



Use of explainable artificial intelligence with high-resolution satellite imagery to assess water status and vine shoot growth in grapevine (*Vitis vinifera* L.)

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Abstract

Grapevine is an essential socio-economic crop in the Mediterranean regions. However, its cultivation is threatened by climate change, particularly due to the increase in drought events. Traditional indicators of plant water status, i.e., pre-dawn leaf water potential (Ψ_{pd}), are helpful but labor-intensive. Furthermore, another index based on visual assessment of the shoot apex (i.e., iG-Apex), has been recently used to evaluate the water stress of grapevine plants. The application of remote sensing technologies and machine learning models gives the possibility to monitor grapevine spatio-temporal variability of plant physiological indicators in a non-destructive way. This study aims to develop an explainable artificial intelligence (XAI) framework to predict Ψ_{pd} and iG-Apex in two rainfed vineyards using high-resolution multispectral imagery from the Planet SuperDove constellation. Five machine learning models—extreme gradient boosting, random forest, support vector regressor, ElasticNet, and Linear Regression—were trained and compared. Extreme gradient boosting achieved the best performance for Ψ_{pd} prediction ($R^2 = 0.778$), while random forest outperformed for iG-Apex prediction ($R^2 = 0.615$). SHAP and ICE analyses were carried out for models' explainability. The analyses revealed that visible and NIR bands were the most important predictors, influencing both Ψ_{pd} and iG-Apex prediction. Our results highlight the potential of combining XAI and remote sensing to support grapevine management under Mediterranean conditions, providing a useful tool for early water stress detection.

Keywords Predawn leaf water potential · Drought · IG-Apex · Water stress · Physiology · SHAP · Machine learning · Remote sensing · Planet

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Introduction

Grapevine (*Vitis vinifera* L., 1753) is one of the most important tree crops; with a rich history that is estimated to have originally started in the Caucasus during the Neolithic period, it still has a significant impact on the rural traditions and economies of different regions of the world (Zohary and Hopf, 2000; McGovern 2007). In addition to wine, grapes are also widely used for fresh consumption and the production of other derived products. Especially in Europe and the Mediterranean regions, grape cultivation has a significant socio-economic impact, with France, Italy, and Spain as major producers (Aurand, 2017). Given the socio-economic importance of viticulture, it is necessary not only to protect the traditions and cultural value of the sector, but also to adopt innovative management strategies to ensure sustainable production. In this context, sustainable viticulture is proposed as an integrated model that combines advanced farming practices, such as input optimization and preservation of soil fertility (also through advanced monitoring methods), with an increasing focus on adaptation to the effects of climate change (Romero et al. 2022; Giannico et al. 2024).

However, the sustainability of viticulture is made increasingly challenging by the effects of climate change (Hannah et al. 2013), especially in the Mediterranean basin, which is considered a climate change hot-spot area (IPCC, 2022). Rising temperatures, altered precipitation patterns, and increased frequency of extreme weather events represent significant challenges to grapevine growth, development, productivity and quality; particularly, the rainfed vineyards, relying solely on natural precipitation, are vulnerable to these changes, especially those concerning water availability (Somkuwar and Dhole 2025; Funes et al. 2024). Water stress, induced by prolonged drought periods or insufficient rainfall, is one of the major limiting factors of grapevine physiology, impacting photosynthesis, growth, and berry development (Van Leeuwen and Darriet 2016; Ojeda et al. 2002).

Therefore, the accurate and timely assessment of vine water status is essential for implementing effective and sustainable irrigation strategies, as well as for adopting appropriate vineyard management practices to mitigate the adverse effects of water stress (Bahal et al., 2024; Sánchez-Ortiz et al. 2024). Among the most common indicators of vine water status are measurements of plant water potential, such as stem (Ψ_s), leaf (Ψ_l), and predawn (Ψ_{pd}) leaf water potential (Tosin et al. 2021; Maldera et al. 2024). Despite their accuracy, these methods are time-consuming, require specialized instruments, and involve intensive fieldwork to capture sufficient spatial variability, especially the Ψ_{pd} , which must be measured before sunrise (therefore in a short

time window). Moreover, the high variability of Ψ_{pd} within different vineyards under severe water stress conditions further increases the sampling effort needed to support precise irrigation scheduling. To overcome these limitations, scalable approaches to monitor vine water status and support precision viticulture are strictly necessary (Ojeda et al. 2005; Taylor et al. 2010; Poças et al., 2020).

An index based solely on in-field vines observation, the vine shoot growth index (iG-apex), has also been developed (Pichon et al. 2021a). It is based on a visual assessment of the shoot apex, which is classified into three categories: apex in full growth (FG), moderate growth (MG), and stopped growth (SG). To quantify this observation, numerical values are assigned to these categories (1 for FG, 0.5 for MG, and 0 for SG), then used to calculate the index. Research has shown a clear linear relationship between iG-Apex classes and the Ψ_{pd} (Pichon et al. 2023). Generally, lower iG-Apex values indicate that the vines are experiencing water stress but the index shows limitations under severe water stress conditions. Specifically, when the Ψ_{pd} is lower than -0.80 MPa, shoot growth is significantly reduced or stops (Schultz and Matthews 1988). This decrease in shoot growth weakens the correlation between iG-Apex and Ψ_{pd} at these high stress levels; consequently, the iG-Apex approach could be most effective when used as a complementary tool to the Ψ_{pd} , particularly for detecting stress levels inside its optimal range of sensitivity (Pichon et al. 2023).

In recent decades, advances in remote sensing technologies have offered promising alternatives for rapid, non-destructive, and spatially explicit monitoring of vegetation health and water status over large areas. Remote sensing involves the detection and monitoring of an object's characteristics on the Earth's surface by measuring its reflected or emitted radiation (Weiss et al. 2020). Different types of multispectral, hyperspectral, thermal, drone-mounted, aircraft- and satellite-mounted sensors can support farmers and technicians in monitoring the water status of grapevines (Zarco-Tejada et al. 2013; Matese et al., 2015 ; Helman et al. 2018); moreover, the use of geographical information systems (GIS) technologies in agriculture can improve data management and planning at field and regional scales (Hinojos Mendoza et al. 2020; Costanza et al. 2024). High-resolution satellite images can significantly enhance decision support for farming practices in viticulture, due to the ability to highlight differences with high resolution, compared with lower-resolution satellites (e.g., Landsat). For instance, the SuperDove constellation (Planet Labs PBC) acquires multispectral images with high spatial (3 m) and temporal resolution (daily).

The integration of advanced modeling techniques with remote sensing technologies can further improve the estimation of key physiological parameters of crops (Campi et

al. 2024); particularly, the use of machine learning (ML) and deep learning (DL) approaches for remote sensing data analysis is continuously growing in agricultural contexts (Mzid et al. 2023; Jeong et al. 2022). ML algorithms have emerged as powerful tools to analyze complex datasets and identify patterns that may not be immediately detectable through traditional statistical methods. In the context of viticulture, ML has been used to model the relationship between spectral information obtained from remote sensing and key ecophysiological parameters, such as stomatal conductance, photosynthetic activity, and water stress levels (Yang et al. 2022; Garofalo et al. 2024). Recently, Damásio et al. (2023) have developed a ML approach to model the grapevine Ψ_{pd} from meteorological and physiological data with high performance. A self-learning artificial intelligence (SL-AI) algorithm was used by Tosin et al. (2022) to predict Ψ_{pd} , considering proximal spectrum and grapevine ecophysiology data. The methodology that SL-AI models use is based on the covariance-mode (CovM) that isolates the noise coming from spectral data, modeling the relationship between the target parameter and the spectral data (Barroso et al. 2021). They found that this algorithm performed better than Artificial Neural Networks with Principal Component Analysis (ANN-PCA) and Partial Least Squares (PLS), for both classification and regression analysis. Furthermore, the increasing demand for transparency and interpretability in artificial intelligence-driven decision-making systems has led to the development of explainable techniques (e.g., SHAP), which aim to provide insights into the reasoning behind the predictions of ML models (Novielli et al. 2025).

This study aims to develop an explainable ML approach to predict the Ψ_{pd} and iG-Apex of rainfed vineyards in southern France using a freely available dataset (Zhang et al. 2025). The predictive performance of different ML algorithms has been compared. Models were trained using remote sensing data from the Planet satellite SuperDove constellation. Through the presented framework, we aimed to obtain ML models useful for the high-resolution spatio-temporal monitoring of the ecophysiological response of vineyards in the Mediterranean area.

Materials and methods

Data collection and experimental vineyards

In this study, a freely available dataset was used, published by Zhang et al. (2025), containing data of two grapevine growth and status indicators, the pre-dawn leaf water potential (Ψ_{pd}) and the iG-Apex. They were measured in five different rainfed vineyards of 'Syrah' located in Villeneuve-lès-Maguelone, southern France (Fig. 1A). The

Köppen-Geiger classification of the area is CSa; the climate is mostly warm and temperate, with hot and dry summers. As reported by the authors, the soil was classified as deep (1 m in depth) and by USDA classification as calcisols and cambisols with a high silt content (Gras et al. 2023). The grapevines were trained in a vertical shoot positioning (VSP) system supported by a three-wire trellis; vine density ranged from 3,300 to 4,000 vines per hectare.

