

Article

Improving the Accuracy of Seasonal Crop Coefficients in Grapevine from Sentinel-2 Data

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Highlights

What are the main findings?

- This research presents a novel method to increase the accuracy of grapevine crop coefficients using spectrally unmixed vegetation indices from Sentinel-2 open-source data.
- Spectral unmixing improves the prediction accuracy of crop coefficients in Shiraz, Cabernet Sauvignon, and Chardonnay grapevine cultivars, and our models show transferability across regions and cultivars.

What is the implication of the main finding?

- High-accuracy crop coefficients can increase the efficiency of water use by irrigators and thereby improve sustainability.
- The methodology presented here can be applied to other crop parameters that are modelled using low-resolution satellite data.

Academic Editors: Ramona Magno, Paolo Filippucci and Ran Meng

Received: 24 June 2025

Revised: 22 September 2025

Accepted: 27 September 2025

Published: 4 October 2025

Citation: Guevara-Torres, D.R.; Luo, H.; Do, C.M.; Ostendorf, B.; Pagay, V. Improving the Accuracy of Seasonal Crop Coefficients in Grapevine from Sentinel-2 Data. *Remote Sens.* **2025**, *17*, 3365. <https://doi.org/10.3390/rs17193365>

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Abstract

Accurate assessment of a crop's water requirement is essential for optimising irrigation scheduling and increasing the sustainability of water use. The crop coefficient (K_c) is a dimensionless factor that converts reference evapotranspiration (ET_0) into actual crop evapotranspiration (ET_c) and is widely used for irrigation scheduling. The K_c reflects canopy cover, phenology, and crop type/variety, but is difficult to measure directly in heterogeneous perennial systems, such as vineyards. Remote sensing (RS) products, especially open-source satellite imagery, offer a cost-effective solution at moderate spatial and temporal scales, although their application in vineyards has been relatively limited due to the large pixel size ($\sim 100 \text{ m}^2$) relative to vine canopy size ($\sim 2 \text{ m}^2$). This study aimed to improve grapevine K_c predictions using vegetation indices derived from harmonised Sentinel-2 imagery in combination with spectral unmixing, with ground data obtained from canopy light interception measurements in three winegrape cultivars (Shiraz, Cabernet Sauvignon, and Chardonnay) in the Barossa and Eden Valleys, South Australia. A linear spectral mixture analysis approach was taken, which required estimation of vine canopy cover through beta regression models to improve the accuracy of vegetation indices that were used to build the K_c prediction models. Unmixing improved the prediction of seasonal K_c values in Shiraz (R^2 of 0.625, RMSE = 0.078, MAE = 0.063), Cabernet Sauvignon (R^2 = 0.686,

RMSE = 0.072, MAE = 0.055) and Chardonnay ($R^2 = 0.814$, RMSE = 0.075, MAE = 0.059) compared to unmixed pixels. Furthermore, unmixing improved predictions during the early and late canopy growth stages when pixel variability was greater. Our findings demonstrate that integrating open-source satellite data with machine learning models and spectral unmixing can accurately reproduce the temporal dynamics of K_c values in vineyards. This approach was also shown to be transferable across cultivars and regions, providing a practical tool for crop monitoring and irrigation management in support of sustainable viticulture.

Keywords: spectral unmixing; crop coefficient; evapotranspiration; canopy modelling

1. Introduction

Water management in agriculture has become increasingly critical due to the scarcity of freshwater resources, exacerbated by climate change impacts on water availability and agricultural productivity [1,2]. The rise in climate variability, marked by more frequent extreme events, such as prolonged droughts, is expected to impact agricultural systems beyond the gradual effects of climate change [3]. The wine industry is particularly vulnerable, as climate change will impose increasingly warm and dry conditions on vineyards, affecting wine quality and yield [4]. In arid and semi-arid regions, irrigation scheduling is essential to optimise water applications, achieve production goals, and build resilience to climate change [5], especially for wine regions in Australia, where more than 90% of vineyards relied on irrigation other than rainfall in 2019–2020 [6], precision irrigation technologies and irrigation scheduling [7–9] are especially considered necessary for sustainable production.

Advances in the understanding of grapevine irrigation over the last two decades have involved the assessment of vineyard and vine water requirements, as well as the effects of water stress on vine performance [10]. Also, newly designed precision irrigation systems like variable rate drip irrigation (VRDI) report ~10% yield increases with ~17% higher water use efficiency [7]. The winegrape industry has experienced a transition from experience-based irrigation to data-driven irrigation, as the former has become unreliable under shifting weather conditions [11]. Among various data-driven strategies, particularly those utilising soil and crop water status measurements, the evaporative demand strategy has demonstrated the highest water use efficiency in premium winegrape vineyards [9]. This strategy involves calculating the crop's water use or evapotranspiration (ET_c) to estimate the amount of water needed in the next irrigation cycle [8]. This strategy is advantageous because it accounts for the environmental factors that drive water loss from the soil and the plant. ET_c can be calculated directly using a lysimeter, eddy covariance, the Bowen ratio, and soil water balance methods [12,13]. However, these methods are expensive to implement and often provide a limited representation of the spatial variability in ET_c across a vineyard. Hence, ET_c is often estimated using the Penman–Monteith energy balance model, which combines reference evapotranspiration (ET_0) with a crop coefficient (K_c), a key parameter used to assess water requirements, crop health, and stress [14].

Accurate seasonal K_c values are essential for improving the precision of ET_c calculations and estimating water use. Seasonal K_c values should reflect the unique characteristics of winegrape cultivars, vine size, and training systems, incorporating the inherent variability present in vineyards [15]. Healthy vegetation with high canopy coverage is associated with high K_c values, as the K_c is proportional to canopy size and influenced by factors such as the crop's phenological stage, training systems, pruning practices, and vegetative

growth, all of which affect vine transpiration and soil evaporation by shading the ground [8,16]. Thus, the K_c is affected by vineyards' spatial and temporal variability, which is driven by factors such as disease, irrigation practices, and soil quality [17]. Current measures employed to estimate the K_c are not only resource- and time-consuming, but spatially limited. Traditional methods in vineyards include direct measurements using lysimeters and light interception techniques like the Paso Panel [18]. However, these methods are time- and labour-intensive, requiring manual measurements and several visits to the vineyard over the growing season. Alternatively, automated systems, such as Eddy Covariance Flux towers, estimate actual evapotranspiration (ET_a) but involve substantial infrastructure costs [19]. Moreover, the data from these methods are point sources and provide limited spatial coverage, restricting their usefulness in assessing irrigation needs across large vineyards.

