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The predictive power of crowdsourcing users' behaviour: case study on drought risk in viticulture

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ABSTRACT

Monitoring vine water status at regional scale is a key challenge in viticulture, especially in the context of climate change. Crowdsourcing projects produce large datasets of geolocated and timestamped field observations collected by farmers and wine industry professionals. However, most studies have focused exclusively on the explicit information provided by contributors, while the implicit information embedded in their behavioural patterns has received little attention. In this study, it was hypothesised that the timing of observations by viticulture professionals reflects their expert perception of drought risk, and that this behavioural signal could improve drought risk predictions early in the growing season. The study was carried out over 2020–2024 in southern France across three wine regions: Languedoc-Roussillon, Provence, and Vallée du Rhône. Observations from the Apex-Vigne crowdsourcing application were used, including 16,809 observations across 1776 different plot-years. Drought risk classes were assigned to each plot-year using hierarchical clustering of climatic variables derived from SAFRAN meteorological data. Two Random Forest models were trained to predict drought risk classes and compared. The first was a climatic model relying solely on the Climatic Dryness Index (CDI), and the second was a crowdsourcing-enhanced model incorporating both CDI and Date of First Observation (DFO), defined as the day of the year when a contributor began monitoring a given plot. The results showed that the crowdsourcing-enhanced model consistently outperformed the climatic model, with accuracies exceeding 90 % across all years. The improvement of the crowdsourcing-enhanced model was particularly significant during the driest years, reaching up to 16.7 %. These results show that user behaviour in crowdsourcing projects is a valuable, low-cost source of implicit information in viticulture.

KEYWORDS: citizen science, smartphone mobile application, vine water status, *Vitis vinifera*

INTRODUCTION

Vine water status significantly influences both yield (Pou *et al.,* 2023) and wine quality (Zufferey *et al.,* 2020). To make the best decisions possible for vineyard management, vinegrowers seek to identify and anticipate situations in which vine water status reaches levels that may impair vine performance. These "drought" situations occur under certain conditions of environmental water scarcity (Scholasch & Rienth, 2019). Therefore, vinegrowers seek to estimate, as early as possible in the season, whether their plots are likely to face such a drought situation by the end of the season. Estimating the risk of drought at the regional scale is of significant interest for the wine sector in terms of anticipating harvest logistics (Pichon *et al.,* 2022) providing technical advice to farmers (King & Shellie, 2023) and to characterise and monitor the terroir in a context of climate change (van Leeuwen *et al.,* 2018). However, the drought risk exhibits substantial spatiotemporal variability due to climatic conditions, which can vary significantly depending on factors such as altitude, soil characteristics, and cultural practices related to soil and canopy management (Taylor *et al.,* 2010). Monitoring drought risk at the regional scale is therefore a major challenge because it requires reliable, high-resolution spatiotemporal data. Nevertheless, it is difficult to find data sources that can fulfil this need at an acceptable cost in an operational context (Acevedo-Opazo *et al.,* 2008).

Crowdsourcing of spatial observations has emerged as a credible data source, capable of providing observations in sufficient quantity and quality for characterising dynamic agricultural systems (Minet *et al.,* 2017) at different spatial scales. This approach, by leveraging a network of contributors equipped with personal smartphones, enables the generation of massive datasets of time-stamped and geolocated field observations (Muller *et al.,* 2015). Therefore, crowdsourcing presents an interest for monitoring a spatiotemporal variable like vine water status at a large spatial scale. Pichon *et al.* (2022) successfully tested this approach for monitoring vine water status at the regional scale in southern France.

In agriculture, particularly viticulture, crowdsourcing involves participants who are professionals in the wine industry. In this context, data collection is driven by contributors' professional interest and guided by their expertise (Minet *et al.,* 2017). These contributors are mainly winegrowers or advisors rather than enthusiastic amateurs. In crowdsourcing projects in viticulture, participation is therefore motivated by pragmatic utility; contributors engage when it serves their own operational interests (Van Etten *et al.,* 2019). They collect observations only when these are critical for decision-making in their vineyards. Consequently, contributors' behaviours (*e.g.*, the timing and frequency of their observations) are driven by the phenomenon being observed. Studying contributors' behaviours should therefore provide information about this phenomenon. Goodchild (2007) described this approach with the concept of "humans as sensors".

However, most existing studies utilising crowdsourcing for regional-scale data acquisition focus exclusively on the explicit attribute values collected by contributors, such as canopy measurement (Francone *et al.,* 2014) and plant identification (Bonnet *et al.,* 2018). The implicit information, corresponding to the hidden knowledge contained in contributors' behaviour, is almost always overlooked (Guo *et al.,* 2020). However, in contexts that require high domain expertise, such as viticulture, this behavioural dimension may be crucial. Since viticulture stakeholders rely on deep, experiential knowledge to guide their actions (Krzywoszynska, 2016) their behavioural patterns could constitute a valuable, although underexploited, source of information. In this work, it was hypothesised that contributors to crowdsourcing projects in viticulture, drawing on their experience and knowledge, would behave differently depending on how high they estimated the drought risk to be. Therefore, studying their behavioural patterns could provide information about this drought risk.

This hypothesis was tested on a crowdsourcing project called Apex-Vigne, briefly summarised hereafter and presented in detail by Pichon *et al.* (2022). Apex-Vigne was selected as a case study for several reasons. First, the mobile application has been in use since 2019, allowing for the study of vine water status at a regional scale over seven years. Second, participants in this project are stakeholders in the wine industry (winegrowers and advisors). They monitor the vine water status by observing shoot growth throughout the growing season and measuring the iG-Apex index (Pichon *et al.,* 2023*)*. This index, which describes shoot growth, is a proxy for vine water status under certain conditions. They use this index to make decisions about vineyard management (*e.g.*, mulching, reducing canopy volume, etc.). Data collected is geolocated and time-stamped. Finally, contributors are autonomous and rely on their expertise to decide when to start observations, making this project a suitable test of the hypothesis. Apex-Vigne has generated a massive dataset of more than 30,000 observations, primarily from metropolitan France.

The general approach of this study was to demonstrate that the behaviour of Apex-Vigne users, specifically the timing of their observations, provides meaningful information about the drought risk experienced by the vine during the growing season. The objective of this paper is therefore to investigate the potential of using Apex-Vigne user behaviour as a valuable proxy for refining drought risk assessments at the vineyard level.