The location of the vineyards (field 1 and 2) where Ψ_{pd} and iG-Apex were measured is shown in Fig. 1B. Field 1 and 2 cover an area of 0.71 and 2.32 ha, respectively. Ψ_{pd} and iG-Apex data were collected during the 2022 summer season (from June to August) following a specific framework (for more details, see Zhang et al. 2025).

Climate variables

Temperature (T_{air}), rainfall, and relative humidity (RH) data were obtained from a weather station with a 15-minute recording frequency (for more details, see Gras et al. 2023; Zhang et al. 2025). For better and professional wine water status monitoring, data are usually shown on a daily scale (Zhang et al. 2025). So, we aggregated the data from minute to daily frequency, considering a period between May and September 2022, using the "pandas" library (McKinney 2010) of the Python programming language (Python (v. 3.13.1) — Spyder© IDE, v. 6.0.3 for Windows). Additionally, for each climate variable, we filled a gap from 8th to 17th July using the NASA POWER platform (<https://power.larc.nasa.gov/data-access-viewer/>; accessed on 7th April 2025). This platform, developed by NASA, can be used for climatic and crop modelling applications (Aboelkhair et al. 2019). Once the weather dataset was filled, we calculated the vapor pressure deficit (VPD) that is closely related to plant physiology. High VPD typically leads plants to close their stomata to reduce water loss and prevent excessive tension within the xylem (Bastos Campos et al. 2025), causing a reduction in photosynthetic activity. VPD (kPa) was computed by subtracting the actual vapor pressure (e_a) to the saturated vapor pressure (e_s) (1):

$$VPD = e_s - e_a \quad (1)$$

With:

$$e_s = \frac{[e_0 (T_{min}) + e_0 (T_{max})]}{2},$$

$$e_a = e_0 (T_{air}) \cdot \frac{RH}{100},$$

$$e_0 (T_{air}) = 0.6108 \cdot e^{\left[\frac{17.27 \cdot T_{air}}{T_{air} + 237.3}\right]}$$

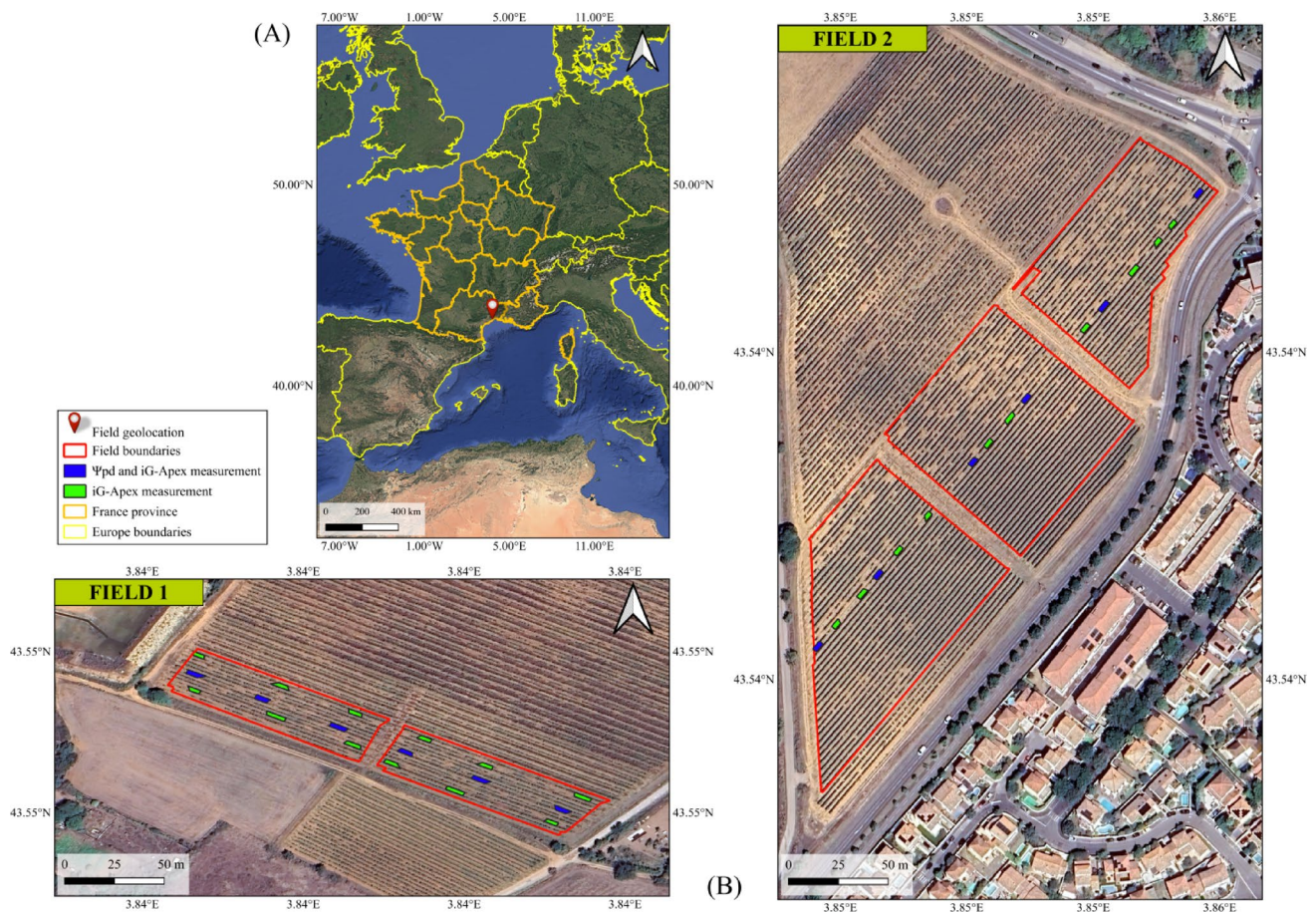


Fig. 1 (A) Vineyards' location, southern France; (B) Google Satellite images of the two experimental vineyards (red boundaries); Blue plots indicate that both Ψ_{pd} and iG-Apex were measured. Green plots indicate that only iG-Apex was taken. (Map data ©2015 Google)

Where $T_{\min}$ and $T_{\max}$ (°C) are the minimum and maximum temperature.

SuperDove imagery and processing

SuperDove's high-resolution images, provided by the third-generation satellite of PlanetScope (Imagery© 2022, Planet Labs PBC, San Francisco, CA, USA), were used to extract reflectance data. The satellite imagery has a spatial resolution of 3 meters, with acquisition times corresponding to equator overpasses between 7:30 and 11:30 a.m. (local solar time). Each image includes 8 spectral bands (SDBs) from the visible region to the near-infrared region: coastal blue (431–452 nm), blue (465–515 nm), green I (513–549 nm), green II (547–583 nm), yellow (600–620 nm), red (650–680 nm), red edge (697–713 nm) and nir (845–885 nm) (Planet, 2022). All images were downloaded through the Planet Explorer platform (www.planet.com/explorer) as orthorectified and radiometrically corrected TIFFs, ensuring consistency across atmospheric conditions and reducing uncertainties in spectral response over time and space. Since each pixel value of optical bands is provided as a digital

number (DN), we divided these values by 10,000 to obtain the surface reflectance (<https://docs.sentinel-hub.com/api/latest/data/planet/planet-scope/>). Moreover, the reflectance value of each band was extracted by selecting the pixel overlapping each sample point within the vineyard fields for Ψ_{pd} , and as the median of all pixels within each plot polygon for iG-Apex, using the Python libraries “rasterio” (Gillies 2013) and “rasterstats” (Perry, 2023), respectively. The images were downloaded on the date of the ground truth data collection; in case of cloud cover, images from the previous or following day were used. Additionally, in this study, from the spectral bands reflectance values, we calculated Vegetation Indices (VIs) related to the ecophysiological and water status of vineyards (Table 1):

Machine learning analysis

To predict the Ψ_{pd} and iG-Apex (targets), four ML models and a multiple linear regression (MLR) were performed and compared; ML models were: random forest (RF), support vector regression (SVR), extreme gradient boosting (XGB), and elastic-net (EN). The ML analyses were conducted

Table 1 Vegetation indices calculated in this study, with their formula and related reference