Monitoring K_c using remote sensing techniques offers significant advantages for spatial and temporal assessments. Technologies like unmanned aerial vehicles (UAVs) allow access to high-resolution imagery < 50 cm to estimate accurate K_c across vineyards [20]. However, UAV imagery acquisition is limited by operational flexibility, high costs, and expertise in data processing [21]. In contrast, satellite imagery has greater spatial and temporal flexibility [7,22]. Open-source satellites provide moderate spatial resolution imagery (band-dependent), such as the products of Landsat 8 (15, 30 and 100 m) and Sentinel-2 (10, 20, and 60 m), with revisit times of 16 and 5 days, respectively, facilitating the construction of dense time series over large areas [23]. Satellite-derived datasets offer an advantage over UAV imagery by enhancing the development of more robust models for estimating K_c , as they provide broader spatial coverage and more comprehensive time frames, despite occasional cloud cover. Several studies have focused on directly estimating K_c using satellite spectral bands from satellite imagery, including grapevine [24]. IrriSAT, an open-source weather-based irrigation scheduling service, uses linear models based on the normalised difference vegetation index (NDVI) at 30 m resolution to estimate K_c [25]. Other studies have utilised spectral and thermal indices, such as the NDVI and the crop water stress index (CWSI), as well as structural attributes, such as the canopy size, leaf area index (LAI), and shaded area, to predict K_c [24,26–31].

In row crops with small crop sizes, such as in vineyards, it remains challenging to accurately predict grapevine K_c using open-source satellite imagery (e.g., Sentinel-2, Landsat 8/9, etc.) due to the mixed spectral signal. Vineyards have a regular canopy orientation but with low density and leaf coverage compared to planophile crops, such as corn [32]. Furthermore, common row and vine spacings ($0.5\text{--}3.0$ m $\times$ $1.0\text{--}3.7$ m, [17,33]) in vineyards are generally less than the spatial resolution of Sentinel and Landsat products, with inter-rows often covered by native or planted vegetation, such as cover crops ([34]). As a result, a single satellite pixel contains different land covers (bare soil, other vegetation), different from the crop of interest, and adds considerable noise to the pixel spectrum and the following vine assessments [35–37]. If directly interpreted, mixed spectral information could lead to inaccurate assessments of the crop [38].

To address the mixed pixel problem and retrieve the spectral information on different land covers, various approaches have been developed [39]. While probabilistic, fuzzy, or geometric-optical models represent pixel mixtures through probability distributions, fuzzy memberships, or canopy geometry, spectral unmixing uniquely decomposes the observed spectrum into pure endmembers and their corresponding abundances, making it the most widely applied method over the past four decades [39–42]. Spectral unmixing typically involves two steps: (i) decomposition of each mixed spectrum into a set of endmembers; and (ii) estimation of the abundances of each endmember in the pixel [43]. Depending on the underlying assumptions, unmixing models are generally categorised as linear or nonlinear. Linear spectral unmixing is by far the most widely applied, as it is

well-suited to scenes with spatially segregated land-cover patterns, although nonlinear formulations often achieve better performance in complex environments, such as dense tree canopies [41]. To the best of our knowledge, there are no reports in the literature on spectral unmixing of Sentinel-2 pixels to improve K_c estimation in vineyards. This study aims to fill this gap.

2. Materials and Methods

2.1. Study Site

This study was conducted on three winegrape cultivars from vineyards in the Barossa Valley in South Australia (Figure 1a), one of the world's most renowned red-wine-producing regions [44], with bottled wine exports under GI label claims exceeding 6.7 million litres worth AUD 116 million in 2023–24 [45]. This study took place in one vineyard block of mature Shiraz ($34^{\circ}29'47.7''\text{S}$, $138^{\circ}54'12.8''\text{E}$), one vineyard block of mature Cabernet Sauvignon ($34^{\circ}30'03.9''\text{S}$, $138^{\circ}54'05.3''\text{E}$), and one mature Chardonnay vineyard block ($34^{\circ}37'19.8''\text{S}$, $139^{\circ}02'17.8''\text{E}$). Both vineyards presented a cover crop dominated by native vineyard vegetation comprising permanent swards, and the vines were well-irrigated throughout the growing season. However, the composition of vineyard floor vegetation differed between the two vineyards, as the Chardonnay block was located near a woody area. Vines were harvested in late February, late March and mid-February for Shiraz, Cabernet Sauvignon, and Chardonnay, respectively.

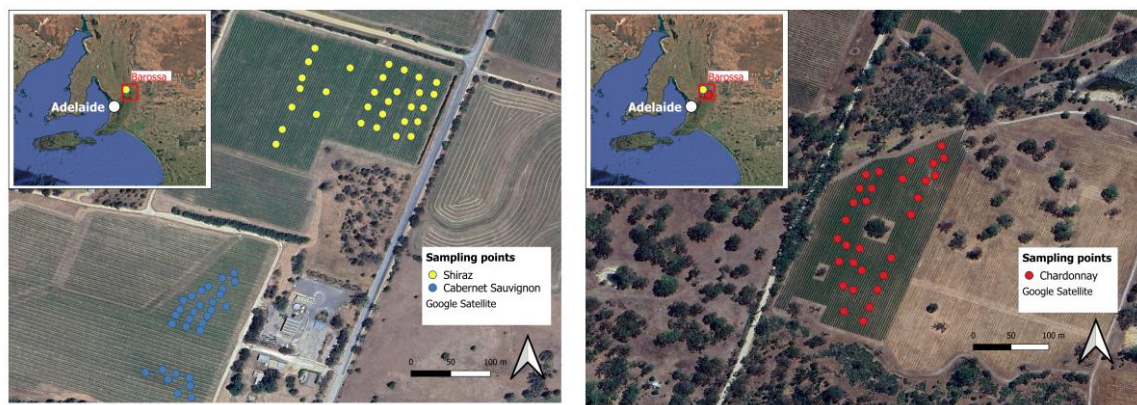


Figure 1. Vineyards locations in Barossa Valley ($34^{\circ}32'\text{S}$, $138^{\circ}57'\text{E}$) and Eden Valley (34.641°S , 139.098°E), South Australia; (a) sampling points Shiraz (in yellow, $34^{\circ}29'47.7''\text{S}$, $138^{\circ}54'12.8''\text{E}$) and Cabernet Sauvignon (in blue, $34^{\circ}30'03.9''\text{S}$, $138^{\circ}54'05.3''\text{E}$) in Barossa Valley; and (b) Chardonnay (in red, $34^{\circ}37'19.8''\text{S}$, $139^{\circ}02'17.8''\text{E}$) in Eden Valley.

2.2. Crop Coefficient Ground Data

A custom-built flexible solar panel called the 'Paso Panel' was used for K_c ground truthing [18]. The Paso Panel's estimation of the K_c involved measuring the ratio of incident to intercepted light from the sun. The panel was positioned perpendicular to the cordon during the canopy measurement, 10–15 cm above the ground. The Paso Panel was positioned parallel to the ground, ensuring the vine shadow covered the centre of the panel and that no shadows unrelated to the specific vine were cast on the panel. Sampling consisted of under-vine measurements on both cordons for each vine selected randomly across the vineyard. Sampling locations were registered with an Emlid Reach RS2+ GPS

receiver (Budapest, Hungary). Calculations for the K_c s were computed using Equation (1) proposed by [46], where L_p is the length of the Paso Panel and W_r is the row spacing. I_s and I_c are the current readings made under full sun and the canopy shade, respectively.

$$K_c = 1.7 \times \frac{L_p}{W_r} \left(1 - \frac{I_c}{I_s}\right) - 0.008 \quad (1)$$

The Paso Panel measurements were conducted at key phenological stages of vine growth, starting in October 2023 (near flowering stage) and finishing in March, April, and February 2024, with 660, 191, and 140 sampling points for Cabernet Sauvignon, Shiraz, and Chardonnay, respectively.

