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ORIGINAL RESEARCH ARTICLE

Characterisation of Grapevine Canopy Leaf Area and Inter-Row Management Using Sentinel-2 Time Series

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ABSTRACT

Accurate data on crop canopy are among the prerequisites for hydrological modelling, environmental assessment, and irrigation management. In this regard, our study concentrated on an in-depth analysis of optical satellite data of Sentinel-2 (S2) time series of the leaf area index (LAI) to characterise canopy development and inter-row management of grapevine fields. Field visits were conducted in the Ouveze-Ventoux area, South Eastern France, for two years (2021 and 2022) to monitor phenology, canopy development, and inter-row management of eleven selected grapevine fields. Regarding the S2-LAI data, the annual dynamic of a typical grapevine canopy leaf area was similar to a double logistic curve. Therefore, an analytic model was adopted to represent the grapevine canopy contribution to the S2-LAI. Part of the parameters of the analytic model were calibrated from the actual grapevine canopy dynamics timing observation from the field visits, while the others were inferred at the field level from the S2-LAI time series. The background signal was generated by directly subtracting the simulated canopy from the S2 LAI time series. Rainfall data were examined to see the possible explanations behind variations in the inter-row grass development. From the background signals, we could group the inter-row management into three classes: grassed, partially grassed, and tilled, which corroborated our findings on the field. To consider the possibility of avoiding field visits, the model was recalibrated on a grapevine field with a clear canopy signal and applied to two fields with different inter-row management. The result showed slight differences among the inter-row signals, which did not prevent the identification of inter-row management, thus indicating that field visits might not be mandatory.

KEYWORDS: Remote sensing, Sentinel-2, leaf area index, grapevine, characterisation, canopy, inter-row management

INTRODUCTION

Grapevine (*Vitis vinifera* L.) cultivation is one of the most widespread cultivations worldwide, and its practice in the Mediterranean is millennia-old (Corti *et al*., 2011). According to reports given by an international organisation of grapevine and wine (Roca, 2022) on the world, viticultural surfaces covered around 7.3 million hectares in 2021, with 3.3 million hectares within the EU (European Union) zone; Spain (13 % of the grapevine area) produced the most wine with France (11 %) in second.

Grapevines mostly require good soils and, for table grapevines, good water resource management, too (Darouich *et al*., 2022). Conventionally, grapevines have been rainfed perennial woody crops as irrigation was prohibited by authorities for several wine qualities (Darouich *et al*., 2022). Nevertheless, because soil water stress seriously impacts the growth, yield, and grape quality (Zarrouk *et al*., 2012), irrigation practices have become more and more frequent, specifically across dry areas of South Europe (Esteban *et al*., 2001; Permanhani *et al*., 2016). Irrigation practices can vary a lot according to various factors: the soil type, the climatic demand, or the target in production quality. Inter-row management might differ by the management of the grass cover between the rows of grapevine. The grass can be kept in the field, leading to constant coverage that might have a positive impact on runoff, infiltration, and erosion, while a higher water consumption from the inter-row and an increased fire hazard might negatively impact the crop performance (Steenwerth and Belina, 2010; Whitmore and Schröder, 2007).

On the contrary, the grass is removed by frequent tillages, leading to opposite benefits and drawbacks. An intermediate situation is where part of the rows are tilled while in the other part, the inter-row is left grassed. In the context of climate change, there is an increasing need to irrigate perennial woody crops as vineyards that were rarely irrigated until now, especially with wine grapevine to gain in quality. Moreover, there is also a willingness to enhance ecosystem services of cropping systems, the management of inter-row being one of the levers to go in that direction. Therefore, delineating the green cover between the grapevine canopy and the vegetation in the background is an important issue for both the characterisation of the grapevine water need and, thus, the amount of irrigation and the detection of inter-row management practices. Moreover, Abubakar *et al*. (2023) have shown that inter-row management may lead to confusion in mapping the different perennial woody crops.

During the last decades, remote sensing is playing a significant role in crop supervision. Earth-observing (EO) satellites can record multispectral images with constant temporal revisit occurrence, documenting variations in spectral patterns among surfaces. This allows the detection of the spatial and temporal differences in crops. In recent times, the utilisation of remotely sensed information to promote decision and policy rulings has raised within the sectors of agriculture and forestry (Borgogno-Mondino *et al*., 2018; De Petris *et al*., 2019; Sarvia *et al*., 2019; Testa *et al*., 2014). Regarding viticulture, airborne and spaceborne sensors can be utilised to characterise crop's yield spatial variability and describe soil features, crop varieties, and crop diseases (Arnó *et al*., 2009; Hall *et al*., 2003; Hall, 2018; Hall and Wilson, 2013; Karakizi *et al*., 2016a). Vegetation indices (VI) derived from multispectral reflectance can be exploited to acquire data on phenology, vegetation water content, and biomass over a growing season. In the past decades, several VI were unfolded (Gao, 1996; Huete, 1988; Motohka *et al*., 2010; Qi *et al*., 1994), with NDVI (normalised difference vegetation index) being the most widely used for crop growth dynamic descriptions. However, despite that fact, NDVI can be faced with some limitations like sensitivity restriction to vegetative photosynthetic dynamics (Wang *et al*., 2017), whereas biophysical variables like LAI (leaf area index) can be substituted to VI and were used advantageously to delineate different crop types (Abubakar *et al.*, 2022). Interpretation of the VI times series can bring advanced information on crop systems (Beniaich *et al*., 2022), management practices (Abubakar *et al*., 2022), irrigation needs (Darouich *et al*., 2022), and risk assessments on soil erosion (Rizzi *et al*., 2021).

The spatial resolution has a strong impact on the way to interpret remote sensing data, especially for perennial woody crops, which have spatial patterns (row, tree crown) that may be larger than the resolution. With a very high-resolution satellite (resolution lower than 5 m as WorldView-2 (Karakizi *et al*., 2016a)), it is possible to investigate within canopy details, for instance, the separation of the canopy and the soil background. However, such spaceborne sensors are mostly owned by private companies/firms, generating costs. Moreover, the revisit time might be large, preventing access to times series data capable of grasping the temporal feature over a crop cycle. Nonetheless, larger spatial resolution can be used to characterize vineyard inter-row management using time series, thanks to the difference in vegetation growth dynamics between grapevine and inter-row (Palazzi *et al.*, 2022). As an alternative, decametric resolution satellites such as the European Sentinel-2 (S2) can offer 10 m spatial resolution imagery and fine temporal revisits while being free of charge. Such spatial resolution does not permit a direct separation of the different field's components, but the free access and the possibility to access densely sampled times series are interesting properties to build applications.

Vaudour *et al.* (2010) used imageries coming from the SPOT satellite to zone viticultural terroirs in South Africa, while in Spain, Landsat images were used to detect grapevine fields by Rodriguez *et al*. (2006). Semmens *et al*. (2016) estimate daily field-scale evapotranspiration from satellite data coming from Landsat-8, MODIS (Moderate Resolution Imaging Spectroradiometer), and GEOS (Geosynchronous Equatorial Orbit Satellite) across two vineyards. Johnson *et al*. (2003) used multispectral high-resolution satellite imageries coming from IKONOS to characterise wine grapevine's leaf area. High-resolution satellite imageries were used, and it was observed that satellite information possesses the possibility to characterise or delineate quality parameters of wine grapevines (Kandylakis and Karantzalos, 2016). Landsat-8-derived NDVI (normalised difference vegetation index) was found to be highly correlated with aerial imagery-derived NDVI at the grapevine plot scale when evaluating grapevine vigour to build recommendation maps (Borgogno-Mondino *et al*., 2018). Nevertheless, some conducted research showed that the spatial resolution images coming from medium-resolution satellites are rarely adequate for grapevine field assessments because of the narrow spacing of the inter-row; such constraint is more evident among grapevine fields with huge heterogeneity, and higher resolution satellite information is capable of producing similar or equivalent results using aerial platforms (Erena *et al*., 2016; Matese and Filippo Di Gennaro, 2015). For instance, a detailed comparative analysis of grapevine multispectral imagery delivered by decametric satellite resolution (S2) and low-elevation UAV (unmanned aerial vehicle) platforms was proposed by (Khaliq *et al*., 2019). The success of S2 imagery and the UAV's high-resolution images was assessed while considering the known relation between NDVI and crop vigour. Comparisons were made between the information obtained from UAV and the S2 imagery by evaluating three different NDVI indices to accurately examine the grapevine's different spectral contribution in the surroundings by taking into note: (i) the total cropland surface (ii) the grapevine canopies only, and (iii) the grapevine inter-row. The results showed that the resolutions of the raw S2 satellite imagery might not be directly used to delineate grapevine variability. In reality, the inter-row surface contribution to the remotely sensed information might influence the NDVI estimation, leading to biased crop descriptors. Conversely, vigour maps calculated from the UAV imagery using pixel representation of crop canopies tend to be more linked to the in-field evaluation in comparison to the S2 satellite imagery. In a different study on the characterisation of grapevines using high-resolution imagery, an object-based classification framework for grapevines was designed, developed, and evaluated to detect grapevine canopy and variety separation (Karakizi *et al*., 2016b). Innovative features (spectral, spatial, and textural), rules, segmentation scales, and a set of frameworks were suggested according to image analysis (object-based). The proposed methodology was evaluated on WorldView-2 (multitemporal) satellite imagery in Greece across four diverse regions for viticulture. The performed quantitative assessment showed the suggested approach detected over 89 % of grapevines with high completeness and correct detection rates. Evaluation of the grapevine canopy extraction was above 96 %, while the quantitative evaluation of the variety separation was above 85 % at the plot scale, although it is important to note that such satellite imagery with a very high spatial resolution (0.5 m) is not freely accessed. Anastasiou *et al*. (2018) aimed to assess spectral vegetation indices obtained via satellite and proximal sensing across different growth phases (veraison to harvest) of table grapevines of which NDVI and GNDVI (green normalised difference vegetation index) were computed by employing Landsat-8 satellite imagery and proximal sensing to examine the grapevine yield and quality characteristics. In this study, the proximal sensing was more accurate concerning the grape yield and quality in comparison to the satellite sensing.