Vegetation indices	Formula	References
Normalized Difference Vegetation Index (NDVI)	$(\text{NIR} - \text{red}) / (\text{NIR} + \text{red})$	(Rouse, 1974)
Simple Ratio (SR)	$((\text{NIR}/\text{red}) - 1) / ((\text{NIR}/\text{red}) + 1)$	(Chen 1996)
Atmospherically Resistant Vegetation Index (ARVI)	$((\text{NIR} - (2 \times \text{red} - \text{blue})) / ((\text{NIR} + (2 \times \text{red} - \text{blue})))$	(Kaufman 1992)
Optimized Soil-adjusted Vegetation Index (OSAVI)	$(1 + 0.16) \times (\text{NIR} - \text{red}) / (\text{NIR} + \text{red} + 0.16)$	(Zarco-Tejada et al. 2012)
Enhanced Vegetation Index (EVI)	$2.5 \times [(\text{NIR} - \text{red}) / (\text{NIR} + 6 \times \text{red} - 7.5 \times \text{blue} + 1)]$	(Poblete et al. 2024)
Green Normalized Difference Vegetation Index (GNDVI)	$(\text{NIR} - \text{green}) / (\text{NIR} + \text{green})$	(Gitelson and Merzlyak 1998)
Plant Senescence Reflectance Index (PSRI)	$(\text{red} - \text{blue}) / \text{red edge}$	(Merzlyak et al. 1999)
Normalized Difference Red Edge (NDRE)	$(\text{NIR} - \text{red edge}) / (\text{NIR} + \text{red edge})$	(Silva Costa et al. 2023)
Normalized Difference Water Index divided by EVI (NDWI/EVI)	$\text{NDWI}^{(1)} / \text{EVI}$	(Pacheco et al. 2025; Delval et al. 2022)
Plant Cell Density Index or Ratio Vegetation Index (PCD or RVI)	NIR/red	(Jordan 1969)
Leaf Area Index (LAI)	$(3.618 \times \text{EVI}) - 0.118$	(Boegh, 2002)

⁽¹⁾NDWI was adapted with SuperDove spectral bands; (Pacheco et al. 2025)

using the “Scikit-Learn” library (v. 1.6.1), except for XGB, which was implemented using the “xgboost” library (v. 3.0.0). For each model, three separate analyses were carried out using different sets of predictors: (i) SuperDove spectral bands (SDBs) alone, (ii) vegetation indices (VIs) alone, and (iii) a combination of both (BVI). RF is a powerful ensemble learning algorithm developed by Breiman (2001) that randomizes decision trees during the training phase, giving predictions by averaging the outputs of all individual trees. This strategy improves the accuracy of the model by avoiding overfitting and collinearity issues, commonly associated with single decision trees. This algorithm is widely applied in remote sensing and agricultural research due to its high predictive accuracy and its ability to model complex, non-linear, and non-parametric relationships between variables (Garofalo et al. 2024). The SVR model, instead, aims to define a function that approximates the relationship between predictors and a target using a hyperplane that best fits the data within a defined margin of tolerance, finding a balance between complexity and predictive performance (Lee et al. 2020). Due to its strong predictive performance with large datasets and robustness to collinearity, XGB is widely used

Table 2 Fine-tuned hyperparameters via optuna for each studied machine learning model

Model	Fine-tuned hyperparameters (range)
RF	n_estimators (1,1000); max_depth (5, 20); min_samples_split (2, 10); min_samples_leaf (1, 4); max_features (sqrt; log2)
SVR	C (1e-3, 1e3); epsilon (1e-3, 1.0); gamma (scale, auto)
XGB	n_estimators (10, 1000); max_depth (3, 10); learning_rate (0.01, 0.3); subsample (0.5, 1); colsample_bytree (0.5, 1)
EN	Alpha (1e-5, 1.0); l1_ratio (0, 1)

in different scientific fields, as well as agriculture (Garofalo et al. 2024b). The algorithm’s mechanism consists of creating a set of decision trees sequentially, where each tree tries to correct the errors of the previous one through gradient boosting, which updates the model by computing the loss function’s gradient and iteratively adjusting the parameters to minimize prediction error (Prakash et al. 2023). EN is a regularization technique that integrates L1 (Lasso) and L2 (Ridge) penalties to guarantee model stability, reducing overfitting (Lei et al. 2024). MLR aims to model the relationship between predictors and the target by fitting a linear equation to the observed data using a OLS (Ordinary Least Square) approach (Farbo et al. 2024; Ansarifar et al. 2021). For ML models, fine-tuning of hyperparameters is an essential process to improve the final prediction. An automated optimizing approach was implemented using the Optuna library (v. 4.2), which tries to identify the best-performing setups for hyperparameters. In Table 2 are reported the fine-tuned hyperparameters for each machine learning algorithm. For each ML algorithm, hyperparameter optimization was performed using Bayesian optimization with the Tree-structured Parzen Estimator (TPE), executing a total of 100 trials to explore the search space (Akiba et al. 2019).

A five-fold cross-validation was applied to assess and compare model performance. In this approach, the dataset was split into five equal folds; in each iteration, four folds were used for the training set (80%) and the remaining one (20%) for validation. This process was repeated five times so that every data point is used for validation exactly once. Furthermore, to reduce the influence of any single data split on the performance metrics, the k-fold procedure was repeated ten times with different random partitions (Oyedele 2023; Allgaier and Pryss, 2024). Following the cross-validation output, we computed the mean and standard deviation of the selected performance metrics: coefficient of determination (R^2 ; Eq. (2), Root Mean Squared Error (RMSE; Eq. (3), Mean Bias Error (MBE; Eq. (4). These parameters were calculated according to the following formula:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - O_i)^2} \quad (3)$$

$$MBE = \frac{1}{n} \sum_{i=1}^n (P_i - O_i) \quad (4)$$

where SSres is the sum of the squares of the residuals, SS_{tot} is the total sum of the squares, O_i is the actual value, P_i is the predicted value and n is the number of observations.

Once the best-performing model was selected, along with the most informative predictors for both Ψ_{pd} and iG-Apex, it was applied to all available SuperDove satellite images from May to September 2022. For each image, the predicted Ψ_{pd} and iG-Apex were extracted at the locations where Ψ_{pd} had been measured (see Sect. 3.2). The values of each target were subsequently studied using regression analysis to explore their possible physiological significance. For an improved spatial-variability representation of Ψ_{pd} and iG-Apex, for each acquisition date, hexagon maps were produced. Each hexagon was made through a custom trigonometric function (*cos*, *sin*), considering the spatial resolution and field boundaries. Then, to extract the pixel value from the predicted map of Ψ_{pd} and iG-Apex, the pixel value that had the maximum overlap with the single hexagon was considered. For each target and date, hexagon maps were generated with a continuous color scale determined by the range of predicted values (minimum and maximum) found in the corresponding image. Moreover, the median map was obtained by aggregating all predicted available images, computing the median of each single pixel value, and following the previous procedure to produce a hexagon map.

Model's explainability

ML explainability represents an essential approach in this branch, making these models more comprehensible to scientists, stakeholders, and policymakers (Novielli et al. 2025; Ryo 2022). In our study, to improve the interpretability of the best model, SHapley Additive exPlanations (SHAP) was used, a well-known technique derived from game theory, where the average contribution of a player across every possible coalition is determined. SHAP calculates the contribution of each feature to the model's predictions by averaging its impact across all possible feature combinations. The SHAP values were computed on the final optimized model trained using the whole dataset. To complement SHAP, Individual Conditional Expectation (ICE) graphs were used to visualize the expected outcome for each individual instance as a function of a specific feature, holding all other features constant. ICE graphs allow us to observe heterogeneity in feature effects and to identify potential interactions between features that are not readily apparent in aggregate analyses.

This analysis was conducted using the Python shap library (v. 0.47.1) and scikit-learn features (*sklearn.inspection*).

Results

Field data

Agro-climatic conditions

During the grapevine growing season, from May to September (Day Of Year (after here indicated as DOY) 120–274)), daily average temperature increased, reaching a maximum of 31.2 °C (DOY 196) and gradually decreased until the end of September when the lowest value, equal to 16.2 °C, was recorded (DOY 273). Considering the experimental period (i.e., June–August), in June the temperature was lower than in July, with temperatures around ~24.7 °C, with a quick rise at DOY 168 when the average temperature registered was 29.2 °C. July was the hottest month, and mean temperatures remained above 26 °C (Fig. 2A). Rainfall was distributed irregularly across the experimental period, with many dry days and a few rainy ones, mainly in mid-August (40.2 mm on DOY 226) and in September (55.4 mm; DOY 249–88.4; DOY 267) (Fig. 2A). VPD followed a similar trend of the temperature, with a maximum value reached in July (3.25 kPa; DOY 196) while the lowest was recorded in September (0.30 kPa; DOY 257) (Fig. 2B).

