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Monitoring soil substrate influence in vineyards using Sentinel-2 time series and land surface phenology

Thomas Maffei *, Marco Moretto, Pietro Franceschi

Unit of Digital Agriculture, Research and Innovation Centre, Fondazione Edmund Mach, Via E. Mach 1, San Michele all'Adige 38098, Italy

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A B S T R A C T

This work explores the potential of Sentinel-2 time-series imagery to investigate the differences in vineyards associated with varying soil substrates. The investigation was carried out by selecting vineyards in the *Piana Rotaliana* wine growing area of the autonomous province of Trento (Italy). Consistent time-series datasets were defined by selecting vineyards trained under the same trellis system and avoiding plantation renewal between 2017 and 2023. To extract Land Surface Phenology (LSP) the best configuration between vegetation indices and fitting methods for deriving LSP features was investigated. The results indicate that Enhanced Vegetation Index 2 (EVI2) provides better stability with respect to Normalized Difference Vegetation Index (NDVI). For each vineyard statistical metrics were derived like LSP, Growing Season (GS; good observation within the LSP time period) and off Season (good observation outside the LSP time period) metrics. Eight datasets were defined and a Random Forest model was employed to assess classification accuracy and evaluate its stability across the years. Findings suggest that the substrate effect can be distinguished both from off Season and Growing Season metrics. Vegetation water content indices, such as the Global Vegetation Moisture Index (GVMI), emerged as the most effective and temporally stable predictors. The off Season datasets provided generally better results with respect to GS datasets when the model of one year was tested over the remaining years. The results provide valuable insights into the potential influence of soil characteristics on grapevine response over time, by highlighting the water retention capacity of the substrate and the vineyard response.

1. Introduction

Soil texture, water retention, mineral composition and root zone temperature are among the many factors that influence crop cultivation. In viticulture, soil properties may affect moisture and nutrient availability, affect microclimate and impact root growth (Jackson and Lombard, 1993). Understanding the types of soil and their influence on vineyard vegetative development can provide meaningful information helping decision-makers in the selection of appropriate management practices (e.g., irrigation regime) as well as the identification of sustainable grapevine varieties best suited for specific conditions.

Lithological maps encode geological information, such as the composition and physical properties of materials, making them a valuable tool for agricultural purposes. However, being able to combine lithological and agronomic management information across large areas requires extensive field surveys to collect data from multiple sources, a process that is both time-consuming and expensive. Remote sensing can potentially address these limitations, and when combined with IoT field data and Machine Learning (ML) techniques, it could be used to investigate and retrieve more accurate and valuable agronomic information (Weiss et al., 2020).

Despite its potential, however, the application of remote sensing in agriculture, and viticulture in particular, faces several challenges. Effective crop monitoring requires high spatial and temporal resolution (Khaliq et al., 2019; Khanal et al., 2020; Ferro and Catania, 2023; De Petris et al., 2024), which may not always be available or affordable. Moreover, limited digitization and heterogeneity of "ground truth" agronomic data (Teucher et al., 2022; Wu et al., 2022) constrains the training and application of robust machine learning (ML) or deep learning (DL) models. On a more fundamental level, inter-annual variability in weather and phenological development complicates the development of robust models that are generalizable across different growing seasons (Barriguinha et al., 2022; Hoppe et al., 2024).

Remote sensing, a discipline which has emerged in the last decades for precision agriculture (Karunathilake et al., 2023), has been widely applied in viticulture for various studies. The development of different

* Corresponding author.
E-mail address: thomas.maffei@fmach.it (T. Maffei).

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types of sensors and platforms has enabled precision viticulture to explore multiple aspects, including spatial resolution, temporal resolution, and the integration of data from various sources for vineyard characterization (Ferro and Catania, 2023). Key applications of remote sensing in vineyard characterization include pest detection, vine variety mapping, health status evaluation, yield estimation and management assessment. For example, phylloxera infested vineyards have been evaluated using multispectral airborne imagery (Johnson et al., 1996) and, more recently, with Unmanned Aerial Vehicle (UAV) and hyperspectral cameras (Vanegas et al., 2018). Karakizi et al. (2016) demonstrated the ability to detect vine varieties within vineyards using high-resolution multispectral imagery from WorldView-2, collected during the veraison phase. Even if the situation is in rapid evolution, it is worth remarking that with currently available open-source satellite data, it is difficult to achieve enough geometric resolution to discern the vine canopy from the inter-row space. For this reason alternative platforms, such as a UAV, are nowadays often preferred in agriculture applications at the cost of reduced capacity to monitor multiple vineyards over time at regional scale. As far as satellite applications are concerned, time-series analysis is generating significant interest, as temporal patterns can encapsulate more meaningful features compared to single image analysis. Palazzi et al. (2023) assessed the capability of Sentinel-2 time-series vegetation indices for discriminating inter-row vineyard management, while Kamangir et al. (2024) proposed a deep learning method for vineyard yield estimation. Additionally, functional data analysis of Normalized Difference Vegetation Index (NDVI) time-series has been shown to enhance the characterization of seasonal phenology and vineyard development (Vélez et al., 2022).

Great interest relies on the application of remote sensing to derive pedology, soil texture and soil properties information to help the agronomic management. Poppiel et al. (2019) was able to generate from proximal and remote sensing data a digital soil map in an agricultural area. Vaudour et al. (2019) has assessed the capacity of Sentinel-2 images to derive top soil properties over bare soil fields in a Mediterranean region marked by vineyard cultivation. Castaldi et al. (2023) focused on the feasibility of time-series Sentinel-2 images to derive topsoil clay and organic content from bare soil pixels. Despite this, most of this work relies on analyzing bare soil pixel, while research investigating vineyard soil characterization through satellite time series analysis remains limited even if the soil characteristics are expected to have a strong and consistent impact on the crop growing patterns, given that soil properties do not change significantly in the short term. To address these limitations, this study proposes the use of Land Surface Phenology (LSP) derived from multi-temporal satellite imagery as a temporal reference framework which enables a standardized comparison of vineyard development dynamics to track different soil conditions. This approach aims to improve the reliability and transferability of remote sensing-based models by accounting for temporal variability and characterization of soil influence under the same cultivar.

The objective of this study is to explore the potential of Sentinel-2 time series imagery to assess differences in vineyards responses to various soil substrates, particularly by integrating Land Surface Phenology (LSP), growing season (GS) and off Season metrics. To ensure the robustness of the analysis, a set of vineyards with the same overhead trellis system and multiple temporal datasets with different LSP, GS and off Season metrics, calculated annually from 2017 to 2023, have been selected. This approach allows for the evaluation of the stability of these metrics over time and identify which ones are consistently more important classifying soil substrates across all years.

2. Materials and methods

2.1. Study site and soil characteristics

This study focuses on a significant wine-growing area, the *Piana Rotaliana*, located in northeastern Italy within the Autonomous Region of Trentino-Alto Adige (Fig. 1). The area of interest (center coordinates: longitude 11.13667; latitude 46.21536), spans approximately 80 km^2 and is characterized by a high degree of anthropization in the agricultural sector. The primary crop cultivated is grapevine (*Vitis vinifera)*, with smaller-scale cultivation of orchards, primarily apple (*Malus x domestica*). From a topographical point of view, the area of interest where grapes are cultivated is mostly flat and can be considered homogeneous.

Based on previous studies of soil distribution in the Region and new measurements collected during the PICA project (Piattaforma Integrata Cartografica Agro-vitivinicola), detailed soil maps have been produced following recent national and international methodology (Costantini E. A. C. (Ed.), 2007; Priori et al., 2019). These efforts have resulted in high-resolution regional maps at scale 1:25000 or finer (Sartori and Porro, 2022), which was generated by an harmonization of pre-existing soil maps and recent field surveys for validation and characterisation of vineyard areas without a soil map. During the field survey carried out between 2011 and 2018, 1,577 boreholes were drilled and 364 soil profiles were excavated, with an associated laboratory analysis. Soil Typological Units (STU) were classified into 151 groups based on parent material and origin, leading to the definition of broader substrate groups (SG). Across the region, three main SG can be distinguished: the Alluvial Group (AL), the Conoid Groups (CO), and the Glacial Groups. In our study area, the predominant SG types are Alluvial Group and Conoid Groups, as shown in Fig. 1. Alluvial Group soils originate from water erosion and material deposition, and are primarily located in the region's bottom valleys. Conoid Groups soils are formed by gravitative action and are characterized by steep debris slopes and the storage of landslide materials. From a textural perspective, the Alluvial Group is generally characterized by loam to silty loam textures, while the Conoid Group ranges from loam to sandy loam. In terms of water dynamics, Alluvial soils are classified as hydromorphic or highly hydromorphic, whereas soils in the Conoid group are generally non-hydromorphic.

