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# Spatialized system to monitor vine flowering: Towards a methodology based on a low-cost wireless sensor network

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ABSTRACT

Monitoring grapevine phenology during the agricultural season is one of the most important tasks within the vine field since this is a key input for the proper planning of agricultural labor management. Traditionally, vine growers make very few phenological observations at the field level, which are extrapolated to an entire production unit, without considering the field natural spatial variability. This situation generates significant loss of agricultural inputs and energy, which makes the vine system less sustainable, because this vineyard natural spatial variability is not usually considered in the field management. In this study, two models were tested using information recollected by a meteorological weather station and a wireless sensor network (WSN) to estimate vineyard phenology in a key period such as flowering. Therefore, the general objective of this proposal is to develop a low-cost wireless sensor network (WSN) for monitoring the spatial variability of vine phenology in a commercial vineyard. Results indicated that both models presented a better estimation of vine phenology during the second season, given that the first season was affected by the ENSO “La Niña” climatic effect. However, it can be noted that the Parker model (GPV) presented better phenological estimation than the Monomolecular equation-based model (ME), when using a low-cost wireless sensor network. Based on the results, we can conclude that it is possible to develop and implement a low-cost electronic device for the monitoring of spatialized phenological events in the vineyard.

## 1. Introduction

Vine phenology is the study of the growth stages of the crop, which are repeated during all seasons and are mainly related to climatic and hormonal factors (de Rességuier et al., 2020; Jones and Davis, 2000; Mullins et al., 1992; Prats-Llinàs et al., 2020). The annual cycle of the vine begins with budburst, and continues with the vegetative growth, flowering, fruit setting, berry development, veraison, ripening of the berries (harvest) and ends with the fall of leaves (Schwarz, 2003). The knowledge and monitoring of different vine phenological stages during the season presents multiple applications in viticulture, such as (i) geographical characterization of the vineyard to determine the varieties best adapted to the specific climatic conditions (Ortega-Farías et al., 2002), (ii) planning of agricultural work carried out in the fields (irrigation, fertilization, phytosanitary spraying and differentiated harvesting) in order to increase the vineyard production efficiency (Mullins et al., 1992; Valdés-Gómez et al., 2017), (iii) study of the synchronism in the development of the vineyard and its pathogens, iv) the study of the effects of phenology over the final quality of the product, in this case, the wine, and v) indicator and predictor of the effects of climate change on plants (Mullins et al., 1992; Valdés-Gómez et al., 2017). Thus, monitoring grapevine phenology is a very relevant task when it comes to decision-making at field level, which is why its study has led to several investigations at different spatial scales of work (Caffarra & Eccel, 2010; Costa et al., 2019; Duchene & Schneider, 2005; Jones & Alves, 2012; Moriondo & Bindi, n.d.; Nendel, 2010; Ortega-Farías et al., 2002; A. K. Parker et al., 2011; Sadras & Petrie, 2012; Tomasi et al., 2011; Urhausen et al., 2011; Verdugo-Vásquez et al., 2016, 2019; Nicolas Verdugo-Vásquez et al., 2017; Webb et al., 2012), for example, at a meso-scale (Falcão et al., 2010; Hall and Jones, 2009),

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where the analysis of the climate of a vine-growing region is often reduced to the analysis of data collected at one site, considered as representative of the whole study area (Hall & Jones, 2009; Jones & Davis, 2000; Tonietto & Carbonneau, 2004). However, it has been observed that there is significant spatial variability in grapevine phenological development at this spatial scale (Hall & Jones, 2009). This scale of work is not useful for vine growers, whose basic management unit corresponds to the viticultural field (area smaller than 5 ha), which is characterized by presenting the same variety, training system and management practices.

In the previous spatial scale, it is observed that there is an important variability in the vineyard's phenological stages (Verdugo-Vásquez et al., 2016, 2019). This variability can be explained by different factors according to the scale in which it is worked. In this sense, in literature, it is observed that temperature is the main factor affecting growth, composition and quality of grapes (Arrizabalaga et al., 2018; de Rességuier et al., 2020; Jackson and Lombard, 1993; Tonietto and Carbonneau, 2004), for this reason, different studies have been carried out in order to quantify the potential effects of temperature changes on vine phenology in different experimental sites around the world (Fraga et al., 2016; Andrew Hall et al., 2016; Parker et al., 2011; Webb et al., 2012). Due to the relationship between air temperature and development of grapevine phenology, different predictive phenological models have been proposed using climatic variables (Chuine et al., 2013; Ortega-Farías et al., 2002; Ortega-Farias & Riveros-Burgos, 2019; A. Parker et al., 2013; Parker et al., 2011; Reis et al., 2020). These models have been implemented with relative success in different agricultural applications, with the aim of facilitating management within the vineyard field, identifying areas with different yield potential and final production quality. This information is obtained, in general, from automatic weather stations (AWS) located at different distances from the vineyards (generally kilometers) (Ortega-Farías et al., 2002; Reis et al., 2020). Therefore, specific weather information is used to generate phenological estimations in the vineyard and those results are extrapolated to an entire productive unit, assuming that both temperature and phenology are homogeneous across the study vineyard. This methodology has been widely used to predict the vine phenological events, for example, to determine the probable flowering date of a certain variety located at the site where the climatic information was obtained. Thus, the traditional methods used by growers to characterize the vineyard's phenology (spot measurements or use of predictive models) would not be an adequate methodology to represent the spatial variability of the vineyard. In this regard, it can be observed that in the wine industry, field professionals do not perform more than two to three phenological observations per productive unit per season, assuming that these measurements are representative of the entire vineyard (Verdugo-Vásquez et al., 2019). For this, they use AWSs that collects information from a single site, which does not represent the real spatial variability of the vineyard, nor the micrometeorological condition of the plant. Therefore, this traditional method results in inappropriate and inefficient decisions from an agricultural point of view since it does not allow characterizing the vineyard spatial variability in key growth stages to produce high-quality grapes.

In this sense, several authors (Hall & Blackman, 2019; Ortega et al., 2003; Taylor et al., 2005; Tisseyre et al., 2005; Yu et al., 2020) have shown that in viticulture there is a high spatial variability in the fields, understanding this phenomenon as existing differences in a basic productive unit, which can be associated mainly with differences in soil and/or field management (Hall et al., 2003). Recently, the existence of spatial variability in climatic conditions has been studied at intra-predial scale (Matese et al., 2014) and at the level of the valley or productive region, which shows that the recordings made by the AWS do not necessarily represent the microclimatic condition of the vineyard, and therefore, it is not possible to assume that this information represents the entire production unit (Matese et al., 2014). From the above, the following questions arise: What is the representativeness of a weather station? Is it possible to improve the temporal prediction of the vine phenology using weather information collected at the plant level (microclimatic condition)?

On the other hand, it has been observed that there is spatial variability in the phenological development within the vineyard (Verdugo-Vásquez et al., 2016, 2019). Recent research shows that the classical methodology used to temporarily predict vine phenology, should be used with caution due to the significant spatial variability observed, both in climatic variables, and in the vine phenology. The extrapolation of the results of the temporary models obtained from climatic information of a weather station to nearby sites is not trivial, since, given the characteristics of viticulture (high heterogeneity observed at the field level), it is not possible to assume climate and plant homogeneity, limiting the results obtained only to the specific site from which the climatic information was obtained. The above, poses a new challenge for the modeling of vine phenology: Is it possible to model the spatial and temporal variability of the vineyard's phenology? To answer this question, a probable approach can be the use of climatic information obtained from individual temperature sensors located inside the vineyard canopy which represents the vine microclimatic condition. However, due to the high cost of implementation, this alternative may be unlikely (Verdugo-Vásquez et al., 2019). In this sense, it is important to highlight that in recent years, a series of research initiatives have been carried out in the development of low-cost sensors in agriculture (Polo et al., 2015; Viani et al., 2017). Most of these electronic devices have focused mainly on monitoring micrometeorological variables (Hall et al., 2003; Hall & Blackman, 2019; Ortega et al., 2003; Taylor et al., 2005; Tisseyre et al., 2005; Yu et al., 2020), without considering the many practical applications that could be implemented at the field level in a commercial vineyard, that require accurate phenological estimates for optimal grape production, such as the definition of the optimal moment of phytosanitary spraying for fungal diseases, e.g. powdery mildew (*Erysiphe necator*), which should be applied in precise phenological periods, as flowering. In this way, the correct estimation of the vine phenology becomes a fundamental support system for the site-specific management, oriented to the production of high-quality grapes. Based on the aforementioned, it is proposed as a research objective to develop and implement a low-cost wireless microclimatic temperature sensors network at the field level, for the spatialized monitoring of vine phenology, specifically flowering, in a commercial vineyard.

