short term may nonetheless be preferable in the long term.

IV. Limitations

Despite these findings, this study presents several limitations that should be acknowledged. First, the analysis focuses on a single case study, which limits the generalisation of the results to other sectors or climate-related risks, even though the methodological framework is transferable. Second, the frost protection system investment is modelled under a simplified assumption of revision every m years, without accounting for possible earlier decisions, while insurance is assumed to be a constant decision for the remaining years, since it is still an interesting option for covering other types of damage besides frost (Assumptions 2 and 3). Finally, forecast skill is assumed to be sufficiently high whenever information is delivered to the user, while we know it is not always the case (Assumption 1). This simplifies the decision-making process but does not represent the current levels of skill of the climate prediction systems.

V. Conclusions

This thesis assesses the value of a climate service based on seasonal and decadal climate predictions of spring frost. The service has been co-developed with Codorníu and is intended to help wine sector users make optimal decisions and maximise payoffs.

To carry out this evaluation, probabilistic climate information has been integrated into a tool that uses a decision tree methodology which maximises the user’s payoffs. The decisions considered to minimise vineyard damage and ensure wine production are to insure the crop and to invest in a frost protection system.

For seasonal predictions, the tool recommends purchasing insurance in all years, except when the probability of below-normal conditions (i.e., no frost) exceeds 94%, showing a limited value of the prediction, since it confirms the user’s existing practice. For decadal predictions, following the tool’s recommendation to invest and insure in the first year yields the highest total profit over the 32-year period, exceeding both the climatological and

forecast-based non-investment scenarios, although forecast information alone still outperforms climatology in the absence of investment. The added value of decadal climate services lies not only in maximising profit but also in their capacity to represent inter-annual variability.

Our work also shows the importance of applying a co-production process in which user feedback is incorporated throughout the development of the decision tool. Co-production enables a deeper understanding of the user's decision-making context. This results in a tool that more accurately reflects real-world decision processes and supports more effective decision-making, enhancing the value of the climate service. An example of this feedback is the combination of seasonal and decadal predictions in the climate service, which allows users to compare decisions across timescales, recognising the trade-offs between short- and long-term strategies.

Future work could also explore alternative climate indicators and decisions beyond those considered here, incorporate forecast skill explicitly into the model rather than assuming it to be sufficiently high, and explore its potential at different and new timescales (e.g., sub-seasonal, multi-annual, multi-decadal).

While this thesis focuses on a single case study of frost risk management in viticulture, the decision tree framework developed can be transferred to a wide range of decision-making contexts. These include other climate-sensitive within the wine sector, such as water management, as well as applications in other relevant socio-economic sectors, including the humanitarian sector (which has been also studied in the ASPECT project).

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VI. Appendix

Specification	Seasonal	Decadal
Forecast system	ECMWF SEAS5 (v5.1)	DCPP-A (17 forecast systems)
Reference	Johnson et al. (2019)	Boer et al. (2016) , Delgado-Torres et al. (2026)
Ensemble members	25 (hindcast)/51 (forecast)	197 (total)
Spatial resolution	1°x 1°	Different resolutions (0.7°x 0.7° - 2.8°x 2.8°)
Hindcast period	1993–2016	1960–2024
Start dates	1 st day of the month	End of each year
Time horizon	6 months	10 years
Observational reference	ERA5-Land (Muñoz-Sabater et al. 2021)	
Verification metric	RPSS (Wilks 2011)	
Calibration methods	Quantile mapping (Berg et al. 2024)	Variance inflation (Doblas-Reyes et al. 2005)
Downscaling method	Calibration + Interpolation (Duzenli et al. 2026)	
Cross-validation	Leave-one-out cross-validation	

Table I: Description of the seasonal and decadal prediction frameworks used in this study.

Contingency Matrix			
Scenario (Actions; Nature state)	Cfp	Cin	Rev
Invest → Insure			
Invest → insure; AN	1.5	0.025	1
Invest → insure; N	1.5	0.025	1
Invest → insure; BN	1.5	0.025	1
¬Invest → Insure			
¬Invest → insure; AN	0	0.025	0.65
¬Invest → insure; N	0	0.025	0.65
¬Invest → insure; BN	0	0.025	1
Invest → ¬Insure			
Invest → ¬insure; AN	1.5	0	0.90
Invest → ¬insure; N	1.5	0	0.90
Invest → ¬insure; BN	1.5	0	1
¬Invest → ¬Insure			
¬Invest → ¬insure; AN	0	0	0.30
¬Invest → ¬insure; N	0	0	0.30
¬Invest → ¬insure; BN	0	0	1

Figure A1: Contingency matrix. Rows represent the possible scenarios: the four combinations of the investment and insurance decisions, each combined with the three possible states of nature. Columns detail the previously calculated costs of frost protection and insurance, as well as the revenue based on the user's criteria and perspective on damage and risk.