2.2. Vineyards polygons selection

In 2019, at local regional scale, 61 % of vineyards have a surface area of less than one hectare (Camera di Commercio, 2020). This is due to the limited availability of arable land in Alpine areas and the ongoing fragmentation caused by the succession of family ownership over time.

Cadastral parcels were used as the reference unit for delineating vineyards. These polygons represent the extent of vineyards properties and, from an agronomic point of view, it is reasonable to assume that management practices are applied homogeneously within each parcel. Due to the current level of digitalisation in viticulture, the cadastral parcels were selected to exclude other crops by filtering those overlapping existing vineyard soil map, while vectors representing man-made structures were manually removed by inspecting all available aerial orthophoto. This step also highlights the low level of digitalization that still characterises the agricultural sector today.

The vineyards in the area of interest are primarily cultivated using two trellis systems: *Guyot* or *Pergola Trentina*. *Guyot*-trained vineyards are characterized by limited canopy coverage from a nadir perspective during the growing season, meaning that the main contribution to medium-resolution satellite remote sensing signals comes from the grass cover. For this reason, the analysis was limited to vineyards with an overhead trellis system, specifically *Pergola*. During the growing season, vineyards trained with the *Pergola* system show a signal that can be primarily attributed to the vine canopy, as shown by Di Gennaro et al. (2019). As shown in other studies (Sozzi et al., 2020; Vélez et al., 2023) and considering the resolution of Sentinel-2, a 10-meters negative buffer was applied to each cadastral parcel to avoid mixed-pixel effects at parcels boundaries. Subsequently, polygons with fewer than 10 valid pixels were discarded to ensure consistency in the statistical metrics calculated later at the field level. An illustration of the final polygons is shown in Fig. 2.

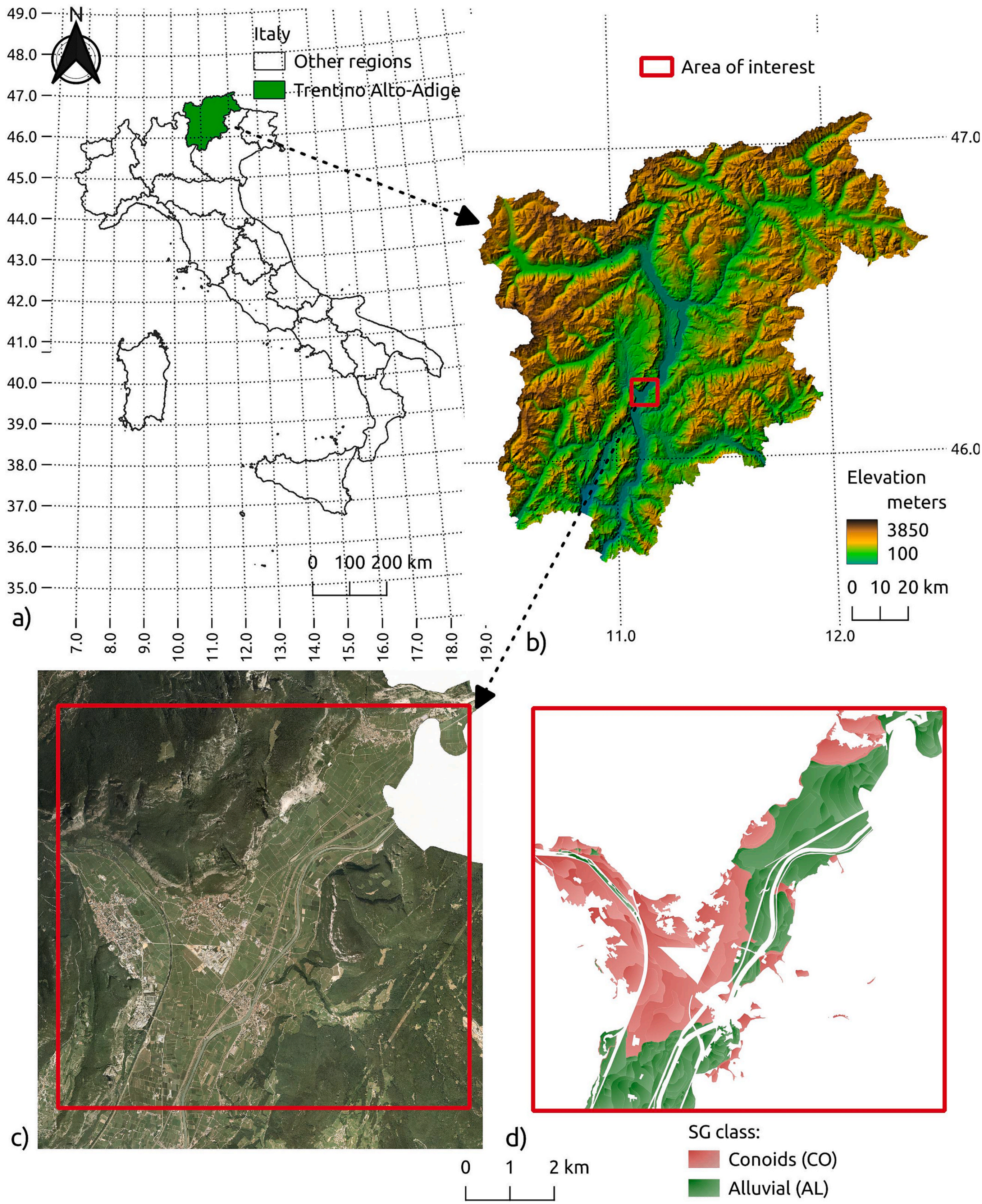

Fig. 1. Overview of the study area and its allocation respect to the national (a) and regional scale (b). At the bottom on the right. (c) An high resolution orthophoto, while on the left. (d) The map of soil Substrate Groups (SG) spatial distribution within the area of interest (red box). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

