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ORIGINAL RESEARCH ARTICLE

Local influence of climate on grapevine: an analytical process involving a functional and Bayesian exploration of farm data time series synchronised with an eGDD thermal index

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ABSTRACT

Climate influence on grapevine physiology is prevalent and this influence is expected to increase with climate change. Climate influence on grapevine physiology can vary depending on the terroir. A better understanding of these local terroir variations is likely to be achieved with analyses that use local data; i.e., farm/vineyard data. Thus, the challenge lies in exploiting farm data to enable grape growers to understand their own terroir and consequently adapt their practices to the local conditions. In such a context, this article proposes an analytical process to site-specifically study climate influence on grapevine physiology by focusing on time series of the weather data often contained in farm data sets. This article focuses on temperature and precipitation influence on yield in the form of a case study. The analytical process includes the Extended Growing Degree Days (eGDD) and the Bayesian functional Linear regression with Sparse Steps functions (BLiSS) methods in order to detect site-specific periods of strong climate influence on grapevine yield. It uses data from three commercial vineyards situated in the Bordeaux region (France), California (USA) and Israel. In general, the periods of climate influence on grapevine yield detected for the three vineyards identified the same stages of yield development, which have already been studied in the scientific literature. However, some vineyard differences were observed, including: i) different periods of influence associated with a given stage of yield development between the vineyards, ii) different influential weather variables between the three vineyards for a given period, and iii) differing duration of the period of influence associated with a given stage of yield development between the vineyards. These results show the potential of the proposed analytical process for analysing the time series of farm weather data in order to extract site-specific climate indicators of grapevine yield.

KEYWORDS: extended Growing Degree Days (eGDD), Bayesian functional Linear regression with Sparse Steps functions (BLiSS), yield development, farm data, operational conditions, weather

INTRODUCTION

Climate influence on grapevine physiology is prevalent and is expected to increase with climate change (Lobell *et al*., 2006; van Leeuwen and Darriet, 2016; Naulleau *et al*., 2020; Naulleau *et al*., 2022). Climate influence on grapevine physiology can vary depending on the terroir (Matese *et al*., 2014; Fraga *et al*., 2016; Neethling *et al*., 2019; de Rességuier *et al*., 2020; Laurent *et al*., 2020; Ohana-Levi *et al*., 2022). A better understanding of these local terroir variations is likely to be achieved with analyses that use local data; i.e., farm/vineyard data. Thus, a real challenge lies in exploiting these farm data to enable grape growers to better understand their own terroir and consequently adapt their practices to the local conditions (Laurent *et al*., 2021).

This challenge is particularly true when addressing climate influence on yield. Temperature plays an important role in defining yield potential and precipitation, through water availability, is one of the main yield limiting factors (Van Ittersum *et al*., 2013); although this influence decreases when the vineyard is irrigated. In addition, both temperature and precipitation can have a reducing influence on yield development during extreme events. Finally, temperature and water availability are known to be particularly influential on yield during specific phenological periods (Ojeda *et al*., 2001; Petrie and Clingeleffer, 2005; Keller *et al*., 2010; Guilpart *et al*., 2014; Pagay and Collins, 2017; Triolo *et al*., 2019). These periods of sensitivity are related to the successive implementation of yield components (Laurent *et al*., 2021) and their timing and duration is hypothesised to vary depending on the terroir, including vineyard management factors.

Farm data include, and will be enhanced by, data collected on-farm for management purposes. Farm data sets generally contain time series of weather data that can be analysed against yield. However, when analysing time series of farm data three issues are encountered.

Firstly, time series data expressed according to the Gregorian calendar are not necessarily consistent with grapevine phenology for different blocks within the same year or different years for the same block. In other words, the same date may not correspond to the same phenological stage for different blocks or years. Therefore, the time series cannot be directly compared according to the Gregorian calendar timeline. To overcome this limitation, this paper proposes to synchronise the time series of farm data according to extended Growing Degree Days (eGDD) thermal index to account for grape site-specific phenology (Laurent, 2021).

Secondly, time series data are defined as a set of observations sequentially organised in time as a realisation of a stochastic process; i.e., the observations are considered as outputs of a succession of random variables (Brockwell and Davis, 2009). Consequently, temporally (and potentially spatially) neighbouring observations are correlated (i.e., they are not independent data points), which leads to a violation of the assumptions around classical methods of analysis, such as multivariate linear regression. To circumvent this issue, most literature studies have focused on using weather variables at a few known key phenological stages (Buttrose, 1974; Pouget, 1981; Pagay and Collins, 2017) or time steps (Guilpart *et al*., 2014; Molitor and Keller, 2017), which can be considered as independent. However, these classical approaches have limitations: i) they depend on choices of climate variables and timing, and ii) it is often necessary to suppress data or to analyse only parts of a time series. Therefore, information about climate influence on grapevine may potentially be missed. In this article, it is assumed that i) time series of weather data can reveal further information to advance the understanding of grapevine physiology if they are analysed with adapted methods and ii) a site-specific analysis of these time series data can detect local climate covariates that will even better explain yield variability than general ones. However, although time series do need to be explored in a more comprehensive way, their use as covariates, for example in a yield model, will still require some reduction in the dimensionality of the information they contain. Thus, this paper proposes to use a Bayesian functional Linear regression with Sparse Step functions (BLiSS, Grollemund *et al*., 2019) to identify parsimonious and site-specific climate indicators in the form of periods of influence within time series of weather data (Laurent *et al*., 2019).

Thirdly, the use of (operational) farm data, rather than the use of research-collected data, presents some limitations: i) these data are characterised by heterogeneous measurement quality, ii) their sampling design is often intended for other purposes, especially management purposes, rather than the current analysis and iii) data sets present overlapping and missing data issues. It is therefore assumed that the volume of farm data available and the use of proper statistics can compensate for these limitations and still lead to the detection of relevant results; i.e., in terms of climate influence on yield here.

Therefore, this paper aims at validating the ability of an analytical process, which includes the eGDD and the BLiSS methods, to explore and reduce the information contained in time series of farm weather data. To achieve this, this article focuses on the case study of temperature and precipitation influence on grapevine yield. It investigates whether relevant periods of temperature or precipitation influence on yield can be found through the analysis of time series of farm weather data from commercial vineyards, and whether these periods are defined differently from one vineyard to another. The three commercial vineyards used in the paper are situated in the Bordeaux region (France), California (USA) and Israel.

MATERIAL AND METHOD

1. Data description

Data was collected from three commercial vineyards situated in the Napa Valley (California, USA), Israel and the Bordeaux region (France). They are noted as Vineyard A, B and C respectively in this paper. Vineyards A and B were composed of different estates; i.e., different groups of blocks

TABLE 1. Characteristics of the Vineyards A, B and C and their data sets.

	Vineyard A	Vineyard B	Vineyard C
Location	California, USA	Israel	Bordeaux, France
Latitude (°)	38	32	45
Type of climate	Semi-arid	Semi-arid	Oceanic
Irrigation	yes	yes	no
Varieties	Cabernet-Sauvignon, Merlot, Petit Verdot	Cabernet-Sauvignon, Merlot, Syrah	Cabernet-Sauvignon, Merlot, Petit Verdot
Number of estates	4	3	1
Number of weather stations	4	1	1
Years of weather data for each weather station	2008 to 2018 2007 to 2018 2012 to 2018 2010 to 2018	2008 to 2019	2001 to 2011 and 2014 to 2015
Number of blocks with phenological observations per estate	3, 20, 5, 5 (33 in total)	6, 17, 15 (38 in total)	79
Mean number of years with phenological observations per block	7.5	4.5	13
Number of blocks with yield observations per estate	3, 23, 8, 5 (39 in total)	58, 32, 42 (132 in total)	79
Mean number of years with yield observations per block	5.6	5.2	13

spaced a few kilometres apart. Both vineyards were irrigated. Vineyard C was a single estate and was rain-fed (Table 1). For each vineyard, the achievement dates of 50 % budbreak, bloom and veraison were routinely recorded by the vineyard staff according to the Gregorian calendar.

Vineyard A was divided into 4 estates. Each estate was equipped with its own weather station and comprised 3, 20, 5 and 5 blocks respectively. Yield and phenological observations were recorded from 2008 to 2018 for each block. Temperature data was recorded at a daily time step of 2008 to 2018, 2007 to 2018, 2012 to 2018 and 2010 to 2018 respectively for each weather station. The years when phenological and yield observations were made differed from one block to another. Therefore, Vineyard A data set contained missing data (missing blocks and years).