However, in this current study, free, open-source multi-temporal data of S2 are used, and field-scale analysis was done. Time series of the leaf area index (LAI) and spectral bands are exploited in this study to characterise features of grapevine, particularly the canopy and inter-row coverage. At the field scale, analysis according to temporal evolutions of the LAI was used to examine inter-field differences of grapevine canopy and soil management strategies (i.e., identification of grassy and non-grassy inter-rows).

Recently, a phenology-based classification of perennial woody fruit crops (orchards, grapevines, and olives) based on S2 temporal profiles was conducted in South-Eastern France (Abubakar *et al*., 2023) with encouraging results. Despite the good results obtained, there is still room for improvement, especially among the grapevine class. The difficulty with the grapevine LAI signal is that confusion can occur between the grapevine canopy and the background leading to both signals having the same order of magnitude leading to some misclassifications. This is not the case with orchards that have a tree canopy contribution to the LAI signal significantly larger than that of the background. Consequently, we arrived at a different scientific question to be addressed in this current study concerning the grapevines classes. Can we separate the canopy signal and background signal, which depends on management practices, from the remote sensing (RS) LAI S2 data.

The objective of this paper is to develop a method based on decametric resolution remote sensing as that of Sentinel-2 or Landsat to characterise two features of interest for grapevine: the canopy leaf area to assess the transpiration and the resulting water need and the interrow management by identifying grassed and tilled interrows. The scientific issue is then to delineate in observed LAI the contribution from the vine and that from the background. In this study, we assumed that the LAI times series derived from remote sensing together with agronomic knowledge of the grapevine development across an annual cycle can be used to separate the contributions of the different vegetation components of a grapevine. The method was developed and implemented in the South-East of France.

MATERIALS AND METHODS

1. Description of the study site and grapevine management

The research was carried out in the Ouvéze-Ventoux areas in the years 2021 and 2022. The area is located in southern France (44° 10' N and 5° 16' E) and covers a surface of 59 km² and an altitude ranging between 230 and 630 m a.s.l (Figure 1.) The study area encompasses forest and crops (mostly vineyards and orchards), the latter 57.7 % of the surface, 34 % of which being vineyards (Abubakar *et al*. 2023). The study site has a typical Mediterranean climate recognised by cold and moist winters with dry, hot summers;

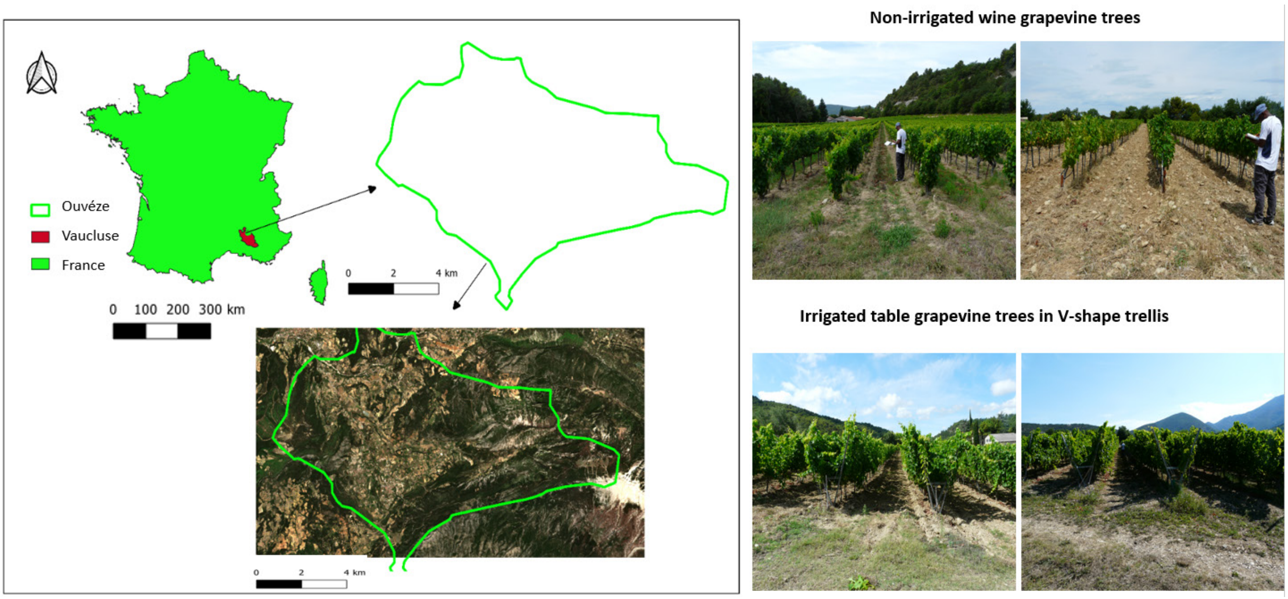

FIGURE 1. Map of France showing the location of the study site (Ouvèze-Ventoux) in the South-Eastern part of the country including photos of irrigated table and non-irrigated wine grapevine fields.

yearly rainfall is roughly 750 mm with a mean temperature of 12 °C.

The grapevines are planted in rows of 2 to 2.50 m apart for wine grapevines and 2.50 to 2.80 m apart for table grapevines. The ‘’V’’ shape trellis was predominantly used for table grapevines. Part of the vineyards are irrigated (mostly the table grapevines) via drip irrigation. Irrigation strategies are different with small inputs in the case of wine grapevines to escape from very dry conditions while the amount of irrigation is much larger with table grapevine to maximise the fruit production. Inter/intra-row grass cover (background) development is governed by rainfalls and inter-row management. There are mainly three modes of inter-row management: tilled with regular harrowing to suppress weeds, grassed inter-row with regular mowing of the grass, and a mix of the two by tilling one inter-row over 2 or 3. Dry summer conditions lead to a drying out of the herbaceous stratum, with a very small remaining fraction of the green grass, whatever the inter-row management method.

2. Ground data

2.1 canopy development and phenology monitoring

The experiment was conducted across two years (2021 and 2022). Eleven (11) plots of grapevines (4 table grapevines and 7 wine grapevines) were selected across the study area (Table 1). In each plot, five grapevine tree were randomly chosen to observe phenology and characterise the leaf development. On each grapevine tree, two branches were selected to count the leaves during the whole growing season (11 field visits every year) to characterise the dynamic of the leaf development. The standard protocol was to count the leaves number on the main branches and the sub-branches. In addition, specific observations were made to establish allometric relationships to infer leaf surface area from the leaf counts. Therefore, at three dates across the grapevine cycle (20-05-2022, 05-07-2022, and 07-10-2022), the leaf lengths (from the petiolar sinus to the end of the apical lobe) of every leaf on a selection of monitored branches (from 58 to 30) were measured. The lengths thus measured were then converted into surface area using a relationship between length and surface area established on sets of leaves of different sizes taken from each of the plots. The results showed that a single relationship was sufficient to characterise the leaf area of the different grapevine varieties monitored in this work. At the end of the process, we obtained three allometric relationships for each of the leaf length measurement dates linking the leaf surface (cm2 per branch) to the leaf number (Figure 2). Figure 2 exhibits a variation of the relationship across the year and, thus, the different relationships were estimated as follows. Up until March 20th, we used the allometric function established on 20-05-2022. From March 21st to October 6th, we applied the second relationship established on 05-07-2022, and finally, the relationship obtained on 07-10-2023 was applied after October 7th. The estimated leaf surface per branch was then averaged at the field level and then normalised using the maximum value of every time series.