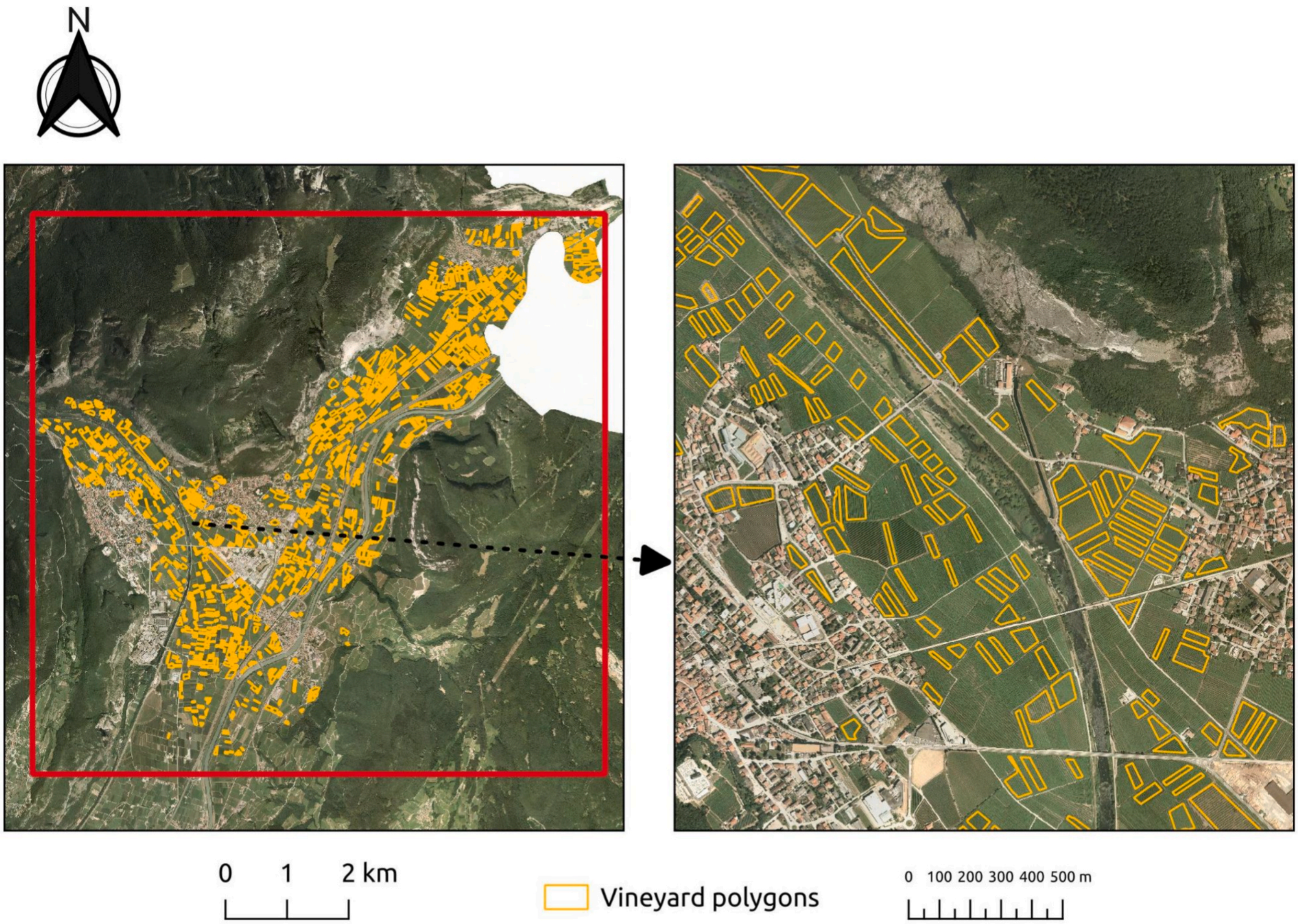

Fig. 2. Map of the selected Pergola vineyards spatial distribution within the area of interest defined by the red box. Each vineyard polygon is highlighted in orange. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

An additional selection of the remaining polygons was performed based on the year of plantation renewal, retaining only those vineyards that had not undergone significant changes during the analysis period. This step was conducted by consulting available aerial orthophotos and monthly Planet basemaps (PBC, 2017). The final dataset includes 1142 polygons, each representing a *Pergola*-trained vineyard with sufficient satellite data coverage and without any replanting action between 2017 and 2023. Based on the arrangement of the two soil SG classes, the dataset can be divided into two independent subclasses with 530 samples belonging to the AL group and 612 to CO.

2.3. Data analysis workflow

The data analysis workflow consisted of four main components: preparation of the Sentinel-2 time series data cube, extraction of the Land Surface Phenology at pixel level, computation of statistics at the polygon level across multiple datasets, and SG classification and comparison. The workflow is illustrated in Fig. 3.

2.3.1. Sentinel-2 time series data preparation

The pair of ESA satellites Sentinel-2A and Sentinel-2B was selected as the source of remote sensing data. The Sentinel-2 satellites have a revisit time of 5 days and are equipped with the Multi-Spectral Instrument (MSI) sensor, which acquires data in the Visible and Near InfraRed (VNIR) and ShortWave InfraRed (SWIR) ranges across 13 bands at varying spectral and spatial resolutions (ESA, 2015):

Due to the latitude of the study area and the overlap between the orbits of the two satellites, the effective revisit time over the area of interest ranges between 2 and 3 days. All data acquired by the two satellites from 2017 to 2023 were downloaded through the Spatio-Temporal Asset Catalog (STAC; https://stacindex.org/catalogs) accessing the Sentinel-2 catalog hosted by Microsoft Planetary Computer (MSI) (Microsoft Open Source et al., 2022).

To access the STAC catalog, and to select and download the data, the R package *rstac 1.0.1* (Simoes et al., 2021) was used. To organize the data acquired from both satellites into a single regular data cube, i.e., a multi-dimensional array (Lu et al., 2018), with consistent spatial resolution and reference system, the R package *gdalcubes 0.7.1* (Appel and Pebesma, 2019) was employed.

Spectral bands with a spatial resolution of 20 m or lower were selected (B02, B03, B04, B05, B06, B07, B08, B11 e B12) along with the Scene Classification Layer (SCL). The selected assets were all retrieved from the Level-2 items of Sentinel-2, which correspond to the atmospherically corrected surface reflectance output. All data were resampled to 10 m using the nearest neighbor approach and saved in netCDF format (Rew and Davis, 1990).

In precision viticulture many vegetation indices have been employed in Earth observation (Giovos et al., 2021). Depending on the wavelengths involved, these indices are associated with different vegetation properties such as pigment, chlorophyll, biomass, greenness, and water content (Hatfield et al., 2019).

The supplementary material provides a summary of the indices used in this study, along with their corresponding definition in terms of the individual Sentinel-2- bands (with direct reference to Sentinel-2 bands

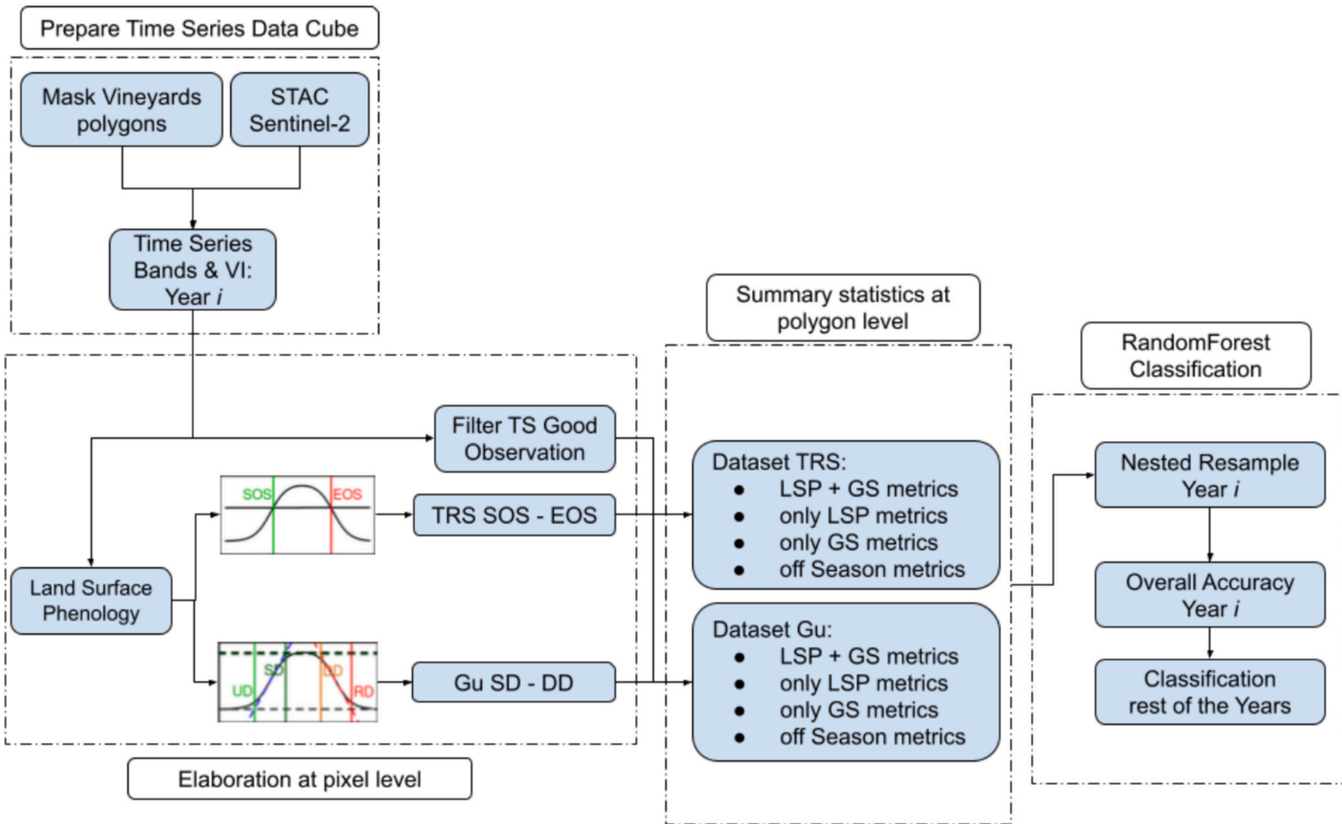

Fig. 3. Scheme of the data analysis workflow proposed in this study. The workflow is composed of four distinct sections. In the first part the time-series of Sentinel-2 data are downloaded from STAC Catalog with respect to a selection of vineyard polygons. In the second section for each pixel two fitting methods to retrieve LSP are applied, and then only 'good' observations of Sentinel-2 are retained. The LSP methods are Threshold (TRS), which introduce Start of Season (SOS) and End of Season (EOS), and the Gu method, which introduces the Stabilization dates (SD) and Downturn date (DD). In the third part four different datasets are prepared with respect to each LSP extraction method, by also defining Growing Season (GS) metrics and off Season metrics. In the last part, a RandomForest analysis is applied to each dataset.