MATERIALS AND METHODS

The general approach of the study was as follows. Actual drought risk at the end of the season was determined by classification, for each field *i* for a given year, based on climatic variables measured throughout the wine-growing season, from date t_0 to date t_{end} (Figure 1) (details in section 1.2). This risk was noted as $R_i^t(t_{\text{end}})$. In an operational context, vineyard managers aim to predict $R_i^t(t_{\text{end}})$ as early as possible

after flowering to anticipate and adapt their water, canopy, and soil management practices. The approach presented in this paper aimed to predict $R_i^t(t_{end})$ at a date t earlier than date t_{end} based on the information available at date t. This prediction was denoted $\widehat{R_i^t}(t_{end})$. Two predictive models were developed (details in section 2). The first one, called the climatic model, used only climatic data available at time t to obtain the prediction $\widehat{R_i^t}(t_{end})$. This model represented a classical approach that uses climate data to obtain the prediction $\widehat{R_i^t}(t_{end})$. The second, called the crowdsourcing-enhanced model, combined the climatic data used in the climatic model with information about users' behaviour also available at time t to obtain the prediction $\widehat{R_i^t}(t_{end})$. This model represented an approach that leveraged information contained in users' behaviour (see section 1.1.2 for users' behaviour definition). The two models and their inputs are summarised in Figure 1 (details in section 2).

To assess the added value of information about users' behaviour, the ability of the two models to predict correctly $R_i^t(t_{end})$ was compared using their accuracy. The analysis covered the 2020–2024 period in southern France. The following sections describe the data and methods in detail.

1. Data

Several terms used repeatedly in this paper need to be defined. First, a mesh-year is a spatial surface (an 8 km by 8 km square) for which time series of weather data are considered for a given year. Secondly, a plot-year refers to a spatial point object corresponding to a farm plot on which shoot growth observations were made via the Apex-Vigne application in a given year. In that context, each plot-year is included in a mesh-year.

1.1. Input data

1.1.1. Weather data

Weather data from SAFRAN (a service providing official weather data for France) were used to determine drought risk. They were provided by Météo-France and were downloaded via the SICLIMA platform developed by AgroClim-INRAE (https://agroclim.inrae.fr/siclima/). The data provided were available daily and covered the whole territory of France (Bertuzzi *et al.*, 2022) (Figure 2). Then, climatic variables for drought risk determination were calculated as described in Table 1.

1.1.2. Users' behaviour

User behaviour refers in this work to the decisions that farmers make and the actions they take regarding their knowledge (Krzywoszynska, 2016). In the case of Apex-Vigne, the protocol is highly standardised, leaving users with little flexibility. The main decision they have to make is the date on which to start monitoring a plot. In this study, the Day of Year of First Observation (DFO) of iG-Apex was therefore chosen as a proxy for user behaviour.

The adoption of such an indicator presupposes that Apex-Vigne users are expert operators possessing an in-depth understanding of viticultural dynamics. Consequently, the hypothesis was formulated that their experiential knowledge, encompassing both knowledge and experience with the specific vineyard plots and the context of the vintage, biased or guided their observational data collection behaviour. In particular, it was hypothesised that the initiation of plot monitoring by the user was conditioned by reaching a perceptual threshold. This threshold corresponded to the day of the year (DOY) when their tacit knowledge suggested that the probability of developing high drought stress on that specific plot was judged to be excessively significant.

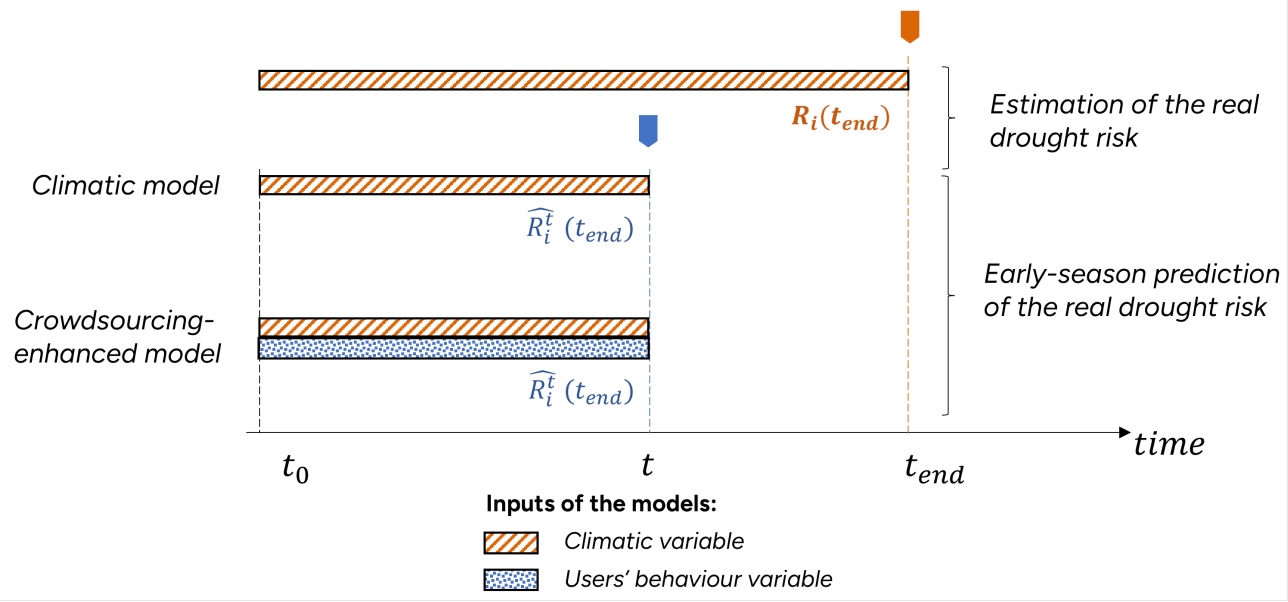


FIGURE 1. Schematic representation of the general approach of the study. Drought risk at the end of the season, $R_i^t(t_{end})$ is determined for each field *i* with climatic variables over the whole season. Drought risk of each field, $\widehat{R_i^t}(t_{end})$, is predicted earlier in the season (at time *t*) with two models: a climatic model relying solely on climatic data and a crowdsourcing-enhanced model incorporating both climatic data and contributor behaviour.

1.2. Drought risk class determination

The objective was to associate drought risk classes to each plot-year for which a time series of Apex-Vigne observations was available.

First, hierarchical clustering (HC) was used to classify the mesh-years. The algorithm was performed using Ward's criterion (Ward, 1963). This criterion measures the increase in within-cluster variance that occurs when two clusters are merged. At each iteration, the pair of clusters selected for merging is the one that minimises this increase. The clustering results are represented by a dendrogram, where the x-axis represents the mesh-years and the y-axis indicates the value of Ward's criterion at each merging step. Using this dendrogram, a natural cutoff point can be identified to determine the appropriate number of clusters to retain and their composition, thereby defining the drought risk classes. To capture the complexity of drought over time, the algorithm used several reference climatic variables and indices, selected from the literature and calculated over different time intervals for each mesh-year (listed in Table 1). Using these variables, the clustering algorithm assigned drought risk classes for mesh-years.

