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SPECIAL ISSUE

Seven years of spatial crowdsourcing in viticulture: lessons learned from the monitoring of vine water status with the Apex-Vigne project

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ABSTRACT

Regional-scale vineyard monitoring is crucial for addressing climate change adaptation, notably water stress. While crowdsourcing offers a promising solution for collecting data at this large spatial scale, its true effectiveness, including participant mobilisation and robustness against sampling biases, remains under-documented. This paper provides a critical analysis of the potential and limitations of crowdsourcing for regional vineyard monitoring, using the seven-year Apex-Vigne project as a case study. Apex-Vigne monitors vine water status via a simple, calculated indicator, iG-Apex, derived from weekly vine shoot growth observations contributed by industry stakeholders (winegrowers and advisors) through a mobile application. The analysis focused on the spatio-temporal distribution of data collected in Metropolitan France and specifically within a 49,500 km^2 study area in the South of France (2019–2025). The project's capacity to generate regional-scale information was assessed by mapping iG-Apex values, and key scientific challenges were identified. Over seven seasons, Apex-Vigne successfully gathered 34,233 observations in Metropolitan France from over 771 contributors on 11,481 fields. Observations were collected following five different contribution patterns resulting from the specific interests of contributors. The Apex-Vigne mobile application was used for on-farm experimentation at the within-field level, field monitoring at the farm level, and reference field monitoring at the regional level. The data volume proved sufficient to spatialise vine water status and illustrate temporal dynamics at the regional level. These results demonstrate the potential of crowdsourcing as a new source of information for regional decision support in viticulture. The study also highlights scientific challenges raised by crowdsourcing projects in viticulture. Social sciences are needed to understand contributors' motivations and new data science approaches should be explored to automatically identify observations with atypical behaviour.

KEYWORDS: citizen science, on-farm experimentation, precision viticulture, smartphone, volunteered geographic information, TERCLIM 2026, *Vitis vinifera*

INTRODUCTION

Monitoring vineyards at the regional scale is essential for understanding regional phenomena like pest development (Mason & Isaacs, 2021), water stress dynamics (Hofmann *et al*., 2022) or frost events (Sgubin *et al*., 2018) and their potential effect on yield and grape quality. It plays a crucial role in anticipating vineyard evolution and identifying effective climate change adaptation solutions (Hamon *et al*., 2024). Among the monitored variables, vine water status is particularly critical. It directly influences vine shoot growth (Pellegrino *et al*. 2005), yield (Medrano *et al*. 2003), and grape quality (van Leeuwen *et al*., 2009). Vine water status also exhibits high spatio-temporal variability at the regional scale, and it is one of the variables that is most impacted by the effects of climate change (Mosedale *et al*., 2016). Monitoring vine water status at the regional scale is a major issue for technical support organisations. This information helps them to identify the areas and periods that are most regularly subject to water constraints. Organisations operating at the regional scale (e.g., cooperative wineries, producers' unions or chambers of agriculture) use it as a collective management tool for i) planning harvest logistics, ii) managing irrigation scheduling, or iii) targeting structural investments. In this context, there is a crucial need for tools capable of objectively characterising vine water status and its temporal dynamics at the regional scale (Brillante *et al*., 2020). However, in operational conditions, few existing methods provide field observations throughout the growing season with a sufficient spatio-temporal density.

Crowdsourcing – or participatory data collection – presents an interesting potential as a source of information at this spatial scale. This approach involves mobilising a large number of contributors who collect field observations and then pool them (Brabham, 2008). It is widely used, for example, to monitor dynamic biological phenomena occurring over large spatial scales such as a region, country, or even continent. One of the most emblematic examples of this type of monitoring is the eBird project (Sullivan *et al*., 2009). In this project, observations by amateur and professional ornithologists enable the tracking of different species of wild birds on a continental scale. Other projects have also been developed for the long-term, large-scale monitoring of the phenology of numerous plant and animal species (Chuine *et al*., 2025). This approach has also been implemented in agriculture, but on a smaller scale, generally ranging from small agricultural basins to the regional or even national level (Ebitu *et al*., 2021). One of the specific features of crowdsourcing projects in agriculture is that contributors are not enthusiastic amateurs but professionals who contribute as part of their agricultural activity (Minet *et al*., 2017).

In viticulture, the crowdsourcing approach has been tested to monitor vine water status (Pichon *et al*., 2021). However, the effectiveness of this approach as a reliable source of information for monitoring vineyards on a regional scale remains poorly documented. Specifically, there is a lack of critical analysis regarding these projects' capacity to sustainably mobilise a sufficient mass of participants, ensure adequate spatio-temporal observation density, and overcome the inherent biases (zones or periods with higher density of observations) associated with participatory data collection. The objective of this paper is to analyse the contribution, the limitations and the issues of crowdsourcing as a method for monitoring vineyards at a regional scale. To this end, the Apex-Vigne project (Pichon *et al*., 2022) was chosen as a case study. This project, which capitalises on seven years of collaborative monitoring of vine water status, offers a unique testbed for assessing the viability and robustness of this method within a real-world viticultural context.

MATERIALS AND METHODS

1. Collection of crowdsourcing observations

The Apex-Vigne project was chosen as a use-case because, to our knowledge, it is one of the most developed crowdsourcing projects in viticulture. The purpose of the Apex-Vigne project is to monitor vine water status at the regional scale by using observations collected by winegrowers and wine industry stakeholders. Vine water status was assessed using an approach based on the characterisation of vine shoot growth. Observations were collected via a dedicated mobile application. The following sections provide detailed descriptions of the observation protocol, the mobile application, and the participation strategy.

1.1. Monitoring vine water status with shoot growth observations

The underlying principle of the observation-gathering approach is based on the physiological response of the grapevine to water deficit: when water availability becomes a limiting factor, vegetative shoot growth slows down and ceases (Pellegrino *et al*., 2005). While this methodology is detailed in Pichon *et al*. (2023), a brief summary is provided herein. The protocol consists of observing 50 apexes (*i.e.*, vine shoot tips) and classifying them into three distinct developmental stages: i) full growth, ii) moderate growth, and iii) stopped growth. Based on these observations, a synthetic indicator, the iG-Apex, is calculated by assigning weight coefficients of 1, 0.5, and 0 to the three apex categories, respectively, and computing a weighted average for the entire sample. Typically, the iG-Apex remains near 1 (full growth) at the full bloom stage and progressively decreases toward 0 (growth cessation) as veraison approaches and water restriction intensifies. Provided that water availability is indeed the primary factor limiting vegetative growth, the iG-Apex serves as a proxy to characterise vine water status (Pichon *et al*., 2023). In practice, contributors generally conduct weekly monitoring throughout the summer period (approximately from full bloom to veraison) to accurately capture growth cessation dynamics and assess vine water status across their fields.