Vineyard B was divided into 3 estates serviced by only a single central weather station. Each estate had 58, 32 and 42 blocks respectively with yield observations, but only had 6, 17 and 15 blocks with phenological observations. Yield and phenological observations were recorded from 2000 to 2019. Temperature was recorded at a daily time step in 1999-2012 and 2014-2019. The years when phenological and yield observations were made differed from one block to another. Therefore, the Vineyard B data set also contained missing data (missing blocks and years).

Vineyard C had 79 blocks in a single estate. All blocks had phenological and yield observations for the years 2002-11 to 2014-15. Weather data was recorded from 2001-11 and 2014-15. The blocks presented phenological and yield observations for the same number of years and the same years.

The main characteristics of the data sets of the three vineyards are summarised in Table 1.

2. Theory

2.1. Theory about the Extended Growing Degree days (eGDD) method

The eGDD method (Laurent, 2021) computes site-specific thermal indices by integrating a Phenological Advancement Speed as a function of Temperature (PAST function). This PAST function represents the operational relationship that links farm temperature data to the vine response in terms of phenology. In the form used here, it includes four temperature thresholds that represent the base temperature from which the vine starts developing (T_b), two optimal temperatures between which the vine develops at its highest speed (T_o^1 and T_o^2) and a critical temperature (T_c) above which the vine stops developing (Figure 1) respectively.

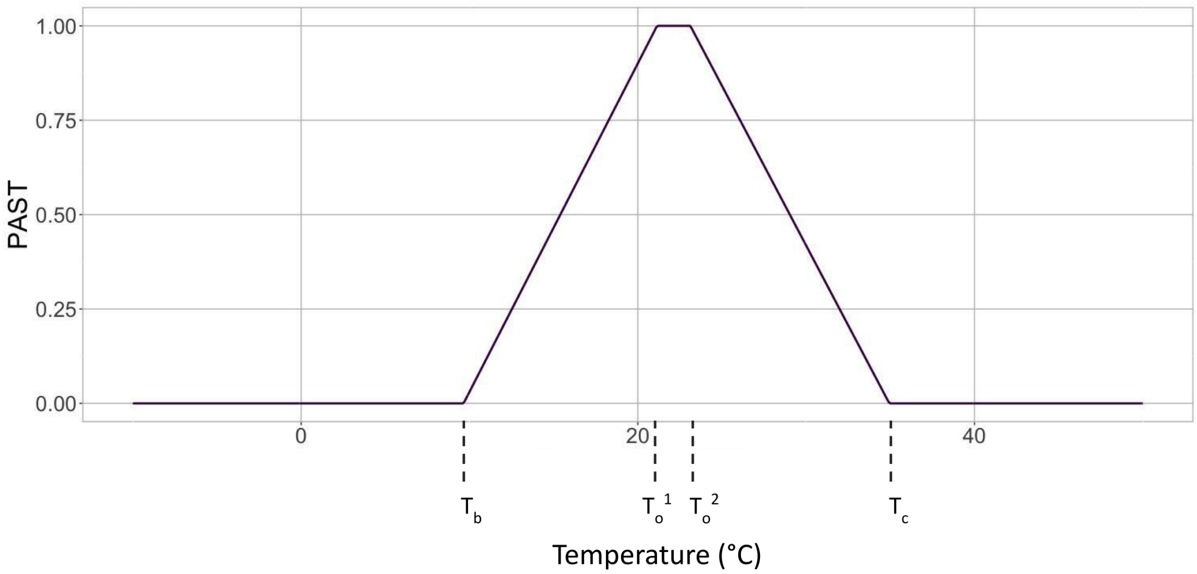

FIGURE 1. Example of PAST function obtained with the eGDD method. *Tb* corresponds to the base temperature, T_o^1 and T_o^2 to the bounds of the interval of optimal temperatures, and T_c to the critical temperature.

These temperature thresholds are site-specifically optimised using a constrained optimisation approach. The optimisation criterion is designed to serve the purpose of Prediction of the achievement date of phenological stages or of Synchronisation of time series of data based on the vine phenology. In the second case, the criterion to be minimised relates to the respective variance of the dates of budbreak, bloom and veraison of all the years for a site when they are expressed in a thermal index and is normalised according to the mean length of the time series (Eq. 1). In this equation, the user is given the opportunity to weight the components of Eq. 1 corresponding to each phenological stage. This allows the user to drive the optimisation towards the best results for a particular phenological stage; e.g., if he/she has more confidence in the observations of each particular phenological stage.

The site-specifically optimised PAST function is then weighted by the photoperiod and integrated over the season to result in a thermal index for each year for the given site as in Eq. 2.

The resulting thermal indices are expressed in Thermally Optimal Daylight Hours (TODH). For further details, interested readers are directed to Laurent (2021).

2.2. Theory about the Bayesian functional Linear regression with Sparse Step functions (BLiSS method)

A functional linear model relates a time series of data taken as a functional covariate x_j to a scalar response variable y. In this paper, x refers to a time series of temperature or precipitation data taken as a functional covariate and y to the yield response (Eq. 3). Each functional covariate x_j corresponds to a linear combination of unitary functions so as to generate a mathematical description of a complex time series (e.g., temperature or precipitation time series), based on a set of basic functional building blocks.

The BLiSS method (Grollemund *et al*. 2019) proposes a Bayesian approach to estimate the β function and most importantly its support (e.g., time). In Bayesian statistics, it is assumed that a certain understanding of β is available. It will be defined by the user and it is called a priori information. The principle of Bayesian statistics is to update this a priori information by processing the newly considered observations, which leads to produce a posteriori information. Both a priori and a posteriori information are formalised as probability distributions. In this sense, the focus is never on the exact value of *β*, which is assumed to be inaccessible anyway, but on the information available on *β,* thanks to the collected data, represented by a distribution of possible values for this parameter.

The BLiSS method is based on a hierarchical Bayesian model. In this model, the support of the coefficient function is taken as a union of possibly overlapping time intervals $I_{1,\dots,K}$. Each interval is defined by two parameters: its position (centre) and its half-length. The prior associated with the position parameter corresponds to a uniform law over the entire time series and the prior of the length parameter is an exponential law. Given these intervals, the functional linear model becomes a multiple linear model involving the partial integrals of the coefficient function over the intervals as covariates as in Eq. 4.

In this way, the BLiSS method leads to the detection of periods during which a covariate (e.g, temperature or precipitation) influences a quantitative response variable (e.g., yield performance). These periods correspond to the intervals I_k during which the BLiSS estimator takes non-null values; i.e., the periods during which temperature or precipitation has a real impact on yield development. The sign of the b_k coefficient indicates whether the covariate is negatively or positively correlated to the response variable during each time interval I_k; i.e., whether an increase in temperature or precipitation promotes or hinders yield.

▸ **Equation 1:** $S = a\sum_{i=1}^{n}\frac{\left(\frac{s_i^{bud}-\overline{s_i^{bud}}}{s_{\max}}\right)^2}{n} + b\sum_{i=1}^{n}\frac{\left(\frac{s_i^{blo}-\overline{s_i^{blo}}}{s_{\max}}\right)^2}{n} + c\sum_{i=1}^{n}\frac{\left(\frac{s_i^{ver}-\overline{s_i^{ver}}}{s_{\max}}\right)^2}{n}$
with n the number of considered years for a given site,
$s_i^{bud,blo,ver}$ and $\overline{s_i^{bud,blo,ver}}$ the observed and predicted scores,
s_{max} the mean maximal score for all years,
a, b and c the weighting for each phenological stage with a + b + c = 1

▸ **Equation 2:** $eGDD\ Thermal\ Index = \int_{season} PAST(t) * photoperiod(t)\,\mathrm{d}t$
with PAST the Phenological Advancement Speed as a function of Temperature
and *t* the time in Gregorian units (days, hours, minutes, etc.)

▸ **Equation 3:** $\hat{y} = \mu + \int_{\tau}\widehat{\beta(t)}\,x(t)_{\mathrm{d}}t$
where $\hat{y}$ is the response variable,
τ is an interval of ℝ,
μ is the intercept,
x is the functional covariates with its coefficient functions β

▸ **Equation 4:** $\widehat{y_i} = \mu + \sum_{k=1}^{K} b_k\, x_i(I_k)$ where $x_i(I_k) = \frac{1}{I_k}\int_{I_k} x_i(t)\mathrm{d}t$
where μ is the intercept, x is the functional covariate, I_k a given interval and b_k the related coefficient.