In a second step, all plot-years within a given mesh-year were subsequently attributed to the same drought risk class.

2. Training and evaluation of predictive models

To test the relevance of the DFO as a predictor of drought risk class, three models were fitted, evaluated and compared: a null model, a climatic model and a crowdsourcing-enhanced model. The null model, without any predictor, systematically predicts for a plot-year the class which is the majority in the training set. The null model served as a baseline for comparison. Indeed, when classes are imbalanced, a null model which does not use any predictor can have good performance in terms of overall accuracy, simply because it favours the dominant class. It was then important to check that the proposed models have even better performance than this null model. For the sake of simplicity, the climatic model was only based on the CDI. It was calculated from October until the DFO, to integrate the climate experienced by the vine during autumn, winter and spring until the first observation was made. The crowdsourcing-enhanced model used both the CDI until the DFO and the DFO itself as predictors. It was hypothesised that the crowdsourcing-enhanced model would perform better than the climatic model and the null model. The predictive models and their inputs were summarised in Table 2.

TABLE 2. The different Predictive models used for drought risk prediction and their specific inputs: CDI and DFO refer, respectively, to the climatic variable and the user behaviour variable mentioned in Figure 1. The null model does not use any input.

Models (Random Forests)	Inputs
Climatic Model	$CDI_{October - DFO}$
Crowdsourcing-enhanced model	$CDI_{October - DFO}$ + DFO
Null model	-

All the models were built on a similar basis, using Random Forest (Breiman, 2001) algorithms. They were calibrated to predict the drought risk at the end of the season. The crowdsourcing-enhanced model and the climatic model were trained and evaluated using the five-year dataset and a leave-one-year-out validation scheme: four years composed the training set, and the remaining year constituted the test set (for example, training using 2021–2024 data, and testing using 2020 data). The null model was not trained, but only predicted the drought risk each year. Models' performances were assessed using confusion matrices and accuracy ($\text{accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)}$, with TP: True Positive, TN: True Negative, FP: False Positive, and FN: False Negative). Only accuracy was used as a metric in this study, as the primary objective was to compare the models to show the existence of predictive information in the users' behaviour variable, and not to optimise an effective tool for predicting the drought risk. Moreover, the importance of the DFO variable was evaluated using a permutation procedure. For each test set (corresponding to data of one year, for instance, 2020 data), the crowdsourcing-enhanced model was tested 100 times on permuted test sets, following the approach described by Breiman (2001). These permuted test sets corresponded to the initial test set in which the DFO values were randomly

TABLE 1. List of climatic variables used for drought risk classification and the time intervals on which they were calculated (y-1 means the previous year and y the current year). The variables were calculated from i) daily minimum, maximum, and average temperature (°C), ii) daily solid and liquid rainfall (mm), and iii) daily potential evapotranspiration (Penman-Monteith formula, mm) data, available for the period January 1st 2019 to December 31st 2024.

Climatic variables	Time interval
Climatic Dryness Index (CDI): Sum over a given period of time of the daily difference between precipitation and evapotranspiration Inspired by Thornthwaite (1948)	October (y-1) - September (y); October (y-1) - July (y); October (y-1) - June (y); October (y-1) - May (y); October (y-1) - April; October (y-1) - March (y); April (y) -August (y); March (y) - July (y); February (y) - June (y); July (y) - August (y); June (y) - July (y); May (y) - June (y); April (y) - May (y); 60 days before the DFO; 30 days before the DFO; October - DFO
Huglin index (Huglin, 1978)	April (y) - September (y)
Winkler index (Amerine & Winkler, 1944)	April (y) - September (y)
Mean daily maximum temperature	October (y-1) - July (y); February (y) - June (y); June (y) - August (y)
Mean daily temperature	October (y-1) - July (y); February (y) - June (y); June (y) - August (y)

permuted between the observations. The median accuracy across the 100 permutations was then compared to the accuracy on the original test set without permutation. The idea was to measure how the prediction error of the model evolves after permuting the values of the DFO, which breaks the relationship between DFO and the true outcome. A decrease in the prediction accuracy means that the model relies on DFO for prediction, and hence shows the importance of this variable.

A spatial evaluation of the prediction error of the climatic model and the crowdsourcing-enhanced model was also provided. Three categories of plot-year predictions were identified. Category 1 corresponded to plot-years where the crowdsourcing-enhanced model was successful at predicting the drought risk class, whereas the climatic model was not. Category 2 corresponded to plot-years where the climatic model was successful, while the crowdsourcing-enhanced model was not. Category 3 corresponded to plot-years where neither model was successful at predicting the drought risk. This procedure was used to verify if there were any spatial patterns in the models' prediction errors.

3. Study zone

The study zone (Figure 2) covered 34,193 km², corresponding to the boundaries of three wine regions in southern France: Languedoc-Roussillon, Provence, and Vallée du Rhône. The climate is Mediterranean, and the majority of soils present a low water-holding capacity (Pichon *et al.,* 2022). Therefore, monitoring vine water status is a major issue for the many wine growers in the study zone. For the period 2020–2024, across 3108 mesh-years, 1776 plot-years with at least three observations were monitored via the Apex-Vigne app in this study zone, for over 16,809 observations in total (Figure 2).

4. Tests of significant differences between drought risk classes

To determine whether CDI and DFO differed significantly across the identified drought risk classes, both variables were analysed using Generalised Least Squares (GLS) models, with class membership as the sole fixed effect. To account for spatial dependence, these models incorporated a spatially structured residual covariance, modelled as an exponential function of the Euclidean distance between observation locations. The significance of the class effect was assessed using a likelihood ratio test comparing each model to a *null model* with a spatial covariance structure but no class effect.

5. Software

All the data processing and statistical analysis were performed using *R version 4.3.2*. PCA and HC were computed using the *FactoMineR version 2.11* library. The Random Forest models were computed using the *randomForest package version 4.7.1.2*. Confusion matrices were generated using the *caret package version 7.0.1*. GLS models were fitted using *the gls()* function from the nlme package *version 3.1-171*. All the maps were produced in *QGIS 3.44.2*.