1.2. Apex-Vigne mobile application

ApeX-Vigne is a mobile application dedicated to the project and designed for winegrowers and wine industry stakeholders. It facilitates the observation, calculation, and interpretation of the iG-Apex index. The application is available free of charge on Android via the Google Play Store (https://play.google.com/store/apps/details?id=ag.GB.apex&hl=fr last accessed 23/01/2026) and on iOS via the App Store (https://apps.apple.com/fr/app/apex-vigne/id1612236678 last accessed 23/01/2026). Originally released in June 2019 exclusively for Android in French, the application underwent a complete redevelopment. In April 2024, it was launched on both Android and iOS platforms in five languages: French, English, Spanish, Portuguese, and Italian. A more detailed description of the application's technical features can be found in Brunel *et al*. (2019).

The Apex-Vigne application features three main screens. The first interface displays the contributor's list of fields (Figure 1a), which can be sorted alphabetically, by the date of the last observation, or by geographic proximity to the contributor. This screen provides essential details for each field, including its name, the most recent observation date, and the iG-Apex value recorded at that time. Upon selecting a field, the contributor accesses the field details (Figure 1b), which lists all observations collected for that specific field over the previous six months. This allows the contributor to review historical observations and monitor the shoot growth dynamics of the field. By clicking the "New Session" button, the contributor is directed to the data entry screen (Figure 1c). On this interface, the contributor observes and classifies each apex by selecting one of the three corresponding buttons. The application also allows the contributor to record the phenological stage and add comments. Finally, the iG-Apex index can be calculated to interpret the observation.

The Apex-Vigne application records the timestamp and geographic coordinates for each observation, with the latter determined via the smartphone's GNSS receiver. Collected data are automatically synchronised with a central database when a 3G (or higher) signal or Wi-Fi connection is detected. In the absence of network coverage, observations are stored locally on the device and synchronised once connectivity is restored. Upon downloading the application, contributors explicitly consent to the use of their data for research purposes.

1.3. Participation strategy

The strategy employed to encourage participation in the Apex-Vigne project was based on leveraging "egoist motivation" (Batson *et al*., 2002). Within this framework, contributors collect observations because they derive a direct benefit from them. This approach is particularly well-suited to contributions made in a professional context, as frequently observed in agriculture (Minet *et al*., 2017). For Apex-Vigne, this direct benefit lies in the ability to perform a simple and rapid diagnosis of vine water status. The underlying hypothesis is that monitoring vine water status represents a critical challenge for potential contributors. Furthermore, according to Rechenberger *et al*. (2015), the simplicity of the observation gathering process is a determining factor in maximising the volume of collected observations. The iG-Apex approach was therefore selected for its rapid implementation and the ease of result interpretation for both winegrowers and wine industry stakeholders.

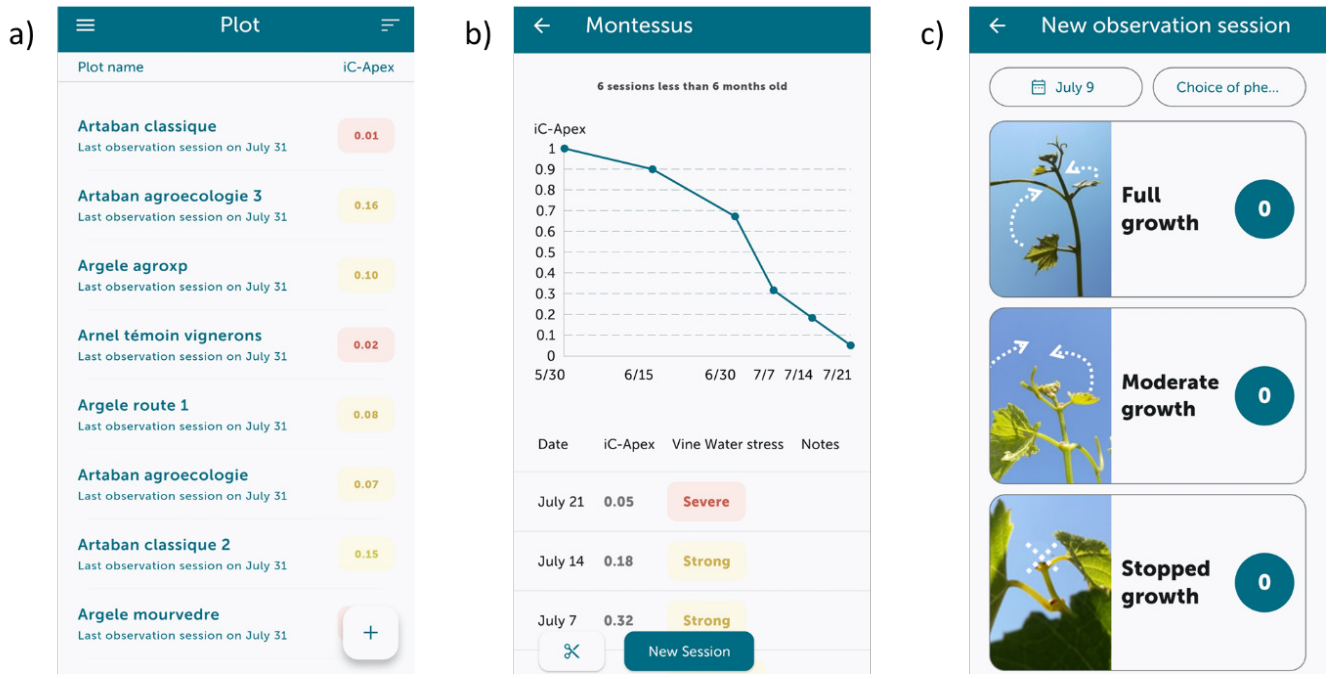


FIGURE 1. Screenshots of the Apex-Vigne mobile application: (a) list of fields, (b) field details, and (c) data entry screen.

The recruitment strategy for Apex-Vigne users relied on communication campaigns emphasising the value of Apex-Vigne as an accessible and user-friendly decision-support tool for winegrowers and wine industry stakeholders. The application was promoted mainly via the specialised technical press where articles were published when the app was launched and for each new release. The app has also been promoted every two years at a wine industry trade fair. The French Institute for Vine and Wine (*Institut Français de la Vigne et du Vin*) and local Chambers of Agriculture played a key role in disseminating the tool and establishing its legitimacy among professionals. On their own initiative, they decided to promote the Apex-Vigne app at local meetings and working groups, as they considered it to be a useful tool for wine-growing professionals.

2. Study period and area

The observations considered in this paper were collected with the Apex-Vigne mobile application from 2019 to 2025. Two study areas were considered: i) mainland France, and ii) southern France. The scale of France was selected due to the high diversity of its wine-growing regions, which encompass a wide range of pedoclimatic conditions and cultural practices. The country of more than 632,000 km^2 included 363 different controlled designations of origin encompassing, among others, the vineyards of Bordeaux, Champagne, or Burgundy wine regions (Figure 2a). It contains > 790,000 ha of vineyards and > 59,000 winegrowers (Agreste, 2020). France also remained the only country to date where a structured dissemination strategy for the Apex-Vigne project targeting winegrowers and wine industry stakeholders has been deployed. The scale of the Southern France region was chosen because of its Mediterranean climate. The higher prevalence of water stress justified greater adoption of the Apex-Vigne application and, consequently, a higher number of observations. The Southern France study area covered approximately 49,500 km^2 (Figure 2b). It encompassed the vineyards of the *Languedoc*, *Provence*, and *Côtes du Rhône* wine regions. Its shape has been defined on the basis of nine French administrative departments. This study area contains 57 different controlled designations of origin with > 300,000 ha of vineyards (Figure 2b) and > 22,500 winegrowers (Agreste, 2020). The soils of the region are diverse, and the majority of them have a low water-holding capacity (< 100 mm).

