

EVALUATION OF THE EFFECTS OF USING UAV-BASED SPECTRAL DATA AND ENVIRONMENTAL INFORMATION ON THE ESTIMATION OF GRAPEVINE WATER STATUS AT CANOPY LEVEL

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ABSTRACT: Monitoring and management of grapevine water status (GWS) over the critical period between flowering and veraison, plays a significant role in producing grapes of premium quality. GWS is an integrated response to cultivation practices, climatic, and soil/terrain factors, but which of these variables are the main drivers of GWS variation remains unclear. An understanding of this is essential to irrigation management and decision-making. The goal of this study is to provide viticulturists insights into how the variation in canopy GWS relates to vegetation, climatic, and soil/terrain variables over the critical period. An unmanned aerial vehicle was flown over canopies and normalized difference vegetation index (NDVI) images with a 4.3 cm pixel resolution were created of the canopy volume for individual grapevines. Other data included soil and terrain variables, slope and elevation extracted from the digital elevation model (DEM), and apparent electrical conductivity (EC_a) obtained from an EM38 survey. Weather variables from an automated weather station provided continuous air temperature, humidity, rainfall, windspeed, irradiance, and modelled evapotranspiration (ET) data. Three machine learning algorithms (elastic net, random forest regression, and support vector regression) were used to regress 30 variables against stem water potential (Ψ_{stem}), measured by pressure bomb and used as a proxy for GWS. The results showed that, in our study vineyards, a machine learning model can be useful in multivariate modelling, with the best modelling performance ($R^2=0.76$, RMSE=137) obtained when using ET, irradiance, elevation, NDVI, rainfall, and slope as inputs for random forest regression. In addition, Shapley Additive exPlanations (SHAP) analysis (a statistical tool that weighs the importance of each variable in a model) indicated that monthly total ET was the most important variable in our studied vineyards. The temporal effects of monthly ET and irradiance, as well as daily rainfall were significant to GWS variation. This study has provided proof of the concept of developing regression models that would be beneficial for continuous GWS monitoring and irrigation management, whilst the clarification of the relationship between relevant variables assists in the decision-making of cultivation practices to attain optimal grape quality.

1. INTRODUCTION

Studies have demonstrated that grapevine water status (GWS) is a key factor in berry composition, affecting both vegetative growth and the fruit metabolism (Van Leeuwen et al., 2009). The berry composition determines the final quality attributes at harvest. During the important phenological stages such as bloom and veraison (Acevedo-Opazo et al., 2013), grapevine water status is ideally under controlled water deficit to benefit berry development by suppressing competition for photosynthetic resources from vegetative growth (Intrigliolo & Castel, 2009). This husbandry promotes the accumulation of sugar and anthocyanins (Etchebarne et al., 2010), and prevents oxidative damage to canopies through the production of reactive oxygen species resulting from severe water stress (Min et al., 2019). The ever-changing hydration status in vines is an integrated response to cultivation practices, climatic, and soil/terrain factors and displays differently across the fields, leading to variability in vine growth and then berry development. To minimize the variation in grape quality within blocks, it is important to monitor the temporal and spatial variability of GWS, while carrying out corresponding practices to try and keep water status within an optimal range.

The vine vegetative expression can be characterized by vigour, leaf area, and canopy volume (Steduto et al., 2012). Leaf area is responsible for solar irradiance interception and water consumption through transpiration. It is determined by canopy size as a result of trellis management (Williams & Ayars, 2005). Measuring electromagnetic radiation from plants has become popular because it is associated with physiological status, phenological stage, and other intrinsic variables of the plants (Liu et al., 2016). In combination with the use of an unmanned aerial vehicle (UAV), it can provide high spatial resolution images for the whole vineyard in an efficient manner. Normalized difference vegetation index (NDVI) is a well-known vegetation index for identifying photosynthetically active and well-watered vegetation (Dobrowski et al., 2002). In addition, 3D canopy information derived from RGB bands using structure from motion (SfM) is a cost-effective method to estimate canopy volume, which has a high agreement with vine vigor (Matese et al., 2017) and NDVI (Matese et al., 2019).