## 2. Materials and methods

### 2.1. Experimental site description

The experiment was carried out in a vineyard cv. Cabernet Sauvignon (1.56 ha) located in the Panguilemo Experimental Station of the University of Talca (Maule Valley), Chile (35°22.2′ S, 71°35.39′ W, WGS84, 121 m.a.s.l.) during the 2011–12 and 2012–13 growing seasons. The vineyard was established in 1998 using ungrafted plants with a spacing of 1.5 m between vines and 3.0 m between rows with E-W orientation. The vines were trained in a vertical shoot positioned system and watered by furrow.

### 2.2. Development of a spatialized phenological sensor

The proposal research consists in developing a system to monitor a key phenological stage (flowering) of the vineyard, through the implementation of a low-cost wireless sensor network (thermo-hygrometers), which will allow characterizing intra-predial spatial variability at the field level.

The distribution of the sensors in the vineyard was defined based on the spatial variability of the vegetative expression (canopy porosity) and soil physical properties, previously described by (Acevedo-Opazo et al., 2013) in this same vineyard. In this sense, it was decided to install 8 spatially distributed sensors to characterize the phenology of the vineyard. The distribution of the spatialized sensors and the weather station is shown in Fig. 1. The system was used for mapping the absolute error in days of the estimates of vine phenology during the flowering period.

Before going into further details, it is important to note that the alternatives to this system are 3; Automatic Weather Station (AWS) at the cost of USD 4240 to USD 16,000 (per measuring point), Individual sensing of monitoring points at the cost of USD 2656 (per measuring point), and finally, button-type Thermo hygrometers at the cost of USD 200 (per measurement point). In contrast to these alternatives, the system developed in this research has a total cost of USD 150 per measurement point, which is why we believe that it qualifies as a low-cost system. In addition to this, it is important to consider that this system, asides from and being cheaper, has have characteristics that commercial systems do not have, such as the centralization of information in a unit, which facilitates the downloading of data by the user.

### 2.3. Micro controller

The micro controller is responsible for processing all the information generated by the wireless sensors network (WSN) and allows serial communication with the antenna. An Arduino board was implemented only in the central module, given that in this one the following shields were connected: i) LiPo Power shield to deliver energy, ii) XBee shield to connect the communication antenna and iii) SD-RTC Shield to store the sensor information in an SD memory card with the date and time. To avoid using Arduino in all modules, a simplified printed circuit board (PCB) that integrates the ATmega328-PU micro controller, communication card and sensor was designed. The developed card includes a base for the ATmega328-PU, a 16 MHz oscillator crystal, two 22pF capacitors, one 1 K Ω resistor, a 3.3 V voltage regulator circuit with two capacitors (to filter both the input voltage and output) and a 3-pin terminal block (to connect the sensor). The design of the electronic board was developed with the Software EAGLE and made with a CNC Bungard CCD/2.

### 2.4. Wireless communication systems

Within the wireless communication systems available in the market, there are three types of networks: personal (WPAN), local (WLAN) and global (WWAN). In the case of wireless personal area networks (WPAN), there is a communication protocol called Zigbee, which is based on the IEEE 802.15.4 standard. This is basically a simple type of communication, created in 2004. The main advantages offered by this technology are i) low-cost devices and low power consumption ii) operation under the free band of 2.4 GHz, iii) supports multiple network topologies, iv) AES encryption, blocking the network and prevents other nodes from connecting and v) programming, control, and simple setup.

The ZigBee protocol allows the development of point-to-point network topologies, multipoint, peer-to-peer (all nodes connected), or complex network sensors that interconnect two or more mesh networks. The most used topologies are Tree, Mesh and Star. When choosing the optimal interconnection system, it is essential to consider each system's advantages and disadvantages. In this sense, for Tree Topology it must be considered as advantages the low electrical consumption and the high transmission range, however, as disadvantages, we must consider that it is a complex topology, it is not resilient to failure in the nodes, and the energy consumption is unequal in the nodes. In the case of the Mesh topology, we can mention its high fault tolerance, however, the high current consumption, increased latency, and redundant paths must be considered when designing and optimizing a system. Finally, in the case of the star topology, we have the main advantage that the failure in the nodes does not affect the other measurement devices, additionally, the networks in this topology generally have low electricity consumption, however, despite these attractive advantages, it must be considered that a failure in the central node will make the entire network to fail and additionally these networks will have a low transmission range with respect to the other topologies. According to those mentioned above, the proposed system used the star topology mainly due to the robustness that this system presents when a remote measurement device fails.

**Table 1**
Technical characteristics Xbee Pro 63mW RPSMA - Series 2B.

| Characteristics | Specifications |
|---|---|
| Power supply | 3.3 V – 295 mAh |
| Range | 1600 m |
| Output power | 63 mW (+17 dBm) |
| Transference rate | 250 Kbps |
| Antenna connector | RPSMA |
| Serial Data Interface | UART, SPI |
| Configuration method | Command AT y API |
| Frequency bands | ISM 2.4 Ghz |
| Digital I/O | 15 |
| Operation Temperature | −40 °C to +85 °C |

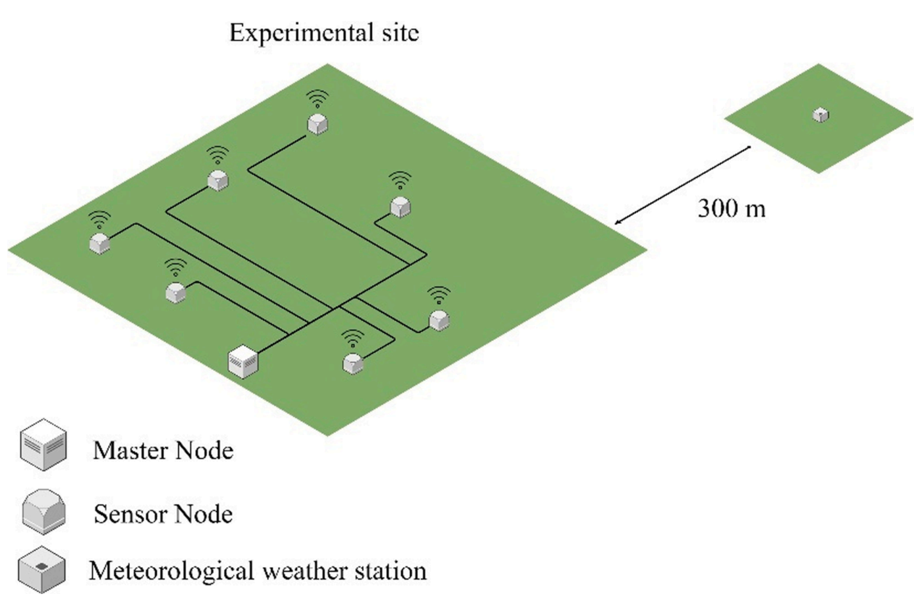


**Fig. 1.** Experimental site and system location.

On the other hand, for this research, the communication board XBee ProS2B was used (features available in Table 1). The used wireless network is based on the star topology, in transparent mode or AT. With this configuration the central node can send and then receive the requested information to each slave nodes connected to the network. Thus, the network will have a central node that is programmed as Zigbee coordinator AT and seven remote nodes programmed as Zigbee end device AT, where the central module stores the information of all sensors. This type of communication systems has a great interest for agricultural aplications because it facilitates the labor of collection and storing information.