3. Method for assessing crowdsourcing for regional vineyard monitoring

3.1 General approach

The analysis was carried out on all the observations collected within the study area and during the study period. According to Mehdipoor *et al*. (2015), it was considered that outlier observations accounted for only a tiny fraction of the total number of observations collected. No pre-processing or filtering steps were therefore carried out prior to the data analysis. The general approach was structured into three main stages. First, the temporal dynamics of observation gathering within the Apex-Vigne project were characterised. Second, user contribution patterns underlying these dynamics were analysed to identify distinct contribution profiles. Finally, the capacity of the resulting database to generate regional-scale maps of vine water status was evaluated. These three stages are detailed hereafter.

3.2 Temporal dynamics of observation gathering

The temporal dynamics of observation gathering were analysed through a twofold approach: a global analysis encompassing the entire Apex-Vigne project duration, followed by a detailed interannual study. First, the overall

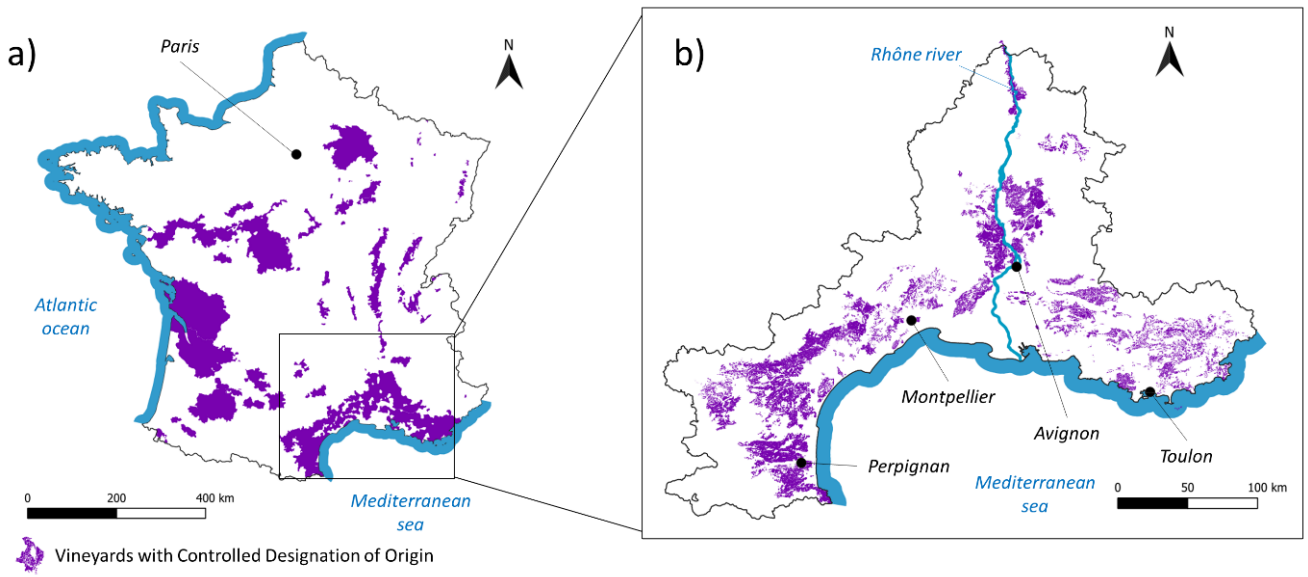


FIGURE 2. Distribution of controlled designation of origin vineyards across the two study areas: (a) mainland France and (b) southern France. Data adapted from INAO (2020) and IFV (2021).

dynamics were characterised by quantifying the weekly volume of observations gathered over the seven-year study period. Second, interannual variations were compared by normalising the data into cumulative percentages of annual observations. This approach allowed for the analysis of both the precocity and the rate of observation gathering across years, independently of the total annual data volume. Years 2023 and 2025 were particularly studied as an illustration. To compare their seasonal acquisition dynamics, a non-parametric Kolmogorov-Smirnov test was performed. This test was used to quantify the maximum distance between these two distributions, providing a statistical basis to identify global shifts in the temporal patterns of observation gathering.

3.3 User contribution patterns

The study of user contribution patterns was conducted by calculating specific behavioural metrics and running a clustering analysis. The considered metrics were the number of observations per field, the number of fields monitored per year, and the spatial distance between monitored fields. An Agglomerative Hierarchical Clustering (AHC) approach was selected for its suitability in exploratory analysis, as it enables the identification of natural groupings without an a priori specification of the number of clusters. AHC operates iteratively, starting from individuals and then merging, at each iteration, those individuals or clusters of individuals whose merger minimises the Ward criterion (Ward, 1963). This criterion measures the increase in intra-group variance that occurs when two groups are merged. The optimal number of clusters was selected by identifying the merger that caused the greatest increase in the Ward's criterion and choosing the number of clusters preceding that merger. Differences in the different metrics among identified clusters were assessed using a one-way ANOVA. When significant, a Tukey's Honest Significant Difference (HSD) post-hoc test was applied to identify statistically distinct groups ($p < 0.05$).

3.4 Mapping and characterisation of spatial structure dynamics

A classical geostatistical approach was employed to characterise spatial autocorrelation through semi-variogram analysis (Leroux & Tisseyre, 2019). Assuming second-order stationarity, total variance was partitioned into two distinct components: i) the random variance or nugget effect (c0), and ii) the spatially structured variance or partial sill (c1). These parameters were derived by fitting semi-variogram models to experimental data. The Cambardella index (c0/(c1 + c0); Cambardella *et al*., 1994) was used to characterise the spatial autocorrelation of the data. According to the authors, a ratio below 0.25 indicates strong spatial dependence, between 0.25 and 0.75 moderate spatial dependence, and above 0.75 weak spatial dependence. Semi-variogram models were also used to generate interpolated maps of iG-Apex observations by ordinary kriging (Oliver & Webster, 2015). Experimental variograms were modelled using the linear-to-sill model. The predictive performance of the ordinary kriging interpolation was assessed through a leave-one-out cross-validation procedure, comparing observed and predicted values using the Root Mean Square Error (RMSE) as an error metric. Colours were mapped using linear interpolation between breakpoints based on 5-class quantiles, providing a continuous visual gradient that reflects the statistical distribution of the data.

4. Software and tools

Analyses and graphs were performed using R 4.5.2 (R Core Team, 2026). Semi-variograms were fitted with gstat package using REML (Pebesma, 2004) and maps were produced using QGIS 3.40.13-Bratislava (QGIS Development Team, 2026).

RESULTS

1. The population of contributors collects observations on a seasonal basis

Across the whole of Metropolitan France, 34,233 observations were collected during 7 years on 11,481 different fields. The average number of observations collected per year was 4890 observations, but this average was 7134 observations over the last three years (2023 to 2025). Every year, observations were collected over the same short period of time, approximately three months, indicating a seasonal observation gathering process (Figure 3). In 2022, 2024, or 2025, up to 700 to 800 observations were collected each week, compared to 300 to 400 observations per week in 2021 or 2023.