Vine growth is largely controlled by soil moisture. This is a result of soil texture determining plant available water holding capacity (PAWC), the total volume of water that a soil can store and supply to the crops within their root zones. Variation in soil layers and textures have variable water availability in response to uniform irrigation application, leading to spatial variability of vine water content (Tramontini et al., 2013). Electromagnetic induction is a non-destructive technique that allows depth-weighted average measurement of apparent soil electrical conductivity (EC_a) by inducing an electrical current in the soil (McNeill, 1980). The measured EC_a variations, under non-saline conditions, are primarily related to soil texture and water content (Doolittle & Brevik, 2014). EC_a has been demonstrated to be a tool to assess spatial changes in stem water potential ($R^2 = 0.56$) since the growth performance is caused by differences in soil water availability (Yu et al., 2020). As GWS represents spatial variability across the field resulting from various factors, identifying its main drivers is essential for vineyard management in terms of GWS optimization. For describing the relationship between GWS and these factors, machine learning techniques have recently arisen as an attractive alternative due to their ability to model both linear and nonlinear patterns (Kuhn & Johnson, 2013), while being applied to simulating plant water status based on multivariable regression (Suter et al., 2019). However, the downside of machine learning models is that their results are limited to feature importance or variable weight, which sometimes leads to incomplete interpretation (Mangalathu et al., 2020). As a comparison, SHAP, introduced by Lundberg and Lee (2017), is capable of providing deeper insights into the trained models. It is not only able to address

multicollinearity but also uncover synergistic effects between multiple factors (Lundberg et al., 2020).

As vineyard management is strongly linked to the hydration state of vines, an understanding of the dominant drivers or indicators of GWS would be indispensable for grape quality. To the authors' knowledge, this is the first study where SHAP analysis has been used in the investigation of the relative contribution of those variables to variation in GWS. The goal of this study is to provide grapevine growers and viticulturists insights into assessing the variation in canopy GWS relationship with vegetation, weather, and soil/terrain variables over the critical period, using machine learning algorithms for regression analysis. The main procedures undertaken were (i) training and validating machine learning algorithms for modelling GWS; (ii) determining which combination of the variables would best describe the variation of GWS. (iii) assessing the contribution of the selected variables to GWS based on SHAP.

2. METHODOLOGY

2.1. The Context of the Study Vineyards

The study vineyards are located at Martinborough in the Greater Wellington Region in New Zealand (NZ). Both vineyards are sited on a complex of Recent alluvial soils overlying gravels, developed from sedimentary quartzo-feldspathic alluvium associated with the nearby Ruamahanga and Huangarua Rivers (Figure 1). The study site comprises two commercial vineyards owned by Palliser Estate and are named Wharekauhau and Pencarrow. Our study areas in these two vineyards are 6.6 and 6.7 ha, respectively. Pinot Noir was chosen as the target cultivar in this study, due to its requirement for relatively precise irrigation management. The Pinot Noir vines were planted in the vineyards in 1998–2000 and trained with two-cane vertical shoot positioning. Inter- and intra-row planting space is 2.2 X 1.7 m for Wharekauhau and 2.2 X 1.8 m for Pencarrow. The annual growth cycle of grapevine in NZ comprises budburst, shoot growth, and flowering (September–November), fruit set and veraison (December–February) followed by berry development and harvesting (March–May). Cultivation practices, such as shoot thinning, bud rubbing, and leaf plucking, are regularly conducted from October to December during the growing season. From flowering to veraison, the management of GWS in this timeframe is the most critical determinant in final berry quality.