Ecophysiological parameters

Descriptive metrics for the two ecophysiological targets (Ψ_{pd} and iG-Apex) were reported in Table 3. For Ψ_{pd} , with a total of 720 observations, values ranged from a minimum of −0.82 MPa to a maximum of −0.16 MPa. The mean value was −0.36 MPa, with a median of −0.32 MPa, indicating a left-skewed distribution. The data showed a standard deviation of 0.14 MPa, suggesting moderate variability across the measurements. On the other hand, iG-Apex varied between 0.05 (min) and 0.90 (max), with a mean of 0.56 and a median of 0.58, closest to a symmetrical distribution. The standard deviation was 0.23, indicating a higher variance compared to Ψ_{pd} . During the measurement period (DOY 161–234), both Ψ_{pd} and iG-Apex showed temporal variability (Supplementary Table S1). At the beginning (DOY 161–178, June), Ψ_{pd} values were medium-to-low, ranging from −0.16 to −0.40 MPa, with a mean around −0.22 MPa (Deloire et al. 2020). Instead, iG-Apex values showed high values (0.76–0.82). Then in July (DOY 185–210) Ψ_{pd} mean started to increase from −0.25 MPa (DOY 185) to −0.47 MPa (DOY 210). The highest mean value was recorded on DOY 220 (−0.57 MPa), as well as the corresponding minimum

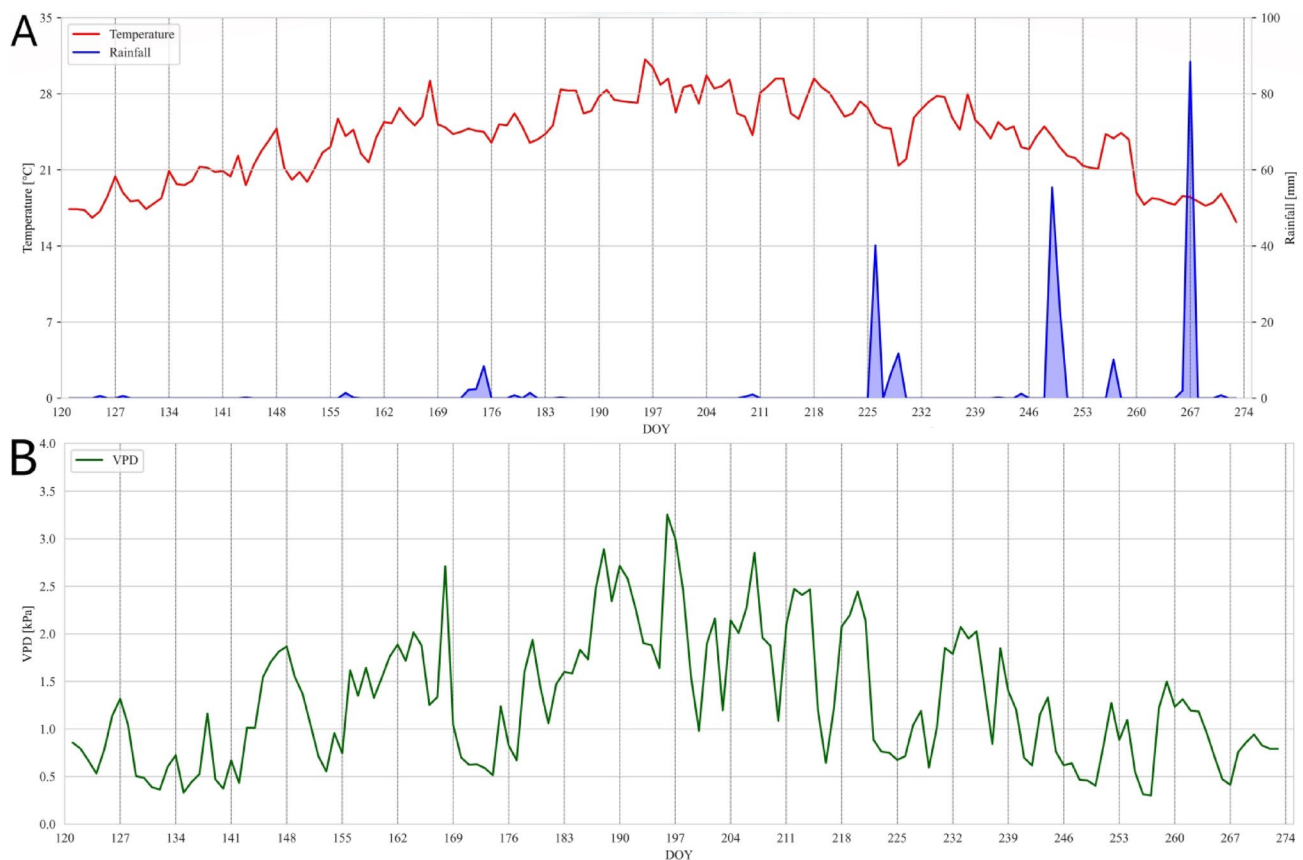


Fig. 2 Daily variation of average air temperature (°C), rainfall (mm), and vapor pressure deficit (VPD, kPa) (B) recorded in the study area (“Vil-leneuve-lès-Maguelone”, South-France)

Table 3 Descriptive statistics of predawn leaf water potential (Ψ_{pd} , MPa) and iG-Apex values measured during the experimental period

Target	Min	Max	Median	Mean	std	n_obs
Ψ_{pd}	-0.82	-0.16	-0.32	-0.36	0.14	720
iG-Apex	0.05	0.90	0.58	0.56	0.23	179

(-0.82 MPa). An opposite trend was observed for iG-Apex, where the mean value decreased from 0.65 (DOY 185) to 0.28 (DOY 220). By the end of August (DOY 220–234) Ψ_{pd} showed mean values around -0.51 MPa, while iG-Apex reached its minimum on DOY 234 (0.14).

Models' performance

The results about the performance of ML models were reported in Table 4. According to the RMSE (0.068) and low MBE (0.002), for Ψ_{pd} prediction, the best performance was observed with XGB using BVI ($R^2 = 0.778$). On the other hand, for iG-Apex, RF outperformed with respect to the other models ($R^2 = 0.615$), using BVI as predictors. This result was confirmed by the low RMSE and MBE (0.138 and 0.001, respectively). In the supplementary material, figure S3 shows the scatterplots of the observed and predicted values for Ψ_{pd} using the BVI as predictors. The XGB

scatterplot with BVI as predictors demonstrated a strong relationship between Ψ_{pd} observed and predicted values, especially within the range of -0.2 to -0.6 MPa. Slight misalignments were observed at the most extreme values, such as -0.8 MPa. For the iG-Apex, the RF scatterplot (using BVI as predictors) showed a clear concentration of points in both the central and extreme value ranges. However, compared to the previous model, it displayed greater variability in predictions, especially at the edges of the plot (Supplementary materials, Figure S6). Then, RF with SDBs as predictors showed metrics closest to best models, with an R^2 equal to 0.777 and 0.614 for Ψ_{pd} and iG-Apex prediction, respectively. Regarding Ψ_{pd} , the scatterplot of RF (trained with the SDBs) followed a similar layout of XGB (BVI), with a misaligned for the extreme regions (Supplementary materials, Figure S1). Conversely, the scatterplot for observed and iG-Apex predicted with SDBs showed more scattered points, meaning lower prediction accuracy

Table 4 Performance metrics (mean and standard deviation across Cv folds) of the machine learning algorithms, using the superdove spectral bands (SDBs) and vegetation indices (VIs) as predictors to modeling grapevine Ψ_{pd} and iG-Apex (the best algorithms' performance metrics for Ψ_{pd} and iG-Apex, according to R^2 , RMSE and MBE, are reported in bold characters)

Model	Predictor	Ψ_{pd}			iG-Apex		
		R^2	RMSE	MBE	R^2	RMSE	MBE
EN	SDBs	0.339±0.051	0.118±0.007	-0.0001±0.012	0.26±0.106	0.193±0.019	-0.001±0.034
	VIs	0.275±0.061	0.124±0.006	0.0001±0.013	0.167±0.097	0.205±0.020	0.001±0.033
	BVI	0.367±0.052	0.115±0.007	0.0001±0.012	0.289±0.106	0.189±0.020	-0.001±0.033
RF	SDBs	0.777±0.029	0.068±0.005	0.001±0.006	0.614±0.128	0.138±0.027	0.0001±0.026
	VIs	0.502±0.056	0.102±0.007	-0.001±0.010	0.252±0.112	0.194±0.022	-0.002±0.032
	BVI	0.770±0.029	0.069±0.005	0.001±0.007	0.615±0.116	0.138±0.026	0.001±0.024
SVR	SDBs	0.652±0.042	0.086±0.006	0.002±0.008	0.574±0.111	0.145±0.021	0.012±0.026
	VIs	0.361±0.067	0.116±0.007	0.003±0.012	0.114±0.114	0.211±0.017	-0.035±0.029
	BVI	0.410±0.074	0.111±0.009	0.007±0.013	0.436±0.223	0.165±0.039	0.012±0.030
XGB	SDBs	0.770±0.03	0.069±0.005	0.001±0.007	0.602±0.148	0.140±0.029	0.002±0.026
	VIs	0.502±0.062	0.102±0.007	-0.0001±0.010	0.306±0.124	0.187±0.024	-0.003±0.028
	BVI	0.778±0.028	0.068±0.005	0.002±0.006	0.607±0.152	0.138±0.031	0.002±0.025
LR	SDBs	0.341±0.051	0.118±0.007	-0.0001±0.012	0.244±0.121	0.195±0.018	-0.0001±0.035
	VIs	0.278±0.064	0.123±0.006	-0.001±0.013	0.023±0.081	0.222±0.016	0.001±0.037
	BVI	0.348±0.069	0.117±0.007	-0.0001±0.012	0.269±0.118	0.192±0.021	-0.001±0.034

(Supplementary materials, Figure S4). For both, Ψ_{pd} and iG-Apex, the worst results were achieved using only the VIs as predictors, as demonstrated by the scatterplots, which show a marked misaligned of the points (Supplementary materials, Figure S2 and S5). Moreover, SVR and EN (with BVI as predictors) showed a lower performance (R^2 : 0.410 and 0.367, respectively). LR provided the weakest outcomes when using SDBs, with an R^2 of 0.341.