Observation acquisition dynamics remained consistent throughout the study period, with the cumulative percentage of observations following a sigmoid curve (Figure 4). The initial 10 % of observations were recorded between weeks 20 and 23. Subsequently, the observation acquisition dynamics accelerated, reaching their maximum velocity as the cumulative percentage of collected observations approached the 50 % threshold. The timing of this maximum exhibited interannual variability, occurring between weeks 25 and 29 depending on the year. Finally, the rate of observation acquisition decelerated, with the remaining 10 % of observations typically gathered between weeks 31 and 34.

The specific dynamics of each year exhibited distinct interannual variations. As an illustration, Figure 4 highlights the acquisition patterns of 2023 and 2025. Although both years follow a similar seasonal trajectory, their dynamics are statistically distinct (Kolmogorov-Smirnov test, $p < 0.001$), revealing notable differences in observation acquisition dynamics. In 2023, the initial 10 % threshold was reached as early as weeks 20–21, whereas a relative delay was observed in 2025, with the same percentage reached only in week 23. This initial two-week gap narrowed as the season progressed, leading to a convergence in which the 50 % of collected observations threshold was crossed almost simultaneously in both years (weeks 26–27). This trend reversed toward the end of the season. The final 10 % of observations were gathered between weeks 30 and 31 in 2025, while 2023 exhibited a one-week lag, reaching this threshold between weeks 31 and 32. When considering the

core acquisition window – defined as the interval between the 10th and 90th percentiles of total observations – this period lasted approximately 7.5 weeks in 2025, compared to 11 weeks in 2023. Consequently, the observation gathering timeframe was considerably more compressed in 2025 than in 2023. On a broader scale, across all observations collected in Metropolitan France throughout the seven years of the Apex-Vigne project, the mean duration of this window was 9.5 weeks, with a standard deviation of 1.3 weeks.

2. Contributors deploy a variety of observation gathering strategies

These 34,233 observations were gathered by 771 contributors. Ascending hierarchical classification identified five distinct clusters, representing five different contribution patterns among these contributors (Figure 5).

Contributors from cluster 2 performed regular monitoring (2 to 5 observations per field over the season; Figure 5a) across a range of a few dozen fields (Figure 5b) located in

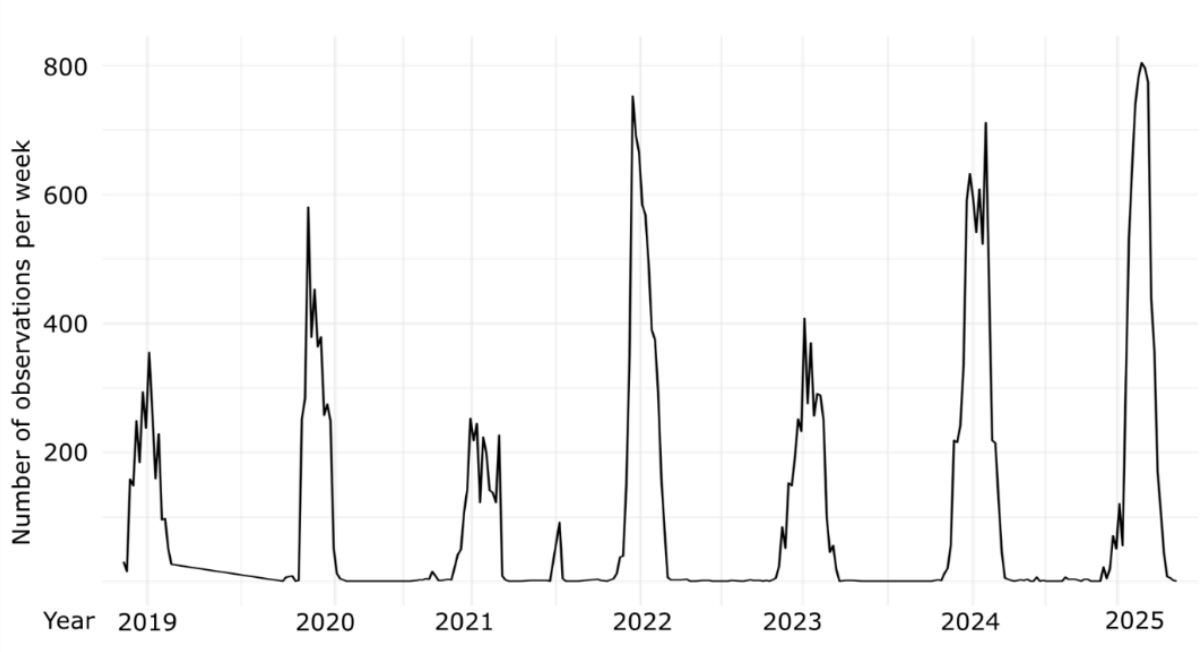


FIGURE 3. Temporal distribution of the 34,233 observations collected by contributors with the Apex-Vigne mobile application from 2019 to 2025 in Metropolitan France.

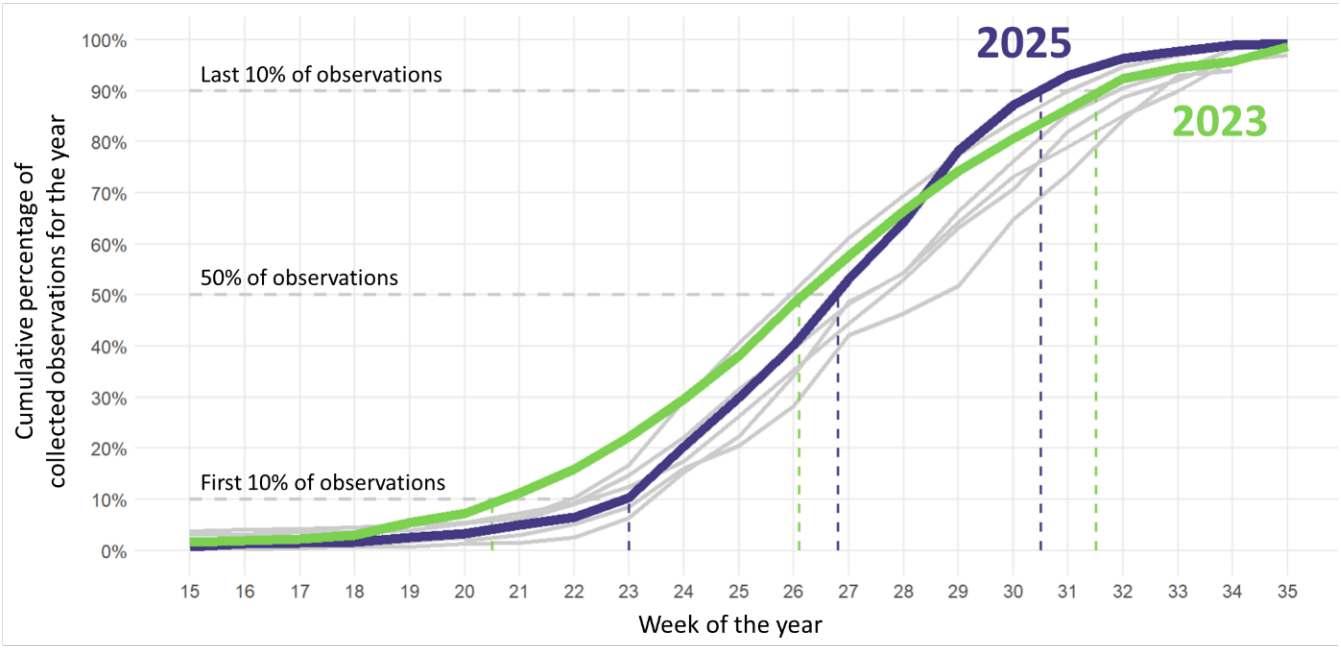


FIGURE 4. Cumulative percentage of observations collected in Metropolitan France over time for each year of the Apex-Vigne project (from 2019 to 2025). Two years with very different behaviours are highlighted: 2023 in green and 2025 in purple.