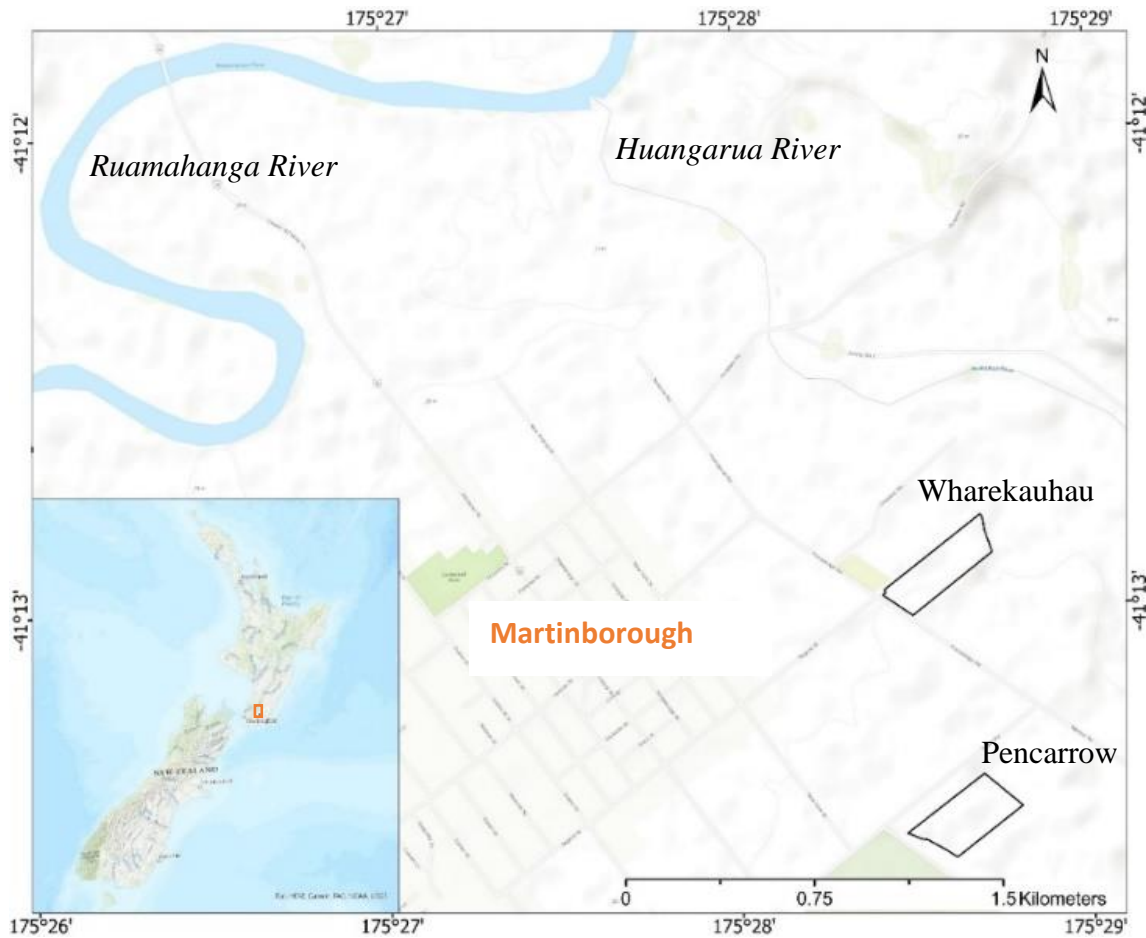


Figure 1. Location of study vineyards.

2.2. Study Period

The trials undertaken in this study took place from late November 2020 to early February 2021. The measurement dates, that avoided rain days and matched the most critical period for GWS management, were 27 November 2020, 4 December 2020, 14 January 2021, 22 January 2021, and 1 February 2021. During the study period, the daily mean temperature varied from 10 to 24 °C, and daily accumulated rainfall ranged between 0 and 30 mm at the vineyards. Due to adequate rainfall in late November, the two vineyards were not irrigated in the study period when GWS was at a moderate water deficit, desirable for berry quality. At Palliser Estate, the GWS of Pinot Noir during the critical period targetted close to -1300 kPa. Each measurement is described below.

2.3. Measurement of Grapevine Stem Water Potential

Stem water potential (Ψ_{stem}) was chosen as a proxy for GWS, and has been expressed as a comprehensive indicator for early water deficit in vines during the day (Patakas et al., 2005). On each measurement date, several healthy vines were sampled in grids to account for the variability across the vineyards, using two mature and fully expanded leaves from the middle part of the canopy. A pressure chamber (model: 610, MPS, Albany, NY, USA) was employed between the

hours of 12:30 and 15:30 to assess Ψ_{stem} (kPa). Prior to the measurement, the sampled leaves were covered with sealable plastic bags for around 1 h. The higher the reading, the more dehydrated the vine is. These two measurements per vine were averaged to represent the canopy water status. A total of 85 separate canopies were surveyed, and each of their trunk locations was recorded using a global navigation satellite system (GNSS) with real-time kinematic (RTK) correction (model: GPS1200+, Leica Geosystems AG., Heerbrugg, Switzerland).

2.4. Soil Variables

An EM38-MK2 electrical is an electromagnetic induction (EMI)-based sensor (Geonics Ltd., Mississauga, Ontario, Canada). The return reading (apparent electrical conductivity (EC_a)), is a weighted average based on depth-related sensitivity of the instrument and the depth-dependent drivers of EC (McNeill, 1980). Spatial patterns of EC_a values have been found to be relatively temporally stable between measurement dates (Heil & Schmidhalter, 2017). Recommended practice is to undertake measurements when soils are near field capacity when the difference among EC_a -based soil variability is at a maximum (Brevik et al., 2006). In this study, EM38-MK2 was operated in the vertical dipole mode, with the instrument taking integrated EC_a measurements at about 1.5 m depth. An EMI survey was undertaken on 27 May 2021 by towing the EM38-MK2 at the back of an all-terrain vehicle with a Trimble Yuma 2 tablet including a GPS receiver onboard to geo-reference all point data from the EC_a (mS/m) survey. EC_a points were measured approximately every 3-10 m along transects and 10 m apart, and values less than 0 mS/m were removed before carrying out interpolation. The geostatistical interpolation method, Empirical Bayesian Kriging (EBK), was used to transform point data onto a continuous surface raster with 1 m resolution in ArcGIS Pro 2.9 (ESRI, Redlands, California, USA).