Explainability

SHAP values were computed for all predictors in the XGB and RF models, providing the interpretation of each SDBs and VIs influence on the prediction of Ψ_{pd} and iG-Apex. Figure 3A and B show the SHAP summary plot; the SHAP dependence plots are reported in Supplementary material (Figure S7). SHAP plot (Fig. 3A) suggests that the most influential SDBs for Ψ_{pd} prediction were coastal blue and nir. On the other hand, ARVI and EVI resulted in the most influential VIs. High reflectance values for the coastal blue band contributed negatively to the model output, thus reducing the predicted Ψ_{pd} . In opposite, lower values tended to increase the predicted Ψ_{pd} . Significant changes in contributions were observed around the reflectance values of 0.045 (Figure S7). Both nir and green2 showed a similar pattern, where higher reflectance values contributed positively to the model's prediction, while medium-to-low reflectance values were associated with a negative impact. For the nir band, significant impacts on model prediction were observed at reflectance values of 0.30, while, for the green2 band, they occurred at reflectance values between 0.09 and 0.10. Regarding the green1 band, medium-to-low reflectance values had a negative influence on Ψ_{pd} prediction. On the

contrary, high and low reflectance values had a slightly positive effect. For this band, the SHAP dependence plot indicated changes between 0.06 and 0.08. The yellow band negatively influenced Ψ_{pd} prediction when reflectance values were in the medium-to-high range, while it had a slightly positive effect at mid-range ones. Values between 0.10 and 0.13 accounted for the most significant variations in the yellow band's influence on Ψ_{pd} prediction. The red and red-edge bands followed a similar trend, where high reflectance values positively influenced the model's performance, while medium reflectance values showed a slight negative effect. SHAP dependence plot suggests that changes in contribution to the model performance occurred at ~0.13 and ~0.17 for red and red-edge band, respectively (Figure S7). Finally, blue band results had a minimal influence on model performance. Among the VIs, ARVI and PSRI showed a negative effect on Ψ_{pd} predictions at extreme values (both high and low), with mid-to-low values having a minor positive or neutral influence (Fig. 3A); significant changes to contribution for ARVI were shown at 0.41 while 0.35 for PSRI. NDWI_EVI, EVI, NDRE, OSAVI, and LAI indices showed overall a similar influence on Ψ_{pd} model prediction, with medium-to-low values that negatively impacted the model prediction. Except for NDWI_EVI, which showed an increasing trend from 0.95, for the other VIs, significant changes occurred at 0.225 (EVI), 0.25 (NDRE), 0.30 (OSAVI), and 0.75 (LAI), respectively. GNDVI showed the opposite trend, with high values tending to increase the predicted Ψ_{pd} . For this index, with a sinusoidal pattern, the main changes corresponded between 0.50 and 0.55 and further to 0.55 (Figure S7). The remaining indices (NDVI, SR, and PCR_RVI) suggest that they had a minimal effect on the model's performance. For iG-Apex prediction with RF

Fig. 3 SHAP summary plots for the XGB and RF models predicting Ψ_{pd} (A) and iG-Apex (B), respectively. Both plots indicate the distribution of SHAP values for all predictors, with point colors representing the corresponding feature values (low to high). Positive SHAP values contribute positively to the model's prediction, while negative values indicate a negative influence

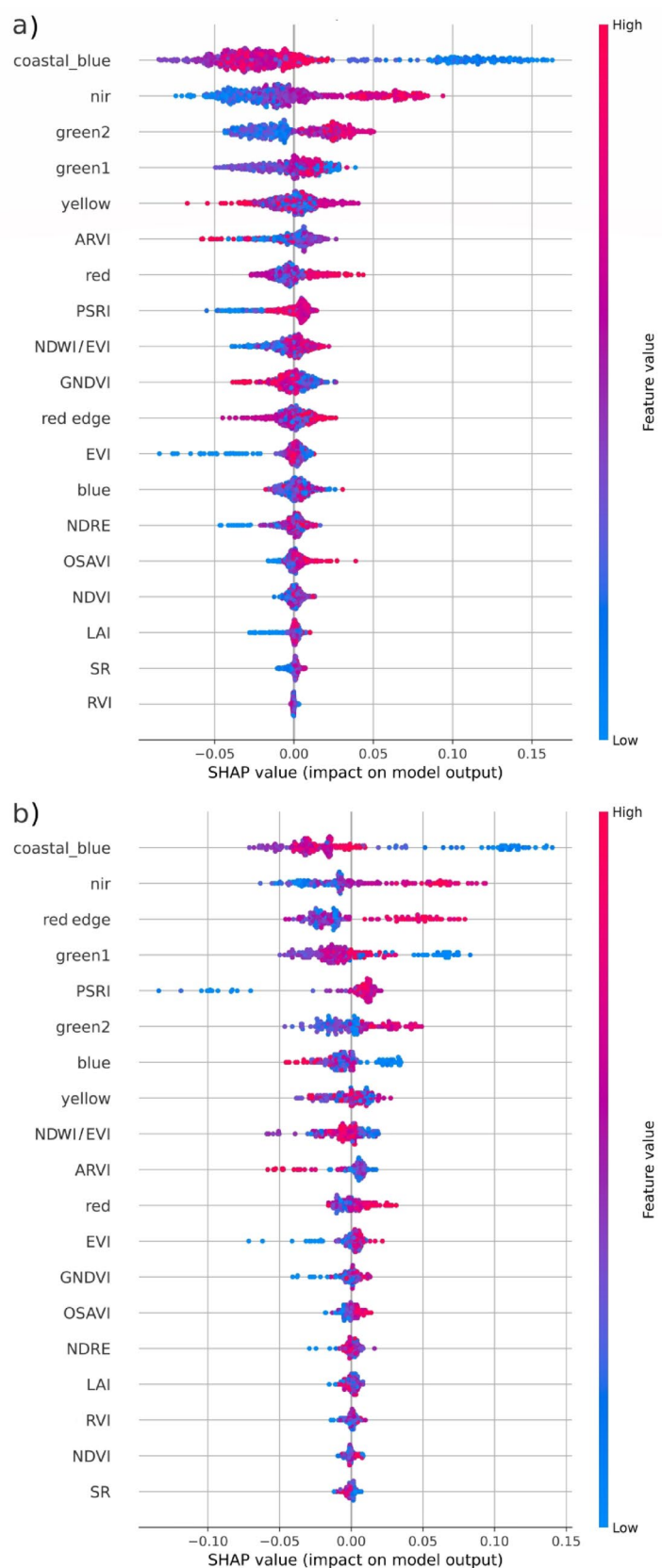




Fig. 4 Individual Conditional Expectation (ICE) plots for the models predicting predawn leaf water potential (ψ_{pd}). Each subplot shows the predicted value (Partial dependence) for a single feature across its

range, with each light blue line representing the prediction for an individual instance in the dataset

model, SHAP plot suggests that the most influential SDBs were always coastal blue and nir, as well as PSRI for VIs (Fig. 3B). Low reflectance values for the coastal blue band contributed mainly positively to the model output, thus increasing the predicted iG-Apex. In contrast, the medium-to-high values of coastal blue caused an increment in the predicted iG-Apex. As for Ψ_{pd} , significant changes in contributions of the blue band were observed at reflectance values of 0.045 (Figure S8). Nir and red-edge bands followed a

similar trend: high reflectance values positively influenced the model, and medium-to-low reflectance values had a negative effect. Relevant shifts in SHAP contributions occurred at approximately 0.30 for nir and 0.17 for red-edge. Regarding the green1 band, high-to-low reflectance values had a negative influence on iG-Apex prediction. On the contrary, high and low reflectance values of the green1 band had a slightly positive effect, for which the SHAP dependence plot indicates significant changes between 0.06 and 0.08.

For the iG-Apex prediction, green2 had a negative effect at medium-to-low reflectance, while medium-to-high values showed a moderate positive influence. Values ranged from 0.08 to 0.09 reflected the main changes in green2 band contributions to iG-Apex prediction (Figure S8). Blue band reflectance in the medium-to-low range showed a neutral influence on the model, whereas high values were associated with a negative impact and low values with a slight positive effect. In contrast, the effect of the yellow band was not as well defined, showing reduced variability between positive and negative influence across its reflectance spectrum. Finally, red band showed a positive effect on iG-Apex prediction with high reflectance values (Fig. 3B), with significant shifts at 0.12 (Figure S8). Regarding VIs, the PSRI index negatively influenced iG-Apex predictions at both high and low values, leading to decreased predicted values. In contrast, medium-to-high values had a neutral to slightly positive effect; significant changes to contribution for PSRI were shown at 0.35. The other indices that showed a similar trend to PSRI were: EVI, GNDVI, and NDRE. The opposite behavior was shown by the ARVI index, where a high value corresponds to the negative impact on iG-Apex prediction. Main changes in the performance contribution were correlated to a 0.45 value. The remaining indices (OSAVI, LAI, PCR_RVI, NDVI, and SR) suggested that they have no effect on the model's performance.