relatively close proximity (mostly around a dozen kilometres; Figure 5c). They accounted for just under 27 % of contributors (207 out of 771). Each of the other clusters was a variation of the contribution pattern described by cluster 2.

For example, cluster 1 corresponds to contributors who collected fewer observations than those in cluster 2 (1 to 2 per season; Figure 5a) on a smaller number of fields (between 2 and 5 fields; Figure 5b) that were close to each other (approximately 1 km; Figure 5c). This cluster included more than 67 % of contributors (521 out of 771). Cluster 3 corresponds to contributors who monitored less frequently than in cluster 2 (only 2 observations per field per season; Figure 5a) but on a much larger number of fields (between 100 and 200 fields; Figure 5b). This cluster accounted for approximately 2 % of contributors. Cluster 4 corresponds to a monitoring similar to cluster 3 (~ 2 observations per field per season; Figure 5a) but on a smaller number of fields (from 5 to a few dozen fields; Figure 5b) and, above all, over a much larger area (~ 100 km). It represents only 1.5 % of contributors (11 out of 771). Cluster 5 corresponds to contributors who monitored relatively few fields (approximately 4 or 5 fields; Figure 5b) that were fairly close to each other (between 1 and 10 km; Figure 5c). However, they carried out very detailed monitoring throughout the season, with more than 20 observations per field (Figure 5a). This behaviour accounted for around 2 % of contributors (14 out of 771). These different contribution behaviours are illustrated by the spatial representation of observations collected by the same contributor (Figure 6).

In Figure 6a, the groups of observations, collected at different dates, are distributed across the various fields of the farm. Each group of observations represents a specific monitoring site selected by the contributor to characterise the vine shoot growth dynamics of that particular field. This behaviour appears to be consistent with clusters 1 and 2. On Figure 6b, the groups of observations collected at various dates were spatially aggregated in very close proximity, reflecting a high-resolution sub-sampling of the same field. It is likely that the objective in selecting these sites was not to characterise the general dynamic of the field, but rather to compare the distinct dynamics of different within-field zones. This specific behavioural pattern may reflect "on-farm experimentation" practices, where contributors leverage the Apex-Vigne application to evaluate spatial variability or treatment effects at the within-field scale. This behaviour appears to be consistent with cluster 5. In Figure 6c, groups of observations were scattered across an entire viticultural small region. This contribution pattern may reflect a strategic monitoring of reference fields at a small regional scale corresponding to clusters 3 and 4.

3. Ability to map vine water status at a large spatial scale

These 771 contributors have collected observations across all French vineyards (Figure 7a). The region with the highest density of observations collected was the Mediterranean area in the south of France, encompassing the Languedoc, Provence, and Côtes du Rhône vineyards. This region had more contributors, more monitored fields and more observations collected than anywhere else in France. In this region, certain areas were particularly dense in terms of observations (Figure 7b).

This high density of observations in the Mediterranean region was used to evaluate the suitability of the collected observations for mapping vine water status at the regional scale. Year 2024 was chosen as an example because a large number of observations were collected during that year. Furthermore, it is the year with the highest number of weeks during which several hundred observations were collected within the study area. As an illustration, observations collected during weeks 23 and 29 this year were used to produce regional maps of iG-Apex (Figure 8).

In the Mediterranean region, throughout the 2024 season, 220 observations were collected within the study zone during week 23, compared to 608 for week 29. Spatially, these observations encompassed the full extent of the vineyards within the study area. The ordinary kriging interpolation of mean-centred iG-Apex yielded a Root Mean Square Error (RMSE) of 0.063 and 0.157 for week 23 and week 29, respectively. Both interpolated maps (week 23 and week 29) reveal a well-defined spatial structure, characterised by significant regional heterogeneity. Specifically, they highlight distinct patterns: areas exhibiting iG-Apex values above the average are represented by green-to-blue colours, while zones with lower-than-average values are represented by orange-to-red colours (Figure 8). This spatial structure is corroborated by the Cambardella index values, which were 0.17 and 0.5 for weeks 23 and 29, respectively. These results indicate that crowdsourced iG-Apex observations exhibited significant spatial autocorrelation, thereby validating the use of kriging for spatial interpolation and mapping.

The week 23 map identifies two main areas where iG-Apex values fell below the average (Figure 8a). These regions were situated in the southern *Rhône* Valley near Avignon and in the far southwest around Perpignan. In these regions, the cessation of vine shoot growth occurred earlier, which may indicate a higher water restriction. Conversely, the region surrounding the city of Montpellier exhibited higher iG-Apex values, which may result from a lower water constraint. Six weeks later, the map based on observations of week 29 (Figure 8b) shows that the region around Perpignan, in the far southwest, continued to exhibit lower iG-Apex values than the rest of the study area, which still may indicate a higher water restriction. The area of lower iG-Apex values around Avignon also persisted, but appeared to have shifted from east to west. Meanwhile, the area around Montpellier, which previously showed above-average iG-Apex values, has contracted significantly and was limited to a small coastal area by week 29. Finally, even if the figures are from two specific moments, more detailed information could be explored in other growing seasons and at different periods of the year.