The number of intervals I_k is constrained by the hyperparameter *K*. In parallel, the probability for a given time to be in the β function support (i.e., the probability for a given time to be included in a period of influence) is established. Its posterior distribution provides an assessment of the reliability with which the intervals I_k are detected. In other words, a probability distribution of the possible effect on yield is given for each period within the time series of a weather variable such as temperature or precipitation. Therefore, the most interesting periods to study are those for which the a posteriori distribution is very close to a value different from 0. For further details on the BLiSS approach applied in this context, interested readers are directed to Laurent (2021) and Laurent *et al*. (2019).

3. Data analysis strategy

The analytical process proposed in this paper comprises three steps in chronological order: Step 1 corresponds to the implementation of the eGDD method in order to obtain synchronised time series, Step 2 corresponds to the discretisation of the weather data time series according to an optimised time step and, finally, Step 3 corresponds to the implementation of the BLiSS method to detect periods of influence on yield. These three steps are summarised in Figure 2.

The eGDD method is preliminary used to compute a timeline consistent with grapevine phenology. This time-series synchronisation is needed to unequivocally detect periods of weather influence on yield with the BLiSS method. The BLiSS method requires each time series to be discretised at a given time step as an input parameter. This time step corresponds to the minimal time step based on which the time series will be passed into a functional data; i.e., the maximum number of basic functions whose linear combination will lead to the functional data. The time step will be henceforth termed as the discretisation time step. The discretisation time step was defined according to the eGDD thermal indices. However, several discretisation time steps were possible for each time series; for example, a time series could be discretised into periods of 200, 250, 300, etc. TODH. Therefore, to further the synchronisation of the time series according to grapevine phenology at the vineyard scale, the discretisation time step was optimised so that there was at best a unique discretised period or at least two successive discretised periods for the respective scores of budbreak, bloom and veraison across all years and all blocks for a given vineyard. Once this was achieved, the shortest discretisation time step was chosen for the time series of each block (or groups of blocks for vineyard B). By way of example, for Vineyard A, all time series were discretised into 17 periods. Budbreak, bloom and veraison unfolded in periods of rank 2 or 3, 4 or 5 and 7 respectively for all years and blocks of Vineyard A. However, these periods lasted 300 TODH for block 1 and 320 TODH for block 2. This corresponds to the initial hypothesis that each block has its own rhythm; i.e., its own phenology.

A minimum of five years of phenological and weather data has been empirically identified to ensure a correct implementation of the eGDD method (convergence of the optimisation problem). Consequently, it was possible to apply the eGDD method at the block, estate or vineyard scale. Thus, the eGDD method was applied at the finest spatial scale possible, depending on the available data: blocks for Vineyard A and C and groups of the same estate and planted with the same variety for Vineyard B. In contrast, the BLiSS method implementation requires the largest data set possible

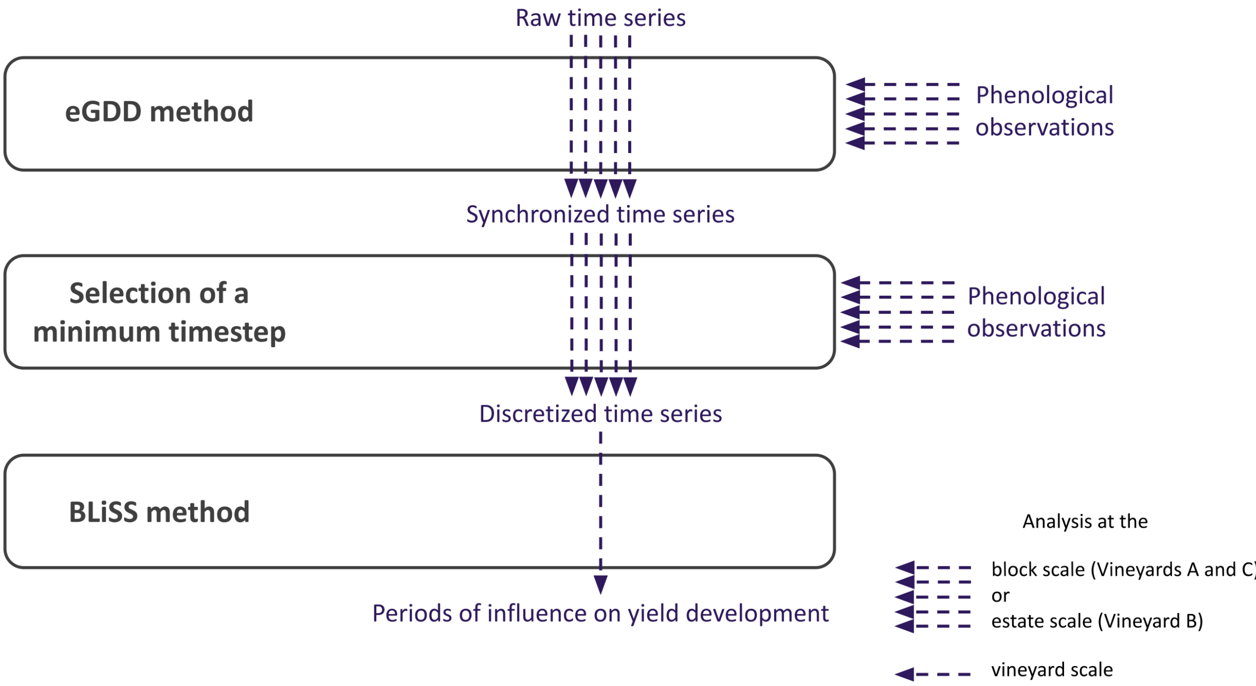

FIGURE 2. Description of the proposed analytical process aiming at identifying periods of climate influence on yield for each vineyard. Time series of weather data are synchronised according to thermal indices computed with the extended Growing Degree Days approach (eGDD method). Then, the synchronised time series are discretised according to an optimised time step and they are analysed with the BLiSS method.

to limit estimation problems. Therefore, it could only be computed at the vineyard scale.

3.1. Step 1: implementation of the eGDD method

The eGDD method with Synchronisation option (cf. Eq. 2) was employed to compute site-specific thermal indices. A eGDD thermal index was computed for each block in Vineyards A and C. Regarding Vineyard B, some of its blocks only had a low number of years with phenological observations, which prevented the eGDD method from being applied at the block scale. To address this issue, a eGDD thermal index was computed by groups of blocks localised in the same estate and planted with the same variety for Vineyard B. Therefore, the computed PAST functions were likely to integrate inter-estate differences that were modulated by the variety. Equal a, b and c coefficients were used (Eq. 1).

3.2. Step 2: Discretisation of the weather data time series

For each block (or estate for Vineyard B) and each year, the time series of the daily mean, maximum and minimum temperature and precipitation were expressed according to the corresponding eGDD thermal index. A discretisation time step was optimised (minimised) in a block or in an estate-specific way with the constraint that the respective scores of budbreak, bloom and veraison were preferably defined in different intervals within a year and within a block (or estate), but that each phenological stage for a given vineyard was synchronised into the same interval across blocks (or estates) and years. In the cases where a solution could not be found, this constraint was relaxed to permit the possibility of having two consecutive intervals assigned to a specific phenological stage.

Each time series was then discretised according to its site-specific time step by averaging the mean, minimum and maximum daily temperature over each period for the two years before harvest (noted years n-1 and n) so as to cover the assumed duration of yield development cycles (Carmona *et al*., 2008; Vasconcelos *et al*., 2009; Guilpart *et al*., 2014; Bonada *et al*., 2020).

3.3. Step 3: Implementation of the BLiSS method

For each vineyard, the discretised time series of all blocks and years were regressed to the yield data using the BLiSS method. The *K* hyperparameter, which defines the number of influence periods searched for in the time series, was tuned using a Bayesian selection approach based on a Bayesian Information Criterion (BIC) (Grollemund *et al*., 2019).