2.2 Assessments of background coverage

Standardised RGB photos were taken using a digital camera to characterise the background coverage using vertical views in three locations in the plot inter-row, the location remaining the same across the season to maintain the same ROI (region of interest). To estimate the degree of soil surfaces covered by the background vegetation, the percentage of the ground cover was estimated using the SegVeg model for semantic segmentation of RGB photos into soil background portion, green vegetation portion, and senescent portion as described

TABLE 1. Descriptions of the eleven selected grapevine fields.

Plot ID	Variety	Inter-row management strategy	Irrigation
45	Table grapevine	Grassed	Irrigated
203	Wine grapevine	Partially grassed	Non-irrigated
204	Wine grapevine	Constantly tilled	Non-irrigated
1901	Table grapevine	Grassed	Irrigated
2026	Wine grapevine	Tilled	Non-irrigated
2335	Wine grapevine	Tilled	Non-irrigated
3064	Table grapevine	Grassed	Irrigated
3121	Table grapevine	Tilled	Irrigated
3138	Wine grapevine	Tilled	Non-irrigated
3140	Wine grapevine	Tilled	Non-irrigated
3358	Wine grapevine	Partially grassed	Non-irrigated

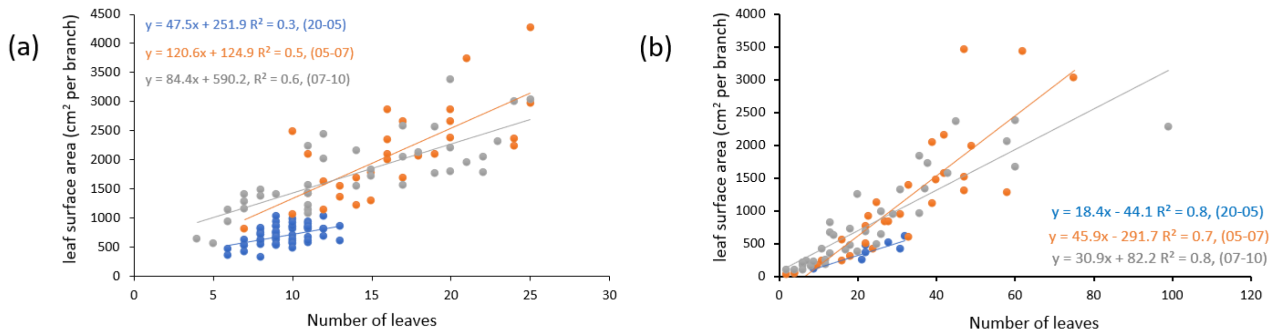

FIGURE 2. The three linear allometric relations (a) for main branches and (b) sub-branches used for the conversion of leaves number to surface area for the year 2022.

by Serouart *et al*. (2022). It is in conformity with the U-net model that delineates vegetation from the background (after training across a dataset that is very large and diverse). Pixels of the vegetation are subsequently classified using a Support Vector Machine (SVM) shallow machine learning approach trained on grids extracted pixels applied to the RGB photos. We used an already trained SegVeg model (Serouart *et al*. 2022), leading to a vegetation cover fraction ranging from 0 to 1. The presence of senescent vegetation (pruned residues or dried grasses) was not taken into account in the vegetation cover. A qualitative assessment of the results was done, leading to the removal of images with shadows from the analysis.

3. Rainfall conditions at the experimental site.

Among the components of weather, only rainfall data was used. The rainfall data used in this study were extracted from the weather station of Entrecheaux for both years (2021 and 2022) located in the studied area with a distance to the fields that range from 1 to 5 km. The cumulated rainfall value for 2021 was 664.8 mm, and for 2022 was 754.8 mm, respectively. In particular, the year 2022 was wetter (more precipitation) than 2021 but also had the driest summer. Rainfall data analysis was useful to examine grass dynamics, especially in the summertime when grass regrowth might be stimulated by a rainfall event.

4. Satellite data

In this study, we used Sentinel-2 (S2) time series (optical images) collected from both Sentinel-2A and Sentinel-2B, considering all cloud-free images during the years 2021 and 2022. Images were provided by an open-source service centre named *THEIA* (https://www.theia-land.fr/, accessed on 17 January 2023). We worked with S2 level 2A, which is spatially registered and corrected for atmospheric effects. The products are delivered with a cloud mask used to filter the images. The number of used images varies across the two years; for instance, there were 50 and 53 available images in 2021 and 2022, respectively.

The leaf area index (LAI) utilised in this research was calculated via the BVNET algorithm (Weiss *et al*., 2002), which is based on the green (B3), red (B4), and near-infrared (B8) bands. The quality of this algorithm was proven and thus it was incorporated into the ESA (European Space Agency) S2 toolbox. The algorithm is based on the neural network trained on simulated spectral reflectance using the SAIL radiative transfer model (Weiss *et al*., 2002). The SAIL model is adapted to homogeneous canopies as field crops, and using it to structured plant cover such as orchards and vineyards remains questionable. However, in Abubakar *et al.* 2023, it was found that the LAI derived from the BVNET algorithm can track the leaf development dynamic. The LAI was computed on each 10m resolution pixel, and then the LAI average was computed for every field using the R function of zonal statistics (*Zonal Statistics in R | GeoProfesja*, 2016). To avoid any border effect, a buffer of 20 m from the field limit was removed before the averaging.

5. Analytic model and calibration

In this study, we assumed that the vine leaf area dynamic can be represented by a double logistic model (Fisher *et al.*, 2006; Fisher and Mustard, 2007), which has proved to be efficient in describing the LAI dynamic of orchards and vineyards (Abubakar *et al.*, 2023). The analytic relationship is given in Equation 1.

$$Eq.1: V(t) = vmin + vamp\left(\frac{1}{1+e^{m1-n1t}} - \frac{1}{1+e^{m2-n2t}}\right)$$

where V(t) represents a vegetation index (LAI in our case) at time t, *vmin* is the minimum V value, and *vamp* is the amplitude of V variations. Parameters *m1, n1, m2, n2* are the curve-shape controlling parameters. The *n1* and *n2* parameters represent the slope at inflexion points, as shown below in Figure 3a, while *m1* and *m2* are the timing of the inflexion point. The problem with the vineyard is that there is a risk of confusion between the grassed background, which has its dynamic on the grapevine canopy since both components might have a similar weight in the overall LAI (Figure 3c). This hampers the possibility of determining the double logistic model parameters and consequently prevents identifying the vine canopy development. Such a feature was noticed in Abubakar *et al.* (2023) with the possibility of vineyard misclassification due to early grass development that provides leaf growth earlier than expected with grapevine. The results of the leaf development observations are displayed in Figure 3b. The observed leaf surface should be considered as a proxy of the LAI, whose main characteristic is to describe the temporal dynamic of the canopy development. The leaf surfaces were normalised using the maximum value observed in each field. Figure 3b clearly shows the relevance of using the double logistic model and shows a good synchronisation of the temporal patterns over the growing and plateau phases.

These observations were the foundation of the additional hypothesis used to constrain the fitting procedure. Based on the field observations, we can determine critical dates that correspond to *vmin*, *vmax=vmin+vamp,* and intermediate points in the growing and senescence phases corresponding to (*Vmin*+¼*Vamp*), ½, and ¾ of the amplitude (see Figure 3c). To determine the V value at those critical times, we need to