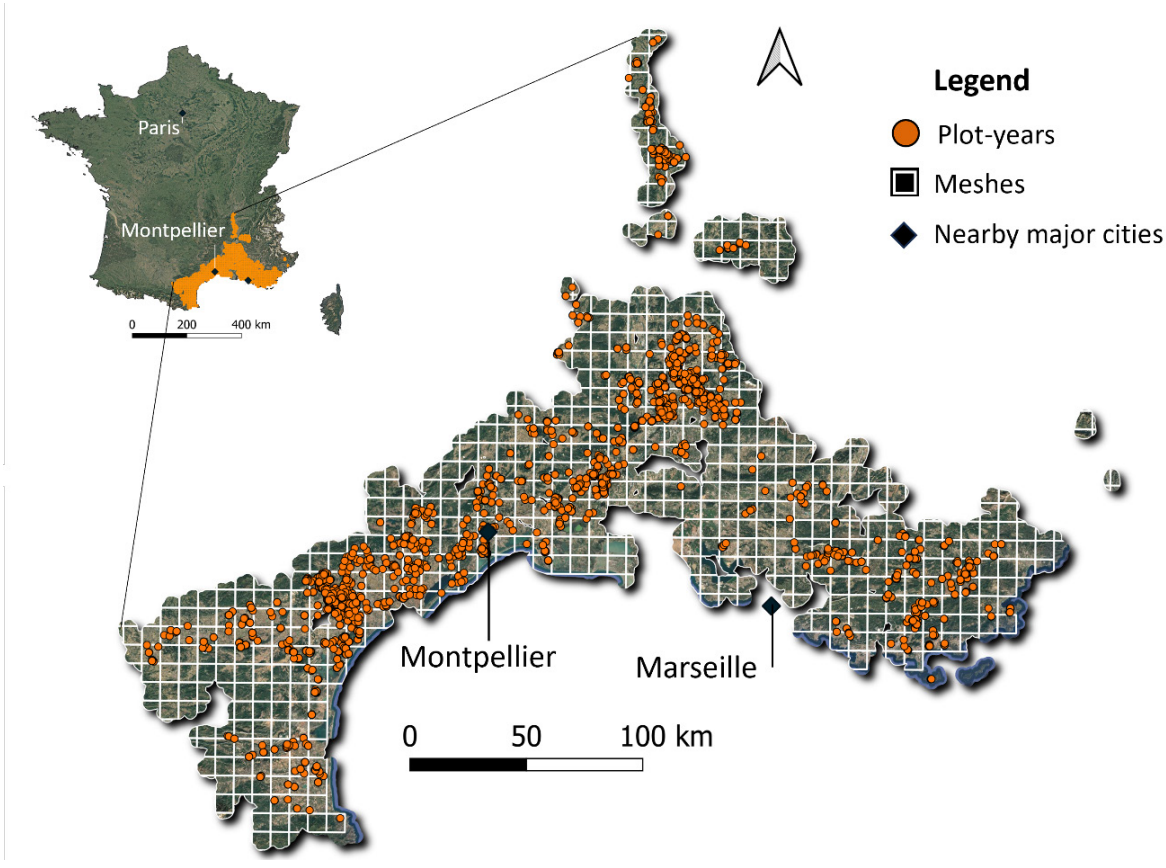


FIGURE 2. SAFRAN meshes and spatial distribution of the 1776 plot-years considered in this study, a plot-year being defined by three observations performed with the Apex-Vigne app in the same field and the same year.

RESULTS

Figure 3 shows the clustering results of the 3108 mesh-years following the HC. The dendrogram revealed a cutoff point for the Ward criterion, where two vertical lines are crossed. The long branches indicated a strong internal cohesion within two obvious classes and a clear distinction between them (Figure 3a). Two classes of mesh-years were therefore kept. These two classes respectively contain 1890 and 1218 mesh-years (Figure 3b). The median CDI was approximately –478 mm and –661 mm, respectively, for classes 1 and 2 (Figure 3b). Based on these results, class 1 was characterised by drier conditions and was therefore defined as the *high drought risk* class, while class 2 represented the *low drought risk* class. The GLS models showed that the CDIs are indeed significantly different between the two determined risk classes, for each year (see supplementary data in appendices). These designations, *high drought risk* and *low drought risk*, resulting from the clustering, will be used throughout this paper.

The geolocation of the mesh-years allowed visualisation of drought-risk spatiotemporal trends in the study zone. The spatial distribution of high and low drought risk classes revealed strong spatial coherence, with organised spatial patterns that evolve from year to year while maintaining a consistent overall structure (Figure 4). Regardless of the year, a downward gradient of drought risk was observed from the coast to the inland areas. This pattern provided qualitative spatial validation of the clustering results, as coastal zones are known to experience warmer climatic conditions than inland zones. The years 2020, 2021, and 2024 have shown a relatively large number of mesh-years with low drought risk. Conversely, 2022 and 2023 were characterised by predominantly high drought risk across most mesh-years, indicating drier conditions compared to the other years. This determination of drought risk classes was then used to train and evaluate the predictive models.

The accuracy of drought risk class prediction early in the season (at DFO) varied from year to year for all the models tested (Figure 5). The year-by-year analysis revealed the crowdsourcing-enhanced model to be very stable (always above 90 % accuracy) and consistently more accurate than the other models. In contrast, the accuracy of the climatic model varied more significantly across years, from 75.6 % to 92.9 %. The accuracy gap between the climatic and crowdsourcing-enhanced models widened by 14.3 % and 16.7 % in 2022 and 2023, respectively. Both crowdsourcing-enhanced and climatic models outperformed the null model in 2020, 2021, and 2024. However, during the driest years (2022–2023), the null model significantly outperformed the climatic model (by 16.2 % and 16.3 % in 2022 and 2023, respectively). Finally, the crowdsourcing-enhanced model consistently outperformed the results obtained with the permutation procedure for all years except in 2022. In that year, their accuracies were very close to each other (< 2 % difference).

The confusion matrices for the drought risk class predictions early in the season offered a detailed assessment of model accuracy and predictive performance. For illustrative purposes, the results presented here focus on the 2024 growing season (Table 3), but similar results were observed in years 2020 to 2023. In 2024, the climatic model achieved a prediction accuracy of approximately 85.5 % (556 correct predictions and 94 errors). In comparison, the crowdsourcing-enhanced model significantly outperformed, yielding an accuracy of 93.1 % (605 correct predictions and 45 errors). Indeed, the crowdsourcing-enhanced model corrected the prediction of drought risk for 53 plots (18 false negatives instead of 71) compared to the climatic model. However, it also resulted in a false prediction of drought risk class for 4 supplementary plots (27 false positives instead of 23). The null model predicted with an accuracy of 77.4 %. The permutation procedure gave an accuracy of 86.2 %.