name) and the vegetation properties they target:

2.3.2. *Land surface phenology estimation*

2.3.2.1. Time series reconstruction and curve fitting. Given the resolution of the satellite data, using the term *phenology* to describe the state of the culture is not entirely accurate, as it is not possible to precisely identify the various transitions between phenological phases. For this reason, the concept of Land Surface Phenology (LSP) has been introduced, referring to the study of the spatiotemporal patterns of a vegetated surface (De Beurs and Henebry, 2005). Deriving phenological metrics from satellite remote sensing data generally involves the following steps (Zeng et al., 2020):

- data cleaning and flagging;
- data smoothing and time-series data reconstruction;
- phenological metrics extraction based on the reconstructed time series data;

In this study, the R package *phenofit 0.3.9* (Kong et al., 2022) and its approach for calculating various LSP metrics were adopted. In addition to being open-source, it provides users with multiple options for smoothing, time-series reconstruction, and phenological metrics extraction. The weighted Whittaker method (Kong et al., 2019) was selected for reconstructing the time series for each year. The Whittaker filter (Whittaker, 1922) was chosen for its highly computationally efficiency, its ability to balance between smoothness and roughness, its treatment of missing values through a weighting vector w, with weights ranging from 0 to 1, and its use of a single smoothing parameter, λ (Eilers, 2003).

The weights proposed by *phenofit* 0.3.9 (Kong et al., 2022) for Sentinel-2 SCL class, were slightly optimized to assign only to class 'Vegetation' and 'Not Vegetation' the maximum weight. No growing season division within each year was applied since grapevine has a single vegetative season within the calendar year.

To the best of current knowledge, no studies in the literature specifically address the calculation of phenology from vineyard-specific satellite data. Therefore, it was necessary to first determine the optimal vegetation index to be considered in the classification analysis. NDVI (Rouse, 1973) and Enhanced Vegetation Index 2 (EVI2; Jiang et al., 2008) have been used in several recent studies as a vegetation index for phenology applications (Abubakar et al., 2023; Tian et al., 2021; Wagenseil and Samimi, 2006; Wu et al., 2017; Yan et al., 2016). The use of NDVI to track phenology was already employed with Advanced Very High Resolution Radiometer (AVHRR) on polar orbiting satellites by Justice et al. (1985). EVI2 retrieved by Visible Infrared Imaging Radiometer Suite (VIIRS) was found to better track phenology than NDVI (Zhang et al., 2018) and to be more suitable for ecosystems with a strong seasonality (Bolton et al., 2020).

Once the time series has been reconstructed, it is necessary to fit a model to derive LSP. In the literature, two main types of fitting models are commonly used: double logistic and piecewise logistic function. For this reason two double logistic functions, such as Beck (Beck et al., 2006) and Elmore (Elmore et al., 2012), and two piecewise logistic functions, such as AG (Jönsson and Eklundh, 2004) and Zhang (Zhang et al., 2003), were evaluated. The fitting function formula is reported in Table 2 from the supplementary material.

To evaluate which vegetation index, NDVI or EVI2 (see next section), and which curve fitting method gives the most reliable fit across the years, the mean R^2 and Root Mean Square Error (RMSE) were calculated for each year and vegetation index with respect to the four curve-fitting methods using 200 random locations within the study area vineyards.

2.3.2.2. LSP metrics extraction. Once the vegetation index and curve fitting method have been selected, it is necessary to determine how to extract phenological metrics such that they reflect the boundaries in Day of the Year (DOY), of the period during which vine leaf cover is predominant. This approach ensures that reflectance is assessed during timeframes representative of the grapevine canopy conditions, regardless of variety, and helps to mitigate the influence of seasonal variations across years. Two methods in the literature are particularly relevant for this purpose:

- Threshold Method (TRS) (White et al., 1997);
- Gu Method (Gu et al., 2009);

The TRS metrics are defined as the day of the year when a specific percentage threshold of the NDVI amplitude is reached, either during the green-up (Start of Season, SOS) or senescence (End of Season, EOS). In this study, a 50 % threshold of the vegetation index amplitude was adopted.

The four Gu metrics, Update Date (UD), Stabilization Date (SD), Downturn Date (DD), and Recession Date (RD) identify five phases of vegetative growth: Pre-phase, Recovery Phase, Stable phase, Senescence Phase, and Termination Phase. The third phase (Stable Phase), defined between SD and DD, corresponds to a period of sustained photosynthetic activity. In the context of this study, which focuses on vineyards trained under the *Pergola* system, this phase is particularly relevant, as it can be reasonably assumed that vine foliage dominates the canopy during this period. Consequently, Sentinel-2 observations are more likely to be representative of the crop itself. To better understand the LSP metrics extracted from the two methods, please refer to the Fig. 1 of the supplementary material.

2.3.3. Statistics at polygon level and datasets

In order to perform the analyses at the vineyard level, pixel-level observations were aggregated at the polygon level. This strategy was in keeping with the assumption of homogeneous crop management within each cadastral parcel, and was also useful to reduce the expected pixel-to-pixel variability. Aggregation was performed on Land Surface Phenology (LSP) metrics extracted from the temporal reconstruction and valid Sentinel-2 observations filtered by pixel classification.

For each polygon the following statistics were calculated from the LSP metrics:

- Basic statistics: mean, median, minimum, maximum, standard deviation, quantiles (5th, 25th, 50th, 75th, 95th percentiles);
- Mean absolute deviation (MAD): $\frac{1}{n}\sum_{i=1}^{n}|x_i - \underline{x}|$
- Coefficient of variation (CV): $\left(\frac{\sigma}{\mu}\right) \times 100\%$
- Moran I (Spatial Autocorrelation): Let x_i be the observed value at location i, $\bar{x}$ the global mean, and w_{ij} the spatial weight between observations i and j. Then Moran's I is calculated as:

$$I = \frac{n}{W}\cdot\frac{\Sigma_i\Sigma_j w_{ij}\left(x_i - \underline{x}\right)\left(x_i - \underline{x}\right)}{\Sigma_i\left(x_i - \underline{x}\right)^2}$$

where

$$W = \sum_{i=1}\sum_{j=1} w_{ij}$$

The same statistics, except for Moran's I, were derived for valid spectral band values and vegetation indices. Valid observations from Sentinel-2 were selected based on the Scene Classification Layer (SCL), where pixel values of 4 and 5 correspond to "Vegetation" and "Not Vegetated," respectively, as defined by the European Space Agency (ESA), n.d. A second filter was carried out with respect to the corresponding LSP results. Growing Season (GS) metrics are those derived within an LSP period, which is between SOS and EOS for TRS method and between SD and DD for Gu method. An effect of the soil properties should be emphasised especially during periods when there is no human agronomic management, as the latter aims to mitigate growth deficiencies during the growing season. For this reason an off season dataset was made and metrics outside the LSP period will be referred to as off Season metrics.

Eight distinct datasets were constructed, as reported in Fig. 3, each defined as follows:

- Gu:
  - "Gu − LSP + GS": Both LSP and GS metrics derived using the Gu extraction method and its corresponding time interval.
  - "Gu − LSP": Only LSP metrics derived using the Gu method.
  - "Gu – GS": Only GS metrics derived within the phenological period defined by the Gu method.
  - "off Season Gu": Only off Season metrics derived outside the phenological period defined by the Gu method.
- TRS:
  - "TRS – LSP + GS": Both LSP and GS metrics derived using the TRS extraction method and its corresponding time interval.
  - "TRS – LSP": LSP metrics derived using the TRS extraction method.
  - "TRS – GS": GS metrics derived within the TRS-defined phenological period.
  - "off Season TRS": Only off Season metrics derived outside the phenological period defined by the TRS method.

2.3.4. Vineyard's substrate classification and evaluation

To classify the soil substrate associated with each vineyard, a supervised Random Forest classifier (Breiman, 2001) was trained for each year on the seven different datasets. A key advantage of employing a machine learning algorithm such as Random Forest (RF) lies in its ability to provide interpretable outputs via variable importance scores.

To identify the optimal model hyperparameters and estimate the generalization error, a nested cross-validation approach was adopted (Bischl et al., 2023). This approach enables the construction of an unbiased predictive model and provides insights into the variables that consistently exhibit high importance across outer resample iterations over multiple years.