### 2.5. Temperature sensor

The DHT22 sensor was used, due to its low cost and high accuracy. It is important to consider that this sensor works using a digital input port of the micro controller and does not require a pull-up resistor. In the central module, the sensor is connected to digital pin D5 and all remote modules are connected to digital pin D4, corresponding to the physical number 6 of the ATmega328-PU.

To evaluate the quality of the information delivered by the sensor under field condition, a test was carried out in which the temperature of the measurement was compared with commercial sensors under field conditions, were DHT22 sensor was compared to a Vaisala Probe following a similar methodology to proposed by (Mahan and Yeater, 2008). The sensors were placed on a reference grass surface to carry out this test, where continuous measurements were carried out during a week. Therefore, a wide sensor temperature range was achieved to evaluate the sensor's performance.

### 2.6. Data storage

Data loggers are devices that allow to store information (usually as a text file) measured by any sensor in a memory. When a specific sensor is retrieving data, it is especially important to know the time when it was collected. To carry out this task, Arduino has a function called millis (), which allows the use of program delay function. So, if Arduino has a feature that allows time to be recorded, why should an external Real Time Clock (RTC) be used? This is because the function millis () only takes the notion of time by being turned on, and when turned off it completely unconfigures. The RTC used correspond to DS1307, that uses a CR1225 battery, allowing Arduino to maintain the date or time when the system is turned off. Considering the above, the monitoring system was configured to generate a text file that stores the data of temperature 24 h at time intervals of 60 min. The following is an example of the daily data collected by sensors 1 and 7 for fifht of October of season 1 (Fig. 2).

### 2.7. Charging source and power supply

The wireless sensor network has an individual power system whose main source of energy is a mono crystalline photovoltaic panel which delivers a voltage of 9 V and a power of 5 W. The panel is connected to a voltage regulator board (Fig. 3), also developed for this prototype. The regulator chosen for the circuit design is a linear regulator (LM7805) that delivers a maximum current of 1A (with input voltages ranging from 7 V to 25 V). Then the voltage regulator card is connected via micro-USB cable to the LiPo power shield. Finally, the LiPo power shield is connected directly to the central node and the remote nodes using the 5 V and GND pins.

### 2.8. Operation and prototyping of the modules

The central module is responsible for controlling the entire wireless network and requesting the data collected by the slave modules. The first action executed by the central module is to send a "0" through the serial port, to wake up all the slave modules and collect the temperature measurements of the entire network (Fig. 4). Subsequently, it sends the sensor the number from which it will collect the information through the serial port, to receive and store the data generated by this one. The same procedure is repeated for each of the slave modules installed in the field.

Regarding the encasing of the electronic components of the device, a

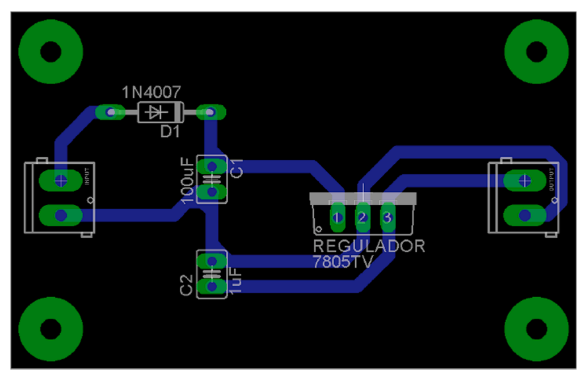


**Fig. 3.** Voltage regulator board.

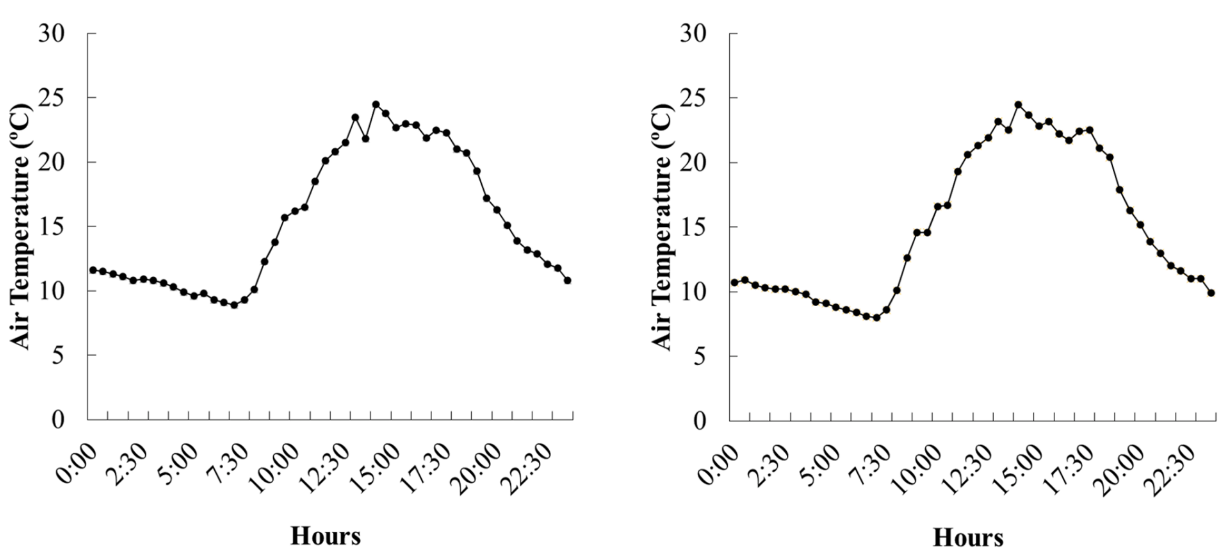


**Fig. 2.** Daily data collected by sensors 1 (a) and 7 (b) for fifht of October of season 1.

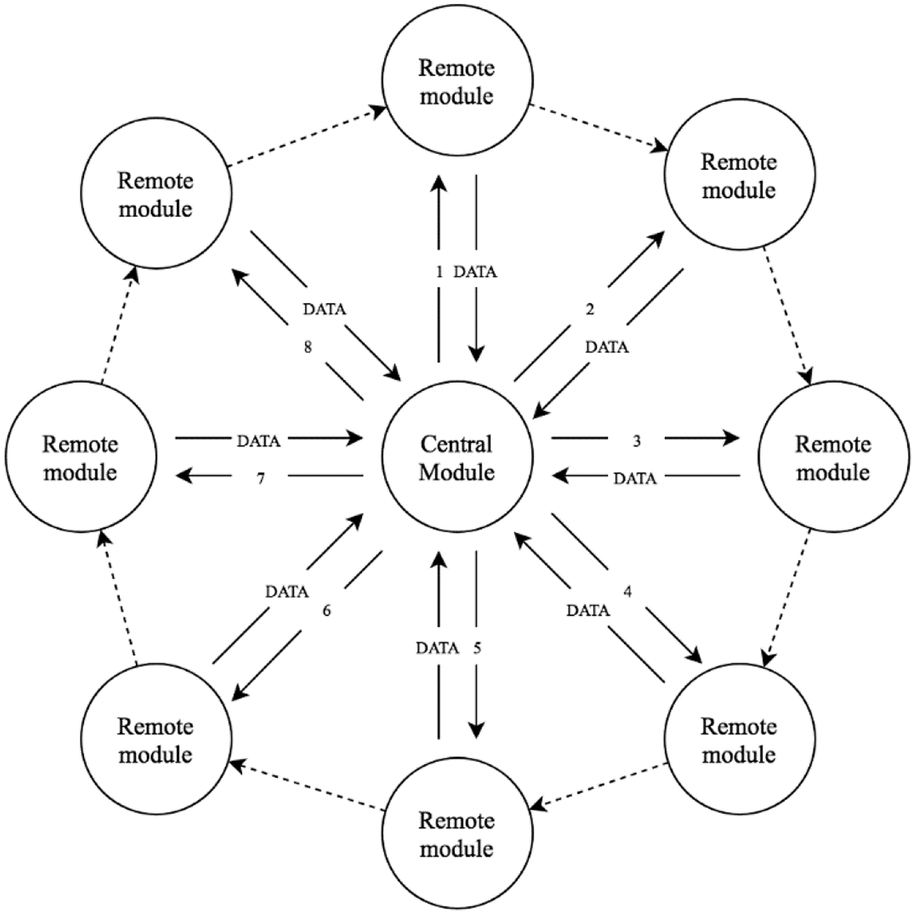


**Fig. 4.** Schematic model of data transfer.

Stevenson Screen designed and printed in 3D using white ABS using a Printer Model Prusa I3 Hephestos was used. Evidence not shown in this investigation indicated that there were considerable differences between the type of plastic used at a practical level. While polylactic acid (PLA) presented a very noticeable degradation under natural operating conditions, ABS did not suffer deformations or damages. It is important to consider that at the farm level, the climatic conditions are the cause of the degradation of the material used for prototyping, but that the Fertilizers and Pesticides that are applied directly on the foliage should also be considered. Faced with this last situation, ABS proved to be resistant to the application of these products. Regarding the operating range, the manufacturer indicates that these sensors can work from −40 °C to +125 °C (+−0.5 °C). However, in our research, the sensors were deployed only during the study period (September to November) in which the temperatures ranged between 0 and 31 °C. On the other hand, the sensor was not directly exposed to solar radiation since it was installed inside the foliage, given that it is a sensor manufactured to evaluate the microclimatic temperature of the plant.