RESULTS

1. The three vineyards were characterised by different temperature profiles

The daily mean temperatures in each vineyard for the whole year are given in Figure 3 for all years. The four weather stations in Vineyard A (Figures 3a to 3d) showed the same annual pattern of mean daily temperatures. The sites corresponding to Figure 3b and 3c appeared to be slightly cooler, with temperatures of around 7° C rather than 10 °C in winter and temperatures of around 20 °C rather than 22 °C in summer. Considering the number of years, the temperature

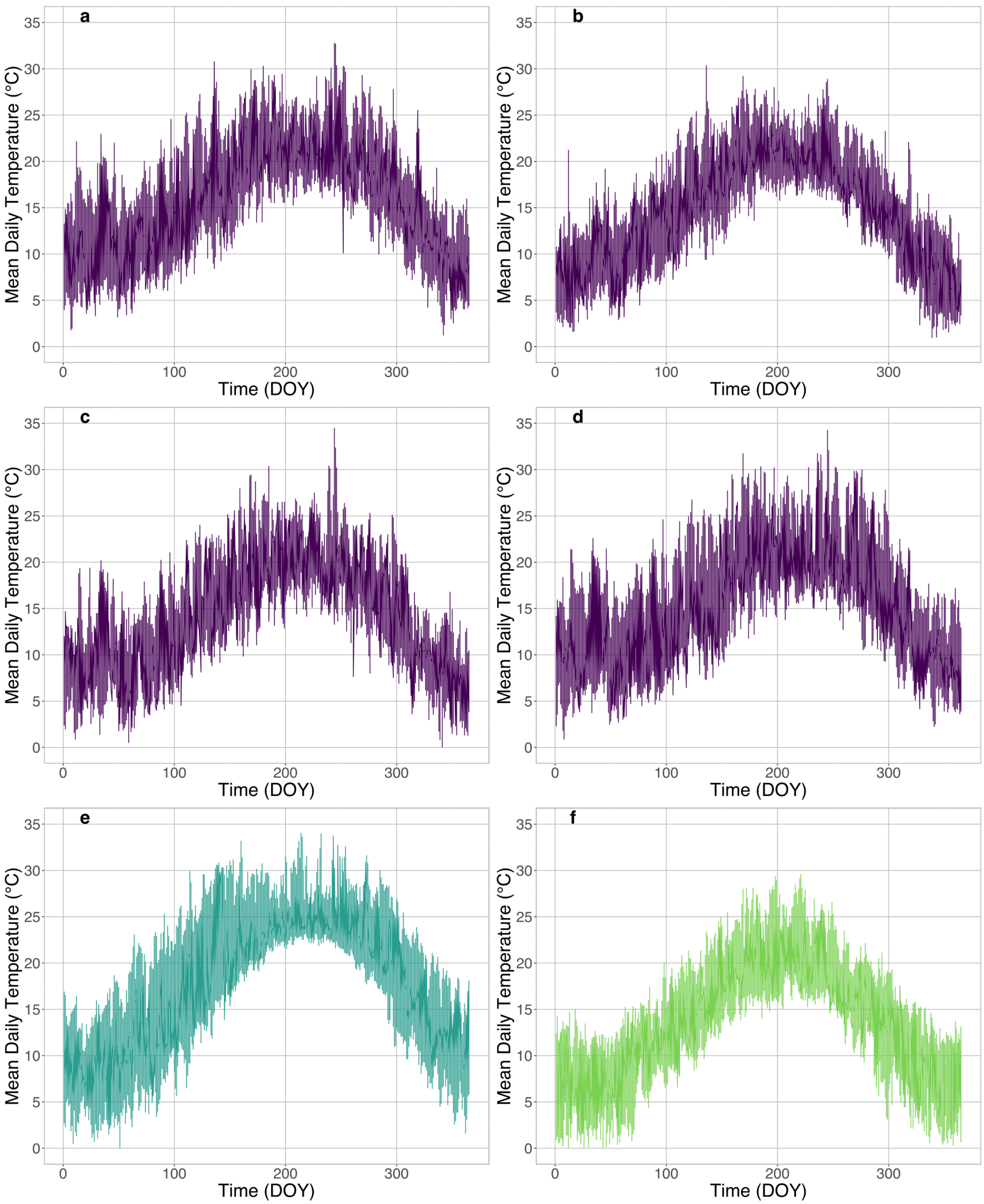

FIGURE 3. Daily mean temperatures in each estate of Vineyard A (a, b, c and d), in Vineyard B, which has a single weather station for the 3 estates (e), and in Vineyard C, which is composed of a single estate with a single weather station (f). The years displayed are 2008 to 2018 (a), 2007 to 2018 (b), 2012 to 2018 (c), 2010 to 2018 (d), 1999 to 2012 and 2014 to 2019 (e), 2001 to 2011 and 2014 to 2015 (f) respectively.

dispersion in Figures 3a, 3c and 3d was comparable and seemed lower in the case of Figure 1b. Vineyard B showed a large temperature dispersion during the year, but this was probably due to the number of years considered. (Figure 3d). The daily temperature profile of Vineyard B showed winters with temperatures of between 5 and 10 °C and with a long hot season: the average daily temperatures were generally higher than 20 °C from DOY 120 to 300; i.e., from before bloom until well after veraison. Vineyard C presented the most temperate thermal profile (Figure 1f), with winter temperatures ranging from 5 to 10 °C and summer temperatures of around 20 °C. The hot season was the shortest season for all three vineyards, with temperatures exceeding 20 °C only between DOY 170 and DOY 230; i.e., between flowering and veraison. The daily dispersion of temperatures in Vineyard C was the lowest of the three vineyards.

2. The three vineyards obtained different site-specific eGDD thermal indices

Figure 4 presents the PAST functions obtained with the eGDD method. They were described according to the values of T_b, T_o^1, T_o^2 and T_c that were optimised block by block for Vineyards A and C, and by estate and variety for Vineyard B. The eGDD thermal indices of Vineyards A and B were more dispersed than those of Vineyard C. For Vineyard A, the PAST functions showed a large range of values for each temperature threshold for T_b and T_c: from -4 to 13 °C and 25 to 50 °C respectively. The values of T_o^1 and T_o^2 were consistent between the blocks of the same estate and ranged from 18 to 25 °C, and the [T_o^1, T_o^2] interval ranged from a single value to a 4 °C interval depending on the blocks. The slope between T_o^1 and T_o^2 was relatively constant for the whole vineyard. The values of T_c, and consequently the slope between T_o^2 and T_c, varied significantly between blocks; the decrease in phenological advancement speed for temperatures above 25 °C varied between blocks. For Vineyard B, the values of the temperature thresholds ranged from -10 to 6 °C for T_b, from 21 to 32 °C for T_o^1 and T_o^2, whose interval ranged from a single value to 3° C, and from 30 to 4 °C for T_c. The slope between T_b and T_o^1, as well as between T_o^2 and T_c, were different between the different estates. Overall, the PAST functions in Vineyard B showed the highest intra-vineyard variation. For Vineyard C, the values of temperature thresholds ranged from 8 and 11 °C for T_b, from 19 to 21 °C (with an exception at 27 °C) for T_o^1 and T_o^2 and from 31 to 45 °C for T_c. The values of T_b, T_o^1 and T_o^2, as well as the slope between T_b and T_o^1, were very similar between blocks, while the values of T_c, and therefore the slope between T_o^2 and T_c, presented significant differences between the blocks. However, this part of the PAST function related to only a few temperature observations actually recorded in the field (Figure 3).

3. The three vineyards obtained different discretisation time steps

Table 2 presents the results of the optimisation of the discretisation time steps for each vineyard. The maximum number of periods that could be discretised for Vineyards A, B and C was 17, 18 and 19 respectively. For some vineyards, phenological stages were assigned to two consecutive time periods to account for inter-block and inter-annual variations; e.g., budbreak in Vineyard A. 10 and 7 blocks for Vineyard A and C respectively were excluded at this stage, because the periods in which budbreak, bloom and veraison were positioned showed at least two periods of difference to the optimised fits in Table 2. For example, a block of Vineyard C with time period ranks of 2 and 5 for budbreak and bloom respectively would be excluded, because most blocks reached budbreak in the rank 1 period and bloom in the rank 3 period. No blocks were excluded from Vineyard B since the eGDD thermal indices were already computed for groups of blocks.

The discretisation time steps differed between vineyards in accordance with the differences in the eGDD thermal indices.