A 5-fold cross-validation repeated 5 times was defined for the outer resampling procedure. For each outer resample, a further 5-fold cross-validation repeated 5 times was implemented as the inner resample. Hyperparameters optimization was conducted during the inner resampling using a fine grid search strategy to determine the optimal values for the RF parameters including the number of variables randomly selected at each split (*mtry*), the number of trees, and the *minimum node size*. Optimal parameters were selected based on the value of the Area Under the Curve of the Receiver Operating Characteristic (AUC-ROC).

For each dataset this validation scheme produces 25 ranked feature lists per year, each containing the top ten predictors. To assess the temporal stability of these features across years, the frequency of each variable's appearance in the top ten rankings was analysed, along with its median rank and corresponding standard deviation. For each dataset, the five most stable and influential features, defined as those appearing in the top ten rankings in at least five out of the seven years, allow for the identification of variables that consistently demonstrate high importance across different years.

Following the assessment of unbiased accuracy and identification of the best hyperparameters for each year, a final model was trained on the entire dataset corresponding to year *i*, and its accuracy was evaluated on data from the remaining six years.

All the procedures were implemented in *R* using the *tidymodels* framework (Kuhn and Wickham, 2020).

3. Results and discussion

The results of this study will be reported below following the logic of the workflow, i.e. as first step find the best model and VI combination to extract LSP metrics. This is important to understand how to define the dataset of analysis. Next, the results of the nested resamples for each dataset will be reported and it will be determined which variables are the most important and constant across years. The results will be concluded by looking at the accuracy of the best models in predicting the other years.

3.1. Vineyard land surface phenology assessment

The best approach to assess the LSP parameters both in terms of vegetation index (NDVI/EVI2) and of modeling of the seasonal growth curve (double logistic or a piecewise fitting) was assessed considering the stability of the results in the 2017–2023. A lower variability in the results is indeed expected to yield more reliable estimations on the LSP metrics. Although past studies on LSP retrieval from satellite imagery have assessed their results using phenocam network across a wide range of ecosystem or through field survey, in this case the decision was made due to the absence of a site specific phenological field survey within the area of interest and the lack of a phenocam network dedicated to monitoring vineyard phenology.

The variability of the median RMSE in the 2017–2023 period for NDVI and EVI2 is shown in Fig. 4. The plot indicates that even if the overall level of fitting of the models was comparable across the years, the results obtained with NDVI showed a slightly larger variability suggesting that EVI2 could be a better choice for LSP estimation.

In addition to the median RMSE, the standard deviation of the LSP parameters (between 2017 and 2023) was extracted from AG and Beck models to assess stability of the models and the results are reported in Fig. 4. All the Gu LSP metrics extracted from Beck fit had a lower variability, and comparable results were obtained for the TRS estimate of the starting of the season (TRS SOS). The only parameter where AG seemed to outperform Beck was on the determination of the TRS end of season (TRS EOS). On the basis of these results and considering that the double logistic model enforces the continuity of the growth pattern along the season –as it can be expected in the vineyard - we decided to rely on the Beck model for the LSP assessment.

3.2. Vineyards soil classification accuracy and VIP

The results of the full set of annual classification models are summarised in Fig. 5. All models showed high and comparable classification accuracies (around 0.85), with the sole exception of those containing

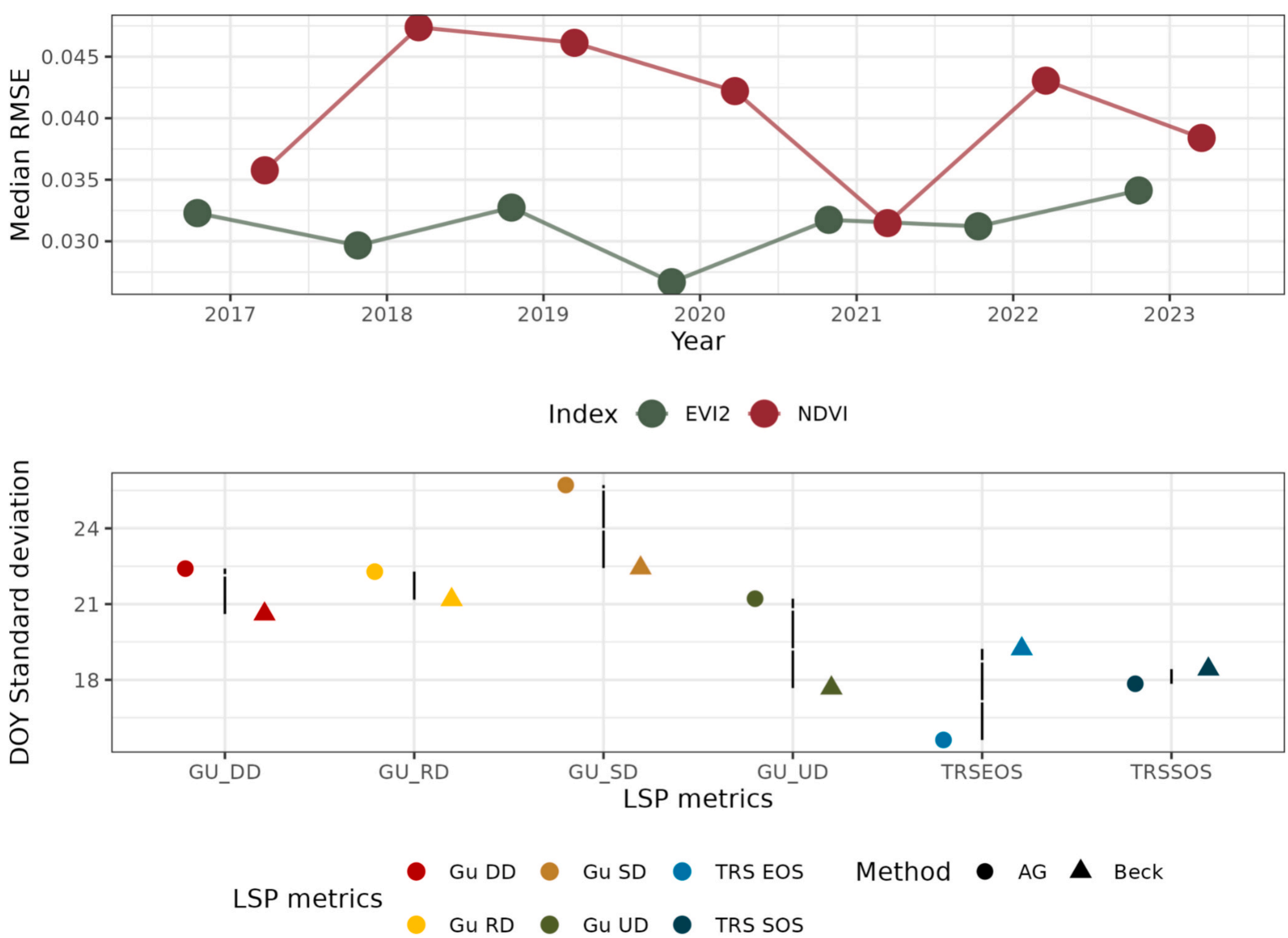

Fig. 4. In the upper side the median RMSE with respect to the two vegetation indices NDVI and EVI2 are reported. The median is calculated on the results of all the four methods. At the bottom side the standard deviation for each year of the LSP metrics extracted with AG and Beck method are reported.