ICE graphs provided insights into the predictive behavior of the models at the single instance level. For the predictions of Ψ_{pd} by the XGB model, where coastal blue, nir, and various vegetation indices (e.g., ARVI) were among the most influential (Fig. 3A), the ICE graphs revealed considerable heterogeneity in the relationships between these and other spectral features and the predicted Ψ_{pd} (Fig. 4). In particular, graphs of features such as coastal blue, nir, ARVI, EVI, GNDVI, PSRI, and NDWI/EVI showed considerable scatter and frequent crossing of individual lines. Similarly, for the predictions of iG-Apex by the RF model, where the coastal blue, nir, red-edge, and green bands were identified as key influential features in SHAP analysis (Fig. 3B), the ICE graphs also revealed significant variability and interaction effects for many of these predictors. While some features showed more clustered responses, others, particularly nir, red edge, and the green bands, showed significant scatter and crossing of individual lines, indicating that their impact on the prediction of iG-Apex is also strongly dependent on the spectral context of each observed instance (Fig. 5).

Remote sensing ecophysiology prediction

Figures. 4, 6 shows the trend of Ψ_{pd} (A) and iG-Apex (B) throughout the whole period, from 1st May to 30th September 2022. The graphs also include the observed values

recorded from 10 June to 28 August 2022. The predicted values for Ψ_{pd} and iG-Apex were obtained by applying XGB and RF with BVI, respectively... Predicted Ψ_{pd} values began at -0.53 MPa on DOY 124 and decreased to a minimum of -0.57 MPa on DOY 127. By DOY 128, values generally increased, reaching -0.45 MPa on DOY 128, -0.462 MPa on DOY 130, and stabilizing around -0.40 MPa by DOY 141. Between DOY 155 and DOY 200, Ψ_{pd} values varied from -0.4 to -0.2 MPa. During August (DOY 213–243), Ψ_{pd} values tended to decrease again at the beginning of the month (minimum -0.57 at DOY 220); then in the last week of August, Ψ_{pd} increased, reaching a value of -0.33 . Finally, from DOY 241 to the end of the monitoring period (DOY 274), the Ψ_{pd} values remained stable, mostly oscillating around -0.3 MPa (Fig. 6A). The predicted iG-Apex value started at 0.319 on DOY 124 and showed a regular increment, reaching a value of 0.388 (DOY 130). With an irregular pattern (increase-decrease) during DOY 160–180, iG-Apex reached a maximum of 0.73 (DOY 179) and a minimum of 0.38 (DOY 170). From DOY 182 to DOY 273, the predicted iG-Apex values changed without following a specific trend. The values ranged from a minimum of 0.24 (DOY 226) to a maximum of 0.65 on DOY 197 (Fig. 6B). Additionally, for Ψ_{pd} (Fig. 6A), the predicted values are in line with the ground-based observations, confirming the efficiency of the XGB model with BVI in monitoring vine water stress. On the contrary, for iG-Apex (Fig. 6B), the model is inclined to underestimate the observed values at the beginning of the season (DOY 161–178) and to overestimate them at the end (DOY 220–234). Between DOY 185 and 210, the predicted values closely aligned with the observed, indicating a suitable performance of the RF model with BVI to predict iG-Apex. Figure 7 provides a spatial overview of model predictions across the two vineyards for Ψ_{pd} and iG-Apex. These hexagon maps were generated by applying XGB and RF models. For each target, the final maps represent the median for the corresponding pixel, computed across all available satellite images from May to September (DOY 124–173). The lowest median Ψ_{pd} values were mainly located in the northwestern zone of Field 1. A spatial shift to less negative values was observed across the central and south-eastern areas. Instead, in Field 2, a different spatial distribution of predicted median Ψ_{pd} values was observed across the three main sections of the vineyard. In the top section, Ψ_{pd} values were more negative in the north-east part, with a progressive reduction to lower values on the south-east side. The central section showed a more homogeneous pattern with a little spatial variability, except for some fewer negative values in the northern part. In the bottom section, the southern side was characterized by high Ψ_{pd} values, while the northern boundaries presented more negative values. Regarding iG-Apex, the spatial distribution pattern was



Fig. 5 Individual Conditional Expectation (ICE) plots for the Random Forest model predicting the iG-Apex. Each subplot shows the predicted value (Partial dependence) for a single feature across its range,

with each light blue line representing the prediction for an individual instance in the dataset

similar to Ψ_{pd} ; however, the corresponding hexagon values were inversely related—areas where Ψ_{pd} was higher showed lower iG-Apex values, and vice versa. This was confirmed by the linear relationship found between predicted Ψ_{pd} and predicted iG-Apex (Fig. 8) ($R^2=0.71$; $p<0.0001$).

Discussion

Nowadays, assessing vine water stress is fundamental (Deloire et al. 2020), given its impact on yield, wine quality (Laurent et al., 2021), and its contribution to climate change mitigation strategies (Cogato et al. 2022). The application of XGB and RF algorithms with BVI achieved the best results in Ψ_{pd} and iG-Apex prediction. Studying plant water relations requires the integration of physiological parameters

considering their spatial and temporal variability (Groenvelde et al. 2023).

Future projections from the Intergovernmental Panel on Climate Change (IPCC) indicate that most viticultural areas are expected to face decreased summer precipitation and rising temperatures at least during the mid-century (IPCC 2021). Soil available water capacity (SAWC) is another parameter related to Ψ_{pd} . According to Yuste et al. (1999), Ψ_{pd} go up quickly as SAWC increases. Moreover, Groenvelde et al. (2023) research demonstrated that in rainfed soil, Ψ_{pd} is equal to Ψ_{soil} . According to Zhang et al. (2025), areas with higher SAWC typically show reduced vine water stress, whereas lower SAWC is associated with more negative Ψ_{pd} values. Several studies suggested that high temperature promotes a rapid advancement of grapevine phenology (Cameron et al. 2021, 2022). Pichon et al. (2021b) observed that

during the summer season, a stop of growth shoots occurred, due to the limited climate conditions (i.e., high temperature, low rain); this phenomenon was associated with a decrease in the iG-Apex index. Figure 4B showed a similar trend, with the main reduction of predicted iG-Apex observed during August. At the beginning of September, a recovery of the predicted iG-Apex was observed, because of a secondary growth in response to the drought stress (Pichon et al. 2023). Moreover, lower predicted iG-Apex values, in both fields, were found in zones with higher water stress due to climate conditions and a lower SAWC.

The XGB algorithm using BVI outperformed with respect to the other models for monitoring grapevine Ψ_{pd} . Few studies employed XGB to predict vine water status. Using a proximal hyperspectral sensor, David et al. (2023) predicted the Ψ_{pd} using XGB regression, yielding an