Although the sensor was tested in the phenological period of flowering, it could also be used to monitor the rest of the stages of the phenological cycle where the plant lacks foliage (e.g., sprouting). For these situations, the sensor together with the protection structure described above, are adapted to direct sunlight conditions since the multilayer dish-type parasols (stevenson structure) allows to avoid direct sunlight. Situations of operation under direct exposure of this type of structures can be observed in Bai et al. (2016)

### 2.9. Climatic model description

Two models to estimate phenological stage were considered to predict the flowering event (phenological stage PS = 23 of the Coombe Scale (Coombe, 1995).

1. Monomolecular equation based model (ME): The first model corresponds to the formulation developed by (Ortega-Farías et al., 2002) on a Cabernet Sauvignon vineyard. This methodology is based on the monomolecular equation of Mitscherlich proposed by (Thornley and Jonson, 1990) (eq. (1)). This model estimates the phenological stage using the accumulated Growing Degree Days (GDD) as a basis from the date of the budburst (phenological stage PS = 4 of the Coombe Scale (Coombe, 1995) until the harvest event (phenological stage PS = 38 of the Coombe Scale (Coombe, 1995), based on 10 °C.

$$PS = Psf - (Psf - Psi)^{*}exp^{-k^{*}GDD} \tag{1}$$

where: $PS$ = current phenological stage, $Psf$ = last phenological stage corresponding to PS = 38, $Psi$ = first phenological stage corresponding to PS = 4, $k$ = rate of phenological development and GDD = sum of Growing Degree Days (heat units) from the date corresponding to $Psi$ to the date of $PS$.

According to the above, the model calibrated by (Ortega-Farías et al., 2002) is shown in eq. (2):

$$PS = 39 - 28.81^{*}exp^{-0.00204^{*}GDD} \tag{2}$$

2. Parker model (GPV): The second model was proposed by (Parker et al., 2013) and it was based on the methodology proposed by (Hunter and Lechowicz, 1992; Robertson, 1968; Wang, 1960). In this model, a specific phenological stage occurs when a critical forcing

state $S_f$, which is defined as a the sum of Growing Degree Days from a start date $t_0$, reaches a particular value $F^*$ (Eq. (3)).

$$S_f(t_s) = \Sigma_{t_0}^{t_s} R_f(x_t) \geq F^* \tag{3}$$

The state of forcing is described as a daily sum of the rate of forcing, $R_f$, which starts at $t_0$, defined as the DOY 241 (southern hemisphere) for (Parker et al., 2013) (Eq. (4)). Flowering is therefore simulated independently of prior developmental stages.

$$R_f(x_t) = GDD(x_t) = \left\{ \begin{array}{c} 0 if \ \ x_t \leq T_b \\ x_t - T_b if \ \ x_t > T_b \end{array} \right\} \tag{4}$$

where: $T_b$ corresponds to a base temperature set at 0 °C for (Parker et al., 2011), above which the thermal summation is calculated, $x_t$ is the daily arithmetical means temperature (the sum daily minimum and maximum temperature divided by two). Thus, the $F^*$ value for Cabernet Sauvignon cultivar corresponds to 1299 heat units.

Observed values corresponding to dates (expressed in days of the year) of phenology (from pre-budburst to flowering) for each site of the vineyard were recorded during two consecutive seasons, using the phenological scale. For this purpose, phenological observations were performed every 5–7 days systematically for each selected site.

It is important to consider that wireless sensors were installed inside de plant's canopy at a height of 1.5 m above the soil (recording data at intervals of 60 min). On the other hand, climatic data (air temperature) obtained from an automatic weather station (Adcon Telemetric, A730, Klosterneuburg, Austria), installed on a grass surface located 300 m from the vineyard under study, was also collected. The information recorded by these electronic devices (spatialized sensors and automatic weather station) was used to model the phenological events of the vineyard, through the methodologies proposed by (Ortega-Farías et al., 2002; Parker et al., 2013). The results obtained from these simulations were used to study the spatial behavior of both models during the flowering phenological event.

### 2.10. Statistical analysis

For sensor data validation, a comparison between the observed and estimated values was carried out using the root mean square error (RMSE) and mean absolute error (MAE) (Mayer and Butler, 1993; Willmott, 1981; Willmott et al., 1985). Likewise, the evaluation of the behavior of both models was carried out by comparing the absolute value of the differences in days, between the measured value and the estimates made during both study seasons. In this regard, 4 days was defined as the criterion of maximum error allowed by growers to make an adequate phenological estimation when using predictive models during the flowering phenological event.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{1}^{N} (\mathrm{O_i} - \mathrm{E_i})^2}{\mathrm{N}}} \tag{5}$$

$$\mathrm{MAE} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} |\mathrm{E_i} - \mathrm{O_i}| \tag{6}$$

where $\mathrm{E_i}$ represents the estimated values by the model and $\mathrm{O_i}$ is the observed flowering date and N is the number of observations.

## 3. Results

### 3.1. Climatic characterization of the experimental site

The two seasons evaluated during the experiment showed different climate behavior. The first season (S1) was strongly influenced by the ENSO "La Niña" climatic phenomenon. Due to the occurrence of this phenomenon, higher average temperatures were observed during this season, registering an average increase of 0.56 °C compared to the second season (S2). On the other hand, rainfall registered during the summer of the first season (September to March) was scarce, reaching 44.6 mm, which is considered normal for a Mediterranean climate, under the influence of "La Niña" event. For the second season, the situation changes drastically, due to the influence of normal weather conditions for Mediterranean climates. In this sense, rainfall increases considerably during the summer period, reaching 138.7 mm (three times more than the previous season). When observing the reference evapotranspiration (ETo) recorded during both seasons, the first season presented a higher evaporative demand (ETo: 1010.02 mm) compared to the second season (ETo: 921.6 mm), observing a difference of 9.6% with higher water consumption during the first season. Finally, it is important to highlight that the climatic differences observed between both study seasons had a significant effect on the predictive behavior of the two proposed phenological models, which is explained below.