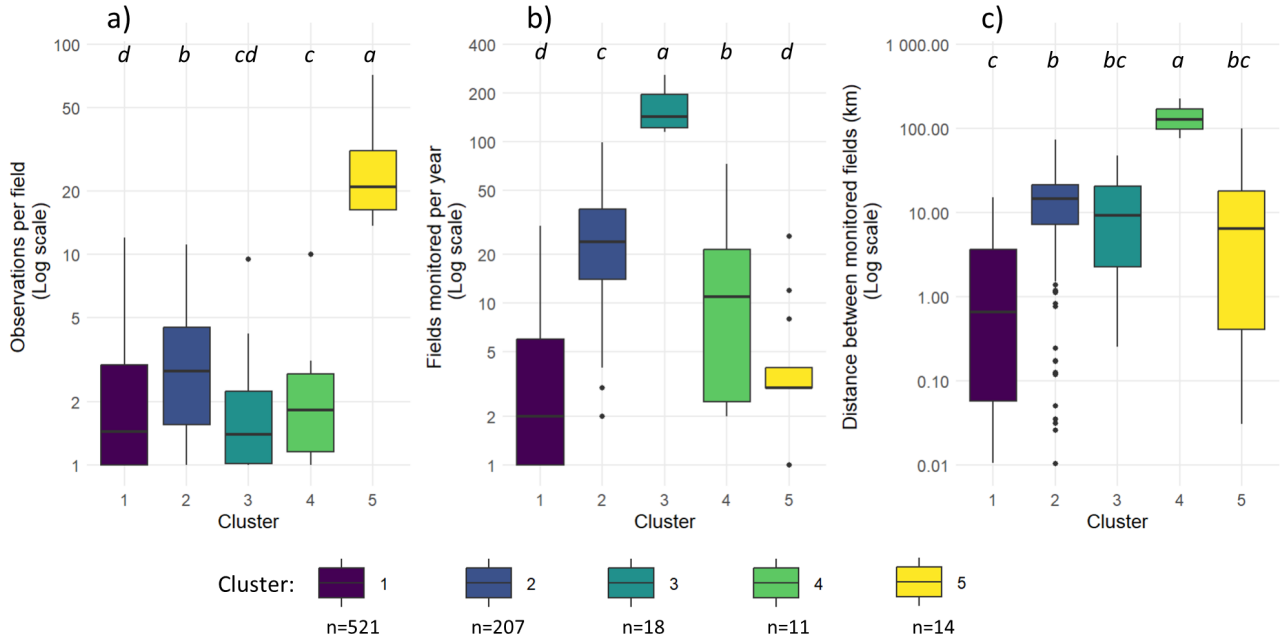


FIGURE 5. (a) Number of observations per field, (b) number of fields monitored per year, and (c) distance between monitored fields for each of the contributors' clusters obtained by Ascending Hierarchical Classification. Compact letter display indicates significant differences between clusters based on Tukey's HSD test ($p < 0.05$). Clusters sharing the same letter are not significantly different.

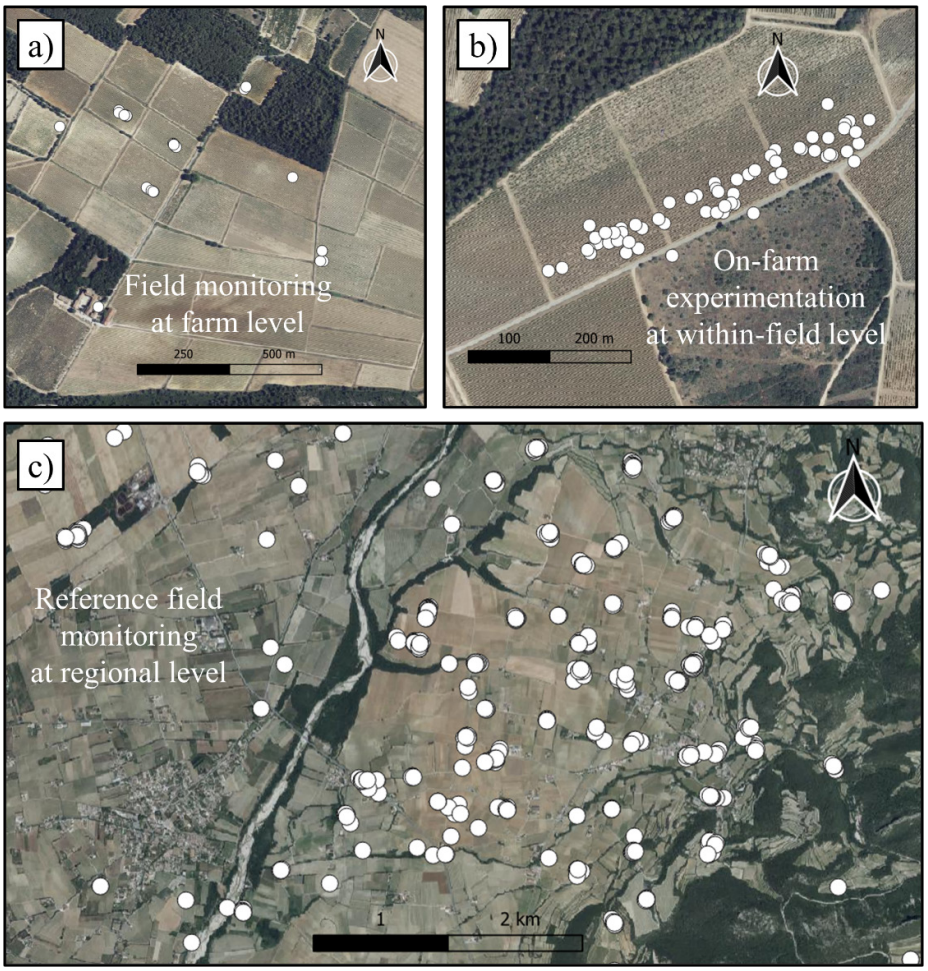


FIGURE 6. Illustrations of observations collected by single contributors for (a) field monitoring at farm level, (b) on-farm experimentation at within-field level, and (c) reference field monitoring at small region level.