Elevation (m) and slope (degree) information of the location for each sampled canopy were obtained from the ‘Wellington LiDAR 1m DEM (2013-2014)’ layer provided by Land Information New Zealand data service (<https://data.linz.govt.nz/>). This digital elevation model in 1 m resolution was generated by aerial LiDAR captured between 2013 and 2014 for the Greater Wellington region. For each grapevine, the mean values of EC_a , elevation, and slope within 0.5 m distance of the trunk were computed using “zonal statistic as table” in ArcGIS Pro.

2.5. Vegetation Parameters

Aerial images were obtained between 11:00 and 12:30 under sunny conditions on the same date of measuring Ψ_{stem} data to ensure comparability and to minimize the influence of sun angle and shadow. The reflectance, with a spatial resolution of 0.043 m, was recorded by DJI Phantom 4 multispectral UAV (DJI, Shenzhen, China) in the blue, green, red, red edge, and near-infrared regions. Photogrammetric processing was applied to the aerial data using Pix4Dmapper (Pix4D SA, Lausanne, Switzerland) to generate various outputs, namely digital surface models (DSM), digital terrain models (DTM), and reflectance maps. To increase imagery spatial accuracy, several ground control points were recorded by GNSS-RTK in each vineyard, and later imagery alignment was performed. For each grapevine, their canopy boundaries are about 0.8 m, and only the vegetation component within 0.5 m distance of the trunk was considered for computing vegetation variables in this study since the shoots of adjacent grapevines are often overlapping and intertwined. The acquisition of specific canopy pixels was carried out by overlapping the buffer zones (using recorded trunk location as the center of a circle with a radius of 0.5 m) with the binary raster of canopy height. Subsequently, canopy volume and normalized difference vegetation index (NDVI) for each sampled grapevine were calculated based on pure canopy pixels using “zonal statistic as table” in ArcGIS Pro.

2.6. Weather Variables

Weather data was recorded by the on-site weather station (175.4741, -41.2247 WGS84) established by HARVEST.com (<http://harvest.com/>). The target variables include air temperature (°C), relative humidity (%), rainfall (mm), wind speed (km/h), irradiance (W/m²), modeled evapotranspiration (mm/h). Reference modelled evapotranspiration was estimated using the FAO-56 Penman-Monteith equation (Allen et al., 1998). These variables then were used to compute maximum temperature, mean temperature, mean relative humidity, total rainfall, mean wind speed, mean irradiance, total irradiance, and total evapotranspiration based on monthly, weekly, and daily intervals before each measurement date.

2.7. Modelling Pipeline

The total samples (n = 85) for each measurement date were split into training (n = 59) and test (n = 26) sets using a 70/30 ratio. The split was carried out and stratified according to the date of measurement, to ensure that both training and test sets have corresponding percentages of samples for each date. Due to the limited size of training sets, validation was implemented for model training by applying 10-fold cross-validation to the training set. Subsequently, the average performance of the algorithm was then calculated. The test dataset was set aside during model training and was not used until the evaluation of modelling performance. The splitting process was undertaken using “train_test_split” from the sklearn package in Python 3.9.

Spearman correlation was used to determine the strength of the monotonic relationship between ranked response (the Ψ stem of each vine) and ranked predictor variables as well as between ranked predictor variables. The closer to ± 1 , the stronger the monotonic relationship. This correlation was implemented using “spearmanr” from the scipy library in Python. To reduce input dimensionality, input variables were grouped, and combinations of predictor variables as modelling inputs were formed by picking one variable from each group or not picking any variable, which means the combinations may include or exclude that group. The total combinations of input variables are 802,816.

Table 1. Groups of predictor variables that were used in this study. The term in bracket is the abbreviation for the preceding variable.

Group Number	Including variables
1	Monthly maximum temperature (m_Tmax), weekly maximum temperature (w_Tmax), daily maximum temperature (d_Tmax), monthly mean temperature (m_Tmean), weekly mean temperature (w_Tmean), daily mean temperature (d_Tmean)
2	Monthly mean relative humidity (m_RHmean), weekly mean relative humidity (w_RHmean), daily mean relative humidity (d_RHmean)
3	Monthly total rainfall (m_Rtotal), weekly total rainfall (w_Rtotal), daily total rainfall (d_Rtotal)
4	Monthly mean wind speed (m_WSmean), weekly mean wind speed (w_WSmean), daily mean wind speed (d_WSmean)
5	Monthly total irradiance (m_IRtotal), weekly total irradiance (w_IRtotal), daily total irradiance (d_IRtotal), monthly mean irradiance (m_IRmean), weekly mean irradiance (w_IRmean), daily mean irradiance (d_IRmean)

6	Monthly total evapotranspiration (m_ETtotal), weekly total evapotranspiration (w_ETtotal), daily total evapotranspiration (d_ETtotal)
7	EC _a (EC)
8	Slope
9	Elevation
10	Day after flowering (DAF)
11	Normalized difference vegetation index (NDVI)
12	Canopy volume (canopy size)