2.3. Remote Sensing Data Acquisition

From October 2023 to April 2024, a time series of the harmonised Sentinel-2 dataset (S2_SR) in Google Earth Engine (GEE) was obtained. The datasets were processed with a cloud filter of less than 1%, as suggested in the developers' documentation [47]. Following the developers' documentation, raster values were extracted from Sentinel-2 bands (Table 1) for each ground sampling point [48]. A buffer of 10 m allowed us to calculate a median value for each band in each location before the extraction. The feature collection was exported as a Comma Separated Value (CSV) file containing the information on Sentinel-2 bands for each location across the time series.

Table 1. List of spectral bands used in random forest classifications.

Bands	Description	Central Wavelength (nm)
B2	Blue	490
B3	Green (G)	560
B4	Red (R)	665
B5	Red-edge (RE)	705
B8	Near-infrared (NIR)	742
B11, B12	Short Wave Infrared (SWIR)	1610, 2190

2.4. Vegetation Indices

A total of 16 spectral indices were calculated for each sampling location, representing key vegetation properties, including vigour, chlorophyll sensitivity, water status, and soil background adjustment (Table 2). These included the normalised difference vegetation index (NDVI) and the enhanced vegetation index (EVI), two indices commonly used in vegetation classification analysis [49]. Vegetation indices associated with vegetation greenness, such as the green normalised difference vegetation index (GNDVI) and the green index (GI), were also included. Additional vegetation indices included those with red-edge bands that are significant for vegetation analysis [50,51], including the normalised difference red-edge index (NDRE), chlorophyll index (CI_{RE}), inverted red-edge chlorophyll index (IRECI), red-edge chlorophyll absorption index (RECAI), red-edge position index (REP), and normalised difference red-edge index, RENDVI2. The normalised difference water index (NDWI) and the normalised difference infrared index (NDII) were also considered, both used to monitor vegetation water content, as well as the moisture stress index (MSI), used to measure vegetation moisture levels [50]. A further inclusion considered the soil-adjusted vegetation index (SAVI) and its red-edge version (SAVI_{RED}), the modified soil-adjusted vegetation index (MSAVI), to account for soil background effects to enhance the accuracy of vegetation measurements [52,53].

Table 2. List of vegetation indices used in random forest classifications.

Index	Formula	Index Purpose	Reference
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NDVI	$\frac{NIR - R}{NIR + R}$	Canopy vigour	[54]
EVI2	$\frac{2.5 \times (NIR - R)}{NIR + 2.4 \times R + 1.0}$	Canopy vigour	[55]
GNDVI	$\frac{NIR - G}{NIR + G}$	Vigour/chlorophyll	[56]
GI	$\frac{G}{R}$	Canopy vigour	[57]
NDRE	$\frac{NIR - RE}{NIR + RE}$	Chlorophyll sensitivity	[58]
CIRE	$\frac{NIR}{RE1} - 1$	Chlorophyll sensitivity	[59]
IRECI	$\frac{NIR - RE1}{(RE2/RE3)}$	Chlorophyll sensitivity	[60]
RECAI	$\frac{RE1}{RE3}$	Chlorophyll sensitivity	[51]
REP	$700 + 40 \times \left(\frac{R670 + R780}{2} - R720 \right) \frac{R740 - R720}{RE2 - R}$	Chlorophyll sensitivity	[61]
RENDVI2	$\frac{RE2 + R}{NIR - SWIR1}$	Chlorophyll sensitivity	[51]
NDWI	$\frac{NIR + SWIR1}{NIR - SWIR1}$	Water	[62]
NDII	$\frac{NIR + SWIR1}{SWIR1}$	Water	[63]
MSI	$\frac{NIR}{(NIR - R)}$	Water	[64]
SAVI	$\frac{(NIR - R)}{(NIR + R + 0.5)} \times 1.5$	Soil correction	[53]
SAVIRED	$\frac{(NIR - RE1)}{(NIR + RE1 + 0.5)} \times 1.5$	Soil correction	[52]
MSAVI	$\frac{2 \times NIR + 1 - \sqrt{(2 \times NIR + 1)^2 - 8 \times (NIR - R)}}{2}$	Soil correction	[65]

R: red band (~665 nm); G: green band (~560 nm); NIR: near-infrared (~783–842 nm); RE1/RE2/RE3: red-edge bands (705, 740, 783 nm, Sentinel-2); SWIR1: ~1610 nm; SWIR2: ~2190 nm. R670, R700, R720, R740, and R780 refer to reflectance at respective wavelengths (nm).

2.5. Canopy Cover Data

In this study, canopy cover was defined as the percentage of each Sentinel-2 pixel (10 × 10 m) occupied by vine canopy, expressed as the proportion of the canopy area relative to the total cell area. A 10 × 10 m grid, matching the Sentinel-2 spatial resolution, was overlaid on the vineyards to enhance the correlation between ground canopy estimates and satellite-derived information. High-resolution visible imagery was used to calculate vine canopy area at the initial, full, and senescence phenological stages of Shiraz and Cabernet Sauvignon. The initial low canopy data for both varieties was obtained from an Airbus image (Pleiades NEO red, green, and blue bands) taken on 7 November 2023, with a resolution of 15 cm. Shiraz's full canopy was obtained using a DJI Matrice 600 Pro (SZ DJI Technology Co., Ltd., Shenzhen, Guangdong, China) on 20 December 2023 and Shiraz's senescence was obtained using a DJI Mavic Pro 2 (SZ DJI Technology Co., Ltd., China) on 22 March 2024, achieving a 2.5 cm resolution. Cabernet Sauvignon's full canopy and senescence data were obtained using a DJI Mavic Pro 2 (SZ DJI Technology Co., Ltd., China), with a 2.5 cm resolution. The full canopy image was taken on 15 March 2024, and senescence on 6 May 2024 (the senescence flight took place later due to the stable canopy condition of Cabernet Sauvignon after harvest).

To estimate the area occupied by vine canopy, an image classification was performed in ArcGIS Pro using the support vector machine (SVM) classifier, with accuracy assessed using independent validation samples. The classification achieved an overall accuracy, as

measured by the Kappa coefficient, greater than 0.7 in all classifications. A grid overlay with a 10 m spatial resolution, matching Sentinel-2's pixel resolution, was created in ArcGIS Pro. The canopy area within each cell was extracted from the canopy area classification and expressed as a fractional cover. The extraction was conducted in 28 locations, with no dead vines in each block. Models were then developed to predict canopy cover for multiple dates.