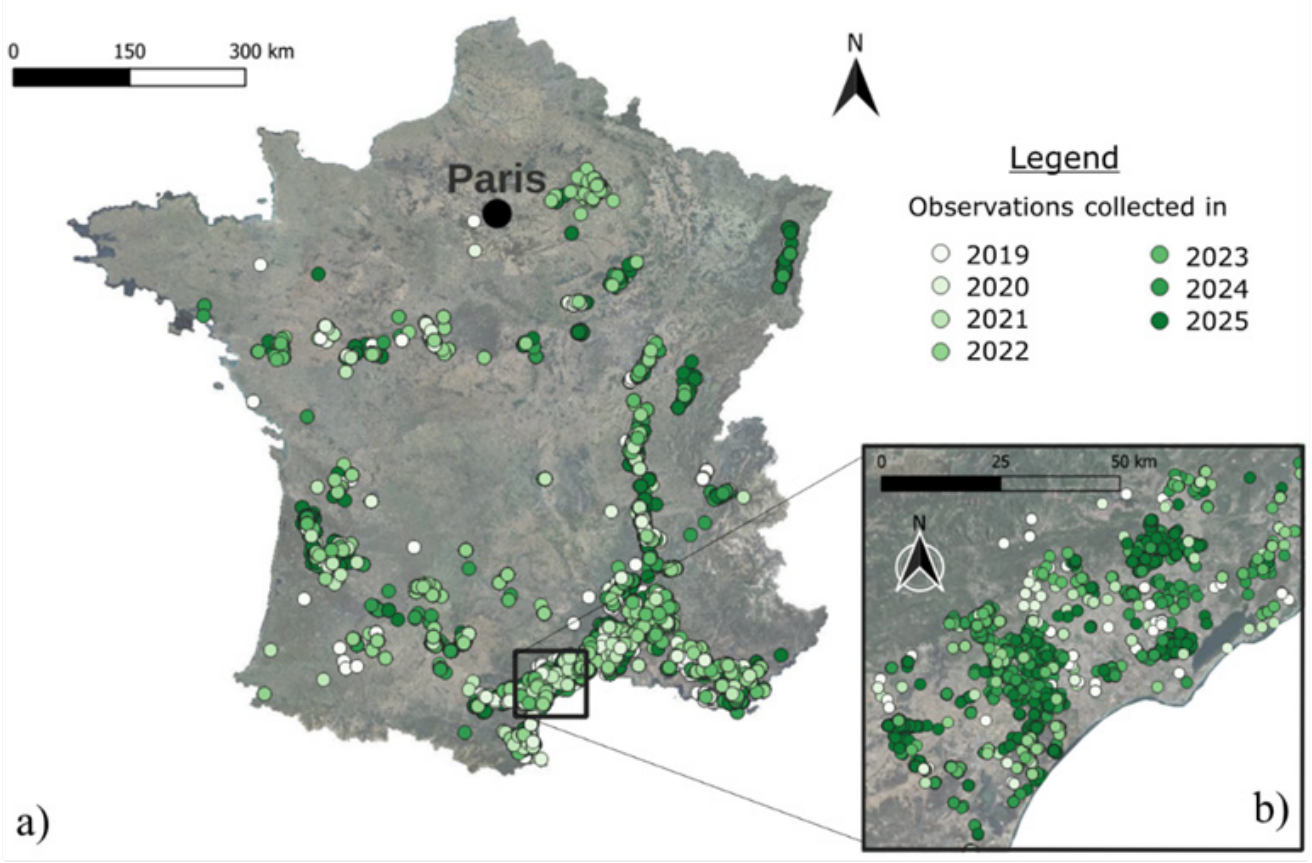


FIGURE 7. Spatial distribution of the 34,233 observations collected by contributors with the Apex-Vigne mobile application from 2019 to 2025 in (a) Metropolitan France and (b) an area with a particularly high density of observations in the South of France.

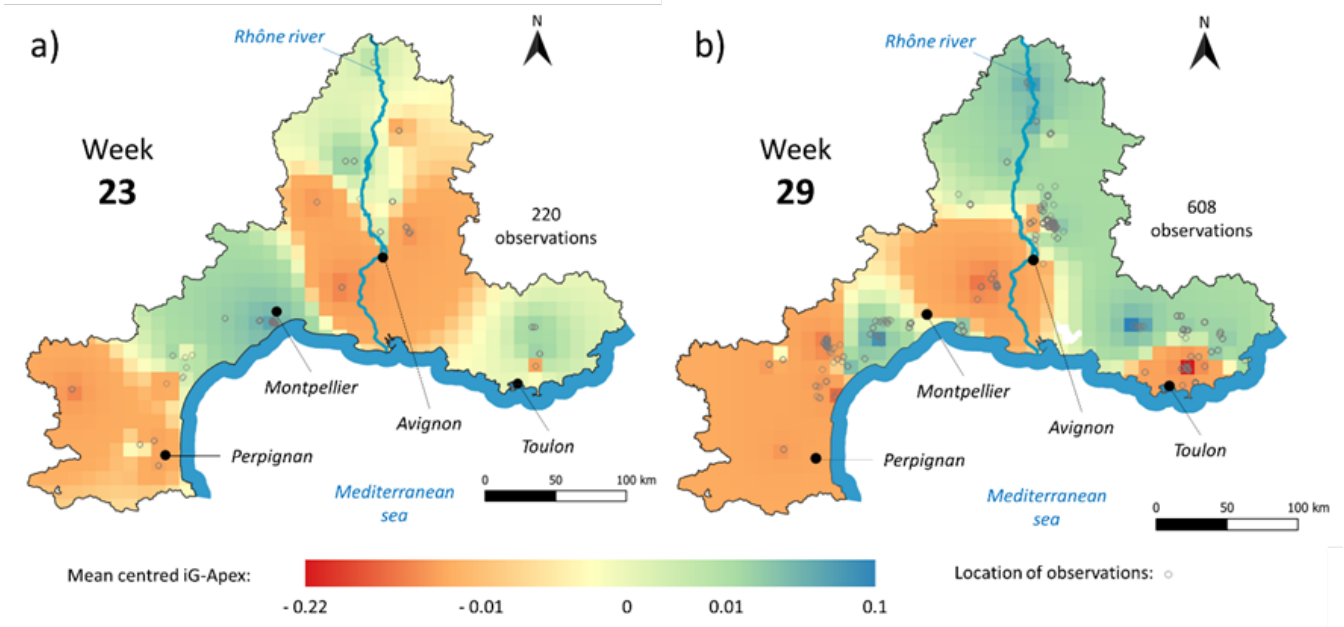


FIGURE 8. Interpolated mean-centered iG-Apex values over the study area. Kriged maps made from observations with the Apex-Vigne mobile application during (a) week 23 and (b) week 29 of the year 2024.

DISCUSSION

1. Crowdsourcing as a source of information in viticulture

The results of this study demonstrate that the crowdsourcing approach in viticulture enables the collection of a large number of observations over broad areas. Although the approach relies on the opportunistic motivation of contributors, which makes it impossible to control the number and location of observations, these observations were collected across the entire French vineyard during the seven years of the Apex-Vigne project. In the south of France, a region where monitoring the vine water status is a major challenge and where the observation density was the highest, the project has demonstrated the feasibility of monitoring vine water status dynamics at a regional scale through crowdsourcing. It also confirmed that the shoot growth monitoring approach, which is simple to implement under real-world production conditions but sensitive to factors other than just water status (Pichon *et al*., 2023), represented an acceptable trade-off for many contributors, particularly in the Mediterranean region. In these conditions, crowdsourcing is an original source of information that provides access to unprecedented spatiotemporal resolution of field observations, far superior to what current institutional or professional observation networks can provide. This new data source also offers a tool for the dynamic characterisation of one of the major determinants of terroir effect (Willwerth & Reynolds, 2020). In a context of climate change and increasing drought intensity and duration, such information could support strategic reflections on the evolution of appellations' delimitations or adjustment of production specifications (*e.g.*, authorised cultivars, cultural practices). By providing objective and localised evidence of vine water status over a large spatial scale, crowdsourcing could also serve as a central tool for defining public policies tailored to the actual conditions of vineyards.

However, in regions where the density of contributions was lower, crowdsourcing was not able to monitor these dynamics at the regional scale. This result shows that contribution and contributor motivation are important issues for crowdsourcing approaches in viticulture and, more broadly, in agriculture. This aspect has been widely discussed in other fields of application (Kaufmann *et al*., 2011). Regarding the Apex-Vigne project, two aspects may explain the geographical heterogeneity of contributions: i) the initial choice made when designing the Apex-Vigne application (Brunel *et al*., 2019), which was based on the principle of egoist motivation, *i.e.*, contributors only collect observations if they see a benefit for the management of their own vineyard (Batson *et al*., 2002). This approach becomes limiting when monitoring vine water status is not a major concern for potential contributors, as was probably the case for regions outside southern France. ii) Promotion of the project by technicians and advisers. In fact, long before the project, the method based on observing apexes had already been adopted by some technicians from technical institutes or advisory organisations. The dissemination of the Apex-Vigne application was therefore perceived as a continuation of existing practices, and it is likely that this encouraged these technicians to promote the application to winegrowers. In regions where the approach was little or not at all developed, it is possible that the lack of promotion by technicians or advisers limited the dissemination of the application and therefore the resulting contributions. This observation highlights the many challenges associated with the success of a crowdsourcing project in viticulture.