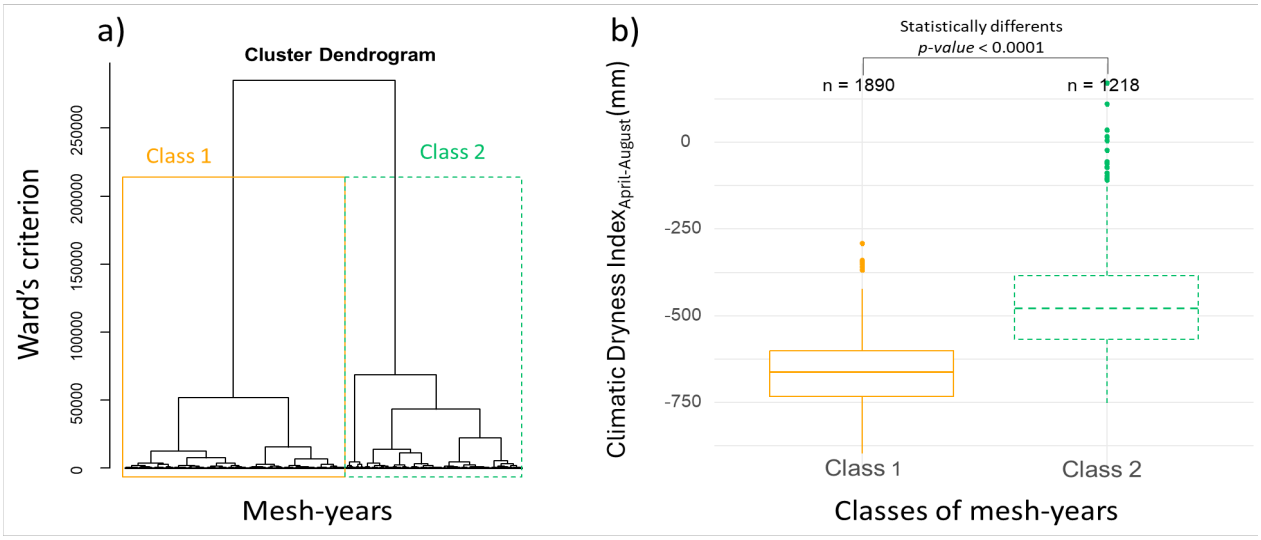


FIGURE 3. a) Dendrogram of the Hierarchical Clustering of mesh-years in the study zone for years 2020–2024 based on weather data. The two classes resulting from the clustering are represented in yellow and green. b) Illustration of the Climatic Dryness Index$_{\text{April-August}}$ for the two classes.

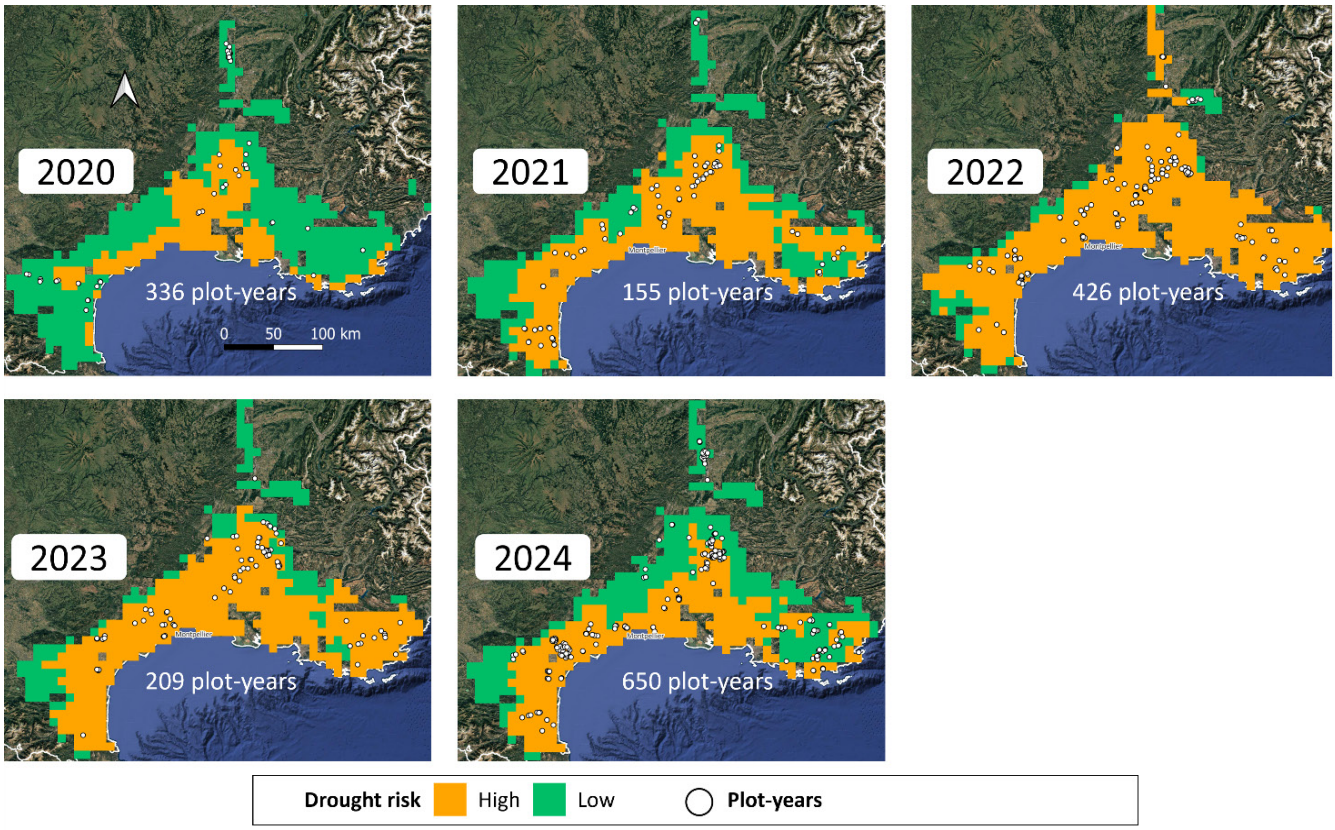


FIGURE 4. Spatial distribution of drought risk in the study zone over the 5 studied years and location of plot-years where Apex-Vigne observations were collected.