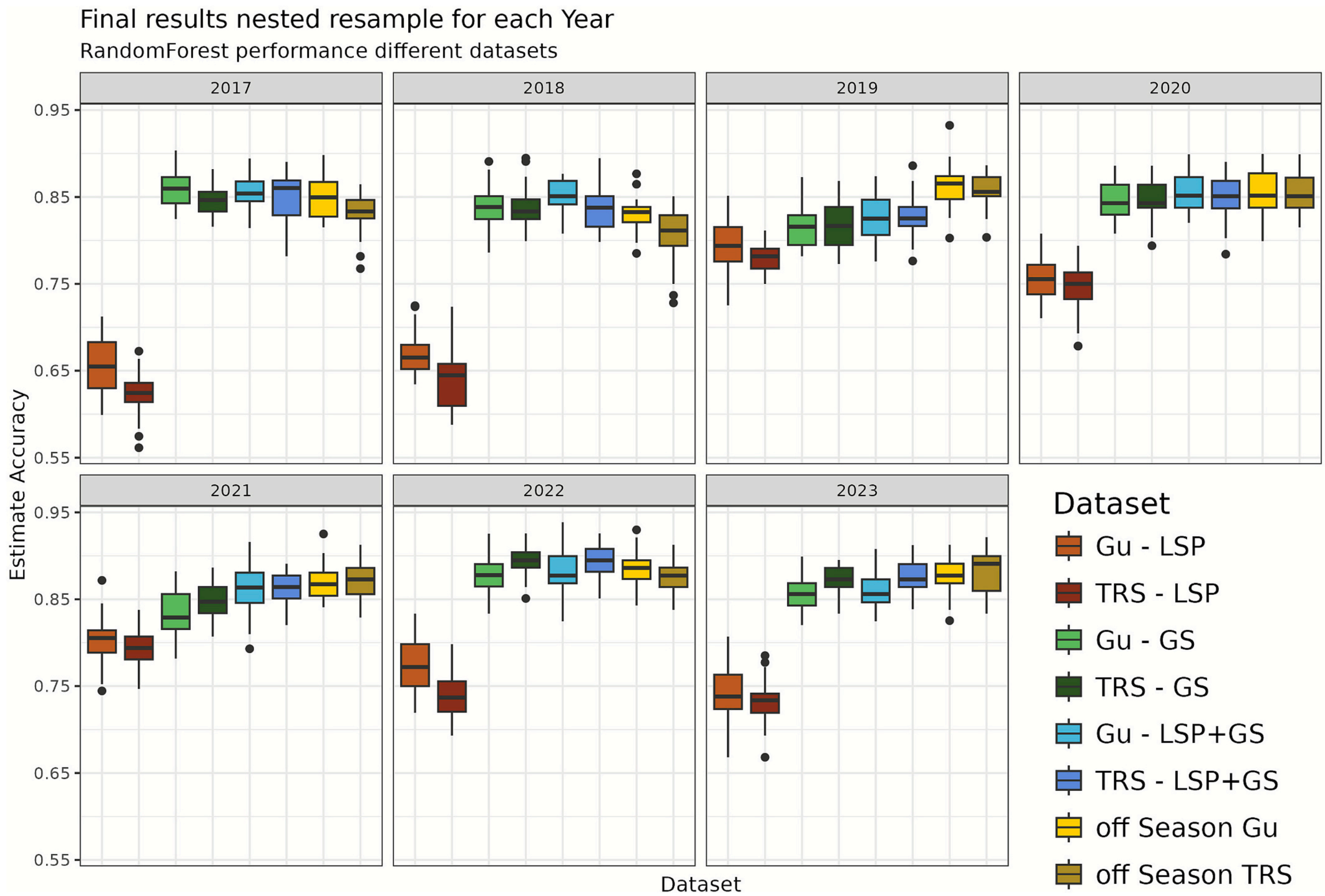

Fig. 5. Estimate overall accuracy obtained from the nested resample. The results are reported for each year with respect to the seven datasets.

only the LSP metrics. Nevertheless, the accuracy of these models exceeded that of a random baseline (see supplementary material Table 4). The baseline was determined by running a Random Forest classifier with default parameters on randomly shuffled class labels, repeating the process 1,000 times for each dataset-year combination. These results indicate that the characteristics of the two soils were always affecting the vineyard characteristics, both in terms of land surface phenology and of vegetation indices derived from satellite images. The fact that the classifier based on LSP metrics alone was able to differentiate the two soils highlights the role of the soil characteristics in determining the dynamics of the growing season. The higher predictive power of the other models, however, suggests also a determinant contribution of the features extracted from the intensity of the satellite signals either inside the growing season or outside.

In order to get a more detailed insight on these considerations, the importance of the predictors on the set of models is shown in Fig. 6.

The results on the LSP models highlight that between the LSP metrics, the fitting accuracy (R2) was the most influential variable in differentiating the two substrate groups. Although fitting accuracy is just an indicator of model performance, it might highlight a difference in canopy development dynamics. Among the other features, the ones associated with the onset of the growing season are almost always relevant (e.g TRS5_sos, GU_UD). Interestingly, when the LSP predictors are joined with the growing season parameters (LSP + GS models) the predictive performance increased and the most influential predictors turned out to be associated to the distribution of the values of the vegetation indices inside the season, like GVMI (Ceccato et al., 2002) and green NDVI (gNDVI; Gitelson et al., 1996), suggesting different vegetation water content and connected vegetation 'greenness' of vineyards from different substrates. The importance of the vegetation indices is demonstrated by the performance of the two classes of models which were constructed only on satellite indices (GS and off season LSP). Their performance is comparable to the larger model indicating that the absolute values of the vegetation indices are sufficient to differentiate the two soil classes. During the off season, as we can see from the last datasets, the minimum GVMI and not anymore the quantiles of the index distribution were the most important variables. In the latter case band 11, band 12 and Normalized Difference Moisture Index (NDMI; Gao, 1996) were all still connected to the vegetation water content.

Local indicators of spatial association (LISA; Anselin, 1995) of the main variables highlighted in Fig. 6 of the datasets 'LSP + GS' are reported (see supplementary materials). LISA was adopted for the capacity to spot potential local clusters. The maps show that the magnitude of local clusters is limited in this case study.

As an illustration of the typical spatial distribution of a discriminative predictor, the 'GVMI_q75′ from the year 2022 is reported in Fig. 7. Lower values of the metric are mostly distributed over the CO group, while as expected higher value spatially follows the AL group. A linear mixed model was fitted to understand, from a statistical point of view, the validity of the variables found to distinguish the effect of the substrate, taking into account a random effect induced by the year, and to investigate a random effect given by the interaction between year and substrate. In Table 1 the summary results are reported. A significant fixed effect between the two substrates is confirmed across the various years of analysis. With regard to the random effect, the year accounts for 23 % of the total variance, while the substrate:Year interaction has no contribution to the variance, confirming that the effect of the substrate is constant over time. Interestingly some areas within the CO group near the boundary between the two soil classes show GVMI_q75 values close to the one typically observed for AL soils. This result indicates that - as it