### 3.2. Validation process of the low-cost wireless sensors network

To evaluate the differences between the real and estimated values using the proposed models, the RMSE and MAE statistics were used. The results obtained are shown in Table 2, where, for the first study season, the ME showed RMSE and MAE values of 5.98 and 5.71 days, respectively, when using the spatialized sensors. However, during the second season, an improvement on error estimates was observed between the estimated and observed values when using the spatialized sensors, showing a RMSE and MAE values of 4.07 and 3.43 days, respectively, values a 50% lower than the statistical values obtained with the Automatic Weather Station (AWS), which were of 8.36 and 7.86 for RMSE and MAE, respectively. The previous results question the use of the AWS as a tool for predicting phenological events, such as flowering, especially in seasons where climatic conditions are atypical, as observed during the first study season.

were; SEN-ME corresponds to estimation of phenology made using (Ortega-Farías et al., 2002) model in combination with spatialized sensors, AWS-ME is the estimation of phenology made using (Ortega-Farías et al., 2002) and meteorological weather station (AWS) data, SEN-GPV is the estimation of phenology made using (Parker et al., 2013) model in combination with spatialized sensors and AWS-GPV is the estimation of phenology made using (Parker et al., 2013) and meteorological weather station (AWS) data

On the other hand, the GPV showed consistent results during both study seasons. For the 2011–12 and 2012–13 seasons, the RMSE values were 3.95 and 1.93 days, respectively for the estimates performed with the spatialized sensors. For the case of measurements made with the AWS, RMSE values were 10.13 and 7.11 for 2011–12, 2012–13 seasons respectively. The above shows stable and better behavioral results for the phenology data estimated with the spatialized sensors during both study seasons when using GPV. In this regard, it is important to note that a maximum tolerable error criterion (<4 days) was defined to make an adequate estimate of the phenological conditions in the vineyard. This criterion is based on the maximum period of tolerance that a vinegrower would have to carry out an opportune work in the field considered as key for the vine production, such as phytosanitary spraying during flowering event.

**Table 2**
Error estimators for estimates made during the two study seasons.

| Statistic parameters (days) | SEN-ME | AWS-ME | SEN-GPV | AWS-GPV |
|---|---|---|---|---|
| **S1: 2011–12** | | | | |
| MAE | 5.71 | 3.57 | 3.57 | 9.57 |
| RMSE | 5.98 | 4.23 | 3.95 | 10.13 |
| **S2: 2012–13** | | | | |
| MAE | 3.43 | 7.86 | 1.71 | 6.86 |
| RMSE | 4.07 | 8.36 | 1.93 | 7.11 |

Regarding the higher error estimates obtained with the AWS, (Verdugo-Vásquez et al., 2016, 2019) showed the existence of a high spatial variability of the vine's phenology at the field level. In this sense, it is important to highlight that the use of an AWS to characterize the variability of the phenology is insufficient to adequately model the spatial structure of phenology in the flowering period at the level of the agricultural field. For this reason, the present investigations raises the need to model this variability. At present, there are no commercial sensors that allow the establishment of wireless monitoring networks at the entire field level, due to the high cost of implementation and maintenance of these monitoring systems, therefore, their use at the small farmer's level is impracticable. In this sense, if we consider the existing technology in the market, it is impossible to model the spatial behavior of the productive variables associated with the plant's microclimate. Therefore, the alternative proposed in this work is a viable solution to model the phenology considering the spatial variability of the vineyard in the flowering period. The adequate performance of this task would allow an adequate management of productive resources within the vineyard.

After calculating the error estimators, the difference in days was estimated between the values observed in the field and the values estimated by the proposed models and they are presented in Table 3. In this regard, it is observed that ME shows estimation results that are below the the maximum tolerable error by the farmer (4 days) when using spatialized sensors, obtaining average values of 3.7 and 2.9 days for the first and second season, respectively. For the case of using AWS, average values of 5.7 and 8.3 days were obtained for the first and second seasons respectively. As in the previous table, these results cast doubt on the stability of the first model, specially in the case of using an AWS, given the erratic results observed in this study.

were; SD corresponds to Standard Deviation (in days), SEN-ME corresponds to estimation of phenology made using (Ortega-Farías et al., 2002) model in combination with spatialized sensors, AWS-ME is the estimation of phenology made using (Ortega-Farías et al., 2002) and meteorological weather station (AWS) data, SEN-GPV is the estimation of phenology made using (Parker et al., 2013) model in combination with spatialized sensors and AWS-GPV is the estimation of phenology made using (Parker et al., 2013) and meteorological weather station (AWS) data.

On the other hand, the GPV showed consistent results during both study seasons. For the 2011–12 and 2012–13 seasons, the estimated mean error values were 3.6 and 1.7 days, respectively for the evaluation of the spatialized sensors. Meanwhile, measurements made with the AWS presented error values of 9.6 y 6.9 days, respectively. The above shows stable results and better behavior for the phenological data estimated with the spatialized sensors during both study seasons. In this sense, it is important to point out that the spatialized sensors, when using the GPV, never exceeded the maximum tolerance criterion defined by the vine growers, as a practical threshold for scheduling agricultural activities in which the correct estimation of phenology in the flowering period is a key information for making decisions in the vineyard.

**Table 3**
Absolute value of the differences in days, with respect to the measured value for estimates made during two study seasons.

| Season | Site | SEN-ME | AWS-ME | SEN-GPV | AWS-GPV |
|---|---|---|---|---|---|
| 1 | 1 | 4 | 9 | 6 | 14 |
| | 2 | 5 | 8 | 5 | 13 |
| | 3 | 4 | 7 | 5 | 12 |
| | 4 | 6 | 2 | 3 | 4 |
| | 5 | 4 | 4 | 2 | 8 |
| | 6 | 3 | 5 | 3 | 9 |
| | 7 | 0 | 5 | 1 | 7 |
| | **MEAN** | 3.7 | 5.7 | 3.6 | 9.6 |
| | **SD** | 1.9 | 2.4 | 1.8 | 3.6 |
| 2 | 1 | 4 | 7 | 2 | 9 |
| | 2 | 0 | 8 | 2 | 9 |
| | 3 | 3 | 6 | 1 | 7 |
| | 4 | 2 | 14 | 0 | 6 |
| | 5 | 5 | 2 | 3 | 3 |
| | 6 | 1 | 6 | 2 | 7 |
| | 7 | 5 | 15 | 2 | 7 |
| | **MEAN** | 2.9 | 8.3 | 1.7 | 6.9 |
| | **SD** | 2.0 | 4.6 | 1.0 | 2.0 |

### *3.3. Spatialized study of phenology.*

To assess the coincidence between the values measured in the field and those estimated by both models, the absolute errors were mapped in days (Figs. 5-6). Thus, it can be observed that the estimates made by the evaluated models are consistently better when the climatic information from the low-cost spatialized sensors is used instead of the information captured by the AWS. In this regard, the ME and GPV showed a greater coincidence with the real date measured in 64.0% and 78.5% of the sites evaluated in the field, respectively, compared to the 14% observed when using climate information recorded with the AWS for both evaluated models (Table 4). On the other hand, when comparing the results obtained during both seasons, it is observed that the first season shows slightly worse results than those recorded during the second season. This may be due to different weather conditions between both seasons. Notwithstanding the foregoing, spatialized sensors always presented consistently better results than those recorded by the AWS. Regarding the results obtained by the spatialized sensors, it can be pointed out that GPV was the one that presented the best estimation results in the phenological period of flowering in the vineyard during the second season, with an average error of less than 3 days in 100% of the evaluated sites (Fig. 6). Finally, it can be indicated that the predictions made with climatic information obtained from the AWS are unable to correctly model the spatial variability of the phenology observed within a vine-growing field.

were; SEN-ME corresponds to estimation of phenology made using (Ortega-Farías et al., 2002) model in combination with spatialized sensors, AWS-ME is the estimation of phenology made using (Ortega-Farías et al., 2002) and meteorological weather station (AWS) data, SEN-GPV is the estimation of phenology made using (Parker et al., 2013) model in combination with spatialized sensors and AWS-GPV is the estimation of phenology made using (Parker et al., 2013) and meteorological weather station (AWS) data

Cartographies corresponding to the simulations carried out for the flowering phenological event during seasons 1 and 2 are presented in Figs. 7 and 8. In these, a similarity of the spatial patterns between the values measured in the field and those simulated by the sensors can be seen. It is also important to note that a relative scale has been used for the cartographies to preserve the spatial variability patterns observed in the phenological flowering event analyzed in this work.

Finally, Fig. 8 shows a remarkably interesting result for the reader. Even though GPV model presents a superior behavior in estimating the flowering phenological event, we can observe in Fig. 7d and 8d than the ME model, despite incorporating only specific information from an AWS, allows to obtain a map with spatial patterns of phenology variability. This could sound contradictory; however, this methodology incorporates into the model the observation of the phenological event of the sprouting, from which it allows to obtain for each site measured within the agricultural plot a value with a phenological scale that can be spatially modeled. On the other hand, the Parker model, when implemented using only a weather station, does not allow generating spatial patterns due to its formulation. In this way, each of the evaluated models presents advantages in its implementation that must be taken into account considering the weather data available at the field level and the management objective to be implemented with these predictive models for the phenological event of vineyard flowering.