2.8. Regression Models

Elastic net (EN), random forest regression (RFR), and support vector regression (SVR) were applied to estimate Ψ_{stem} based on climatic, soil/terrain, and vegetation variables. They were implemented using “ElasticNet”, “RandomForestRegressor”, and “SVR” from the sklearn library in Python. As the performance of regression models is influenced by their parameters (also called hyperparameters), it is necessary to tune the hyperparameters beforehand to prevent overfitting. This enables the regression algorithms to exploit their potential. Grid searching on the training set with 10-fold cross-validation, based on the R^2 value, was used to search for the best combination of hyperparameters. The combination of hyperparameters contributing to the models with the highest R^2 values was considered as optimized. These parameters would then be used on the test set for later evaluation of the model’s generalization performance. This technique was carried out using “GridSearchCV” from the sklearn library in Python. All predictor variables were standardized to have mean values equivalent to 0 and a standard deviation as 1. To compare the performance of regression models and thus choose the optimal one for further analysis, the coefficient of determination (R^2) and root mean square error (RMSE) values were computed by applying the trained models with optimized hyperparameters on the test set.

2.9. Shapley Additive exPlanations

The optimal model then underwent Shapley Additive exPlanations (SHAP), based on game theory, to explore the relationships and quantify the contribution (SHAP values) of each feature according to its marginal contribution to the model output (Lundberg & Lee, 2017). In this study, SHAP values based on the training set were computed using TreeExplainer, since this random forest regression performed the best at modelling and was used in SHAP. Summary plots for the whole dataset were generated to show important features and the directionality of their impact. This analysis was implemented via the shap library in Python.

3. RESULTS AND DISCUSSION

3.1 Spearman correlation

This step provides an indication of promising predictor variables as model inputs for estimating grapevine water status (GWS), while examining collinearity between predictors according to the absolute value of the correlation coefficient. In Figure 2, a high yellow intensity indicates a higher correlation between two variables. For GWS estimation, it appears that DAF, temperature, irradiance, and evapotranspiration (ET) are expected to be selected as important inputs for modelling as they show a strong correlation with variation in GWS. As far as collinearity is concerned, a few variables, including temperature, irradiance, and ET, have relatively high consistency with temporal trends such as DAF. Both irradiance and temperature are highly correlated with ET because ET is modelled based on air temperature, relative humidity, wind speed,

and solar radiation, using the FAO-56 Penman-Monteith equation. Therefore, combinations of predictors and machine learning models were utilized to reduce the dimensionality of inputs and address multicollinearity when performing regression analysis.