2.6. Canopy Cover Models

To estimate canopy cover, separate models were developed for Shiraz and Cabernet Sauvignon based on NDVI values and the number of days elapsed since 11 October 2023, when the vines had few leaves separated (initial phenology stage). For each of the 28 previously selected locations, a direct raster-to-point extraction of NDVI values was performed for dates closely corresponding to the acquisition dates of the high-resolution multispectral imagery. The Google Earth Engine (GEE) developers' documentation guidelines for NDVI calculation and extraction were employed [66]. Canopy cover was estimated using Beta regression models, which are well-suited for proportion data and can effectively account for the variability often seen in ecological data [67]. The 'betareg' package in R (Version 4.3.1, RStudio Version 6.0.421) was used, with 30% of the dataset used for model validation and 70% for model training. To avoid K_c overprediction during the early season resulting from cover crops, a logistic model was developed using the predicted canopy cover from November to January, when the vines reached maximum canopy size. In the case of Chardonnay, the canopy cover was estimated using the beta regression and logistic models developed for Shiraz, as both share similar phenological periods.

2.7. Spectral Unmixing

A linear spectral mixture analysis approach was adopted to determine specific improved vegetation indices of the vines. The unmixing procedure models the mixed pixel reflectance spectra as a linear combination of the pure spectral signatures of endmembers (components), weighted by their fractional cover within the pixel [68]. This approach assumes that all endmembers present in the pixel are considered and that their fractional cover totals one [41,69]. The analysis was simplified to two endmembers representing the cover crop (cc) and vines (Equation (2)). Since other endmembers could be participating in the pixel, we addressed the overinflated unmixed vegetation index values, empirically applying a factor of 0.5 to normalise the results (Equation (3)).

$$VI_{mixed} = VI_{vines} \times f_{vines} + VI_{cc} \times f_{cc} \quad (2)$$

$$VI_{vines} = (VI_{mixed} - (VI_{cc} \times (1 - f_{vines}))) / (2 \times f_{vines}) \quad (3)$$

The canopy cover predicted for each variety, using the beta regression and logistic models previously described, was estimated as the fractional cover of vines. The cover crop fractional cover was calculated as the complement of the vine fractional cover (i.e., 1-(vine fractional cover)). The vegetation index value for the cover crop was obtained from select vineyard reference points where an entire pixel was filled with cover crop vegetation similar to that found in the vineyard inter-rows.

2.8. Crop Coefficient Modelling

To predict K_c in vineyards, the performance of three statistical and machine learning models, run on each variety, was compared. All statistics were computed in the R programming language (Version 4.3.1, RStudio Version 1.4.1106). The first model to be tested was a generalised additive model (GAM), a class of models suitable for handling nonlinear relationships and facilitating the modelling of complex temporal trends [70,71]. To develop GAM models, the 'mgcv' package was employed. Before modelling, a stepwise selection method based on the RMSE was conducted to identify the most relevant variables. The data was split into training (70%) and testing (30%) sets over 100 iterations to ensure a robust data selection. In each iteration, a GAM was fitted, and variables were selected iteratively based on their capacity to minimise the RMSE. The chosen variables from each iteration were aggregated to calculate their mean importance and frequency of

selection. Variables with a frequency greater than the frequency median over 100 iterations were selected for modelling.

The second model employed was a random forest (RF) algorithm, a commonly used machine learning method for remote sensing classifications and regressions. This method has proven efficient in remote sensing analysis, as previously conducted for K_c modelling from UAV multispectral data [20]. RF can handle high-dimensional data and accurately classify complex environments [72]. By producing a large number of decision trees, RF is less sensitive to the quality of training samples and overfitting [73]. Decision trees are a type of model that employs randomly selected training samples to learn the characteristics of the classes that the model will be predicting. In this study, RF models were developed using the ‘RandomForest’ package. To improve the predictive accuracy of RF, hyperparameter tuning was performed to pre-select variables. Using the package ‘caret’, a search over a grid ranging from 2 to 8 was conducted to find the best combination of parameters. A five-fold cross-validation was employed to improve the reliability of the selection. The data was split into training (70%) and testing (30%) sets across 100 iterations to account for variability and ensure reliable results. In each iteration, an RF model was trained using the defined tuning grid and cross-validation setup, and the feature importance scores from the best model in each iteration were extracted and aggregated to calculate the mean importance and count of iterations for each variable. The final variables were selected based on their frequency above the median count over 100 iterations.

The third model employed was a support vector machine (SVM) model with a radial basis function (RBF) kernel. The SVM model is known for its robustness in handling high-dimensional and nonlinear data [74], and has been used in viticulture to estimate ET_c [75]. The RBF kernel maps input features into a higher-dimensional space, facilitating the discovery of optimal hyperplanes for separation in linear and nonlinear data distributions [76]. The ‘e1071’ package was employed in the R software. Before running the SVM model, Recursive Feature Elimination (RFE) with cross-validation was employed to preselect variables. The hyperparameter tuning used for RF was not computed since SVMs do not naturally provide feature importance metrics. RFE is a method for feature selection that recursively removes the least important features based on model performance, helping to enhance the model’s predictive accuracy and generalisability [77]. Cross-validation ensured a robust and unbiased selection of features, reducing the risk of overfitting and improving the model’s stability. The RFE process employed a five-fold cross-validation and utilised a random forest model for feature ranking. This process was repeated 100 times to ensure reliable and consistent feature selection, ultimately optimising the predictors for the SVM model with an RBF kernel. The final variables were selected based on their occurrence above the median count across the 100 iterations.

Modelling was based on field-based observations consisting of 269 samples from nine dates for Shiraz, 191 samples from eight dates for Cabernet Sauvignon, and 140 samples from five dates for Chardonnay. For each modelling process, 70% of the field-based observations were repeatedly selected as random subsets for training, and the remaining 30% were used for model testing. The final set of variables selected for each type of model was employed for K_c predictions. This procedure was conducted 100 times, and the mean R^2 , RMSE, and MAE were calculated to assess model performance. All modelling was conducted in R.

2.9. Model Validation with Ground Control Data

As an additional source of validation, K_c predictions were contrasted to ground-truth data obtained from an evapotranspiration sensor (Model LI-710, LI-COR Inc., Lincoln, NE, USA). The LI-710 employs vertical path-integrated eddy covariance to estimate latent and sensible heat fluxes by analysing high-frequency fluctuations in humidity and vertical

wind speed [78]. The flux data is processed internally and reported as fully corrected outputs at regular intervals (generally every 30 min), providing direct measurements of evapotranspiration over a radius of approximately 100 m and eliminating the need for empirical crop coefficients [79]. The LI-710 was installed in the Cabernet Sauvignon block, approx. 1 m above the canopy. The model predictions were contrasted to the K_c measures obtained by the sensor on the closest day under normal conditions (no extreme solar radiation nor wind) or the mean of proximate dates.

2.10. Projection to Sentinel-2 Rasters

The most accurate and stable model approach was applied to raster stacks from Sentinel-2 to predict K_c s across the block of Shiraz and Cabernet Sauvignon. Applying a trained model per pixel produces a distribution shift; pixel-scale inputs are noisier and less vegetated on average, so the predicted K_c tends to be compressed and biased low. This mismatch arises from the use of 10 m buffers for feature extraction at training time. To restore comparability with point-scale estimates for the same date, a post hoc calibration that matches the first two moments (mean and standard deviation) of the raster to those of a same-day reference set was applied (Equation (4)). Two dates were selected to assess the effectiveness of the projection by contrasting K_c values from mid-season (9 January 2024) and late-season (23 March 2024) from the Shiraz block.