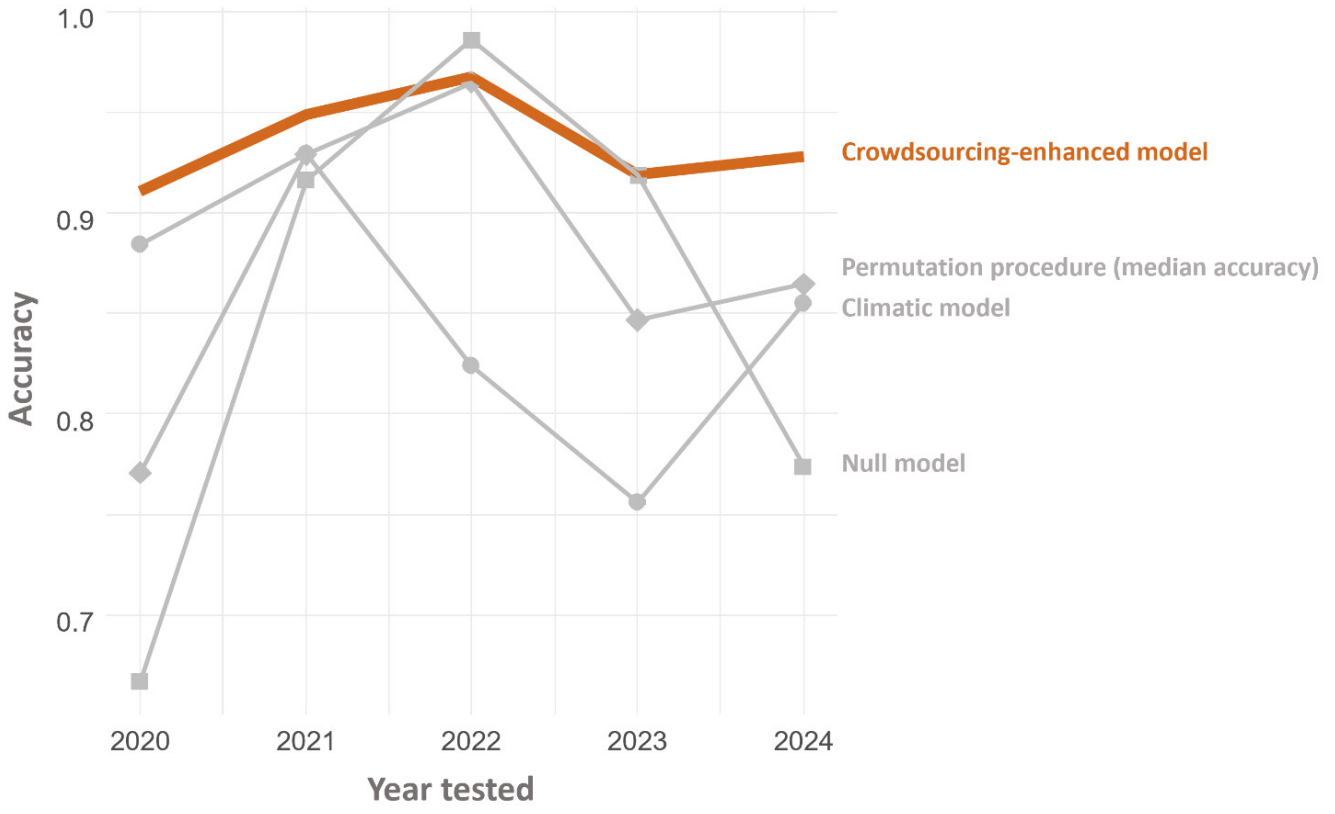


FIGURE 5. Observed accuracy for the different models (2020–2024): null model, climatic model, and crowdsourcing-enhanced model. Early-season drought risk class predictions are compared to the determined class of drought risk at the end of the season, and to results of the permutation procedure (median accuracy).

For all years combined, 181 plot-years had an incorrect prediction of drought risk class with the climatic model but a correct one with the crowdsourcing-enhanced model. Figure 6a shows that they are randomly distributed over the study zone, with a slight predominance in the eastern and south-eastern parts. For these 181 plot-years, adding the DFO in the random forest algorithm allowed a shift from an incorrect drought risk class prediction to a correct one. On the contrary, for 89 plot-years, the drought risk class prediction was correct with the climatic model but incorrect with the crowdsourcing-enhanced model. For these plot-years, the introduction of DFO degraded the quality of the drought risk class prediction. They appeared to be clustered in only a few localised spots over the study zone (Figure 6b). Finally, for 24 plot-years, neither model could predict the drought risk class correctly. These plot-years were clustered in 4 spots, all located in the "Provence" and "Côtes du Rhône" regions (Figure 6c).

In order to understand why the crowdsourcing-enhanced model was better than the climatic model, the distributions of the Dates of First Observation (expressed as the day number of the year) were examined according to the determined drought risk class of plot-years. Across all years, observations for plot-years in the high drought risk class generally began earlier than those in the low-risk class (Figure 7). Specifically, the median DFO for the high-risk class was 165 (mid-June), compared to 173 for the low-risk class. Moreover, some observations began much earlier in plot-years in the high risk of drought, around the 143rd day of the year (roughly the end of May), whereas this was not necessarily the case for plot-years in the low drought risk.

DISCUSSION

This study highlights that the crowdsourcing-enhanced model generally outperformed the climatic model in predicting early in the season the risk of drought that will be observed at the end of the season. It demonstrates that integrating the Date of First Observation (DFO) in a classification model, in addition to the Climatic variable (*i.e.*, Climatic Dryness Index – CDI), significantly improves the accuracy of drought risk class prediction early in the season. Indeed, the results showed that early DFOs characterise plot-years experiencing a higher risk of drought at the end of the season, meaning that the higher the drought risk, the earlier the DFO. The statistical test confirmed a significant difference in DFO between the two drought risk classes. This confirms the non-random nature of user behaviour. The result validates the initial hypothesis that field observers, such as winegrowers and technical advisors, integrate information that extends beyond the scope of climatic data alone. While it remains challenging to precisely characterise the specific clues perceived by these stakeholders at this stage, it is evident that they consider a systemic approach to the growing season. It seems reasonable to assume that by synthesising factors such as post-winter soil water recharge, phenological precocity, and canopy growth, among others, observers can develop a holistic assessment, thereby enabling early anticipation of emerging risks. Although this constitutes a temporal bias, it proves informative for characterising drought risk. Therefore, users could be seen as sensors in this approach. Indeed, this statement is not an isolated case but was also observed in other domains, such as Web crowdsourcing, where crowd behaviour patterns, such as tweets, photos, and other contributions on social media, helped to predict events like social events (Guo *et al.,* 2020) or to monitor natural phenomena such as earthquakes or floods (Cao & Huang, 2018). Thus, when the CDI alone is insufficient to predict the drought risk class accurately, DFO serves as a complementary variable that improves drought risk prediction at the end of the season.