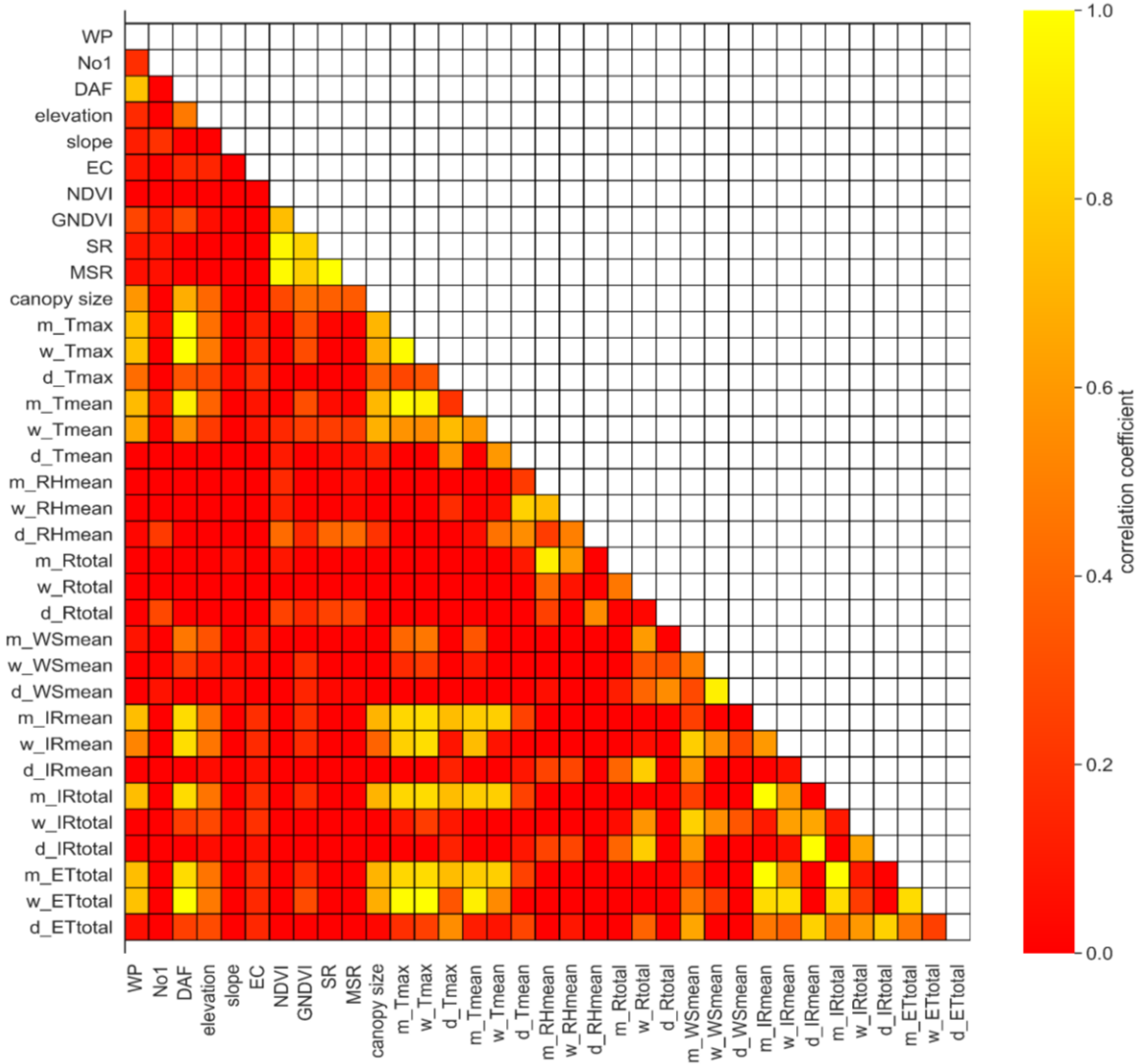


Figure 2. The Spearman correlation heatmap between all variables.

3.2 Modelling performance

Three machine learning algorithms, elastic net (EN), random forest regression (RFR), and support vector regression (SVR), were used to describe the relationship between GWS and different combinations of predictor variables. The best-performing model was selected according to the values of the following evaluation metrics, coefficient of determination (R^2) and root mean square error (RMSE), computed based on the test set. The results showed that RFR outperformed the other two models, with R^2 of 0.76 and RMSE as 137. The promising outcome of RFR may be that the relationships between GWS and the selected inputs are nonlinear (RFR is able to simulate nonlinearity). Another explanation is that RFR has been reported to be capable of achieving high accuracy when using a collinear dataset (Tomaschek et al., 2018). The scatter plot in Figure 3

presents the relationship between observed GWS and predicted GWS when using the best performed RFR model. Although the modelling result is promising, some weaknesses in the input data can be noted. The prediction accuracy of RFR modelling is restricted by the degree of precision and the resolution of the predictors. In this study, weather data was not recorded spatially, so the weather conditions the grapevines were exposed to on the same day of measurement were assumed to be consistent with the recording of the on-site weather station. This assumption is flawed because the microclimate experienced by grapevines is modified by plant structure and leaf area and thus influences individual GWS. A previous study reported that the difference between temperature within the canopy and ambient temperature could be 6-10 °C during the day (Ferrer et al., 2015). The effective range of soil variables affecting each grapevine was assumed to be a circle with a radius of 0.5 m. However, this range may vary according to the size of the root ball of each canopy, so the extracted soil/terrain information such as EC and slope might not completely reflect the individual grapevine conditions. This assumption also applies to the extracted vegetation pixels, which only consider the central part of the canopy as being representative of the whole grapevine.