The most accurate and stable model approach was applied to raster stacks from Sentinel-2 to predict the K_c s. Applying the model to per-pixel rasters introduced a change of spatial support because the model was trained on the median of vegetation indices extracted within a buffer around ground sampling points, resulting in predictions that tend to be shrunk toward the mean and biased low. To correct the mismatch, while preserving spatial ranks, a linear calibration was applied to the predicted K_c raster. For each date, the mean and standard deviation of the predictions on the rasters and the ground sampling points were estimated. The raster was linearly rescaled so it had the same average and the same amount of variation as the field data.

To assess the validity of our approach, model predictions were contrasted to the K_c derived from the NDVI by applying the widely used equation (Equation (4)) in [24], interpreted within the FAO-56 dual-coefficient framework [14]. For the comparison, the Cabernet Sauvignon block was selected since it contained LI-710 ground data for the assessment. The date 30 November 2023 was selected to provide a scenario where cover crops tend to interfere with the vine canopy signal in mixed pixels, allowing for the assessment of unmixing performance.

$$K_{cb} = 1.44 NDVI - 0.10 \quad (4)$$

A flowchart summarising the methods is presented in Figure 2.

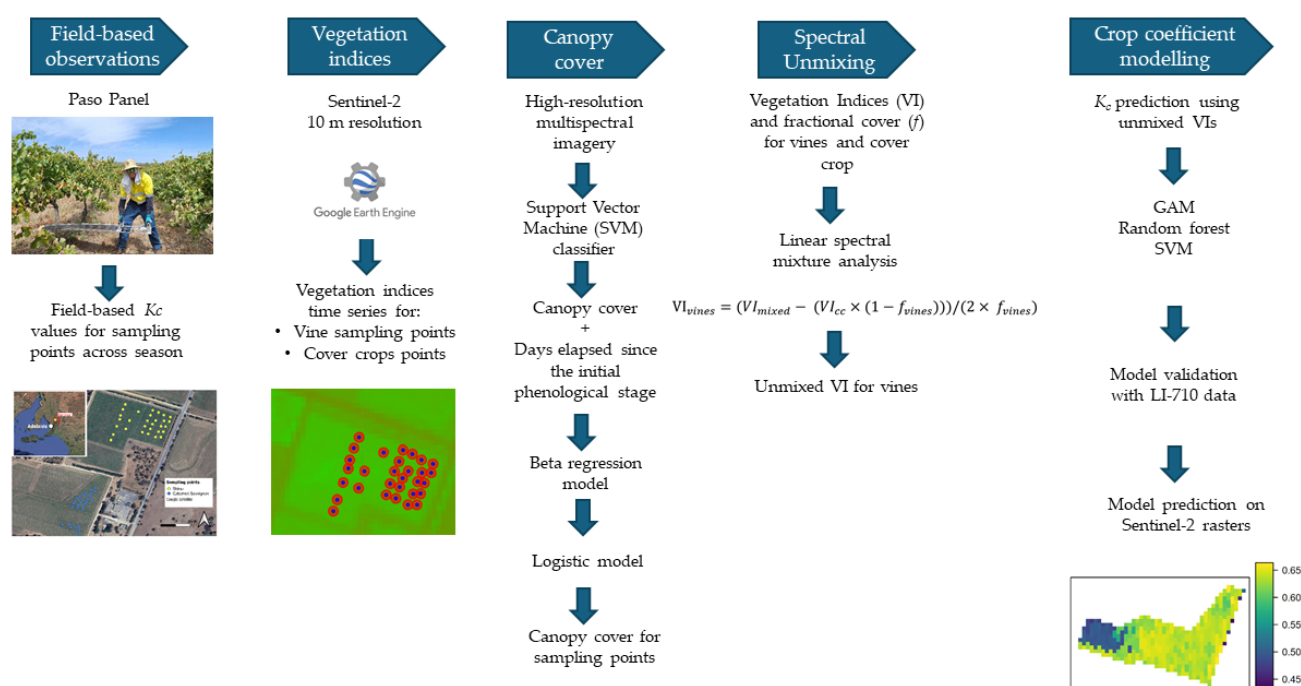


Figure 2. Flowchart showing data acquisition and modelling used in this study.

3. Results

3.1. Crop Coefficient Ground Data

Predictions of the K_c s over the season corresponded to the stages of canopy growth, reaching a peak with canopy expansion by mid-season and decreasing as senescence progressed (Table 3). Cabernet Sauvignon exhibited the most rapid increase in K_c , starting with a K_c of 0.35 in October, followed by 0.53 in mid-November, and reaching a peak of 0.722 in January, before gradually declining to 0.65 in March. Shiraz displayed a slower progression, starting at a K_c of 0.28 in October, followed by 0.46 in mid-November, and reaching a maximum of 0.61 in February, before declining to 0.44 in March. Chardonnay increased more gradually during the early season but accelerated later, rising from 0.28 to 0.64 in early November to peaking at 0.70 in January, followed by a slight decline from February onward. Cabernet Sauvignon contrasts with other cultivars, as it is capable of maintaining photosynthetic activity and canopy transpiration for extended periods, reaching senescence later than other cultivars [80]. Figure 3 illustrates the spatiotemporal distribution of the sampling points in the Shiraz block representing the early stages of vine development (19 October), peak vine development (12 January), and decline (23 March).

Table 3. Mean $\pm$ SD of K_c from Paso Panel measurements in three cultivars: Shiraz, Cabernet Sauvignon, and Chardonnay. n = number of sampling points per timepoint.

Date	Cultivar	n	Paso Panel K_c
11 October 2023	Cabernet	25	0.348 ± 0.088
18 October 2023	Shiraz	30	0.277 ± 0.054
23 October 2023	Cabernet	30	0.603 ± 0.097
28 October 2023	Cabernet	23	0.679 ± 0.042
5 November 2023	Cabernet	29	0.721 ± 0.042
5 November 2023	Shiraz	30	0.345 ± 0.077

7 November 2023	Cabernet	29	0.713 ± 0.049
10 November 2023	Cabernet	21	0.676 ± 0.043
15 November 2023	Cabernet	30	0.648 ± 0.062
17 November 2023	Shiraz	30	0.456 ± 0.063
30 November 2023	Shiraz	30	0.507 ± 0.066
22 December 2023	Shiraz	30	0.567 ± 0.084
9 January 2024	Shiraz	30	0.589 ± 0.067
11 January 2024	Shiraz	30	0.598 ± 0.070
25 February 2024	Shiraz	29	0.608 ± 0.087
21 March 2024	Shiraz	30	0.443 ± 0.086