2. Information embedded within the dynamics of contributions

Beyond the information provided by the contributions, the study demonstrated that the dynamics of contribution could also be a source of information. Indeed, these results showed that observations began much earlier in 2023 than in 2025. However, 2023 was a year with a particularly early drought in the south of France (Météo France, 2023), whereas 2025 presented a large winter replenishment of water reserves, which led to a later onset of water stress (Météo France, 2025). The date on which the first Apex-Vigne observations were made, therefore, appears to be a potential proxy for local drought conditions of the year at the regional level. Although this observation seems obvious, to our knowledge, the dynamics of contributions in crowdsourcing projects in viticulture and, more broadly, in agriculture have never been studied in relation to the dynamics of phenomena such as regional vine water status. In epidemiology, similar approaches are already largely employed for the early detection of phenomena by studying the occurrence of specific events among the population. One of the most emblematic examples of these approaches is the identification of influenza epidemics based on the temporal evolution of online searches within a population (Yang *et al*., 2015). This approach, which epidemiologists call Event-Based Surveillance (World Health Organisation, 2014), is often seen as complementary to a more traditional approach known as Indicator-Based Surveillance, which relies on the systematic collection of structured data from official sources. Regarding Apex-Vigne, our study highlights the importance of operators' field experience in identifying critical observation periods. By adapting the start and end dates of apex observations to the specific characteristics of each year, contributors introduce a constructive expert bias and influence the dynamics of the time series. It is this 'event-based' nature that enables the Apex-Vigne project to produce new agronomic information on vine behaviour. In the future, the combination of event-based surveillance and indicator-based surveillance could justify the use of crowdsourcing projects to generate new knowledge or new approaches to monitoring agrosystems at different scales. This approach opens up particularly original and new research prospects in agriculture, which, to our knowledge, has never been investigated before. Based on this principle, future research could explore the potential of studying contribution dynamics in crowdsourcing projects to complement the monitoring traditionally carried out by institutional or advisory organisations in reference fields for monitoring vine water status at the regional level. Furthermore, future research could focus on understanding

the decision-making processes governing the timing of apex observations. Formalising this constructive expert bias could help identify new information sources or early-warning signals for regional-level vine water status monitoring.

Studying this new data source could facilitate inter-annual and inter-regional benchmarking, allowing for the identification of broad viticultural trends and shifts in regional dynamics. Furthermore, characterising these trends should also make it possible to identify fields, contributors or small regions that behave differently from the general trend. These atypical observations deserve special attention as they may correspond to practices or situations that, for example, enable better adaptation to severe water stress. The study of crowdsourced datasets could then be used for innovation scouting at the regional or even national level. However, this approach requires the development of analytical methods that exploit the spatial and temporal autocorrelation of crowdsourced data to automatically identify atypical observations. Approaches of this type have already been developed on crowdsourced (Wang *et al*., 2024), but the characteristics of crowdsourcing projects in viticulture make them unsuitable and warrant further research.

3. Contributor profiles and behaviours

The results of this study also highlight a high degree of heterogeneity in contributor profiles, characterised by the five identified clusters. Cluster 2 identified an expected contribution pattern that corresponds to what was initially defined in the specifications for the Apex-Vigne application (Brunel *et al*., 2019). These contributors performing a regular monitoring of a few dozen fields relatively close to each other appear to correspond to the regular in-season monitoring of fields belonging to the same farm. Based on their behaviour, it is likely that contributors from this cluster were farmers or seasonal workers employed on a farm who were really using the Apex-Vigne mobile application for their daily tasks. Cluster 1 corresponds to contributors who collected fewer observations than those in cluster 2 on a smaller number of fields that were close to each other. This behaviour is characteristic of contributors with very limited use of the Apex-Vigne application. It may possibly correspond to individual producers or other profiles testing the Apex-Vigne application out of curiosity.

On the other hand, clusters 3, 4 and 5 seem to describe contribution behaviours corresponding to a real appropriation of the application for specific uses. For example, contributors from cluster 3 monitored less frequently than in cluster 2 but on a much larger number of fields. Based on this behaviour, it is likely that this kind of monitoring was carried out by a small collective organisation, such as a wine cooperative or a large production company. Contributors belonging to this cluster were possibly employees of these organisations. Contributors from cluster 4 performed a similar monitoring but over a much larger area (~ 100 km). This behaviour seems to correspond to contributors trying to characterise the vine water status over large spatial areas. This may correspond to contributors belonging to organisations such as chambers of agriculture or large appellation unions seeking to understand the phenomena at work over large territories. Contributors from cluster 5 monitored relatively few fields fairly close to each other but they carried out very detailed monitoring throughout the season, with more than 20 observations per fields. This behaviour possibly corresponds to people carrying out experimental monitoring. In this case, it is likely that the Apex-Vigne application was used to finely characterise the shoot growth stop dynamics and/or to compare several experimental modalities.

According to Coggins *et al*. (2022), this diversity of behaviour illustrates the active appropriation of a crowdsourcing project by contributors. For the Apex-Vigne application, the contribution behaviours differ simply because the approach has been integrated into the contributors' business processes, and they have adapted its use to their specific context. The interpretation of Coggins *et al*. (2022) seems valid for clusters 2 to 5. However, in the case of cluster 1, which represents the majority of contributors (~ 67 %), their low number of observations and monitored fields seems to illustrate a behaviour of curiosity corresponding to contributors who have not yet fully embraced the application or who have used it in a degraded manner.

Furthermore, Delgosha *et al*. (2024) demonstrated that such diversity in contributor behaviour reflects distinct motivational profiles. It is therefore likely that the clusters identified in this study based on contributor behaviour also reflect varied motivational profiles. However, according to Rechenberger *et al*. (2015), contributor motivation significantly influences the number of contributions. Understanding these different motivational profiles is therefore a major challenge for the success of crowdsourcing projects in viticulture. To date, these motivations remain largely unknown. While a few studies have explored this topic in agriculture (Beza *et al*., 2017; Ebitu *et al*., 2021), no study has specifically focused on viticulture. Currently, the available knowledge is based exclusively on behavioural analysis based on the study of contribution metadata, as is the case in this study. In the future, it will be necessary to conduct quantitative and/or qualitative surveys of contributors. Such research, integrating social sciences, would make it possible to better characterise behaviours and understand the underlying motivational drivers.

CONCLUSION

This paper studied the Apex-Vigne crowdsourcing project and its seven years of collaborative monitoring of vine water status. It validated that crowdsourcing is effective in gathering a large number of high-quality observations. This demonstrated the potential of this data collection approach for being a new source of information for decision support at the regional scale in viticulture. However, crowdsourcing projects in viticulture raise multi-disciplinary scientific challenges with social sciences to increase input contributions by understanding contributors' motivations and in data sciences to automatically identify observations with atypical behaviour and deepen data analysis aiming at identifying event-based criteria. This new source of information also provides insights understand the vineyard and its adaptation to climate change at the regional level.

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