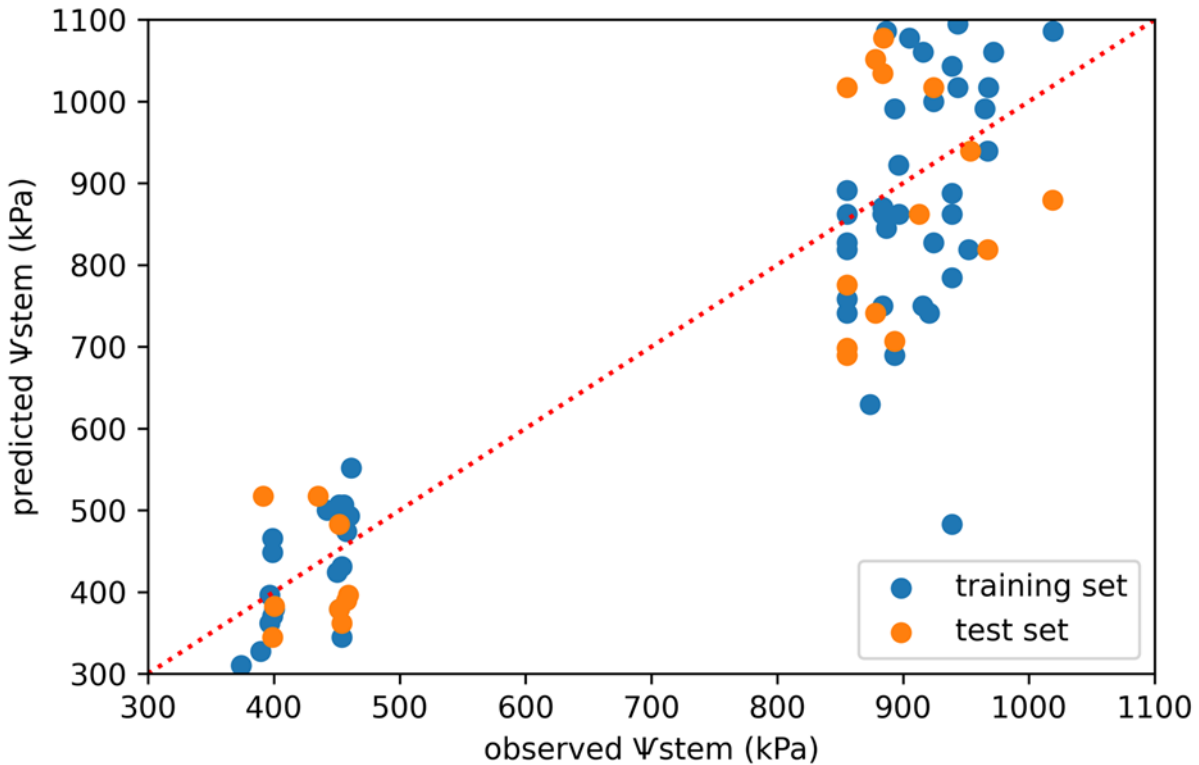


Figure 3. Scatter plots between predicted and observed Ψ_{stem} (kPa) simulated on the training ($n = 59$) and test set ($n = 26$) using the top-performing model, random forest regression. The red dotted line is the 1:1 line.

3.3 Shapley Additive exPlanations (SHAP)

After performing 802,816 combinations of predictor variables, RFR performed the best at estimating GWS using inputs composed of monthly total evapotranspiration (m_ET_{total}), monthly total irradiance (m_IR_{total}), elevation, normalized difference vegetation index (NDVI), daily total rainfall (d_R_{total}), and slope. The SHAP approach allocated SHAP values to every selected variable in every observation, which implies how each selected variable contributes towards the

variation of GWS. The bar plot in Figure 4 shows the mean absolute SHAP value for each variable in descending order, indicating that the monthly total evapotranspiration is the most, and monthly total irradiance is the second most, important factor responsible for the changes in GWS. This outcome is supported by previous studies, which state that weather conditions significantly impact grapevine development and vintage quality, especially temperature and radiation (Irmak & Mutiibwa, 2010; Parker et al., 2011). The variability of air temperature is involved in the calculation of modelled ET, so it is logical ET was selected as an input instead of temperature. The summary plot in Figure 5 shows the directionality of the variables' impact on the modelling output. As the absolute value of water potential was used for the regression analysis, a more negative reading (more dehydrated) of pressure bomb becomes a more positive value of the response variable in the regression analysis. Therefore, positive SHAP values indicate positive contributions to GWS, which means more dehydrated. Negative SHAP values make negative contributions to GWS, so the canopy is more hydrated. Monthly total evapotranspiration, monthly total irradiance, and slope are positively correlated with the dehydration of grapevines, while elevation, NDVI, and daily total rainfall are positively correlated with more hydration status. ET drives the transpiration rates of grapevine, and its influence would be stronger for Pinot Noir, as it is a near anisohydric cultivar that has relatively poor stomatal regulation under water deficit (Gutiérrez-Gamboa et al., 2019). Grapevines located on sloping ground have lower water status than those on flat ground, which may be related to a higher incidence of run-off events and thus lower infiltration of rainfall and irrigation, leading to a lower level of soil moisture availability. This agrees with the study of Jasse et al. (2021). The cumulative response of grapevines to water deficit includes reduced canopy size and vigor, which can be observed via aerial NDVI data. Ferrer et al. (2020) stated that variation of NDVI was positively correlated with changes in leaf area and vigor. Lastly, the function of daily total rainfall can be substituted by irrigation applied within 24 hr, as no irrigation event occurred in the vineyards over the study period. It is common for growers to control vigor by applying irrigation, which regulates GWS to alter the vegetative growth of grapevines (Fuentes et al., 2012).