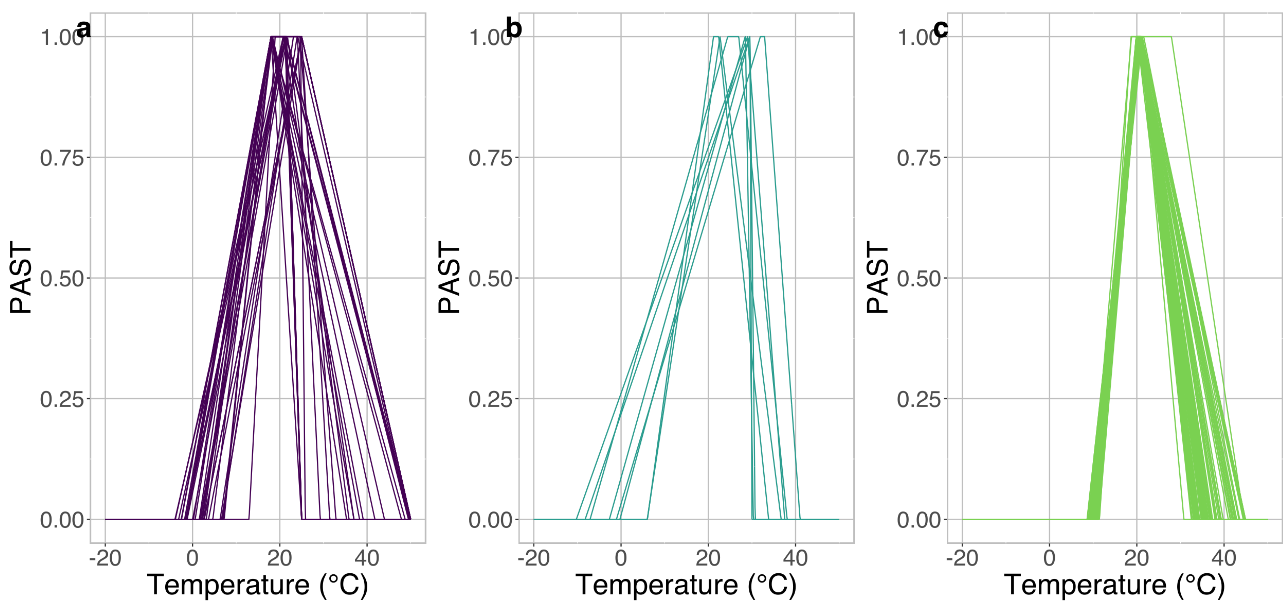

FIGURE 4. Phenological Advancement Speed as a function of Temperature (PAST function) computed with the eGDD method for each block of Vineyards A and C (a and c respectively) and for each estate of Vineyard B (b).

TABLE 2. Results of the time series discretisation for Vineyards A, B and C. The rank of the harvest time period is given as an indicator of the length of the time series (number of discretised periods).

Vineyard	Number of discretised periods over the years n-1 and n	Mean time step (in TODH)	Number of blocks/ estates excluded from the BLiSS analysis	Time period rank corresponding to Budbreak	Time period rank corresponding to Bloom	Time period rank corresponding to Veraison	Time period rank corresponding to Harvest
A	17	354.2	10	2, 3	4, 5	7	9, 10
B	18	252.4	0	1	2, 3	6, 7	8, 9, 10, 11
C	19	191.5	7	1	3	7	9, 10

However, they allowed a similar number of discretised periods over the time series of weather data. It should be noted that the position of budbreak, bloom and veraison was more consistent for Vineyard C than for the other two vineyards. Veraison occurrence was consistent between vineyards: it is always positioned in the 6th or 7th rank. However, budbreak and bloom were positioned in the 1st and 2nd or 3rd periods for vineyards B and C respectively, while they were positioned in later periods for Vineyard A.

4. The three vineyards were characterised by different periods of weather influence on yield

Figure 5 shows the results of the BLiSS analysis of the discretised time series of weather data for the three vineyards. The results correspond to the detection of periods when *Tmean*, *Tmin*, *Tmax* or *Precipitation* influence yield development. The timing and duration (expressed in discretised time periods) of the detected periods, as well as their correlation direction (sign of the BLiSS estimator), were interpreted. The actual values taken by the BLiSS estimator were not interpreted between vineyards, and were considered in a relative sense between periods of influence for each vineyard. The colour gradient in Figure 5 corresponds to the distribution of the posterior distribution of the β estimator. It is interpreted as a confidence indicator for the detection of influence periods with the BLiSS estimator. Therefore, a period of influence corresponding to a non-null BLiSS estimator, but with a well spread or light colour gradient, was detected with very low reliability and could not be considered.

The confidence in the estimation of the β coefficient was lower for Vineyard A (Figures 5a, d and g and j) than for Vineyards B (Figures 5b, e, h and k) and C (Figures 5c, f, i and l); i.e., periods of influence were more strongly detected for Vineyards B and C than for Vineyard A, which is related to the number of available analysed individuals. This was illustrated by the wider colour gradient that tended toward lighter colours around each period in the case of Vineyard A, compared to the other two vineyards.

4.1. *Tmean* influence on yield

For Vineyard A (Figure 5a), only one period of *Tmean* influence on yield could be reliably identified for periods 12 to 14; i.e., around bloom of year n. Two other periods could be presumed from periods 1 to 5 (involving budbreak and bloom of year n-1) and 9 to 11 (around harvest of year n-1). Regarding the periods 12 to 14, the value of the BLiSS estimator was positive; i.e., the daily mean temperature observed during this period was positively correlated with the yield performance (the higher the temperature, the higher the yield).

For Vineyard B (Figure 5b), four periods of *Tmean* influence on yield could be identified from periods 1 to 2 (around budbreak of year n-1), 7 to 9 (between veraison and harvest of year n-1), 10 to 14 (involving budbreak and bloom of year n) and 17 to 18 (after veraison of year n) respectively. A fifth period could even be detected in period 16 (beginning of veraison of year n), although it had not been selected by the sparse step of the BLiSS estimator. The 2nd and 4th mentioned periods were positively correlated with the yield performance, while the 1st, 3rd and 5th periods were negatively correlated with it.

For Vineyard C (Figure 5c), four periods of *Tmean* influence on yield were also detected but with differences to Vineyard B. These were periods 1 to 2 (after budbreak of year n-1), 6 to 8 (around veraison of year n-1), 12 to 14 (around bloom of year n) and 18 to 19 (between veraison and harvest of year n) respectively. The 2nd and 3rd periods were positively correlated with yield performance, while the 1st and 4th were negatively correlated with it.

4.2. *Tmin* influence on yield

For Vineyard A (Figure 5d), three periods of *Tmin* influence on yield could be detected: from periods 1 to 3 (before and around budbreak of year n-1), periods 7 to 9 (during and after veraison of year n-1) and periods 10 to 12 (after harvest of year n-1 and until budbreak of year n) respectively. The 1st and 2nd periods of influence were negatively correlated with yield (i.e., a high *Tmin* favoured low yield), and the 3rd one was positively correlated with yield (i.e., high *Tmin* favoured high yield).

For Vineyard B (Figure 5e), five periods of *Tmin* influence on yield could be detected: in periods 4, 5 to 7 (before and during veraison of year n-1), 8, 10 (after harvest of year n-1) and 17 to 18 (after veraison and until harvest of year n) respectively. It was not clear whether the 4th period could be extended to periods 11 and 12, because the colour gradient was very diffuse. It seemed to be more concentrated around null values of the BLiSS estimator. The 1st and the 3rd periods were positively correlated with yield, while the other three periods were negatively correlated to yield.

For Vineyard C (Figure 5f), four periods of *Tmin* influence on yield could be detected: periods 3 to 9, 10 to 11, 16 to 18 and 19 respectively. The 1st and the 3rd periods of influence were positively correlated with yield, while the 2nd and 4th periods of influence were negatively correlated with yield.

4.3. *Tmax* influence on yield

For Vineyard A (Figure 5g), only one period of *Tmax* influence on yield could reliably be detected from periods 2 to 5; i.e., around budbreak and bloom of year n-1. It corresponded to a positive correlation; i.e., high *Tmax* favoured high yield.

For Vineyard B (Figure 5h), *Tmax* influence was characterised by short periods of influence with a colour gradient clearly favouring non-null values for the BLiSS estimator, but these periods were within longer ones with colour gradients closer to 0. It was decided to consider the short periods only as periods of highest influence of *Tmax* on yield.