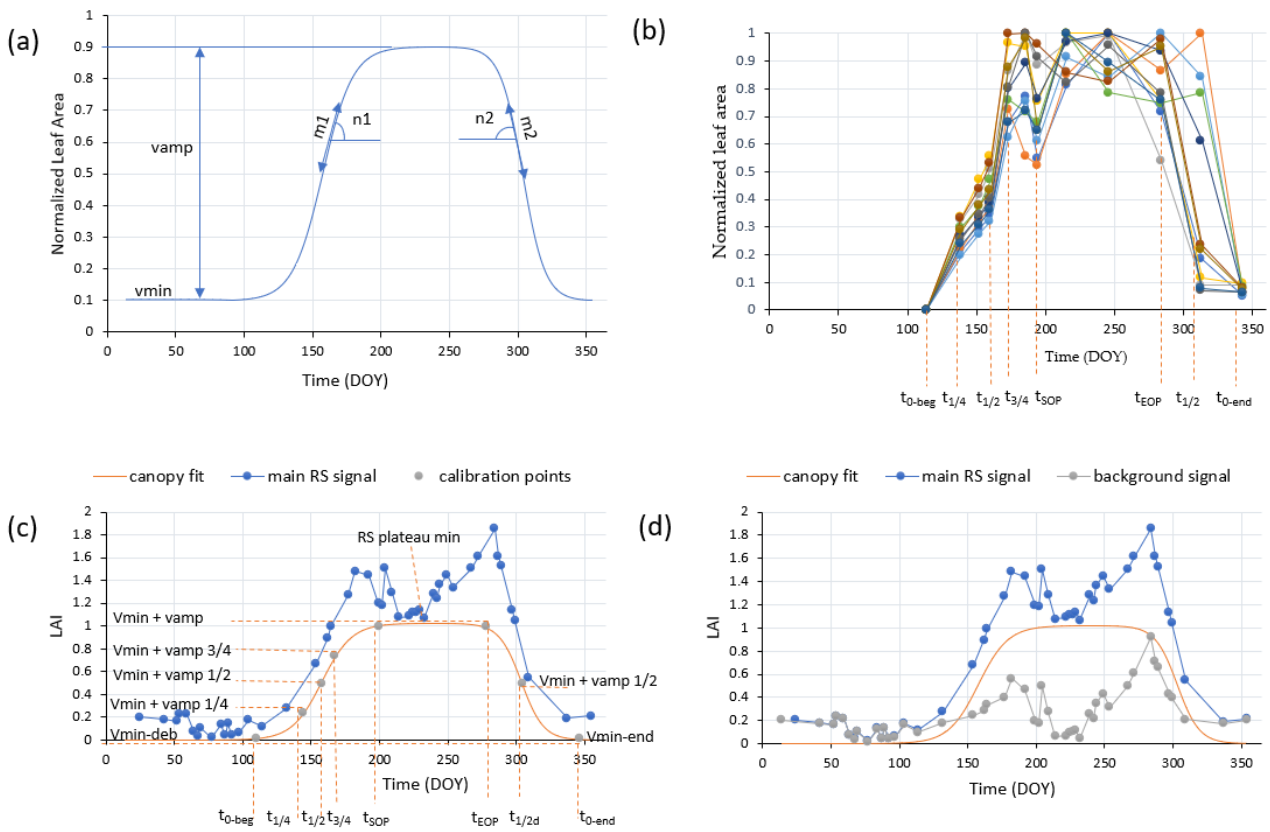

FIGURE 3. (a) analytic model showing Eq. 1 parameter effect (b) canopy developments from the field visits data showing selected time used for the model calibration (c) the simulated canopy from the S2 data showing the calibration points (d) the separation of canopy and background from S2 data of a given irrigated table grapevine field.

determine *Vmax* and *Vmin*. These values were taken from the LAI time series. *Vmin* was derived from a field with a tilled interrow, taking into account the field presenting a flat and the lowest LAI in winter. This value was then applied to all other fields. *Vmax* is characterised on every field's times series by taking the minimum value during the plateau phase. In doing so, the underlying assumption is that, whatever the inter-row management method, there is a point during the summer drought when the vegetation is completely dried out, allowing us to hypothesise that the grassed contribution to LAI is negligible.

From that hypothesis, we can generate a grapevine LAI time series at the critical times mentioned above. Then, the parameters *n1, n2, m1,* and *m2* were determined using a non-linear fitting algorithm (nls function in R). The last step is to remove from the observed LAI time series the fitted vine LAI to obtain the LAI of the background (Figure 3d).

RESULTS

1. Grapevine canopy and background field observation

The data obtained on the evaluation of the grapevine leaf area were presented (Figure 3b) and partially discussed in the previous section. The measurements obtained on a sample of branches provide a good reflection of leaf evolution but do not allow us to compare LAI from one plot to another since the number of branches per grapevine is also an important datum that was not recorded. The evolution clearly shows the growth, plateau, and senescence phases. The first two phases are remarkably synchronous despite the diversity of the grape varieties used (different varieties for wine grapes and table grapes). More marked differences can be observed in the senescence phase. Between the two years, we noted a slight shift of a few days, with vegetation in 2022 ahead of 2021. The surface dynamic shows a drop at the beginning of the plateau, in line with thinning operation. Such an operation could have an impact on the detection of minimum LAI in the plateau phase.

The temporal patterns of the inter-row grass coverage are displayed in Figure 5 for the two years. The temporal patterns reflect the weather nature of the study area by having a significant drop in summer and a rise in both winter and autumn, as shown in Figure 5. From DOY 150 to 215, i.e., when the inter-row decline was observed, strong water deficits were recorded with cumulative daily rainfall of 54 mm (the potential evapotranspiration being 325 mm) in 2021 and 37.6 mm (the potential evapotranspiration being 315 mm) in 2022. Due to the significant variation in inter-row management strategies among the selected grapevines, the drop in the green vegetation still varies among fields with some having a drastic drop (for instance the constantly tilled plots), while in some fields the drop is not so drastic (for instance plots that have grassed inter-row). Such a drop in the summer confirms our hypothesis that in the summer, there are times when the grass contribution to LAI is negligible. However, the hypothesis is questionable with table grapevine fields 45, 1901, and 3064 that had a grassed inter-row and were irrigated. In that case, the grapevine canopy is very high, and the impact of the grassed inter-row might be minimised.

2. Delineation of canopy and soil background from the remote sensing data

The method was applied to each field, considering the specific *Vmax* for each of them. The canopy development for one of the selected grapevine is displayed below with all the calibration points (Figure 5). In this figure, we can make a qualitative assessment of the background dynamic as displayed by the picture. After tillage within some part of the growing season, there is re-emergence of the inter-row grasses coverage as seen in Figure 5 below; which can be explained by rainfall that may stimulate the regrowth between the two tillage events shown in the two mid photos. The regrowth of the grass shown in the last picture is also visible on the background LAI signal. When comparing the grapevine results, we can see that the timing of the growing and senescence phases was consistent. For the background, the overall trend is well reproduced, with high LAI in spring and fall while the grass cover decreases strongly in

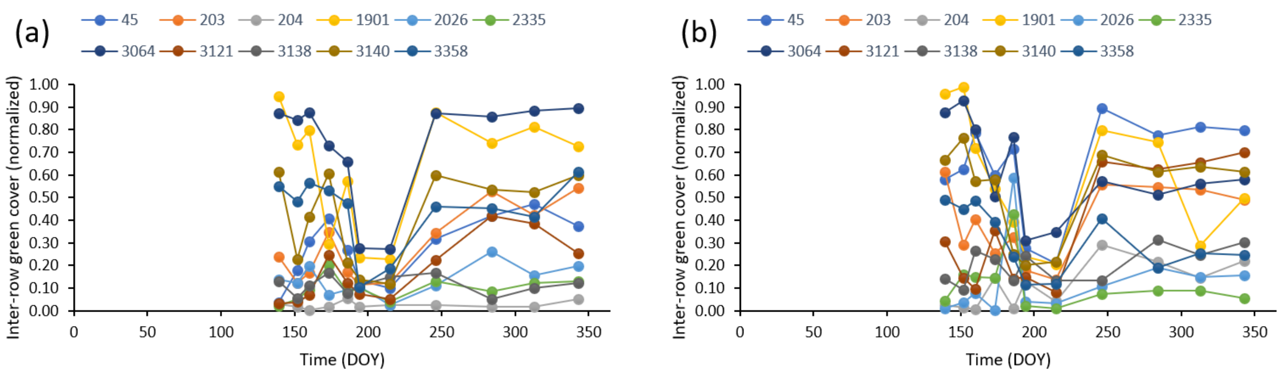

FIGURE 4. Temporal pattern of the inter-row green vegetation cover from the field visits data (with plot ID indicated above the figures) in 2021 (a) and 2022 (b).

summer. Some variations in both signals were not always consistent due to some shifts in acquisition dates and very sharp variations in grass dynamics due to tillage and rainfall. The main parameters used including their timings are *vmin_deb* (110 DOY), *vmin+vamp1/4* (144 DOY), *vmin+vamp1/2* (158 DOY), *vmin+vamp3/4* (167 DOY) *vmin+vamp_SOP* (199), *vmin+vamp_EOP* (272 DOY), *vmin+vamp1/2* (304 DOY), *vmin_end* (346 DOY).

3. Evaluation of the vine LAI

The developped method was evaluated by considering the observations made the 03/08/2023 when the canopy is expected to be fully developped. The average and standard deviation of the canopy width from the five selected grapevine trees were determined across each field. A relation was determined between the remotely sensed LAI (RS-LAI) and the average canopy width (of the same date) for each field with error bars on the ground measurements, as shown in Figure 6 below. The evaluation was done independently for table (Figure 6a) and wine grapevines (Figure 6b), as the grapevine trees are managed differently. The increase in the RS-LAI is somewhat directly linked to an increase in the canopy width, but the strong uncertainties on the ground observations might affect this evaluation strongly.