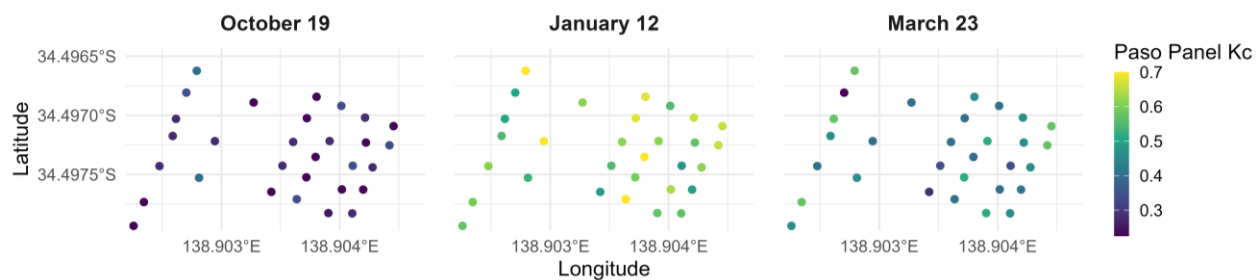


Figure 3. Paso Panel field-measured K_c , obtained at sample points in Shiraz block for early (19 October), mid (12 January), and late (23 March) season.

3.2. Canopy Cover Modelling

Canopy cover model performance for Shiraz yielded a pseudo- R^2 of 0.821, with a root mean square error (RMSE) of 0.027, and a mean absolute error (MAE) of 0.022. Cabernet Sauvignon performed similarly, showing a pseudo- R^2 of 0.818, RMSE of 0.043, and MAE of 0.035. The application of beta regression and logistic models developed for Shiraz resulted in a canopy development pattern that followed a logistic trajectory, characterised by rapid growth during the early season, a plateau at full canopy cover, and a subsequent decline during senescence. The application of models developed for Shiraz on the Chardonnay block resulted in an expected phenological pattern for vine development (Figure 4).

3.3. Spectral Unmixing

Spectral unmixing improved the vegetation indices by reducing cover crop interference, revealing different patterns among cultivars. Unmixed indices were lower than mixed indices during the early season when the vine leaves were small, while unmixed indices remained stable and decreased progressively later in the season when cover crops senesced, and mixed indices dropped in value. However, unmixing in early October was less effective for Cabernet Sauvignon and Chardonnay vines, particularly in the former, which showed higher mixed values during the early season. Most indices agreed with each other and the K_c evolution, following the patterns observed for the NDVI and NDRE (Figure S1), except for the RECAI, NDWI, and SAVI. The disagreement with the RECAI could be associated with the chlorophyll content, which may remain relatively stable even after véraison and harvest. In the case of the NDWI and SAVI during the early season, the exposure of soil underneath the vines (this area is generally free of cover crops throughout the season) and the high soil moisture associated with precipitation and supplemental irrigation could have influenced the values of these two indices.

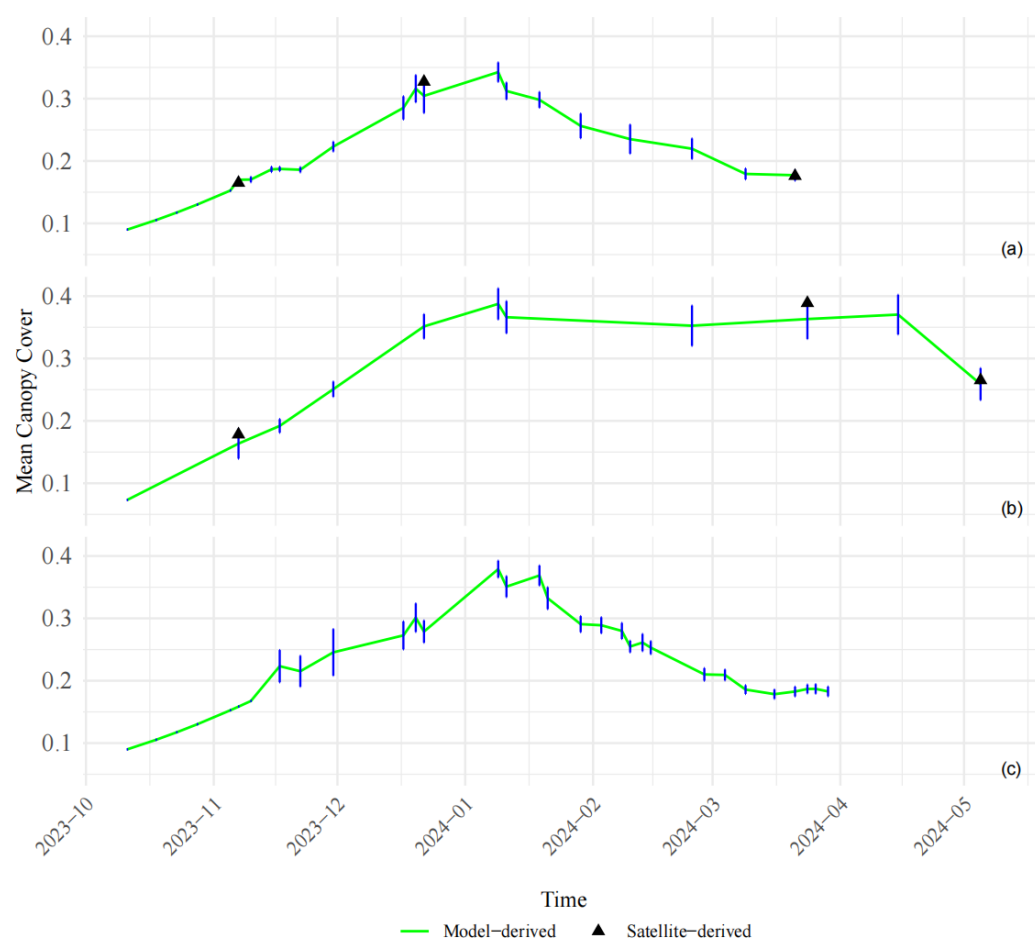


Figure 4. Model-derived canopy cover (green lines, $\pm$ SD in blue lines) fitted from NDVI using beta/logistic regression models, compared with satellite-derived canopy cover (black triangles) at image acquisition dates. Panels show (a) Shiraz, (b) Cabernet Sauvignon, and (c) Chardonnay.

3.4. Crop Coefficient Modelling

Model performance data varied across cultivars and modelling approaches (Table 4, Figure 5). The GAM models achieved higher R^2 values than the RF and SVM models in all cultivars. Chardonnay achieved the highest accuracy with the unmixed ($R^2 = 0.901 \pm 0.015$) and mixed models ($R^2 = 0.877 \pm 0.019$), while the RF and SVM models also performed well (R^2 consistently above 0.75). Cabernet Sauvignon also showed promising performance, with the GAM unmixed ($R^2 = 0.824 \pm 0.028$) and mixed models ($R^2 = 0.763 \pm 0.030$) achieving the highest accuracies, while the SVM and random forest models fell further behind. Shiraz exhibited lower fits, ranging from the GAM unmixed model ($R^2 = 0.679 \pm 0.026$) to the RF mixed model ($R^2 = 0.510 \pm 0.077$). The RMSE and MAE values showed minor variations across modelling approaches within each cultivar, generally differing by less than 0.01–0.02 K_c units, except for Chardonnay. The unmixed GAM in Chardonnay produced the highest errors (RMSE = 0.090, MAE = 0.067), despite having a strong overall fit. Furthermore, model predictions on independent data for dates without Paso Panel data showed that RF presented the most stable predictions following the phenological behaviour of vines, including a K_c decrease in the late season (Figure 5). These results indicate that absolute prediction errors remained relatively consistent across algorithms. Additional validation with the LI-710 evapotranspiration sensor corroborated the reliability of model predictions. Model predictions and sensor-derived K_s showed good agreement until the Cabernet Sauvignon block reached full canopy (Figure 5).