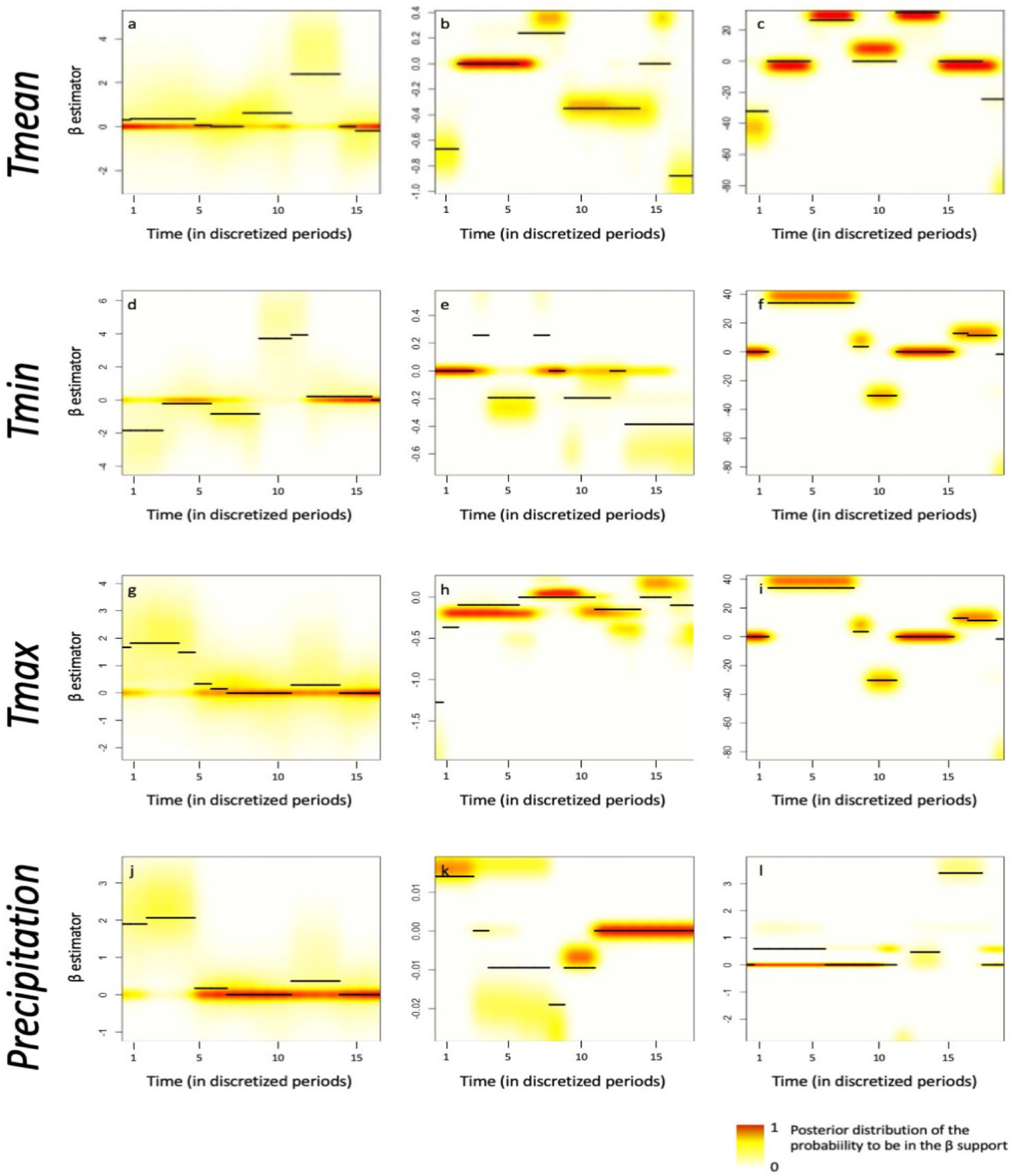

FIGURE 5. BLiSS estimation for the synchronised time series of averaged daily mean (*Tmean*), minimum (*Tmin*), maximum (*Tmax*) temperature data and cumulated daily precipitation (Precipitation) data for Vineyards A, B and C. The discretised periods that graduate the X-axis correspond to a segmentation (discretisation) of the site-specific eGDD thermal indices that were used as a timeline to express the temperature time series. Positive, null or negative values of the β estimator on the Y-axis indicate that the daily mean temperature promotes, does not affect or hinders yield during the considered period.

Thus, four periods of *Tmax* influence on yield could be detected: in periods 1 (during budbreak of year n-1), 13 to 14 (after bloom of year n), 15 to 16 (before and during veraison of year n) and 18 (during harvest of year n) respectively. The 3rd period corresponded to a positive correlation of *Tmax* with yield while the others corresponded to a negative correlation with yield.

For Vineyard C (Figure 5i), four periods of *Tmax* influence on yield could be detected: periods 6 to 8 (around veraison of year n-1), 10 to 12 (around budbreak of year n), 16 to 18 (around veraison of year n) and 19 (during harvest of year n) respectively. The 1st, 2nd and 3rd periods of influence corresponded to a positive correlation of *Tmax* with yield, whereas the 4th corresponded to a negative correlation with yield.

4.4. Precipitation influence on yield

For Vineyard A (Figure 5j), only one period was detected with a colour gradient in favour of non-null BLiSS estimator. It covered periods 3 to 5 (from budbreak to bloom of year n-1) and corresponded to a positive correlation; i.e., high *Precipitation* favoured high yield.

For Vineyard B (Figure 5k), two periods of *Precipitation* influence on yield were detected: periods 1 to 3 (during budbreak and bloom n-1) and 6 to 11 (from veraison of year n-1 until budbreak of year n) respectively. They corresponded to a positive and negative correlation with yield respectively. The 2nd period of influence included a shorter period of increased negative influence of Precipitation during period 8 (after veraison of year n-1).

For Vineyard C (Figure 5l), three periods of *Precipitation* influence on yield were detected: periods 2 to 6 (a large period around bloom of year n-1), 12 (between bloom and veraison of year n) and 13 to 14 (after veraison of year n) respectively. The 1st and the 3rd periods of influence corresponded to a positive correlation with yield and the 2nd period of influence corresponded to a negative correlation with yield.

TABLE 3. Timing, duration and direction of correlation with the yield response (- : negative, + : positive) of the periods of influence detected with the BLiSS method for the time series of daily mean (*Tmean*), maximum (*Tmax*) and minimum (*Tmin*) temperature and Precipitation data of each vineyard. The green colour gradient represents the periods of budbreak, bloom and veraison respectively in year n-1 and year n for each vineyard.There was a different number of discretised periods within the time series of Vineyards A, B and C: 17, 18 and 19 respectively. Therefore, the grey cells complete the rows in the table but do not correspond to periods because the optimisation of the time step to discretise the time series data resulted in a smaller number of periods.

		Periods number over the year n-1										Periods number over year n								
Vineyard	Weather variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
A	*Tmean*												+	+	+					
A	*Tmin*	-	-	-				-	-	-	+	+	+							
A	*Tmax*		+	+	+	+														
A	Precipitation			+	+	+														
B	*Tmean*	-	-						+	+	-	-	-	-			+	-	-	
B	*Tmin*				+	-	-	-	+		-							-	-	
B	*Tmax*	-												-	-	+	+		-	
B	Precipitation	+	+	+			-	-	-	-	-	-								
C	*Tmean*	-	-				+	+	+				+	+	+				-	-
C	*Tmin*			+	+	+	+	+	+		-	-					+	+	+	-
C	*Tmax*						+	+	+		+	+	+				+	+	+	-
C	Precipitation		+	+	+	+	+						-	+	+					

The results of the BLISS analysis of discretised time series of *Tmean*, *Tmin*, *Tmax* and *Precipitation* data are summarised in relation to the vine phenology of the three vineyards in Table 3.

DISCUSSION

1. Contribution of the analytical process to investigating climate influence on grapevine yield contained in a time series of weather data

1.1. The results in terms of climate influence on grapevine yield were coherent with the literature but were site-specific

The periods of climate influence on grapevine yield presented in Table 3 for the three vineyards globally identified the same stages of yield development, which have already been identified and studied in the scientific literature. However, vineyard differences were observed including: i) different periods of influence associated with a given stage of yield development between the vineyards, ii) different weather variables (*Tmin*, *Tmean*, *Tmax* or *Precipitation*) found to be influential between the three vineyards for a given period, and iii) the duration of the period of influence associated with a given stage of yield development differed between the vineyards.