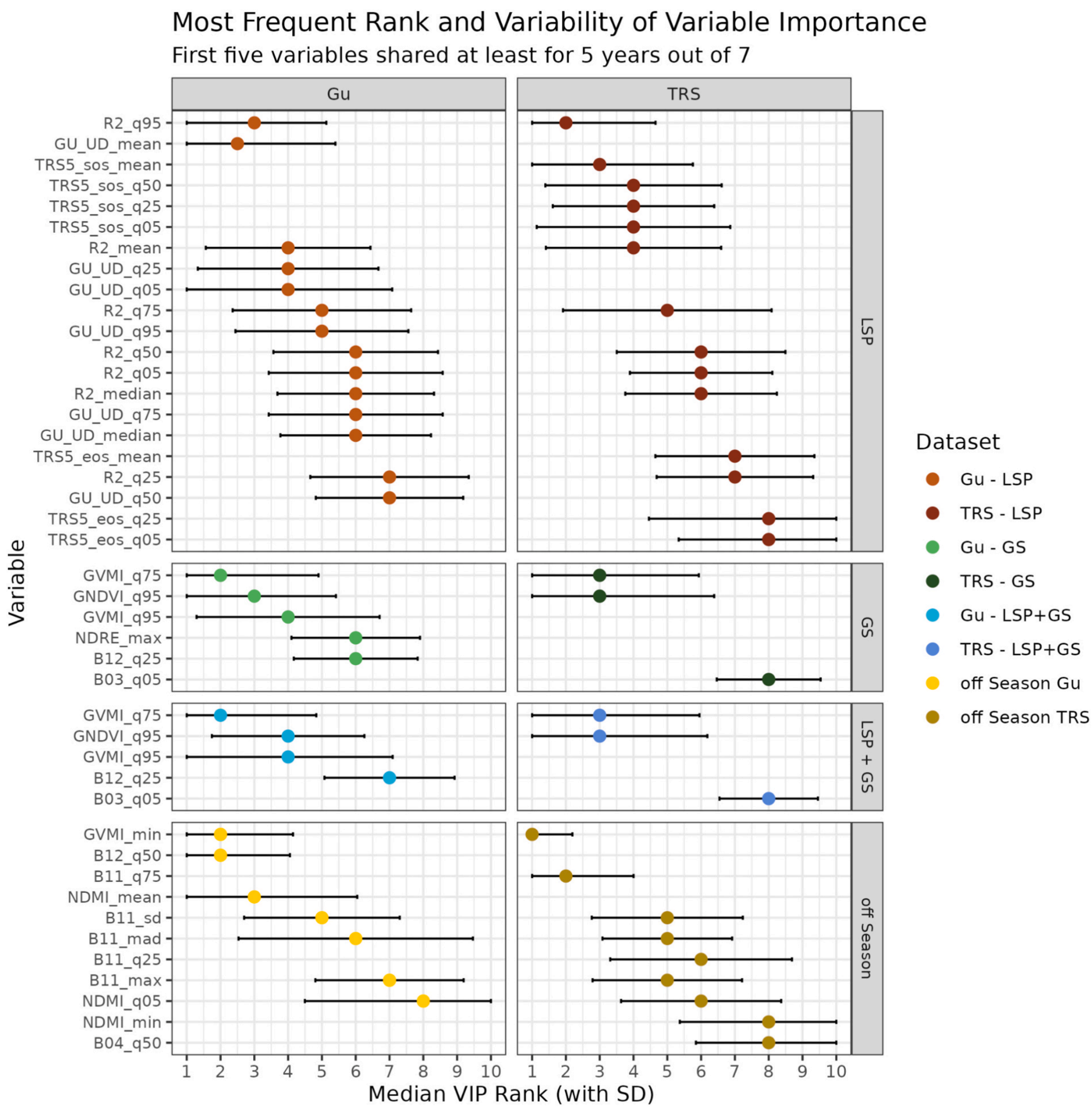

Fig. 6. Top ranked variables shared with at least 5 years out of seven with respect to each dataset. The panels are divided by columns with respect to the LSP metrics extraction, while by row with respect to the datasets metrics groups. The colour dot represents the rank median resulting from all the nested resamples. The dark continuous line represents the standard deviation of the variable's rank position.

can be expected - the switch between the two types of soils is not sharp, but it goes through a transition region with mixed characteristics. This aspect is often not considered in the definition of the soil regional maps. Given the size of the area and the density of the vineyards examined, the possible presence of local clusters was investigated. Local indicators of spatial association (LISA; Anselin, 1995) of the main variables highlighted in Fig. 6 of the datasets 'LSP + GS' are reported (see supplementary materials). LISA was adopted for the capacity to spot potential local clusters. The maps show that the magnitude of local clusters is limited in this case study.

3.3. *Classification between years*

In order to evaluate the importance of seasonal variability on the classification accuracy and, indirectly, assess the extent to which the model generalizes, the *LSP + GS* and *off Season* seasonal models were tested against all the other years. To assess the results over years the datasets with LSP and GS metrics were compared against the off Season metrics. The results in terms of overall accuracy are summarized in Fig. 8.

In the figure a comparison between the models accuracy with GS and LSP metrics against off Season metrics, respectively for Gu or TRS, is reported. As already shown in Fig. 5 all models had comparable performance with lag equal to zero, while a clear decrease in accuracy is visible when the model constructed on one year was tested against the other years. The plot seems to suggest that in all cases the accuracy degraded with the lag even if the trend was not strong. Interestingly, for all lags the classifiers constructed with off Season data outperformed the model with GS and LSP metrics. This denotes higher stability in the off season satellite signals, while the larger decrease in the performance of the models constructed with the growing season data suggests that the characteristics of the growing season are much variable across the years. This could be due to the natural variability in the year-to-year growing patterns associated with different rainfall or also to the effect of different

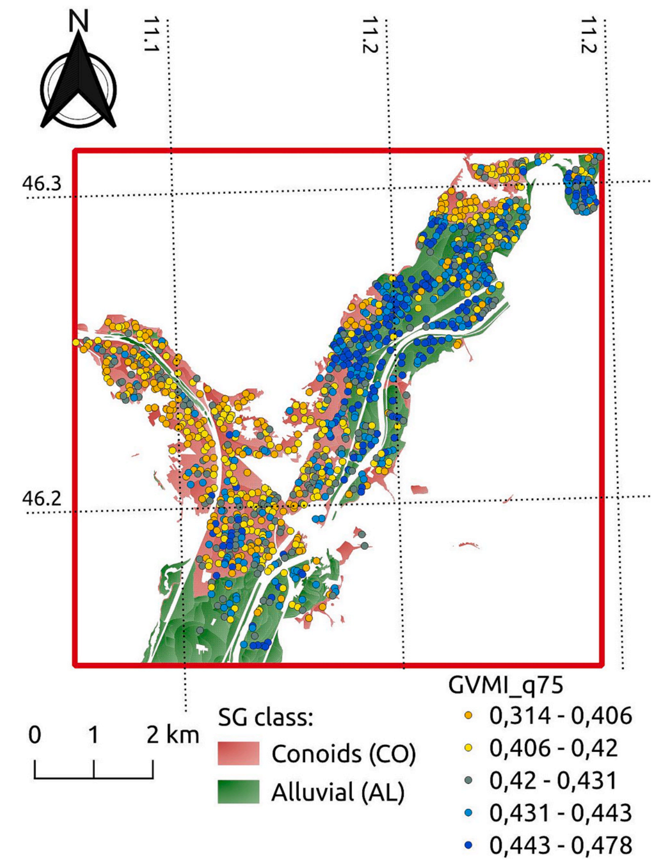

Fig. 7. Spatial distribution of 'GVMI_q75′ variable values with respect to soil substrate groups. For visualization purposes instead of vineyard polygons the centroids have been reported. The metric is derived in this case from the dataset 'Gu − LSP + GS' from 2022.

Table 1
Summary statistics of linear mixed model to predict 'GVMI_q75′ from dataset group 'GS'. Degrees of freedom (df) and p-value estimated with Welch-Satterthwaite method. Number of observations: 7994. Number of groups 'Year': 7. Number of group interactions: 'Substrate:Year': 14. Significance of p-value codes: '***' < 0.001; '**' < 0.01; '*' < 0.05.

	Estimate	Std. Error	df	p-value
Fixed Effects				
Reference Substrate (AL)	0.425	0.00497	6.26	<0.001***
Substrate (CO)	−0.0242	0.00145	6	<0.001***
	Variance	Std. Dev.		
Random Effects				
Year	1.66e-04	0.0128		
Substrate:Year	6.39e-06	0.0253		
Residual	5.339e-04	0.0231		

management of the vineyards. In line with this statement, the supplementary materials include the monthly historical precipitation series and the summary statistics from the weather station T0408 (Table 5.1; Table 5.2 and Table 5.3), located within the study area and freely available from the local weather service (http://storico.meteotrentino.it/web.htm). In this alpine context months like April, June, August, October, November and December show strong variability with respect to the remaining month, while within the time range of this study, the year 2022 experienced a marked drought season whereas 2019 and 2020 showed higher mean monthly precipitation compared with the other years.

It is worth noting that despite the observed decrease in the classification accuracy across the years, the set of highly discriminating variables (Fig. 6) was largely preserved, suggesting that the soil properties are always impacting in the same way the two classes of soils. In other words, the absolute value of the satellite signal can be different from year to year, but the effect of the soil characteristics on the signals is always the same. A plot demonstrating this effect for GVMI_q75 is shown in Fig. 2 of the supplementary material.

3.4. Discussion

Our results indicate that LSP extraction from overhead trellis vineyards can be performed, to do that EVI2 resulted to be a more suitable vegetation index. This can be explained by some limitations of NDVI, such as its tendency to saturate at higher values and its broader range of values throughout the year, whereas EVI2 is more sensitive to increases in Leaf Area Index (LAI) and exhibits narrower range of values. As far as the fitting of the model is concerned, it turned out that, for the vineyard, a double logarithmic curve gave more stable results. This could be connected to the fact that such a type of function is continuous throughout the growing season and this is more in line with the growing pattern and the agronomic management of grapevine.

Our investigation showed that satellite data can be used to effectively separate AL and CO with accuracy values ranging consistently from 0.83 to 0.90. All the one year classifiers pointed out that LSP metrics alone are less effective in predicting the soil characteristics than the actual intensity of the satellite signals. This was true both considering the "growing season", when grapevine coverage is almost complete, than the off-season when the signal is primarily associated with grass cover during grapevine dormancy. This observation reinforces the idea that the differences we are measuring are associated with the characteristics of soil: the effect is visible both for cultivated crops and unmanaged grass cover.

It is important to highlight that this was possible because in an agricultural context - in which the same crop and a broadly uniform management system are adopted - the variability in plant vigor is more likely to reflect more subtle variations, such as those related to soil characteristics. In this context our results highlight the potential of satellite data for the high resolution characterization of the agricultural landscape and this can have important implications for large scale programming.