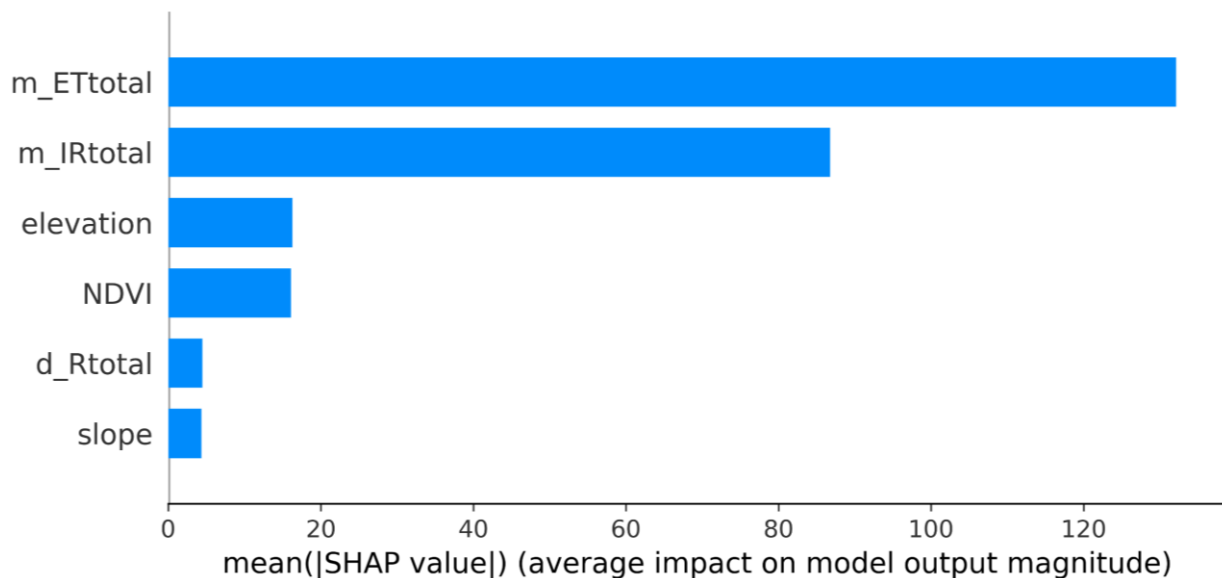


Figure 4. SHAP bar plot of the selected variables used as inputs for the top-performing model, random forest regression. The higher the absolute SHAP value of the variable, the greater the impact of the variable on the model output.

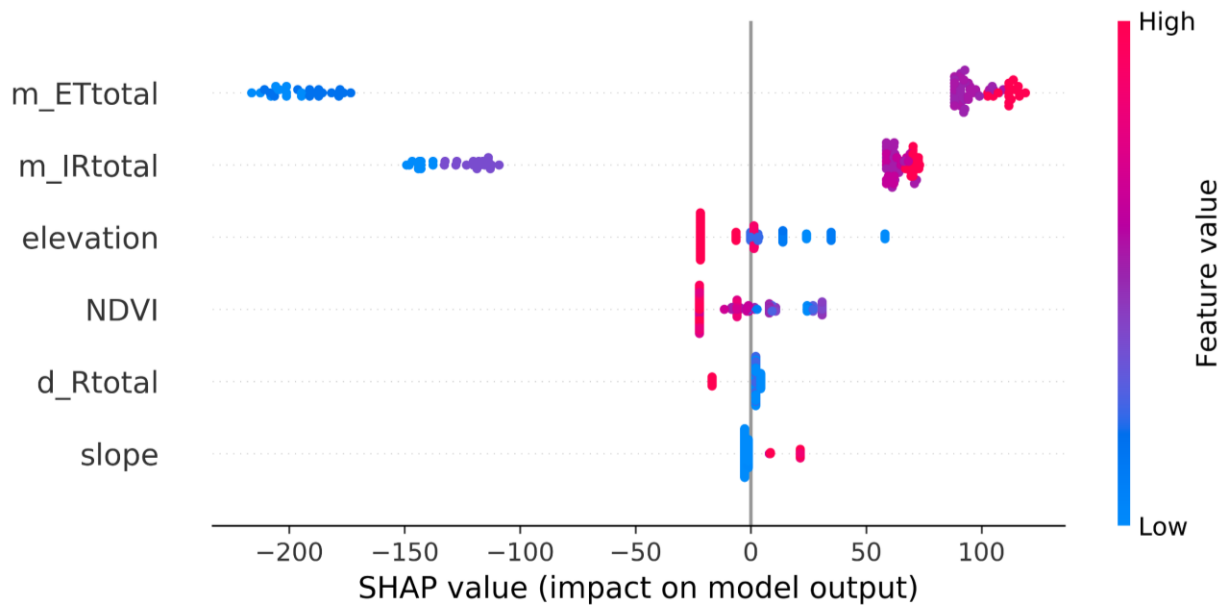


Figure 5. SHAP summary plot of the selected variables used as inputs for the top-performing model, random forest regression. Positive values indicate a positive contribution to the output (more dehydrated), and negative values indicate a negative contribution to the output (more hydrated). Every dot is one observation in the input dataset, and the color of every dot indicates the value of the variable.

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