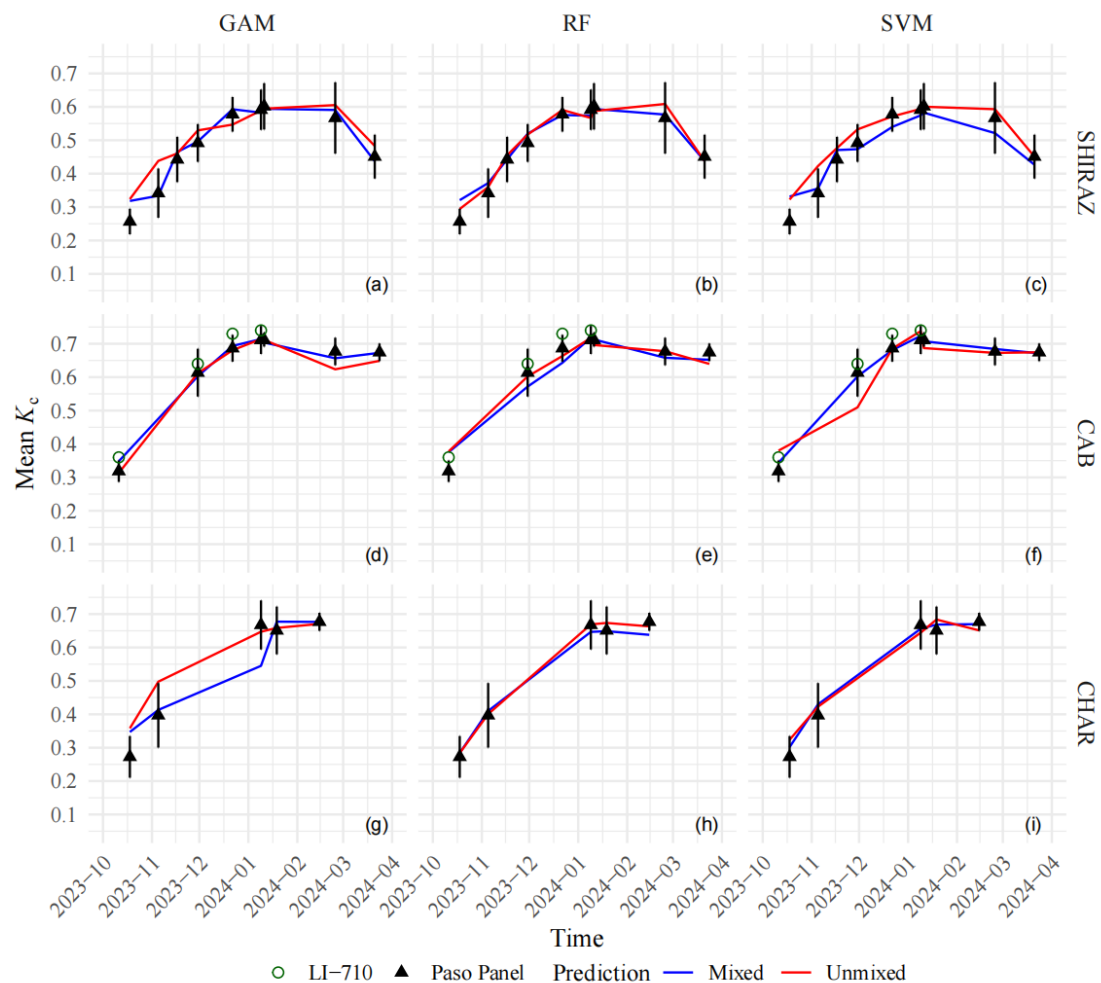


Figure 5. Time-series of mean observed and predicted crop coefficients (K_c) for testing data in three grapevine cultivars. Prediction results are shown for both mixed (blue lines) and unmixed (red lines) vegetation indices. Paso Panel mean values are represented by black triangles and LI-710 data by circles. Panels show (a) GAM, (b) RF, and (c) SVM predictions to Shiraz's seasonal K_c with Paso Panel measurements. (d) GAM, (e) RF, and (f) SVM predictions to Cabernet Sauvignon's seasonal K_c with Paso Panel and LI-710 measurements. (g) GAM, (h) RF, and (i) SVM predictions to Chardonnay with Paso Panel measurements.

Table 4. Performance (mean $\pm$ SD) of the modelling approaches: generalised additive model (GAM), random forest (RF), and support vector machine (SVM) fitted with mixed vs. unmixed indices for the Shiraz, Cabernet Sauvignon, and Chardonnay cultivars. The results are presented as the mean $\pm$ SD (across 100 runs with random splits). The reported metrics are the coefficient of determination (R^2), root-mean-square error (RMSE), and mean absolute error (MAE).

Vine Variety	Model		R^2	RMSE	MAE
Shiraz	GAM	Unmixed	0.697 ± 0.025	0.083 ± 0.005	0.068 ± 0.005
		Mixed	0.670 ± 0.026	0.090 ± 0.008	0.072 ± 0.006
	RF	Unmixed	0.625 ± 0.059	0.078 ± 0.006	0.063 ± 0.004
		Mixed	0.510 ± 0.077	0.090 ± 0.007	0.071 ± 0.006
	SVM	Unmixed	0.615 ± 0.064	0.084 ± 0.007	0.068 ± 0.005
		Mixed	0.512 ± 0.071	0.094 ± 0.008	0.074 ± 0.006
Cabernet Sauvignon	GAM	Unmixed	0.697 ± 0.009	0.084 ± 0.009	0.063 ± 0.006
		Mixed	0.763 ± 0.030	0.081 ± 0.112	0.061 ± 0.007
	RF	Unmixed	0.686 ± 0.067	0.072 ± 0.007	0.055 ± 0.005

Chardonnay	SVM	Mixed	0.649 ± 0.069	0.076 ± 0.009	0.056 ± 0.006
		Unmixed	0.713 ± 0.072	0.071 ± 0.009	0.052 ± 0.005
	GAM	Mixed	0.660 ± 0.081	0.078 ± 0.009	0.057 ± 0.006
		Unmixed	0.901 ± 0.015	0.090 ± 0.024	0.067 ± 0.017
	RF	Mixed	0.877 ± 0.019	0.097 ± 0.014	0.074 ± 0.009
		Unmixed	0.814 ± 0.044	0.075 ± 0.008	0.059 ± 0.007
	SVM	Mixed	0.787 ± 0.056	0.081 ± 0.011	0.064 ± 0.008
		Unmixed	0.818 ± 0.046	0.082 ± 0.012	0.064 ± 0.008
		Mixed	0.824 ± 0.033	0.081 ± 0.008	0.063 ± 0.007