A first grouping of periods of climate influence was found around budbreak of year n-1 (Table 3) and this was coherent with the existing literature that was reviewed by Vasconcelos *et al*. (2009). For Vineyard A, *Tmin* and *Tmax* were found to be negatively and positively correlated to yield respectively, meaning that during this period, high *Tmin* was correlated to low yields, while high *Tmax* was correlated to high yields. In addition, the *Tmin* influence seemed to occur before or during budbreak, while the *Tmax* influence seemed to occur during or after budbreak until bloom. A greater sensitivity of the developing inflorescences to temperature during the period before budbreak was found, compared to the period after budbreak (Vasconcelos *et al*., 2009). The flower number, the flower size and subsequent berry size (Petrie and Clingeleffer, 2005) are supposed to be programmed after budbreak following the branching process of inflorescences. In this way, the two periods of influence may correspond to two successive stages of the branching process. These stages may be sensitive to a different temperature variable between the two periods, because they unfold during periods with different temperature conditions. In addition, during the period before and around budbreak, temperatures were reported to favour the number of inflorescences per vine, but to reduce the number of flowers per inflorescence (Pouget, 1981, Dunn and Martin, 2000, Petrie and Clingeleffer, 2005). In this way, the negative correlation of *Tmin* with yield found during this period may imply that the temperature influence on yield during this period is more related to the flower formation than to the inflorescence formation in Vineyard A. This may be explained by the fact that primary branching had already been completed without any limitation by that time and/or by the fact that the bunches were thinned after this period. Indeed, the variability of bunch number per vine may be smoothed between blocks and years by the practice of bunch thinning. Therefore, bunch thinning may reduce the capacity of the period related to the bunch number development to explain the yield variability. Furthermore, it seemed surprising that influences of *Tmin* and *Tmax* were detected without a *Tmean* influence being detected during the period around budbreak of year n-1. This suggests that night temperatures may be more influential before and during budbreak and that day temperatures may be more influential during and after budbreak than overall temperatures. This may be related to the coexistence of two physiological processes during the period: one driven by photoperiod and influenced by moderate temperatures, and another driven by abiotic stresses, such as low temperature conditions (Tanino *et al*., 2010). For Vineyards B and C, a period of negative correlation of *Tmean* was found during budbreak and bloom of year n-1. Following the same logic as for Vineyard A, this seems to suggest that flower rather than inflorescence formation was impacted by temperature during this period. Both vineyards also underwent bunch thinning.

A *Precipitation* influence was found for the three vineyards. It was concomitant with budbreak and bloom of year n-1 for Vineyards A and B while the period of influence lasted longer, until veraison, for Vineyard C. This influence was coherent with the results of Guilpart *et al*. (2014) who found an increased influence of water constraint on yield centred around bloom of year n-1. In addition, it seems coherent that the *Precipitation* influence stopped around bloom in Vineyards A and B, because irrigation may then take over, whereas the *Precipitation* influence lasted longer in Vineyard C, which was non-irrigated and only rain-fed.

A second grouping of periods of climate influence on yield was found from bloom to after veraison of year n-1 (Table 3). For Vineyard C, *Tmin*, *Tmean* and *Tmax* were all positively correlated to yield meaning high daily temperatures generally favoured high yields. In contrast, for Vineyard B, only *Tmin* was correlated to yield during this period. *Tmin* presented a positive correlation with yield after bloom and after veraison, but a negative correlation around veraison, during the warmest days. This may highlight a threshold effect: cold night temperatures may reduce yield, i.e., the higher the *Tmin*, the higher the yield (positive correlation), but too high night temperatures may also reduce yield (negative correlation). Vineyard B experienced warmer temperature conditions than Vineyard C (Figure 3) and may have reached a threshold for *Tmin* during the summer. The impact of a high *Tmin* on yield during this period could be explained by a poorer carbohydrate export from the grapevine leaf, which could affect the photosynthetic activity during the day (Sawicki *et al*., 2015; Tombesi *et al*., 2018). A period of negative correlation of *Tmin* to yield was also found for Vineyard A after veraison. It can be noticed that a weak negative correlation of *Tmin* with yield was detected by the BLiSS method before and around veraison, but with a lot of uncertainty. Perhaps it would have been detected with more certainty if the Vineyard A data set had been larger.

A third grouping of periods of influence was found from harvest of year n-1 to budbreak of year n (Table 3). For Vineyard A, *Tmin* was positively correlated with yield. For Vineyard B, *Tmean* was negatively correlated with yield. For Vineyard C, *Tmin* and *Tmax* were negatively and positively respectively correlated to yield. Again, these differences may be explained by the negative influence of temperature on the number of flowers and berries per bunch reported in the literature (Pouget, 1981; Dunn and Martin, 2000; Petrie and Clingeleffer, 2005; Jones *et al.*, 2009; Keller *et al*., 2010), and the positive influence of temperature on berry weight found by others (Keller *et al*., 2010). However, they could also be partly explained by the temperatures experienced in each vineyard and particularly the risk of late frost or even early water stress that could go with high temperatures before and around budbreak.

A fourth grouping of periods of influence was found around bloom of year n (Table 3). For Vineyards A and C, *Tmean* was found to be positively correlated with yield, whereas *Tmin* and *Tmax* were found to be negatively correlated with yield for Vineyard B. Again, this difference could highlight a threshold effect: berry development is globally encouraged by increasing temperatures, but too high temperatures may reduce yield (Buttrose and Hale, 1973; Dunn and Martin, 2000; Pagay and Collins, 2017; Gouot *et al*., 2019). Vineyard B experienced the highest bloom temperatures (Figure 3) and may have reached this threshold, which was corroborated by the fact that *Tmin* and *Tmax*, and not *Tmean*, were detected as influential during this period. A *Precipitation* influence was only detected for Vineyard C; it was found to be initially negatively (before bloom) then positively (during and after bloom) correlated with yield. The negative correlation may be explained by a physical inhibition of the flowering process or poor phytosanitary conditions due to high precipitation. The positive correlation may also be explained by water effects on berry development after bloom (Ojeda *et al*., 2001; Triolo *et al*., 2019), especially since Vineyard C was rain-fed.

A fifth grouping of periods of influence was found around veraison of year n. For Vineyard B, *Tmean* and *Tmax* were positively correlated with yield. For Vineyard C, *Tmean* and *Tmax* were positively correlated with yield. Both results seemed coherent with sufficient temperatures generally favouring berry development without reaching any threshold effect. No period of influence was detected for Vineyard A, but this may be due to a low data volume.

Finally, a sixth grouping of periods of influence was detected at harvest time of year n. *Tmean*, *Tmin* and *Tmax* were negatively correlated with yield for Vineyards B and C. Thus, high temperatures at harvest time seemed to reduce yield and it may be related to a loss of berry weight due to dehydration (Rogiers and Holzapfel, 2015; Deloire *et al*., 2021).

1.2. Periods of climate influence on yield were precisely defined within the time series data

The eGDD method allowed thermal indices to be computed that were optimised to model consistent scores; i.e., dates in a thermal index, of budbreak, bloom and veraison over years for each block of Vineyards A and C or groups of blocks for Vineyard B (Figure 4). These thermal indices were optimised to reduce the phenological shift between the analysed blocks and years. Because these scores were better synchronised between years than with the Gregorian calendar or the Growing Degree Days approach (data not shown, but refer to Laurent 2021 for other examples), the time series could be split into shorter periods (Table 2) to enable the BLiSS analysis. Moreover, in the BLiSS method, the a priori probability distribution used for the half-length of each period of influence corresponded to an exponential law, which encouraged the detection of periods of a parsimonious duration. In this way, relatively short periods could be detected; for example, for *Tmin* after veraison of year n-1 for Vineyard B (Table 3). At this time of the year, a period expressed according to an eGDD thermal index corresponded to a period ranging from about ten to fifteen days, which is the finest time step that could be evidenced by Molitor and Keller (2017) with a Windows Pane approach. At this time of the year, such a period would also be equivalent to 100-150 Growing Degree Days, which is often the smallest time step explored in classical analyses (Guilpart *et al*., 2014). As such, the information contained in time series of weather data was considerably concentrated (i.e., reduced in dimensionality) into site-specific and precisely timed periods of climate influence on grapevine yield. These dimension-reduced results could subsequently be used for other analyses based on statistical methods that do not have to account for time series characteristics.

2. Contribution of the analytical process to leveraging farm data

Grapevine response to climate variables, such as temperature or precipitation, was seen as the result of the integration of many factors that cannot be dissociated. This point will be further discussed in paragraph 2.2 and 2.4. Obviously, the volume and quality of the analysed data also influenced the results. The following section explains the issues related to some of these characteristics and how the analytical process proposed in this paper addresses them.

2.1. Small and heterogeneous data sets can still be analysed

The number of individuals involved in the analysis (i.e., the number of time series per block and per year) had a strong impact on the results. Thus, the results obtained for Vineyard B and C were more significant than for Vineyard A, with more periods detected and a greater reliability in their detection. However, the small number of individuals analysed for Vineyard A prevented an analysis of the time series with such a number of discretised periods in a frequentist framework because of estimation problems (the time series were discretised into 17 periods for only 140 individuals which may be too low of a ratio). In contrast, the Bayesian approach included in the BLiSS method still allowed the analysis of the data set and provided information on the uncertainty of the results. Thus, Table 3 only lists the periods of influence that were unequivocally detected for Vineyard A, but an expert analysis of the results could have allowed more periods to be selected.