Surprisingly, during the exploratory phase of this work, iG-Apex values provided by observers using the Apex-Vigne app were less explanatory than DFO. It is hypothesised that the timing of this initial measurement is driven by expert perception very early in the season, before vines experience actual water stress. It is reasonable to assume that stakeholders learn from past experiences and make decisions to prevent risk. Consequently, the measured apex index values at the first observation offer little information at this stage as they generally remain close to 1 (full growth). DFO also presents an operational advantage as it is available early in the season, from the very first observation, unlike other user behaviour variables studied.

TABLE 3. Confusion matrices of drought risk class predictions early in the season for Null, Climatic, and Crowdsourcing-enhanced models, and results of the Crowdsourcing-enhanced model on one test set with permuted DFO values: illustration for the year 2024.

		Year 2024							
		Null Model		Climatic Model		Crowdsourcing-enhanced model		Crowdsourcing-enhanced model on one test set with permuted DFO	
		Actual drought risk		Actual drought risk		Actual drought risk		Actual drought risk	
		High	Low	High	Low	High	Low	High	Low
Predicted drought risk	High	503	147	432	23	485	27	470	57
	Low	0	0	71	124	18	120	33	90

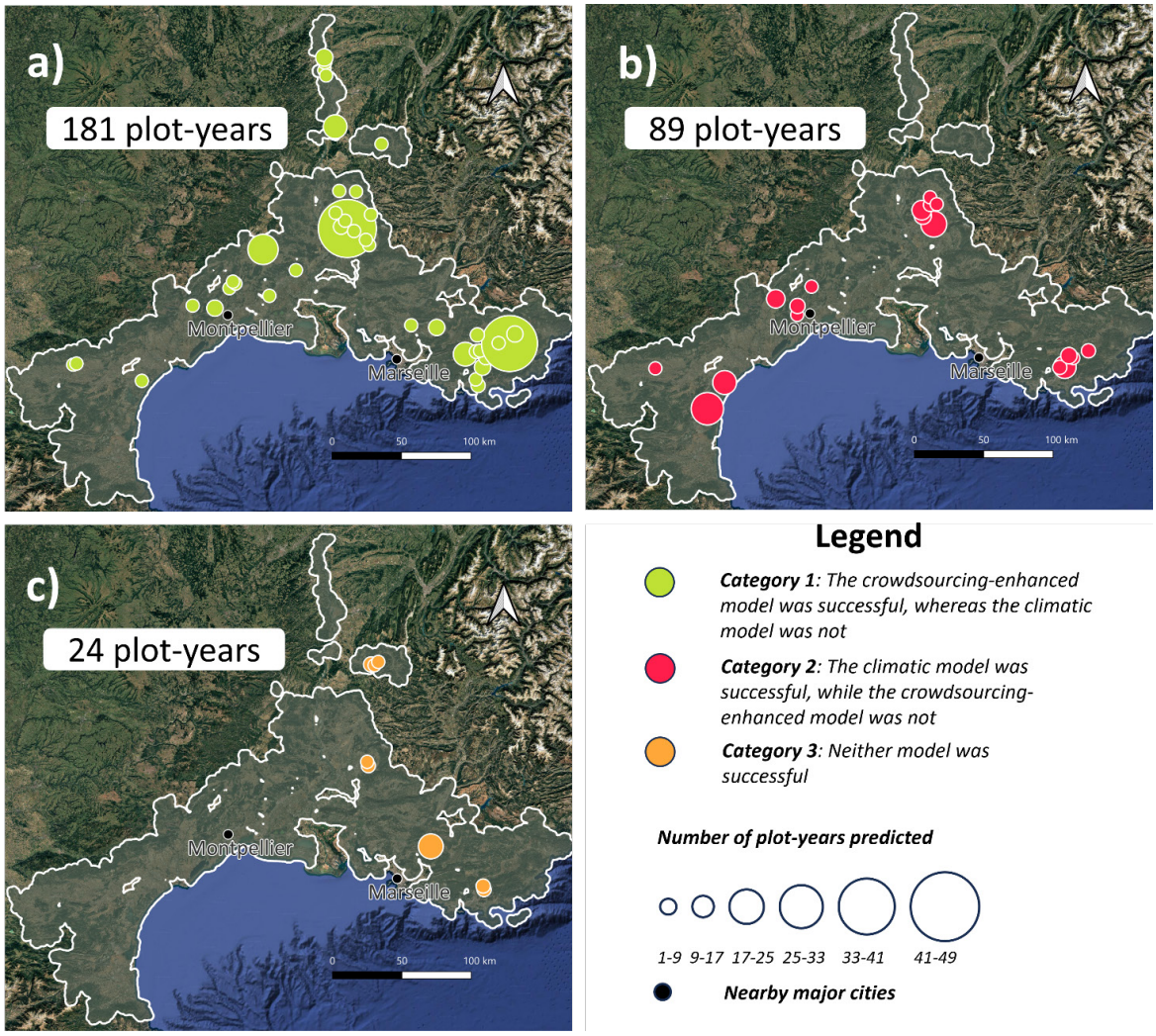


FIGURE 6. Map of plot-years for which the drought risk class was accurately predicted by a) only the crowdsourcing-enhanced model, b) only the climatic model, and c) none of them. Results from all years were combined.

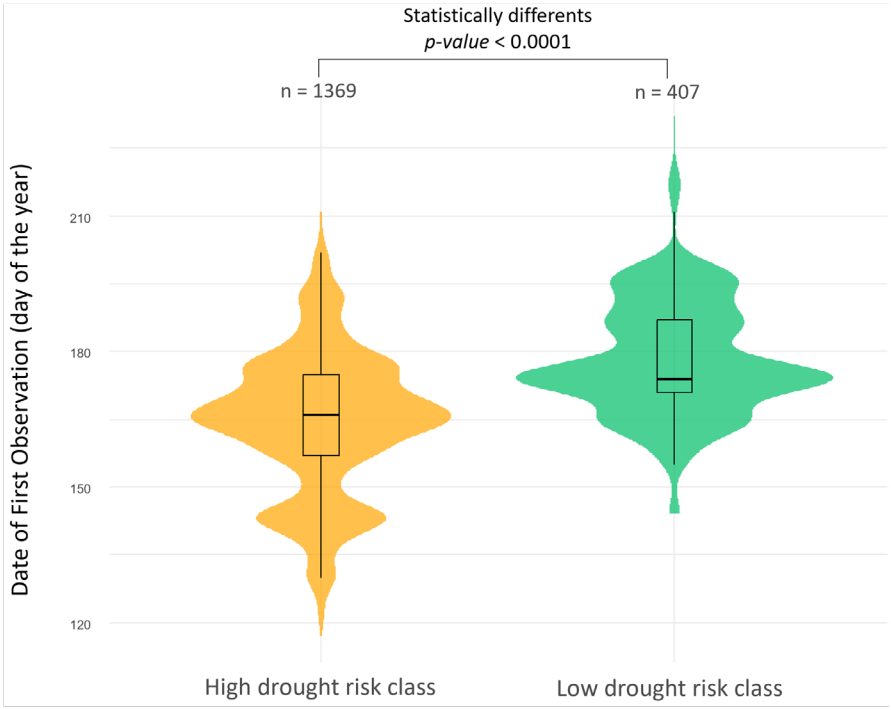


FIGURE 7. Distribution of DFO across drought risk classes, with data from all years combined.