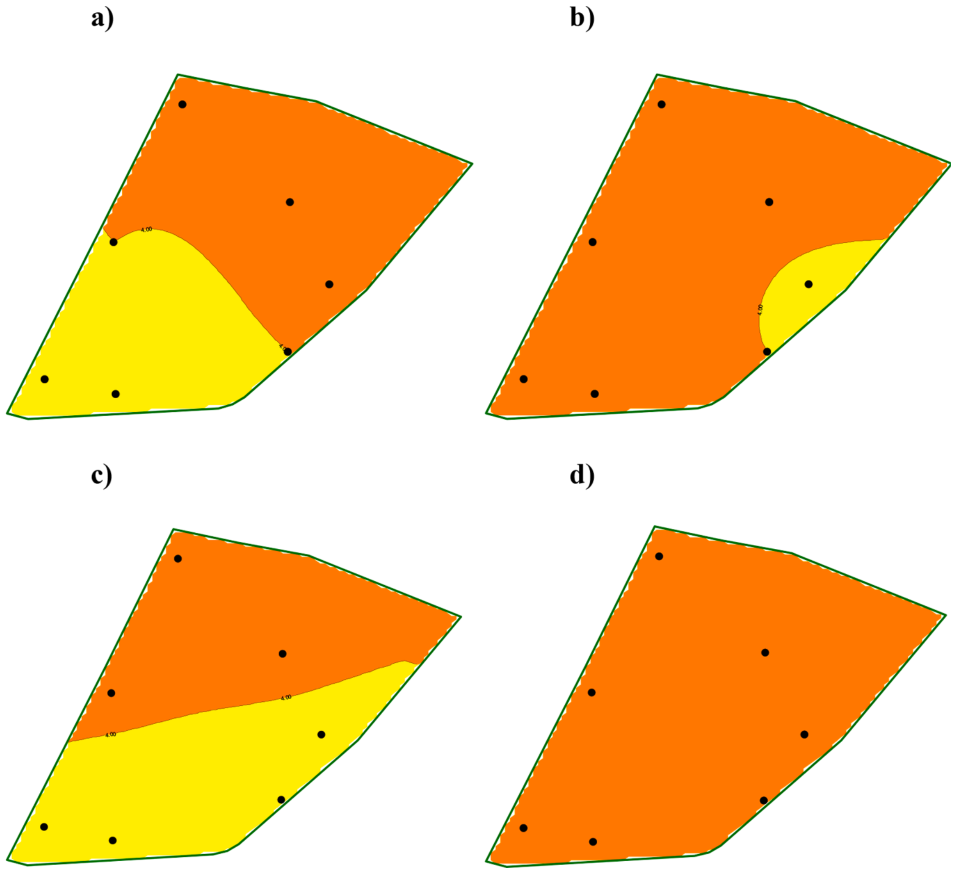


**Fig. 5.** Absolute value of the differences in days, with respect to the measured value for estimates made during season 1 (2011–12). The orange color indicates the measurement points at which values greater than 4 days were observed, on the other hand the points indicated with yellow indicate differences less than 4 days between observed values versus estimated. a): corresponds to estimation of phenology made using (Ortega-Farías et al., 2002) model in combination with spatialized sensors (SEN-ME), b): is the estimation of phenology made using (Ortega-Farías et al., 2002) and meteorological weather station (AWS) data (AWS-ME), c): is the estimation of phenology made using (Parker et al., 2013) model in combination with spatialized sensors (SEN-GPV) and d): is the estimation of phenology made using (Parker et al., 2013) and meteorological weather station (AWS) data (AWS-GPV). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

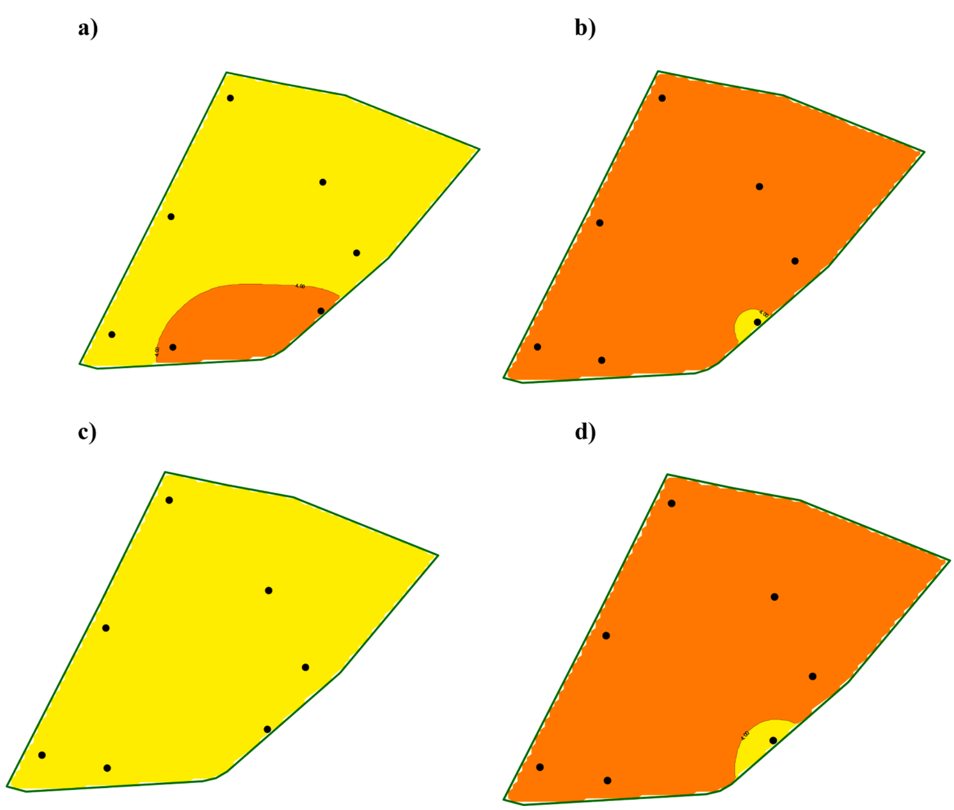


**Fig. 6.** Absolute value of the differences in days, with respect to the measured value for estimates made during season 2 (2012–13). The orange color indicates the measurement points at which values greater than 4 days were observed, on the other hand the points indicated with yellow indicate differences less than 4 days between observed values versus estimated. a): corresponds to estimation of phenology made using (Ortega-Farías et al., 2002) model in combination with spatialized sensors (SEN-ME), b): is the estimation of phenology made using (Ortega-Farías et al., 2002) and meteorological weather station (AWS) data (AWS-ME), c): is the estimation of phenology made using (Parker et al., 2013) model in combination with spatialized sensors (SEN-GPV) and d): is the estimation of phenology made using (Parker et al., 2013) and meteorological weather station (AWS) data (AWS-GPV). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

**Table 4**
Coincidence expressed in percentage between the values measured in the field and those estimated using both models.

| Model | Season 1 | Season 2 | Mean |
|---|---|---|---|
| **AWS-ME** | 14.0% | 14.0% | 14.0% |
| **AWS-GPV** | 7.0% | 17.0% | 12.0% |
| **SEN-ME** | 57.0% | 71.0% | 64.0% |
| **SEN-GPV** | 57.0% | 100% | 78.5% |

## 4. Discussions

### *4.1. Vineyard spatialized monitoring system.*

This study shows the implementation of a spatialized system for estimating of grapevine phenology using field sensor network. The advantage of this approach lies in the ability to measure with high detail the spatial variability within the vineyard, minimizing the cost of monitoring and collecting plant information, through the implementation of a low-cost wireless sensor network. This tool would allow phenological observations of the vineyard with high accuracy during the growing season, including the harvest date (Chmielewski, 2013). Numerous models have been evaluated in the literature, which have