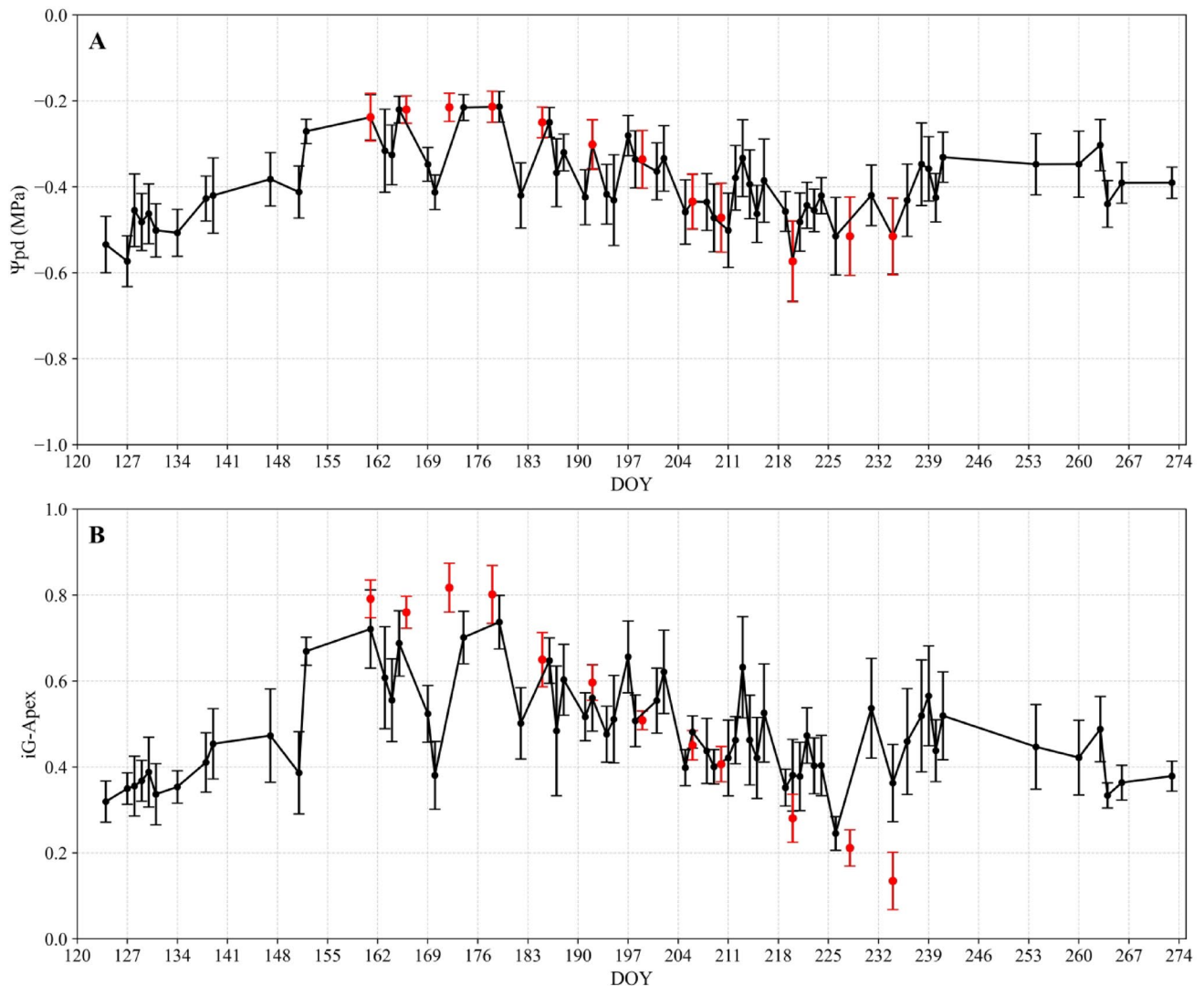


Fig. 6 Mean and standard deviation of the predicted (black) and observed (red) variables – (A) Predawn leaf water potential (Ψ_{pd}) and (B) iG-Apex – per each Day of the Year (DOY). Predicted values are

provided from May to September, while ground-based observations were collected from June to August (see details in Zhang et al. 2025)

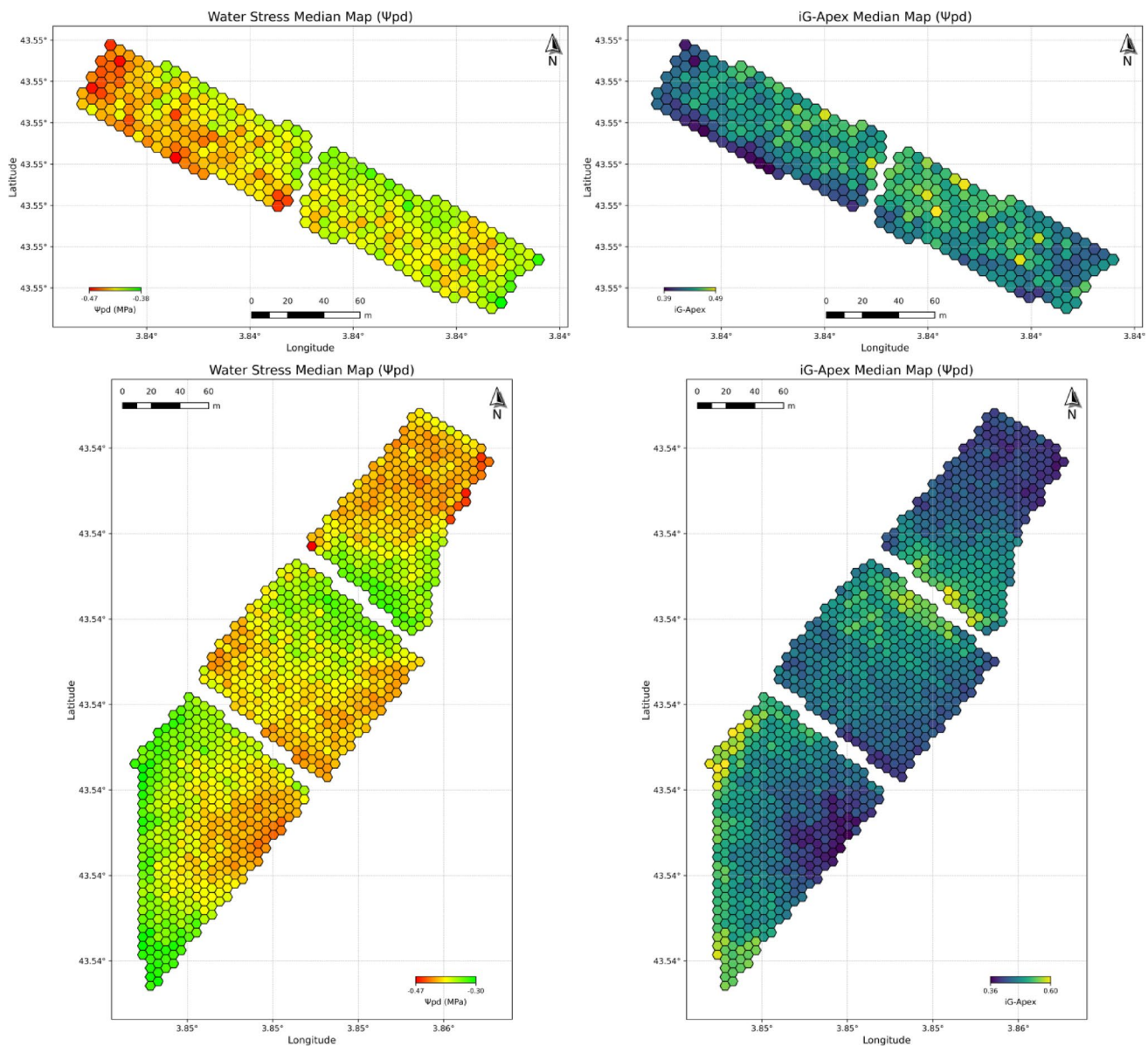


Fig. 7 Predictive hexagonal maps of (A) predawn leaf water potential (Ψ_{pd}) and (B) iG-Apex for both Field 1 and Field 2. The maps were generated by applying XGB and RF models trained with all predictors (SDBs and VIs) to all available satellite images acquired from May

to September, for Ψ_{pd} and iG-Apex, respectively. For each pixel, the final value represents the median prediction across all dates, providing a spatial summary of water stress (Ψ_{pd}) and iG-Apex over the growing grapevine season. Each single hexagon was 3 m

$R^2=0.95$; in South Africa, with a classification approach, Loggenberg et al. (2018) trained XGB and RF for vine Ψ_{stem} prediction using terrestrial hyperspectral data, with RF providing higher results than XGB. Also, Tang et al. (2022) found that RF outperformed XGB for Ψ_{leaf} prediction, using VPD and VIs from UAV (NDRE, PSRI, EVI, GRVI, SAVI, and SR) as predictors. XGB is an ensemble algorithm that uses information from previous trees to create new trees and reduce the error in each iteration, reducing the model variance and the risk of overfitting (Costanza et al. 2025). Previous research on the application of ML to remotely sensed images to predict physiological variables showed different

results. Sometimes the use of spectral bands reflectance data without the VIs yielded great performance in artificial intelligence applications, probably since VIs are usually computed from specific band combinations, and this can lead to information loss and saturation, reducing the spectral sensitivity of the data (Gao et al. 2023). In contrast, sometimes, the addition of VIs may improve the target prediction. As demonstrated by Pôças et al. (2020) in the Douro region, the use of VIs obtained by the combination of NIR and green spectral bands increased the performance in predicting vine Ψ_{pd} . These different predictive results may be attributed to a combination of several conditions, such as

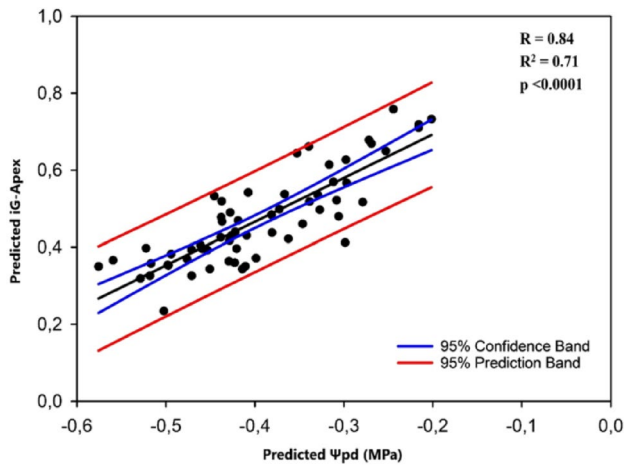


Fig. 8 Relationship between predawn leaf water potential (Ψ_{pd}) and iG-Apex, predicted with XGB and RF, respectively

crops, cultivars, environment, and the studied targets. In this study, the XGB algorithm trained with the BVI was able to capture the variability of Ψ_{pd} in two rainfed vineyards under Mediterranean conditions. For iG-Apex, RF achieved the best result; to our knowledge, this is the first work on the use of ML and high-resolution imagery to predict this index. Zhang et al. (2024) introduced the RDM approach to predict Ψ_{pd} by integrating iG-Apex with weather time series. The model captures temporal dynamics and improves Ψ_{pd} predictions, especially under moderate to severe water deficit conditions. This relationship between Ψ_{pd} and iG-Apex was confirmed by a negative linear regression (Fig. 8) obtained by combining the two predicted targets from XGB and RF model, respectively.