While the crowdsourcing-enhanced model outperformed the climatic model, the magnitude of the accuracy gap between the two models varied significantly across years. This gap was particularly pronounced during the most severe drought years, notably 2022 and 2023, highlighting that the predictive relevance of DFO increases under more severe drought conditions. It is hypothesised that under these conditions, amplified differences in DFO increase its explanatory power. Although the limited number of observation years prevents us from formally testing this hypothesis, future studies should address it.

For a limited number of plot-years (around 5 % of the total), the climatic model outperformed the crowdsourcing-enhanced model, meaning the introduction of the DFO in the model has led to a loss of accuracy. Although rare, these cases highlight the intrinsic limitations of DFO to improve drought risk prediction in some cases. One plausible explanation for this discrepancy is that the DFO does not always align with the actual dynamics of shoot growth cessation. Indeed, decision-making among agricultural stakeholders is a multifaceted process (Singh *et al.,* 2016). The users of Apex-Vigne are from different profiles, and they use the application for different reasons. They use the application mainly to monitor water status or to compare experimental modalities. In that case, the initiation of iG-Apex monitoring may be influenced by factors beyond purely physiological signals. This may include operational constraints, such as restricted plot accessibility following heavy rainfall, or logistical considerations, including the availability of seasonal staff. Furthermore, methodological requirements, such as the necessity for synchronised sampling dates across all plots within an experimental trial, can further decouple the start of observations from the biological reality of the vine's development. In these cases, the information about actual drought risk that is contained in DFO becomes weak or even irrelevant. Consequently, integrating the DFO into a model for predicting drought risk could lead to errors.

It was reported in the literature that some late-ripening varieties were found to be more drought-resistant (Mavromatis *et al.,* 2020), while early-ripening varieties were found to be more sensitive to drought stress (Yang *et al.,* 2026). This means it could be biased by the phenology insofar as the early-ripening varieties would be observed earlier and the late-ripening varieties naturally later, under the same drought conditions. This bias might explain why, in some situations, the DFO does not increase the model performance. However, such situations must be rare, as overall the DFO is linked to the estimated drought risk.

Another plausible explanation of why the DFO is not always able to predict the drought risk class is that the DFO may lack consistency across broad territories where microclimatic variations affect phenology at the vineyard scale. These localised climates, often driven by a combination of topographic features and canopy management strategies (van Leeuwen *et al.,* 2018) can steer vine development independently of regional drought trends. Since the characteristic of drought risk in this study was conducted at a coarse spatial resolution, these granular effects remained uncaptured, thereby reducing the explanatory power of DFO in accounting for site-specific growth dynamics. Although the drought risk determined considers the environmental conditions of the vineyards, it does not reflect the actual drought experienced by vine plants; hence the qualification of "risk". This limitation might also explain why in some cases the predictions are incorrect.

In a small number of cases, accounting for only 1.3 % of the overall dataset, both the crowdsourcing-enhanced model and the climatic model failed to predict drought risk, indicating that both CDI and DFO were insufficient to capture, early in the season, the underlying processes driving drought conditions at the end of the season. One possible explanation relates to the timing of its computation. The CDI was calculated from October of the previous year until the Date of First Observation (DFO); consequently, intense rainfall events occurring after the DFO may alter soil water dynamics, or conversely, high temperatures after rain episodes may occur and decouple the CDI used from summer drought conditions, thereby reducing its predictive relevance.

From an operational perspective, the Date of First Observation (DFO) can support decision-making by providing early indications of drought risk and enabling stakeholders to anticipate the impacts of climate variability. Its use is particularly relevant at a large spatial scale, consistent with the resolution of the climatic data employed in this study (meshes of 8 km × 8 km). At this scale, DFO could inform regional monitoring strategies, support water management planning, or contribute to technical advice provided at a large spatial scale and generally freely.

From a methodological point of view, the choice to use Random Forests to train the models was based on their predictive performance, their reduced risk of overfitting, their robustness to noise, and their rapidity of computation (Breiman, 2001). The leave-one-year-out schema used for models' training and testing aimed at verifying models' ability to predict drought risk for a new year as soon as there is a first observation for a given plot. Indeed, it is quite interesting from an operational point of view to be able to make predictions at the beginning of a season using data from previous years. This approach has been used, for instance, in several studies (Sabo *et al.,* 2026; Schut *et al.,* 2009; Wang *et al.,* 2023). Concerning the climatic model, other climatic variables could have been used in addition to the CDI. However, the goal was not to obtain the best possible climatic model, but to demonstrate the value of incorporating user behaviour. Therefore, the climatic component was kept intentionally simple and relevant.

A key advantage of the approach developed in this study is its ability to detect drought risk early in the growing season using data that are inexpensive to acquire, relatively simple to process, and available at an appropriate spatial resolution. This information could be useful for organisations managing water at a broad scale, as well as for farmers or experimenters, as this approach may be used to confirm their empirical

knowledge. However, for DFO to be reliably implemented as an operational decision-support tool at a large scale, it is essential to ensure a spatial distribution of observations as homogeneous as possible across the territory.

CONCLUSION

This paper tested the hypothesis that the behavioural patterns of contributors to crowdsourcing projects in viticulture could provide information about the status of the vineyard, and particularly the vine water status. In this study, the Date of First Observation (DFO) was used as a proxy for contributor behaviour. Results showed that when this variable was combined with a climatic variable in a Random Forest classification model, it improved early-season predictions of drought risk at regional scale and that this improvement was the strongest during the driest years. This result demonstrated that studying the behavioural patterns of contributors could provide implicit information about vine water status. However, this approach showed some limitations. At finer spatial scales, microclimatic variability and site-specific management practices reduced the explanatory power of the DFO. For some contributors, operational or logistical constraints can also disconnect DFO from the actual physiological state of the vine, weakening its value as a "drought signal". To overcome these limitations, future research is needed to better understand the decision-making processes that govern contributors' decisions to start monitoring. This new source of implicit information also opens perspectives for complementing existing sources of information for monitoring vine water status at the regional scale.

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