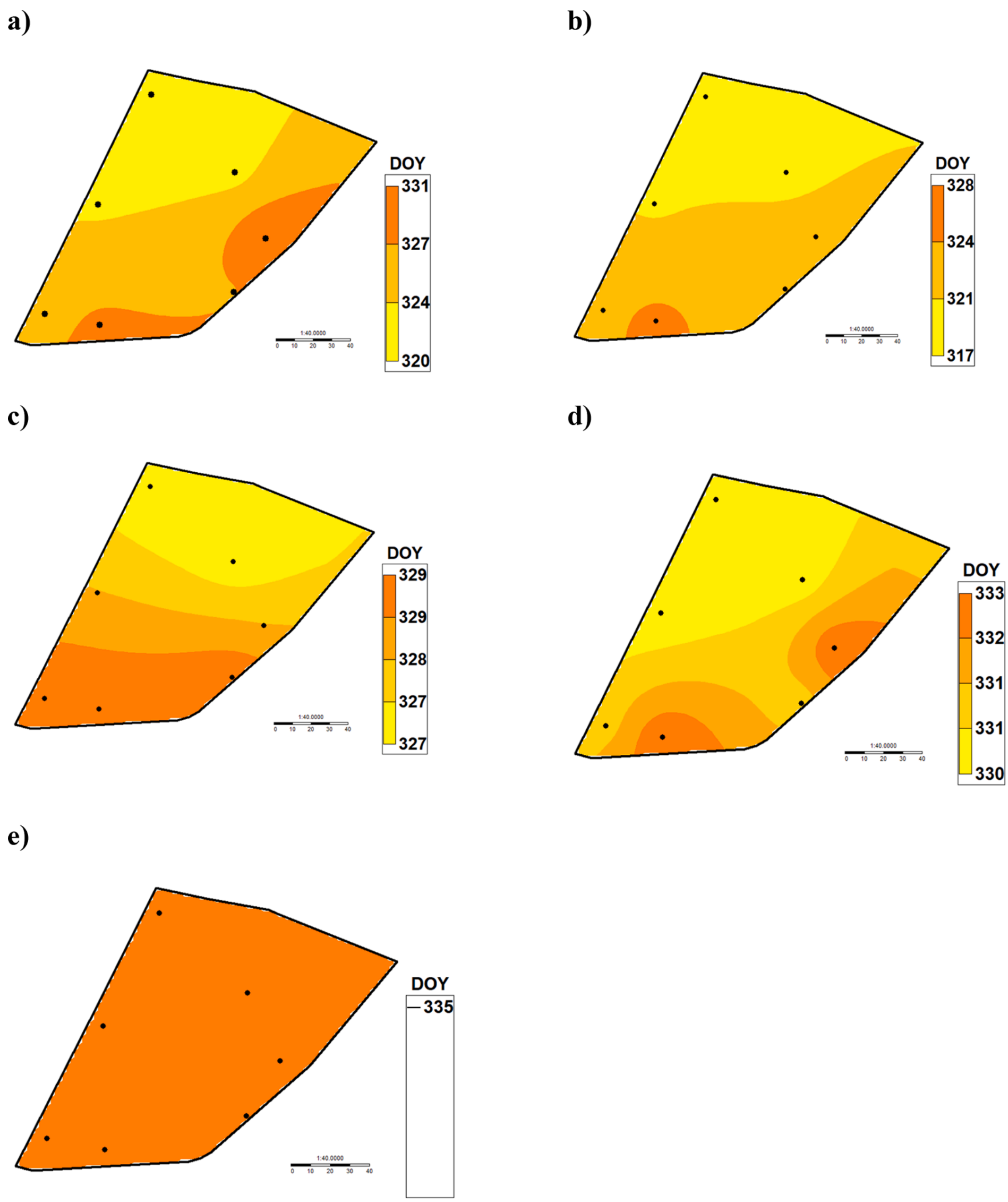


**Fig. 7.** Cartographies corresponding to season 1 were, a): Measured values of phenology, b): is the estimation of phenology made using (Ortega-Farías et al., 2002) and spatialized sensors (SEN-ME), c): is the estimation of phenology made using (Parker et al., 2013) model in combination with spatialized sensors (SEN-GPV) d): is the estimation of phenology made using (Ortega-Farías et al., 2002) and meteorological weather station (AWS) data (AWS-ME) and d): is the estimation of phenology made using (Parker et al., 2013) and meteorological weather station (AWS) data (AWS-GPV).

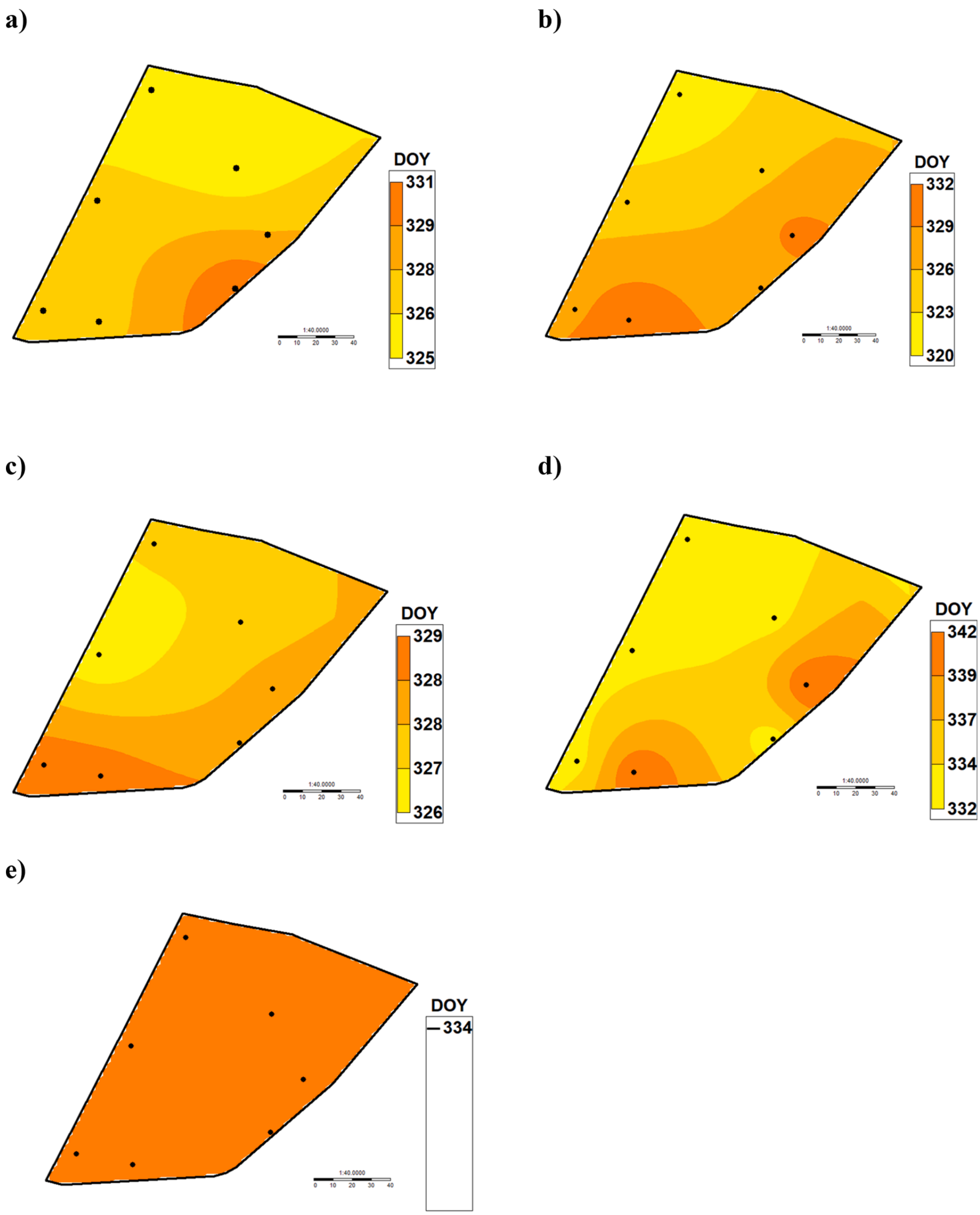


**Fig. 8.** Cartographies corresponding to season 2 were, a): Measured values of phenology, b): is the estimation of phenology made using (Ortega-Farías et al., 2002) and spatialized sensors (SEN-ME), c): is the estimation of phenology made using (Parker et al., 2013) model in combination with spatialized sensors (SEN-GPV) d): is the estimation of phenology made using (Ortega-Farías et al., 2002) and meteorological weather station (AWS) data (AWS-ME) and e): is the estimation of phenology made using (Parker et al., 2013) and meteorological weather station (AWS) data (AWS-GPV).