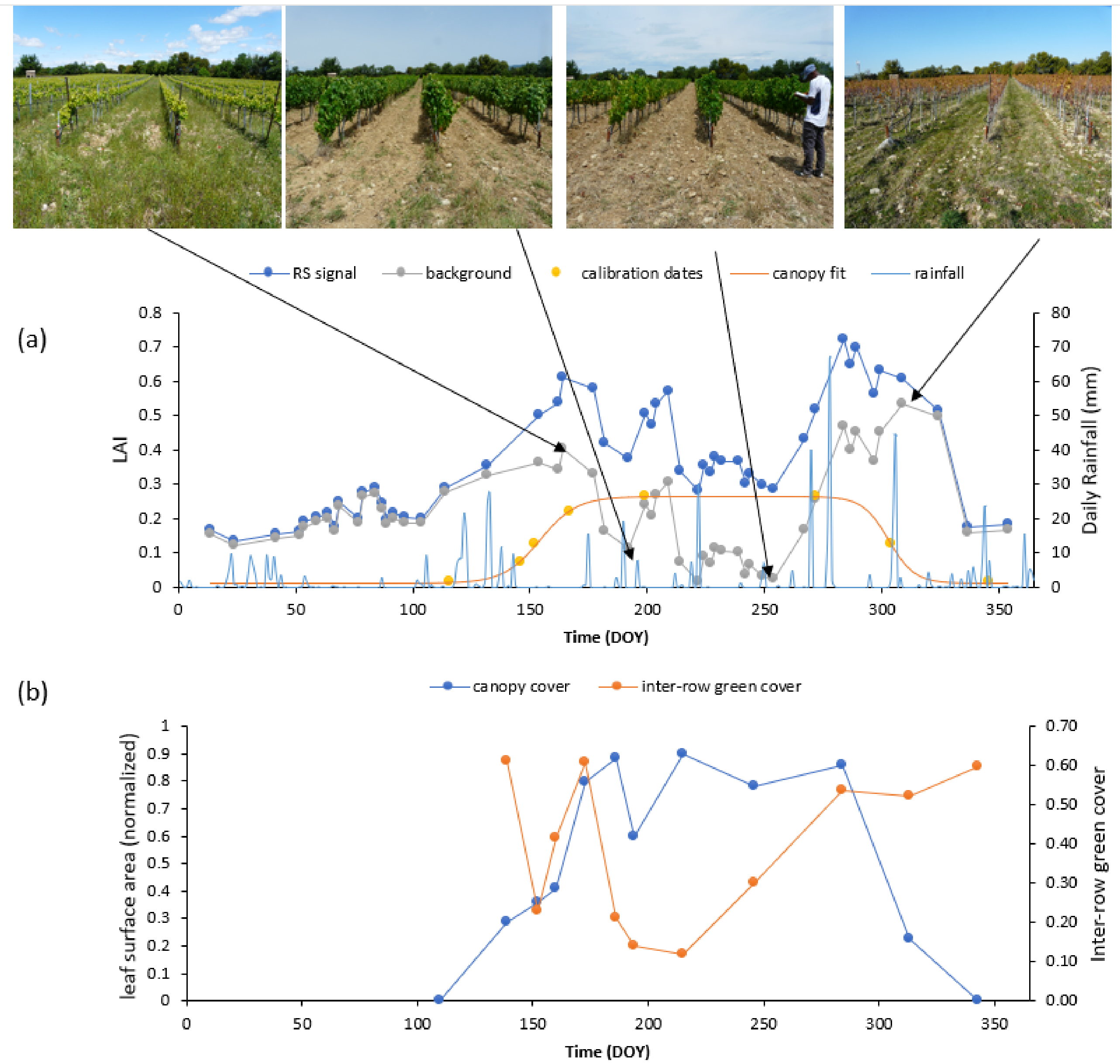

FIGURE 5. Results obtained with field ID 3140: (a) Separation of canopy and background green cover from remote sensing LAI signal and the rainfall data of a grapevine plot with field ID 3140. The points on the yellow curve are those used to calibrate the grapevine LAI curve. In (b), the curves correspond to the observed canopy leaf area and background green vegetation cover.

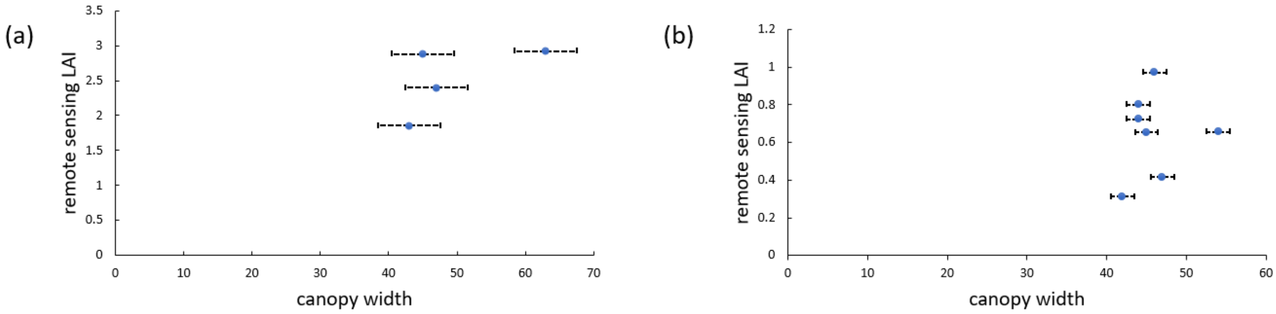

FIGURE 6. Table grapevine RS-LAI and canopy width relations (a) and wine grapevine RS-LAI and canopy width relations (b).

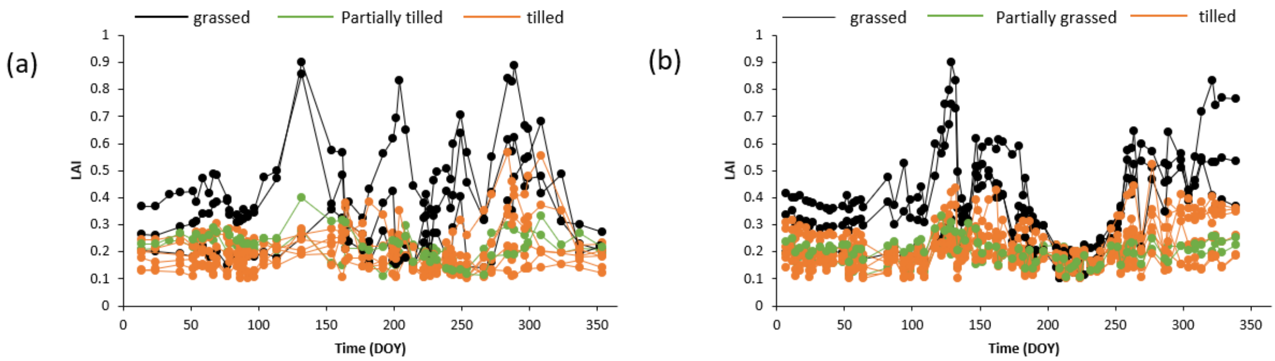

FIGURE 7. Temporal patterns of background LAI time series for 2021 (a) and 2022 (b). The black curves correspond to the grassed, green to the partially tilled, and orange to the tilled inter-row management.

4. Identification of inter-row management strategies from remote sensing data

The background LAI time series are displayed in Figure 7, and the colour scheme is used to distinguish the three management classes: tilled, partially grassed, and grassed. For the grassed class (black lines), we can observe strong variations in LAI that reflect growth, mowing, and summer senescence. Overall, the grassed class presented a yearly average LAI, which was significantly larger than the other modes, with an average of 0.36 compared to 0.19 to 0.21 values obtained with the other two classes. One can note that the differences were even larger when considering the spring period until DOY = 150. Therefore, the yearly (or spring average) average LAI over the year might be a useful metric to separate grassed and tilled inter-rows. As a matter of fact, the lowest yearly average in the grassed class (0.30) is always larger than the maximum obtained in the other class (0.24). On the other hand, the tilled and partially grassed classes are difficult to distinguish. A comparison of the retrieved LAI with the inter-row vegetation cover led to a significant relationship with an $R^2 = 0.4$. The quality of this comparison is affected by the uncertainties in the vegetation cover due to the sampling, the error in image processing, and the difference in time between the remote sensing data and the close field observation. However, a qualitative assessment made with the field pictures as shown in Figure 5 showed consistency between the background LAI time series and the grass development in the inter-rows.