The result of the explainability analyses indicated that coastal blue and nir were the most important predictors than other SBDs and VIs for detecting both Ψ_{pd} and iG-Apex. In a previous study, Yoshino et al. (2022) suggested that the blue band could capture high-temperature damage. The coastal blue band, characterized by a shorter wavelength (431–452 nm), exhibits lower sensitivity to moisture absorption, allowing for more stable detection of changes in leaf coloration (Hashimoto et al. 2025). Additionally, chlorophyll (a+b) and carotenoid contents in the leaves relate mainly into spectra values between 400 nm and 500 nm (Ryckewaert et al. 2023), as well as plants prefer to absorb in the blue region (Kume 2017). Our results align with this previous research because low values of coastal blue have a positive impact on model prediction, thus increasing the prediction of Ψ_{pd} and iG-Apex, indicating that the plants were well-hydrated. The use of nir spectroscopy to detect changes in water status is well-assessed. Nir signal is related to pigments and cell structures that may be altered by water content in the plants. Ryckewaert (2022) found that reflectance values of nir were higher when the grapevine was

irrigated; conversely, low value of nir reflectance was shown in a water stress situation. SHAP plot (Fig. 3) confirms this trend with a high value of nir that indicates a non-stressed situation inside the vineyards, considering the positive impact for modeling Ψ_{pd} and iG-Apex. By extending this interpretability to the level of individual instances, analysis of ICE plots provides deeper and complementary insights into how features are involved in the modelling process. For the Ψ_{pd} (XGB) predictions, the ICE graphs revealed significant heterogeneity in individual responses; features such as coastal blue, nir, some VIs (e.g., ARVI, EVI, PSRI, and NDWI/EVI) showed significant scatter and frequent cross-overs. This pattern indicates strong interactions, meaning that the effect of a feature on the predicted Ψ_{pd} is affected by the simultaneous values of other spectral inputs. Similarly, for iG-Apex (RF) predictions, the ICE graphs showed considerable variability and interaction effects among the features. Overall, ICE analyses for both targets highlight the ability of the models to explore the complex interdependencies among spectral features by capturing fuzzy and case-specific spectral signatures, which are influenced by the interaction of various plant traits (pigments, cellular structure, water content, canopy architecture) (Sims and Gamon 2002). The explainability analysis helps to understand the role of each variable in the predictive model, improving the result reliability and supporting technicians to better understand the relationship between reflectance data and plant physiology (Costanza et al. 2025).

Precision viticulture aims to use remote sensing technologies (i.e., satellite, airborne, and drone) in order to capture inter-annual and spatial variability within the vineyard. The use of satellite imagery to monitor water stress is well-documented (Abbatantuono et al. 2024). Giannico et al. (2024) experimented with the use of Sentinel-2 to monitor Ψ_{stem} in a semi-arid area, obtaining an $R^2 = 0.72$ combining RF and VIs. Furthermore, in southern France, four of twelve spectral bands of Sentinel-2 (Red, Red-Edge, NIR, and SWIR) were used to predict Ψ_{stem} (Laroche Pinel et al. 2021). Authors found that the predicted Ψ_{stem} reveals significant heterogeneity across the vineyards, associated with the presence of natural water sources or differing irrigation methods (drip, sprinkler, or none), collecting positive feedback from the growers to adopt these strategies in the future. However, other satellites like Landsat8, Planet or Worldview offer the possibility to monitor grapevine status. Laroche Pinel et al. (2024a, 2024b) achieved great results using Landsat 8 and machine learning algorithms to predict grapevine cv. Merlot. Helman et al. (2018) employed PlanetScope 4 bands (RGB and NIR) and time-series analysis to estimate Ψ_{stem} in 82 vineyards, showing interesting outcomes. Furthermore, Van Beek et al. (2013) successfully used WorldView-2 satellite imagery to predict Ψ_{stem} in pear

orchards. The use of a satellite from another depends not only on the spectral or temporal resolution, but also on their availability. Although Planet and Worldview imagery have a high resolution, they are not freely available like Sentinel-2 and Landsat-8. Nevertheless, the use of satellites with low resolution may reduce their application at the farm level. Even though satellites could offer the possibility to monitor vineyards for a long period in a continuous way, some peculiarities must be considered. The use of these technologies implies that pixels contain not only the spectral information of the canopy but also the soil and shadow (Matese et al. 2015). To face this problem, De Petris et al. (2024) developed a new approach for extracting the spectral signature of vines with the NDVI obtained by Sentinel-2 spectral bands. The use of drones is justified if it's considered to have a high operational cost and high spatial resolution (<0.01 m). Araújo-Paredes et al. (2022), with a drone equipped with a thermal camera, assessed the vine water status by spatializing the CWSI index. Laroche-Pinel et al. (2024b) used a drone and hyperspectral camera for Ψ_{stem} prediction, and the best model yielded an $R^2=0.54$. Nevertheless, our results ($R^2=0.78$) encourage the use of high-resolution harmonized satellite imagery to estimate these ecophysiological parameters using 8 SDBs and VIs on a daily scale. Finally, several studies explain the potential use of aircraft platforms to optimize the monitoring of vine water status. Bellvert et al. (2021) used an aircraft with a digital multispectral camera (RGB+NIR) flying at 1500 m above ground level, for monitoring 100 ha of vineyards under a spatial resolution of 0.50 m, to improve precision irrigation management.

The agriculture 5.0 has introduced the use of emerging technologies like artificial intelligence, IoT, big data analytics, digital twins, blockchain, 6G networks, robotics, and human-machine interaction to manage crops in a non-invasive way (Taha et al. 2025). ML models and remote sensing technologies are helpful tools for grapevine precision management. The use of satellite multispectral imagery and derivate vegetation indices maps are increasingly applied in viticulture to improve vineyard monitoring with a focus on environmental sustainability and vine quality and yield (De Petris et al. 2024). Furthermore, the application of ML algorithms has been increasing in irrigation scheduling (timing and amount) (Kang et al. 2023). Several studies demonstrated the potential of ML approaches to replicate or even replace expert decision-making: Navarro-Hellín et al. (2016) developed a decision support system for citrus orchards using Partial Least Squares Regression and Adaptive Neuro-Fuzzy Inference Systems. Nevertheless, Digital development may be useful not only for monitoring the water stress of vineyards but also for monitoring other parameters such as vegetative growth, nutritional status, canopy architecture, pest and disease detection, yield, and

quality of grapes (Tardaguila et al. 2021). This study shows the potential of XAI models based on high-resolution satellite imagery for monitoring rainfed vineyards. However, future work should be improved by the integration of real-time climate, soil, and plant data, to guarantee the concept of the soil-plant-atmosphere continuum to manage the water stress. Moreover, the combination of satellite data with proximal sensing technologies and IoT systems could allow the development of multi-source data platforms, leading to more precise and rapid vineyard monitoring solutions. However, this study presents some limitations such as that the ML models were developed and validated under specific Mediterranean conditions and for a single grapevine cultivar (Syrah'), which may limit direct validation in other environments or cultivars. Furthermore, the models were trained using data from a single growing season, thus reducing the possibility of observing the interannual variability in climate and vineyard conditions.

Conclusions

This study highlights the potential of combining machine learning and high-resolution satellite imagery for a non-invasive monitoring of grapevine water status, in a climate change era. The combination of spectral bands reflectance data and vegetation indices allowed accurate daily-scale predictions of Ψ_{pd} and iG-Apex, with extreme gradient boosting and random forest providing the best predictive accuracy. Model explainability through SHAP and ICE analyses revealed that coastal blue and NIR bands were key spectral regions linked to plant water status. Our findings align with other scientific research and illustrate a relationship between Ψ_{pd} and iG-Apex predictions. Compared to other remote sensing technologies (e.g., aircraft, drones), SuperDove satellite constellation offers a well-adapted solution between spatial and temporal resolution. This approach has the potential to be supported as a practical decision-support tool for grapevine growers and agronomists. By providing accurate and spatially explicit information on vineyard water status, the model could be used to optimize resource use, cultivar breeding, and improve crop resilience to drought. Moreover, its integration into digital farming platforms will give the possibility of real-time, data-driven decision-making, contributing not only to agronomic efficiency but also to the economic and environmental sustainability of viticulture. However, further validation across cultivars, environments, and multiple seasons would be necessary to ensure the robustness of the proposed models.

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Data availability The dataset used in this manuscript is freely available at: <https://doi.org/10.5281/zenodo.13992359>.

Declarations

Conflict of interest The authors declare no competing interests.

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