The use of an interpretable Random Forest classification approach allowed us to identify the set of predictors which are consistently important in the models and in all cases. Despite the lower overall accuracy, datasets based solely on LSP metrics identified key phenological markers, such as the start of the season (TRS-SOS or Gu-UD), and the R^2 from Beck's fitting as relevant variables. This may suggest that the quality of temporal fitting varies between soil groups, potentially reflecting differences in canopy development dynamics. In the case of the other classifiers, GVMI related features were always among the most important. Given that GVMI is related to vegetation water content, our results suggest that the observed differences could be attributed to the different water retention capacity between the two substrates. In terms of water dynamics, alluvial soils are indeed classified as hydromorphic or highly hydromorphic, whereas soils in the conoid group are generally non-hydromorphic (Sartori and Porro, 2022). Further consolidation of this interpretation would require an in-situ soil moisture monitoring network. However such a network representing vineyards under the same agronomic management is not present, practical implementation of a robust network is often unfeasible due to systematic challenges like topographical constraints (e.g. sensor placement and data transmission), access to private fields, scalability and maintenance.

The spatial distribution of the most discriminating predictors turned out to be often inhomogeneous, suggesting the possible presence of small scale variability of the soil characteristics within each class, which are often disregarded in the outlining of the soil maps. The presence of high/low vigor patches in the fields is not unexpected, but it is

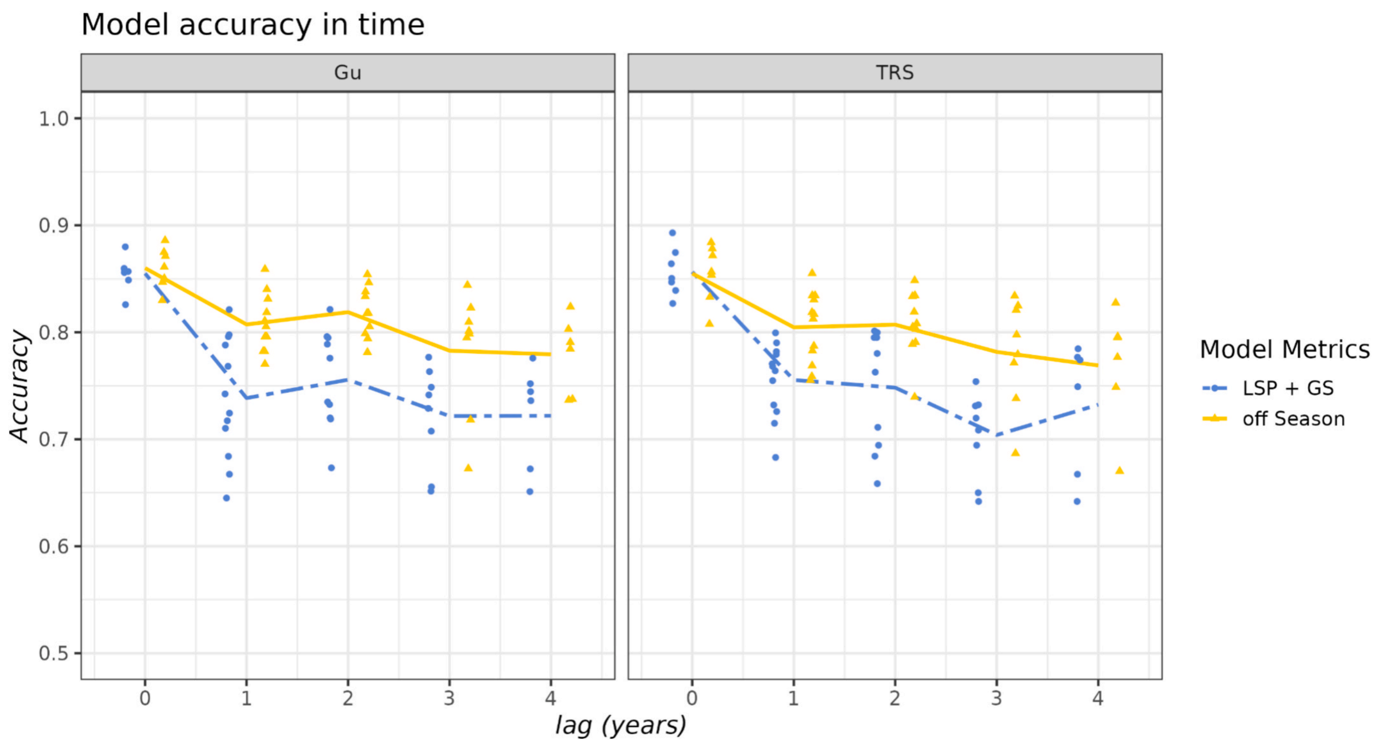

Fig. 8. Predictive performance of the LSP + GS and the off Season models across the different years. The lag indicates the difference in years between the data used for model training and testing. The dots represent the result in accuracy of all final model combinations for a specific lag while lines connect the medians of the point clouds.

unrealistic to think that soil sampling could be performed at sufficient high resolution to characterize such small scale variability. Our results, however, indicate that - in an agricultural context - satellite information could be used to compliment soil sampling and identify optimal sampling locations.

The results obtained for the classification cross years were particularly interesting. A general reduction of the predictive power of the models from one year to another was observed and this is likely to be the mirror of the interannual variation in weather conditions. Nonetheless, the predictive variables were always the same (i.e they always showed values different in the two types of soils), meaning that for those variables the average value was changing from one year to the other, but the "difference" between CO and AL was always preserved. In this respect, the fact that the models constructed on the "off season" data were the more robust ones is particularly intriguing: their predictive power was less affected by the year to year variability. A potential lower variability in the weather conditions could be in part responsible for that, but in winter and early spring the combination of a reduced photoperiod and low temperatures is also restricting plant growth making them less responsive to modifications of the weather conditions. The authors believe that this means that the response of the interrow grass cover is similar from one year to the next and can be used as a key driver to distinguish more or less hydrophilic substrate. In contrast, the other datasets fail to replicate the same performance, indicating that even when the same phenological interval is used across years, the distributions of spectral bands and indices are not sufficiently consistent. Nevertheless the results are still satisfactory considering the fact that during the growing season the overhead vineyards are managed in a way to compensate for possible physiological variance. The results were compared with the existing literature. Several studies have analysed the influence of soil properties on the crop's growth and vigour at the single field scale; from very high resolution images, acquired from aircraft or UAV, the grapevine response detected via spectral indices was linked with soil properties (Hubbard et al., 2021; Pereyra et al., 2023; Alliaume et al., 2024; Delval et al., 2025). This study, despite the recognized limitations, extends this assessment to a broader area by considering a thousand vineyards and an available soil map. The proposed methodology allowed us to understand, at a larger scale, the vineyard response measured by Sentinel-2 in relation to substrate type (which we attribute to water retention capacity) and to verify its consistency over time, as expected.

This methodological framework was designed for a specific vineyard area located between the Alps, and its transferability to other areas with different climates and vegetation patterns is not guaranteed. Nevertheless, the results showing the effectiveness of the off-season dataset in identifying more or less hydrophilic soils suggest that this method could be applied to other crops with development periods similar to vines (e.g. apple orchards). Further investigations are planned to be conducted to assess this.

Transferring this methodology to a completely new area requires in-depth agronomic knowledge and a detailed level of digitalisation. Digitalisation should guarantee access to the spatial distribution of cultivars, up-to-date tracking of phenological development, precise field boundaries, knowledge of the trellis system and the applied agronomic management.

4. Conclusion

This study presents a new methodology for characterising the different responses of vineyards with respect to the soil substrate type. Various methods of extracting LSP on vineyards with the same trellis system were evaluated, assessing which vegetation index and fitting model are most appropriate. The extraction of LSP made it possible to define the limits of comparable one-year time windows and introduce growing season and off season metrics. The long time series provided by Sentinel-2 made it possible to extend the analysis over 7 years and to compare the results between them. The redundancy of the feature ranks of the various years denotes that there is indeed a residual effect of the substrate on the intensity of the signal observed by satellite, and that this effect is detectable by an index correlated with the water content of the vegetation such as GVMI, which can be explained by the different hydraulic capacities of the two substrates. It is interesting how the off season is more effective in its transferability from one year to the next for detecting the residual effect of the soil, thus opening up its applicability even on vineyards with a different trellis system.

These findings support potential applications such as the identification of suitable sites for drought-tolerant grapevine cultivars or the large-scale characterization of soil substrate in the absence of prior field surveys.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to improve readability and language. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

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CRediT authorship contribution statement

Thomas Maffei: Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marco Moretto:** Writing – review & editing, Supervision, Methodology. **Pietro Franceschi:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jag.2025.104977.

Data availability

Data will be made available on request.

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