DISCUSSION

1. Impact of grapevine trimming and thinning management.

Grapevine canopies are subjected to several management practices, such as pruning, trimming, or thinning, among others, for canopy structure manipulations. The shoot trimming is done to regulate the excess growth spread of the grapevines across the fields (regulate shoot vigour) by adopting several approaches of canopy management (shoot trimming or thinning) (Smart, 1985). Thinning or trimming of shoot remains one of the extensively adopted management strategies in viticulture to regulate canopy density, improve interception of sunlight, optimise photosynthetic dynamics, improve fruit microclimate, and eventually enhance fruit yield and quality of the wine (Costa *et al.*, 2016).

Figure 8 displays the temporal data obtained from the field visits and RS-LAI time series. With the field observation, one can notice that, in general, there is a slight decrease in the leaf surface area observations (highlighted with a red circle) on the sixth field visit which corresponds to 12–13 of July 2021.

Such drop in the leaf surface area is ascribed to the first shoot thinning management, as demonstrated by the picture showing the removed shoots left on the ground.

On the contrary, the RS-LAI signals from Figure 8 have failed to display such a reduction in leaf area. It is interesting to implement our approach that needs to take profit of a minimum value, and it is interesting to have it not impacted by a thinning event. However, it also reflects that LAI estimated by remote sensing is not so sensitive to leaf area reduction within the grapevine canopies. This questions the LAI algorithm itself but also indicates that some management practices such as thinning and pruning can not be observable on the 10-metre resolution images delivered by the Sentinel 2 satellite.

2. Is the proposed method dependent on field observations

The leaf growth is governed by the temperature (Malheiro et *al.*, 2013) and is tightly linked to the phenology. It also depends on grapevine varieties, while water stress may impact the grapevine LAI dynamic. In our study, the timing of the plant development as the growth, the plateau, and the senescence phases were set up on ground observations. In other locations having different climates and grapevine varieties, there is a need to adapt the timing of the different phases. One can question the need for field observation and then the resulting burden of collecting leaf area in several fields. One can ask if such an observation step is mandatory or if we can infer the timing characteristics directly from the RS times series. In our data set, we can take profit from vineyards where the LAI time series is dominated by the grapevine canopy. A good candidate for that is a field with an LAI times series having low LAI in winter and spring and a LAI significantly higher during the crop seasons, as shown with field 3121 in Figure 9a. From that curve, we can determine the *Vmax* as done previously and then determine the time corresponding to the start and the end of the season (*t0-deb and t0-end*), the plateau (*tSOP* and *tEOP*), and the intermediate points during the growing and senescence phases (*t1/4, t1/2,* and *t3/4*). These points are displayed in the orange curves in Figure 9a. The differences in time between the remote sensing and field approaches reached a maximum of 17 days for *tSOP* and was, on average, equal to 10 days. The plateau duration was expended by 20 days, and the senescence phase was delayed when using the remote sensing time series in comparison to the field observations. If such differences in the development timing have no impact on the maximum LAI, their impacts on the vegetation component time series might be significant. Figure 9b displays the LAI times series of the background using the two methods (with or without field observation) on three fields representative of the three management classes. As expected, differences were found during the growing and senescence phases. However, such differences remain small in comparison to the differences observed between management practices and, thus, the possibility to identify grassed inter-row remains possible. Such a result is encouraging and opens the possibility of applying the method in different areas with the use of remote sensing data only. This is an important property for the model scalability and its implementation in wide areas.

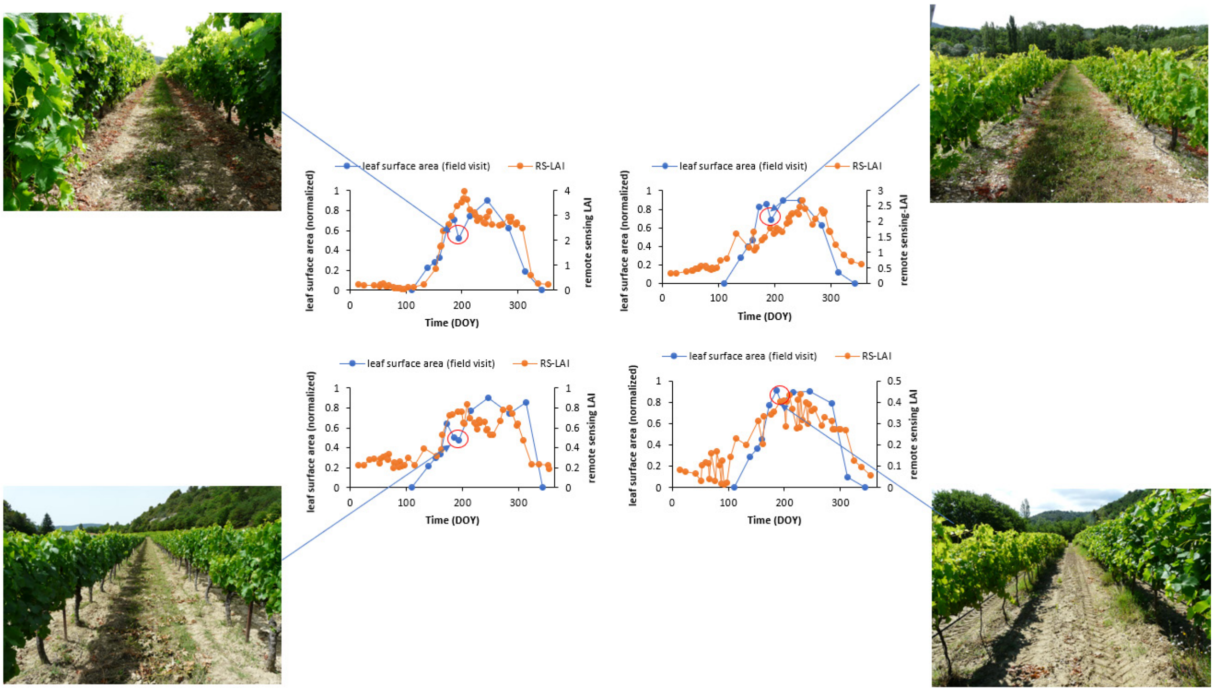

FIGURE 8. Temporal evolution of canopy dynamic and the temporal evolutions of the RS-LAI signal for the year 2021.