2.2. Capturing a constant site effect while analysing a statistically high enough data volume

The site-specific analysis proposed in this work is based on the assumption that grapevine response to climate through its yield performance is determined by a site-specific effect corresponding to the integration of numerous factors, such as plant material characteristics, environmental conditions, cultural practices and vineyard management in terms of production objectives, logistics and technical specifications of any label or geographical indication, etc. Therefore, it implies that the site-specific effect is consistent over time and for all the studied blocks. The finer the spatial scale, the more likely the site-specific effect hypothesis will be valid. For example, it is more likely to be valid at the block scale than at the regional scale, since the block scale embraces only one grape variety that will not change over time and cultural practices that should be planned according to the same logic every year, etc. This assumption determines the quality of the final results: the more consistent the site-effect, the more reliable the detection of periods of climate influence with the BLiSS method. However, a rigorous implementation of the analytical process also required a minimum data volume to statistically detect and consider any site-specific effect. Ensuring a consistent site-specific effect while having sufficient amount of data is not trivial, especially given the variable geometry of vineyards and their data in terms of estates, blocks and other management units. Therefore, each step of the analytical process is subject to a trade-off between the finest spatial scale that can be considered to allow a consistent site-specific effect over time and the minimum data volume at this spatial scale needed. In the first step, grapevine phenology was likely to be consistent over time at the block scale. However, a limit to the quality of the results was apparent when less than 5 years were considered for a site with the eGDD method (data not shown). Therefore, it was sometimes necessary to find a trade-off in spatial scale to allow for a sufficient volume of data to be used in the analysis. For example, there was not enough data to calculate the eGDD indices at the block scale for Vineyard B. However, it is known from previous work that the spatial scale that benefits the most from a site-specific calibration of thermal indices in terms of synchronising time series is the vineyard scale, while taking into account the grape variety (Laurent, 2021). Therefore, applying the eGDD method at the scale of all the blocks of the same estate and of the same grape variety was assumed to be an appropriate trade-off. Secondly, the BLiSS analysis could not be performed at the block or even at the estate level due to the amount of data available. Therefore, it was performed at the vineyard scale, assuming a certain consistency of the effects of, for example, the environment and cultural practices between the estates of the same vineyard. However, the validity of this assumption required the exclusion of some blocks whose phenology was markedly different from the majority of the blocks or whose grape variety was poorly represented in the vineyard.

2.3. Temporally and spatially inconsistent samples are supported by the proposed analytical process

For a variety of reasons, ranging from climatic hazards to logistical failures, the number of individuals (time series per year and per block) can commonly vary between estates/vineyards and years in farm data sets. This issue can lead to an unbalanced sampling of site and year effects within the analysis and to non-robust conclusions that are potentially driven by a small number of individuals. Regarding the site effect, numerous precautions were undertaken in the whole analytical process to assume a constant site effect at the vineyard scale (see paragraph above). Therefore, the imbalance in the number of individuals representing each block (i.e., years per block) was not considered to be a major issue. Each block was considered to be a realisation of the same vineyard-specific pattern that outweighs variations due to inter-block differences within the same vineyard.

However, the reverse of this unbalanced sampling is that the years were also represented with a different number of individuals (i.e., blocks per year). The analysis of the climate effect on yield being inherently prone to incorporate year effects, this unbalanced year sampling was considered to be a red-flag issue which could lead to erroneous results. This was especially true for phenological observations, and hence for the implementation of the eGDD method. As it was not possible to include a random vintage effect in the analysis, the individuals were weighted by the inverse of the number of blocks for their corresponding year. This weighting aimed at balancing the different years. In the case of Vineyard B, which presented the more unbalanced year sampling, performing the eGDD analysis at the estate scale was also a way to gather more individuals representing the same years.

2.4. The analysis of farm data call for an operational interpretation of the results

Vineyards A and B were both split into several estates, whereas Vineyard C comprised a single estate, but with a higher number of blocks. Each estate of Vineyard A was equipped with its own weather station, while the same weather station serviced all the estates of Vineyard B. Vineyard C was also equipped with a single weather station. Therefore, the weather stations of the three vineyards were likely to offer a different representation of the weather conditions actually experienced in each block. In addition, all private weather stations can present different metrological and environmental characteristics. Obviously, these differences may lead to some noise in the results, hopefully, but not certainly, including a consistent bias. This is why these results should be used to draw practical conclusions rather than theoretical ones and should not be directly compared between vineyards without taking some precautions for their interpretation.

Regarding the results of Step 1, the eGDD thermal index was assumed to integrate i) physiological variations in the vine response temperature depending on plant factors as well as environmental factors, ii) spatial variations of temperature conditions between the blocks covered by the same weather station, and iii) the quality of phenological observations and weather data (Laurent *et al*., 2020; Laurent, 2021). In the case of Vineyard A, the eGDD method was applied at the block scale with a weather station being close to each block. Therefore, it can be assumed that the difference in eGDD thermal indices between blocks in the same vineyard mainly correspond to differences in the vine response to temperature or to the data quality, rather than to spatial variations of temperature conditions. This hypothesis was reinforced by the fact that a clear consistency was observed between the eGDD indices of three out of the four estates of Vineyard A, with the last estate being the most spatially extended and comprising the largest number of blocks. In the case of Vineyard B, the fact that the three estates were equipped with only one weather station likely implies that the spatial variations of temperature conditions may play a more significant role in the differences of the PAST functions (Figure 4b) and related eGDD thermal indices between blocks and *a fortiori* between blocks on different estates. In addition, the eGDD method was applied at the estate scale in Vineyard B. Therefore, the resulting indices have to be interpreted as a trade-off between different vine responses to temperature. The clustering of blocks according to their estate and to their variety likely helped with this trade-off. Without this clustering, the constrained optimisation component of the eGDD method would have had difficulties in converging and would have tended to obtain PAST functions with very close temperature thresholds for mathematical reasons; i.e., to cumulate very few heat units (TODH).

Regarding the results of Step 3, the analytical process presented in this paper highlighted site-specific periods of *Tmean*, *Tmin* and *Precipitation* for the three vineyards. These site-specific results do not mean that the physiological mechanisms of yield development were different between the vineyards, but that the site-specific conditions of each vineyard led to some periods (and associated yield development processes) becoming determining or limiting. The site-specific conditions of each vineyard were an integration of plant material characteristics, environmental conditions, cultural practices and vineyard management in terms of production objectives, logistics and technical specifications of any label or geographical indication, etc. This analytical process did not allow a specific explanation of which factor(s) caused the detection of a period of yield sensitivity to temperature or precipitation and its correlation direction to yield. However, it highlighted periods that should be taken into account when monitoring yield development. From a research perspective, these results may reveal hypotheses to be further explored and validated. The diversity of site-specific conditions could lead to a generation of new knowledge on grapevine physiology and ecophysiology. From an operational perspective, these results indicated periods that need to be carefully managed. For example, the period of *Precipitation* influence during the season in years n-1 and n for Vineyard C (rain-fed) showed a sensitivity to water constraint and may advocate for a review of cover crop and canopy management to increase grapevine resilience to water stress. Another example is linked to the periods of negative influence of temperature on yield at harvest time in year n for Vineyards B and C, which should promote the advancement of the date of harvest operations if a heat period is announced by weather forecasts.

CONCLUSIONS

This study proposed an analytical process combining two statistical methods, the eGDD and the BLiSS methods, as an exploratory approach to site-specifically extracting relevant information from time series of farm weather data. The influence of climate on grapevine yield in three different commercial vineyards was chosen as a case study. Vineyard-specific periods of temperature and precipitation influence on yield were found for six key stages of the grapevine yield development cycle. Thus, the potential of the analytical process was shown in terms of i) a site-specific analysis of time series of weather data in order to extract local climate indicators with reduced dimensions and ii) feasibility when working with farm data. The results of such analyses should be carefully interpreted, since they integrate numerous determinisms in relation with the operational reality of commercial vineyards. However, they are of real interest to commercial vineyards as they give them guidelines to operationally interpret their own data to better understand their own vineyards. This analytical process could be applied to other crops, especially perennial crops, and could also relate to other time series data and response variables.

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