placed special emphasis on the phenological state of flowering, since this growth stage presents a high degree of correlation with the harvest date (Reis Pereira et al., 2018). In literature, Models such as Thermal Time model (Cannell and Smith, 1983) also known as the Spring Warming model (Hunter and Lechowicz, 1992), the Parallel model (Kramer, 1994), the Sequential model (Kramer, 1994) and the Unified model (Chuine, 2000), have been used to monitor vineyard phenology. However, these models have been developed for large productive areas and do not consider the natural spatial variability of the vineyard, therefore, the implementation of site-specific models that consider this variability could become key information for the decision-making of winegrowers in function of the spatial variability detected at the field level (Caffarra & Eccel, 2010; Parker et al., 2011).

### 4.2. Modeling of vineyard flowering event.

Precise modeling of the stages of vineyard development requires very detailed work consisting mainly of four stages: i) data collection, ii) model definition, iii) adjustments and iv) model testing (Chuine et al., 1999). As a result of the extensive work required to develop new phenological models, some authors have adapted the original formulations to suit their local environments. Using this method, accurate results have been observed. However, the spatial variability of vineyard phenology has been little studied, due to the limitations in the sensing tools normally used for the precise estimation of phenological events. Taking this into consideration, the present work incorporates the ME model developed for local conditions, and the GPV model, which was developed considering a wide variety of vineyard located in different geographic locations. The results show that both models are consistent with what is observed in the literature; however, when it comes to predicting phenological development in detail, the GPV and ME models perform better when they are incorporated into a network of spatialized sensors strategically distributed within a vineyad. On the other hand, the results obtained from the meteorological station were the ones that showed the worst performance, a situation that had been originally contemplated since the station was located outside the vineyard. The previous results also allow us to conclude that models developed under other conditions are available to be used under different environmental conditions from those in which they were originally calibrated.

On the other hand, it is important to note that although these models are quick and easy to implement when using information collected from a meteorological station. However, the specific local conditions of this information present important limitations that are related to its inability to account for the specific conditions of the field and its spatial variability. Therefore, the most convenient solution at a commercial level consists of the implementation of a low-cost sensors network, which will allow the farmer to accurately determine the spatial variability of phenological development within his vineyard.

### *4.3. Electronic device development.*

The results observed in the present work show that use of spatialized microclimatic device (low-cost electronics) could be an interesting alternative to be implemented at the field level. However, for this technology to be implemented successfully, adequate isolation of the sensors must be carried out during its construction. This is especially relevant at the level of the microcontroller, which should ideally be insulated with resin to avoid conduction electricity. Additionally, it is important to mention that when it is desired to incorporate a wireless communication system to the devices, the tests must be carried out under real operating conditions. In this case, a significant reduction in the data transmission range of the evaluated communication system was observed, due to the wire structure that supports the vineyard's canopy. This vineyards trained structure reduced the communication distance of the devices at the field level by up to 50%. To face this situation, we suggest placing the communication antennas on the crop using cables that allow the antennas to be extended so that they have a direct line of sight between the devices installed in the vineyard. At the field level, this turned out to be an effective strategy to recover a large percentage of the communication range reported by the manufacturer. Another important factor that must be considered in the development of these devices is their electrical energy consumption. Several authors have used microcontrollers from different manufacturers; however, we recommend using simple field-level processing units that consume much less energy than traditional units used (microcomputers). The previous topic is important, since it will allow the development of more economically sustainable devices, since the processing and power modules must meet some minimum requirements, thus optimizing the electricity consumption of the proposed system.

Finally, this study shows that the use of phenological models at specific moments in the vineyard (in this case, flowering) in combination with a low-cost wireless sensor network is essential information for modern vineyard production, which aims to produce very high-quality fruit. Given the results obtained in this work, this proposal could become a tool for field viticultural procedures, by knowing the stage of advance or delay in the vine growth during the season and its relationship with the vineyard historical information. However, the model calibration requires an extensive historical database that could present significant drawback for the commercial implementation of this proposal.

### *4.4. Improvements and perspectives of the proposed system*

During the development of this study, a recompilation of information regarding possible improvements in further studies was made. In this sense, it was noted that some elements of the prototype must be improved to increase the robustness and usefulness of the proposed system. In this research it was possible to identify some environmental and technical factors to consider in a new improved version of the prototype:

- *Improve antenna position in the field*: the main factor that affects the data transmission is the irregular field topography, a situation that is usual in commercial viticultural systems. This condition does not allow direct vision between the antennas of the devices; therefore, a possible solution would be to add extension cables between the XBee and the 2.4 GHz antenna to place the transmitter above the vine canopy.
- *Improve the power supply system*: it is important to consider that the wireless measuring modules are installed during the summer, when the highest solar radiation values of the years are recorded, which ensures efficient operation of the solar panels for recharge the wireless measuring system. However, if the device is intended to measure field information throughout the year, a modification to the power system should be considered. These modifications should be aimed at reducing energy consumption at times of the day, in which the sensor is not taking measurements (sleep mode).
- *Integration of other sensors into the spatialized monitoring system*: for example, foliage temperature sensors; for the calculation of water stress indexes, which is a fundamental variable for crops in which deficit irrigation applications are required.
- *Cloud storage*: implementation of a GSM or GPRS system to send information stored in the central node to a server or mobile phone to display in real-time processed information (mapping of agricultural variables of interest) for taking more efficient decision.

## 5. Conclusions

This proposal presents a practical example of the use of weather information (temperature) for the prediction of phenological events (flowering) in a vineyard. This type of information is highly relevant for decision-making in various practical applications of agricultural interest, such as phytosanitary spraying, fertilization, and irrigation management. This information, along with the development of a wireless acquisition data system presented in this document corresponds to an initial prototype that, given the promising results shown in this study, serves as the basis for further development of new electronic devices that expand the possible applications of new technologies to be performed in the agricultural sector, adding new features to the system, which will be proposed for future research. Based on the results, we can conclude that it is possible to develop and implement low-cost electronic devices for monitoring spatialized phenological events in the vineyard, which can be used in other agricultural species of economic interest (such as fruit trees of high commercial value). In the case of the present study, both the Ortega and Parker models presented better phenological estimates when using a low-cost wireless sensor network compared to the estimate made with the Automatic Weather Station (AWS). However, both models presented a better estimate during the second season, due to the Enso "La Niña" climatic effect observed during the first season, which presented three times less rainfall and 9.6% more water consumption than the second season. Finally, it can be noted that the GPV presented better phenological estimates than the ME with errors of less than 4 days in both study seasons when using a low-cost wireless sensor network. In the case of the ME, only during the second season errors of less than 4 days were observed, when using the spatialized sensors network. Finally, having low-cost spatialized sensors not only consider the temporal dimension in the intrapredial data analysis, but also the spatial dimension, which would allow generating differential managements areas, increasing the sustainability of modern viticultural systems, which are characterized by presenting an important spatial variability in various productive variables of interest.

## CRediT authorship contribution statement

**Fernando Fuentes-Peñailillo:** Conceptualization, Investigation, Writing - original draft, Software. **César Acevedo-Opazo:** Supervision, Conceptualization, Formal analysis, Writing - original draft. **Samuel Ortega-Farías:** Writing - review & editing, Validation, Visualization. **Marco Rivera:** Resources, Writing - review & editing, Data curation. **Nicolás Verdugo-Vásquez:** Investigation, Writing - original draft, Formal analysis, Methodology.

## Declaration of Competing Interest

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

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