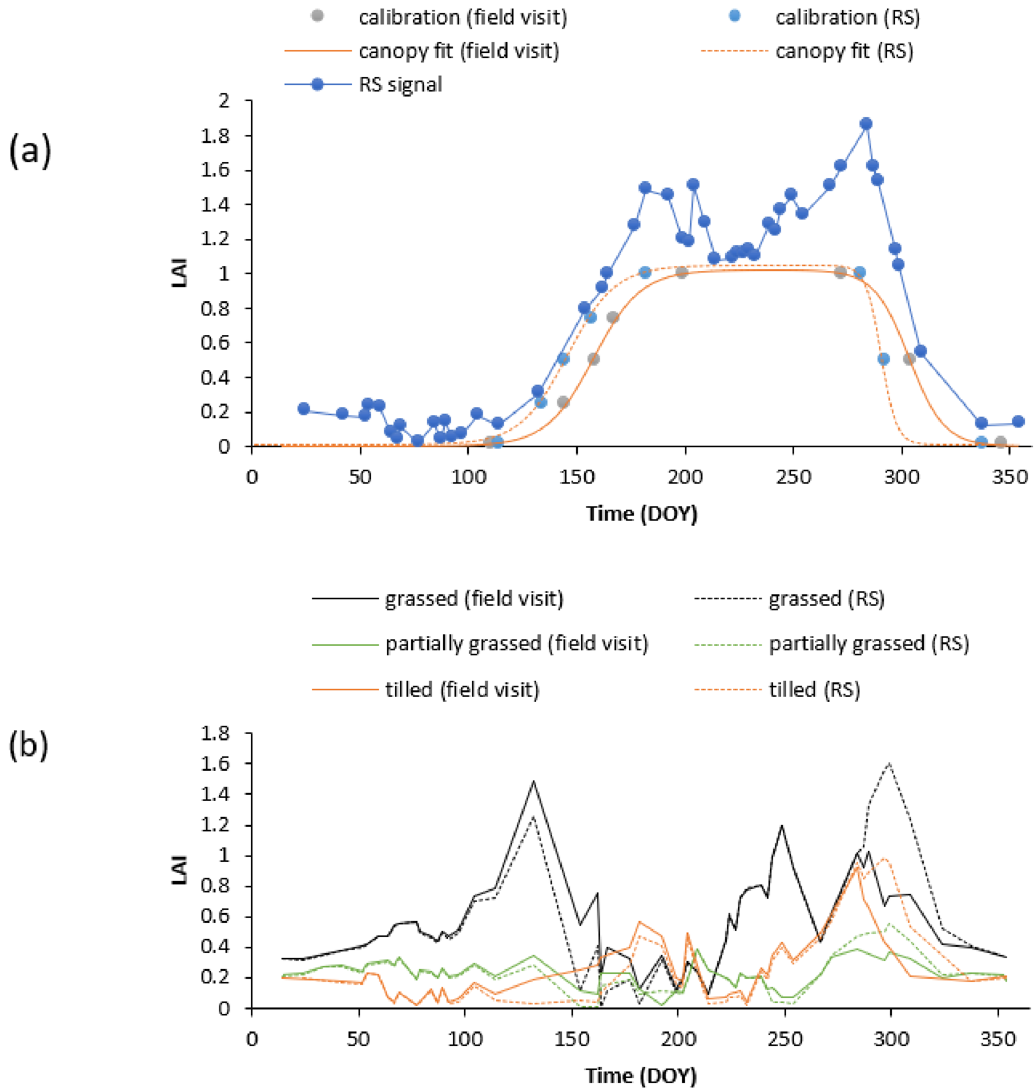

FIGURE 9. (a) RS-LAI signal of a clear and fully grown grapevine tree where a good case was identified with calibration fit from field visit and RS data (b) comparison of the background LAI time series on three fields representative of the different management classes: Grassed inter-row (black for field 1901), tilled interrow (orange for field 3121), and partially tilled (green for field 203). The solid lines correspond to the implementation of the method using field observations, while the dashed lines correspond to the implementation using remote sensing only.

CONCLUSIONS

In this work, we propose a method for characterising two important characteristics of grapevines, namely the LAI of the grapevine canopy and inter-row management. We showed that these data are accessible from the LAI time series derived from a decametric resolution satellite such as Sentinel 2, which has the advantage of offering frequent and free data over the whole globe but at a resolution that does not allow us to enter into the description of the constituent elements of a plant canopy such as the vineyards. The proposed method is based on assumptions about canopy dynamics supported by field observations, and on the presence of periods during the summer when the contribution of the herbaceous canopy may be neglected, due either to tillage or to the drying out of the grass as a result of water stress. The method was applied to eleven (11) vineyards with different types of management and grape varieties. The results obtained led to interesting qualitative results on LAI, and we have succeeded in separating grass-covered vines from vines in which the inter-row is tilled. We have shown that we can dispense with field observation and base our methods solely on remote sensing data. These promising results now need to be evaluated against more quantitative data and applied on a larger scale.

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REFERENCES

Abubakar, M. A., Chanzy, A., Flamain, F., Pouget, G., & Courault, D. (2022). Detection of Irrigated Permanent Grasslands with Sentinel-2 Based on Temporal Patterns of the Leaf Area Index (LAI). Remote Sensing, 14(13), 3056. https://doi.org/10.3390/rs14133056

Abubakar, M. A., Chanzy, A., Flamain, F., Pouget, G., & Courault, D. (2023). Delineation of Orchard, Vineyard, and Olive Trees Based on Phenology Metrics Derived from Time Series of Sentinel-2. *Remote Sensing*, *15*(9), 2420. https://doi.org/10.3390/rs14133056

Anastasiou, E., Balafoutis, A., Darra, N., Psiroukis, V., Biniari, A., Xanthopoulos, G., & Fountas, S. (2018). Satellite and Proximal Sensing to Estimate the Yield and Quality of Table Grapes. *Agriculture*, *8*(7), Article 7. https://doi.org/10.3390/agriculture8070094

Arnó, J., Martínez Casasnovas, J. A., Ribes Dasi, M., & Rosell, J. R. (2009). Review. Precision viticulture. Research topics, challenges and opportunities in site-specific vineyard management. *Spanish Journal of Agricultural Research*, *7*(4), 779. https://doi.org/10.5424/sjar/2009074-1092

Beniaich, A., Silva, M. L. N., Guimaraes, D. V., Avalos, F. A. P., Terra, F. S., Menezes, M. D., Avanzi, J. C., & Candido, B. M. (2022). UAV-based vegetation monitoring for assessing the impact of soil loss in olive orchards in Brazil. *Geoderma Regional*, *30*, e00543. https://doi.org/10.1016/j.geodrs.2022.e00543

Borgogno-Mondino, E., Lessio, A., Tarricone, L., Novello, V., & de Palma, L. (2018). A comparison between multispectral aerial and satellite imagery in precision viticulture. *PRECISION AGRICULTURE*, *19*(2), 195–217. https://doi.org/10.1007/s11119-017-9510-0

Corti, G., Cavallo, E., Cocco, S., Biddoccu, M., Brecciaroli, G., & Agnelli, A. (2011). Evaluation of erosion intensity and some of its consequences in vineyards from two hilly environments under a Mediterranean type of climate, Italy. *Soil Erosion Issues in Agriculture*, 113–160.

Costa, J. M., Vaz, M., Escalona, J., Egipto, R., Lopes, C., Medrano, H., & Chaves, M. M. (2016). Modern viticulture in southern Europe: Vulnerabilities and strategies for adaptation to water scarcity. *Agricultural Water Management*, *164*, 5–18. https://doi.org/10.1016/j.agwat.2015.08.021

Darouich, H., Ramos, T. B., Pereira, L. S., Rabino, D., Bagagiolo, G., Capello, G., Simionesei, L., Cavallo, E., & Biddoccu, M. (2022). Water Use and Soil Water Balance of Mediterranean Vineyards under Rainfed and Drip Irrigation Management: Evapotranspiration Partition and Soil Management Modelling for Resource Conservation. *Water*, *14*(4), 554. https://doi.org/10.3390/w14040554

De Petris, S., Berretti, R., Sarvia, F., & Borgogno-Mondino, E. (2019). Precision arboriculture: A new approach to tree risk management based on geomatics tools. In C. M. U. Neale & A. Maltese (Eds.), *Remote Sensing for Agriculture, Ecosystems, and Hydrology Xxi* (Vol. 11149, p. 111491G). Spie-Int Soc Optical Engineering. https://doi.org/10.1117/12.2532778

Erena, M., Montesinos, S., Portillo, D., Alvarez, J., Marin, C., Fernandez, L., Henarejos, J. M., & Ruiz, L. A. (2016). Configuration and Specifications of an Unmanned Aerial Vehicle for Precision Agriculture. In L. Halounova, V. Safar, C. K. Toth, J. Karas, G. Huadong, N. Haala, A. Habib, P. Reinartz, X. Tang, J. Li, C. Armenakis, G. Grenzdorffer, P. LeRoux, S. Stylianidis, R. Blasi, M. Menard, H. Dufourmount, & Z. Li (Eds.), *XXIII ISPRS CONGRESS, COMMISSION I* (Vol. 41, Issue B1, pp. 809–816). Copernicus Gesellschaft Mbh. https://doi.org/10.5194/isprsarchives-XLI-B1-809-2016

Esteban, M. A., Villanueva, M. J., & Lissarrague, J. R. (2001). Effect of irrigation on changes in the anthocyanin composition of the skin of cv Tempranillo (*Vitis vinifera* L) grape berries during ripening. *Journal of the Science of Food and Agriculture*, *81*(4), 409–420. https://doi.org/10.1002/1097-0010(200103)81:4<409::AID-JSFA830>3.0.CO;2-H

Fisher, J. I., & Mustard, J. F. (2007). Cross-scalar satellite phenology from ground, Landsat, and MODIS data. *Remote Sensing of Environment*, *109*(3), 261–273. https://doi.org/10.1016/j.rse.2007.01.004

Fisher, J. I., Mustard, J. F., & Vadeboncoeur, M. A. (2006). Green leaf phenology at Landsat resolution: Scaling from the field to the satellite. *Remote Sensing of Environment*, *100*(2), 265–279. https://doi.org/10.1016/j.rse.2005.10.022

Gao, B. C. (1996). NDWI - A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment*, *58*(3), 257–266. https://doi.org/10.1016/S0034-4257(96)00067-3

Hall, A. (2018). Remote Sensing Applications for Viticultural Terroir Analysis. *Elements*, *14*(3), 185–190. https://doi.org/10.2138/gselements.14.3.185

Hall, A., Louis, J., & Lamb, D. (2003). Characterising and mapping vineyard canopy using high-spatial-resolution aerial multispectral images. *Computers & Geosciences*, *29*(7), 813–822. https://doi.org/10.1016/S0098-3004(03)00082-7

Hall, A., & Wilson, M. A. (2013). Object-based analysis of grapevine canopy relationships with winegrape composition and yield in two contrasting vineyards using multitemporal high spatial resolution optical remote sensing. *International Journal of Remote Sensing*, *34*(5), 1772–1797. https://doi.org/10.1080/01431161.2012.726753

Huete, A. (1988). A Soil-Adjusted Vegetation Index (savi). *Remote Sensing of Environment*, *25*(3), 295–309. https://doi.org/10.1016/0034-4257(88)90106-X

Johnson, L. F., Roczen, D. E., Youkhana, S. K., Nemani, R. R., & Bosch, D. F. (2003). Mapping vineyard leaf area with multispectral satellite imagery. *COMPUTERS AND ELECTRONICS IN AGRICULTURE*, *38*(1), 33–44. https://doi.org/10.1016/S0168-1699(02)00106-0

Kandylakis, Z., & Karantzalos, K. (2016). Precision Viticulture from Multitemporal, Multispectral Very High Resolution Satellite Data. In L. Halounova, V. Safar, P. L. N. Raju, L. Planka, V. Zdimal, T. S. Kumar, F. S. Faruque, Y. Kerr, S. M. Ramasamy, J. Comiso, Y. A. Hussin, P. S. Thenkabail, S. Lavender, A. Skidmore, P. Yue, P. Patias, O. Altan, & Q. Weng (Eds.), *XXIII ISPRS CONGRESS, COMMISSION VIII* (Vol. 41, Issue B8, pp. 919–925). Copernicus Gesellschaft Mbh. https://doi.org/10.5194/isprsarchives-XLI-B8-919-2016

Karakizi, C., Oikonomou, M., & Karantzalos, K. (2016a). Vineyard Detection and Vine Variety Discrimination from Very High

Resolution Satellite Data. *Remote Sensing*, *8*(3), 235. https://doi.org/10.3390/rs8030235

Karakizi, C., Oikonomou, M., & Karantzalos, K. (2016b). Vineyard Detection and Vine Variety Discrimination from Very High Resolution Satellite Data. *REMOTE SENSING*, *8*(3), 235. https://doi.org/10.3390/rs8030235

Khaliq, A., Comba, L., Biglia, A., Aimonino, D. R., Chiaberge, M., & Gay, P. (2019). Comparison of Satellite and UAV-Based Multispectral Imagery for Vineyard Variability Assessment. *REMOTE SENSING*, *11*(4), 436. https://doi.org/10.3390/rs11040436

Malheiro, A. C., Campos, R., Fraga, H., Eiras-Dias, J., Silvestre, J., & Santos, J. A. (2013). Winegrape Phenology and Temperature Relationships in the Lisbon Wine Region, Portugal. *JOURNAL INTERNATIONAL DES SCIENCES DE LA VIGNE ET DU VIN*, *47*(4), 287–299.

Matese, A., & Filippo Di Gennaro, S. (2015). Technology in precision viticulture: A state of the art review. *International Journal of Wine Research*, *7*, 69–81. https://doi.org/10.2147/IJWR.S69405

Motohka, T., Nasahara, K. N., Oguma, H., & Tsuchida, S. (2010). Applicability of Green-Red Vegetation Index for Remote Sensing of Vegetation Phenology. *Remote Sensing*, *2*(10), 2369–2387. https://doi.org/10.3390/rs2102369

Palazzi, F., Biddoccu, M., Borgogno Mondino, E. C., & Cavallo, E. (2022). Use of Remotely Sensed Data for the Evaluation of Inter-Row Cover Intensity in Vineyards. *Remote Sensing*, *15*(1), 41. https://doi.org/10.3390/rs15010041

Permanhani, M., Costa, J. M., Conceição, M. A. F., De Souza, R. T., Vasconcellos, M. A. S., & Chaves, M. M. (2016). Deficit irrigation in table grape: Eco-physiological basis and potential use to save water and improve quality. *Theoretical and Experimental Plant Physiology*, *28*(1), 85–108. https://doi.org/10.1007/s40626-016-0063-9

Qi, J., Chehbouni, A., Huete, A., Kerr, Y., & Sorooshian, S. (1994). A Modified Soil Adjusted Vegetation Index. *Remote Sensing of Environment*, *48*(2), 119–126. https://doi.org/10.1016/0034-4257(94)90134-1

Rizzi, J., Tarquis, A. M., Gobin, A., Semenov, M., Zhao, W., & Tarolli, P. (2021). Preface: Remote sensing, modelling-based hazard and risk assessment, and management of agro-forested ecosystems. *Natural Hazards and Earth System Sciences*, *21*(12), 3873–3877. https://doi.org/10.5194/nhess-21-3873-2021

Roca, P. (2022). *STATE OF THE WORLD VINE AND WINE SECTOR*. 1–25. https://www.oiv.int/public/medias/8773/pptpress-conf-2022-4-def.pdf

Rodriguez, J. R., Miranda, D., & Alvarez, C. J. (2006). Application of satellite images to locate and inventory vineyards in the designation of origin “Bierzo” in Spain. *Transactions of the ASABE*, *49*(1), 277–290.

Sarvia, F., De Petris, S., & Borgogno-Mondino, E. (2019). Remotely sensed data to support insurance strategies in agriculture. In C. M. U. Neale & A. Maltese (Eds.), *Remote Sensing for Agriculture, Ecosystems, and Hydrology Xxi* (Vol. 11149, p. 111491H). Spie-Int Soc Optical Engineering. https://doi.org/10.1117/12.2533117

Semmens, K. A., Anderson, M. C., Kustas, W. P., Gao, F., Alfieri, J. G., McKee, L., Prueger, J. H., Hain, C. R., Cammalleri, C., Yang, Y., Xia, T., Sanchez, L., Alsina, M. M., & Velez, M. (2016). Monitoring daily evapotranspiration over two California vineyards using Landsat 8 in a multi-sensor data fusion approach. *REMOTE SENSING OF ENVIRONMENT*, *185*, 155–170. https://doi.org/10.1016/j.rse.2015.10.025

Serouart, M., Madec, S., David, E., Velumani, K., Lopez Lozano, R., Weiss, M., & Baret, F. (2022). SegVeg: Segmenting RGB Images into Green and Senescent Vegetation by Combining Deep and Shallow Methods. *Plant Phenomics*, *2022*. https://doi.org/10.34133/2022/9803570

Smart, R. (1985). Principles of Grapevine Canopy Microclimate Manipulation with Implications for Yield and Quality—A Review. *American Journal of Enology and Viticulture*, *36*(3), 230–239.

Steenwerth, K. L., & Belina, K. M. (2010). Vineyard weed management practices influence nitrate leaching and nitrous oxide emissions. *Agriculture, Ecosystems & Environment*, *138*(1–2), 127–131. https://doi.org/10.1016/j.agee.2010.03.016

Testa, S., Mondino, E. C. B., & Pedroli, C. (2014). Correcting MODIS 16-day composite NDVI time-series with actual acquisition dates. *European Journal of Remote Sensing*, *47*, 285–305. https://doi.org/10.5721/EuJRS20144718

Vaudour, E., Carey, V. A., & Gilliot, J. M. (2010). Digital zoning of South African viticultural terroirs using bootstrapped decision trees on morphometric data and multitemporal SPOT images. *REMOTE SENSING OF ENVIRONMENT*, *114*(12), 2940–2950. https://doi.org/10.1016/j.rse.2010.08.001

Wang, S., Zhang, L., Huang, C., & Qiao, N. (2017). An NDVI-Based Vegetation Phenology Is Improved to be More Consistent with Photosynthesis Dynamics through Applying a Light Use Efficiency Model over Boreal High-Latitude Forests. *Remote Sensing*, *9*(7), 695. https://doi.org/10.3390/rs9070695

Weiss, M., Baret, F., Leroy, M., Hautecoeur, O., Bacour, C., Prevot, L., & Bruguier, N. (2002). Validation of neural net techniques to estimate canopy biophysical variables from remote sensing data. *Agronomie*, *22*(6), 547–553. https://doi.org/10.1051/agro:2002036

Whitmore, A. P., & Schröder, J. J. (2007). Intercropping reduces nitrate leaching from under field crops without loss of yield: A modelling study. *European Journal of Agronomy*, *27*(1), 81–88. https://doi.org/10.1016/j.eja.2007.02.004

Zarrouk, O., Francisco, R., Pinto-Marijuan, M., Brossa, R., Santos, R. R., Pinheiro, C., Costa, J. M., Lopes, C., & Chaves, M. M. (2012). Impact of irrigation regime on berry development and flavonoids composition in Aragonez (Syn. Tempranillo) grapevine. *Agricultural Water Management*, *114*, 18–29. https://doi.org/10.1016/j.agwat.2012.06.018

Zonal statistics in R | GeoProfesja. (2016, November 19). http://geoprofesja.pl/en/zonal-statistics-in-r/.