Direct comparison with the Paso Panel's K_c values further confirmed the validity of the modelling results (Table 5). The monthly means from the Paso Panel's K_c and predictions (mean $\pm$ SD across 100 runs from different subsets of data) were in close agreement for the three cultivars, reproducing both the level and the seasonal trajectory (Figure 5). For Shiraz, predictions increased from $K_c \sim 0.32$ in October to ~ 0.58 in December–January and declined to $K_c \sim 0.45$ in March. The model means were typically within 0.01–0.04 of the observed values in Nov–Jan and within 0.03–0.05 thereafter. Cabernet Sauvignon's predictions started around $K_c \sim 0.35$ in October, peaked at ~ 0.70 in December–January, and remained high at $K_c \sim 0.67$ in the late season. The modelled means matched within 0.00–0.04 in all months. Chardonnay's predictions ranged from $K_c \sim 0.28$ to 0.35, which is slightly off from the Paso Panel data (0.27), except for the random forest models ($K_c \sim 0.28$). The models for Chardonnay achieved better accuracy later in January and February ($K_c \sim 0.65$ –0.67). Across cultivars, unmixing generally improved agreement during green-up to peak (November–January), while differences between mixed and unmixed inputs were minor near the summer plateau (February–March). Predictions showed a modest uncertainty (typical $SD \leq 0.05$).

Table 5. Mean Paso Panel (PP) and LI-710 flux tower (ET) measurements and modelled crop coefficients (K_c s) for validation data (n = number of samples) in three cultivars (Shiraz, Cabernet Sauvignon, and Chardonnay). Model approach refers to generalised additive model (GAM), random forest (RF) model, and support vector machine (SVM) model, employing mixed (mx) and unmixed (unmx) data.

Year-Month	Model	Shiraz		Cabernet Sauvignon		Chardonnay	
		n	K_c	n	K_c	n	K_c
October 2023	GAM mx	12	0.318 ± 0.036	5	0.348 ± 0.129	8	0.347 ± 0.062
	GAM unmx	12	0.324 ± 0.030	5	0.313 ± 0.051	8	0.358 ± 0.080
	RF mx	12	0.321 ± 0.042	5	0.375 ± 0.015	8	0.284 ± 0.096
	RF unmx	12	0.294 ± 0.022	5	0.378 ± 0.021	8	0.284 ± 0.056
	SVM mx	12	0.332 ± 0.063	5	0.344 ± 0.108	8	0.302 ± 0.027
	SVM unmx	12	0.323 ± 0.052	5	0.380 ± 0.085	8	0.328 ± 0.054
	PP	12	0.257 ± 0.038	5	0.319 ± 0.0320	8	0.273 ± 0.062
	ET				0.36		
November 2023	GAM mx	22	0.443 ± 0.080	8	0.603 ± 0.060	7	0.413 ± 0.089
	GAM unmx	22	0.486 ± 0.047	8	0.612 ± 0.018	7	0.498 ± 0.166
	RF mx	22	0.458 ± 0.066	8	0.572 ± 0.097	7	0.410 ± 0.033
	RF unmx	22	0.457 ± 0.070	8	0.602 ± 0.035	7	0.401 ± 0.058
	SVM mx	22	0.441 ± 0.070	8	0.602 ± 0.039	7	0.430 ± 0.060
	SVM unmx	22	0.487 ± 0.056	8	0.510 ± 0.123	7	0.423 ± 0.090
	PP	22	0.438 ± 0.088	8	0.614 ± 0.0715	7	0.397 ± 0.097
	ET				0.64		
	GAM mx	8	0.593 ± 0.044	11	0.694 ± 0.032		

December 2023	GAM unmx	8	0.547 ± 0.020	11	0.681 ± 0.028		
	RF mx	8	0.576 ± 0.024	11	0.643 ± 0.090		
	RF unmx	8	0.591 ± 0.011	11	0.663 ± 0.012		
	SVM mx	8	0.540 ± 0.067	11	0.681 ± 0.031		
	SVM unmx	8	0.571 ± 0.022	11	0.685 ± 0.043		
	PP	8	0.578 ± 0.052	11	0.687 ± 0.040		
	ET				0.73		
January 2024	GAM mx	22	0.590 ± 0.026	18	0.709 ± 0.025	19	0.601 ± 0.141
	GAM unmx	22	0.592 ± 0.012	18	0.713 ± 0.020	19	0.652 ± 0.021
	RF mx	22	0.586 ± 0.016	18	0.716 ± 0.026	19	0.648 ± 0.072
	RF unmx	22	0.579 ± 0.020	18	0.708 ± 0.028	19	0.6709 ± 0.043
	SVM mx	22	0.579 ± 0.031	18	0.716 ± 0.030	19	0.6613 ± 0.101
	SVM unmx	22	0.598 ± 0.007	18	0.715 ± 0.035	19	0.6609 ± 0.085
	PP	22	0.598 ± 0.065	18	0.711 ± 0.033	19	0.6605 ± 0.071
	ET				0.74		
February 2024	GAM mx	9	0.591 ± 0.028	8	0.657 ± 0.047	8	0.677 ± 0.0347
	GAM unmx	9	0.605 ± 0.012	8	0.624 ± 0.023	8	0.671 ± 0.0122
	RF mx	9	0.577 ± 0.030	8	0.658 ± 0.068	8	0.638 ± 0.0357
	RF unmx	9	0.609 ± 0.033	8	0.678 ± 0.013	8	0.663 ± 0.0222
	SVM mx	9	0.521 ± 0.067	8	0.684 ± 0.021	8	0.670 ± 0.0188
	SVM unmx	9	0.593 ± 0.051	8	0.673 ± 0.021	8	0.651 ± 0.0199
	PP	9	0.567 ± 0.107	8	0.677 ± 0.041	8	0.677 ± 0.0270
March 2024	GAM mx	8	0.438 ± 0.046	8	0.673 ± 0.058		
	GAM unmx	8	0.483 ± 0.010	8	0.649 ± 0.005		
	RF mx	8	0.438 ± 0.027	8	0.652 ± 0.027		
	RF unmx	8	0.438 ± 0.025	8	0.640 ± 0.016		
	SVM mx	8	0.427 ± 0.028	8	0.671 ± 0.034		
	SVM unmx	8	0.451 ± 0.012	8	0.674 ± 0.018		
	PP	8	0.451 ± 0.066	8	0.674 ± 0.026		

3.5. Contribution of Spectral Unmixing and Choice of VIs

The application of spectral unmixing had an overall positive effect on model performance, although the magnitude of improvement was more evident in Shiraz compared to Cabernet Sauvignon and Chardonnay (Table 4). For Shiraz, unmixing increased model accuracy across all three approaches, showing that R^2 values between mixed and unmixed improved from 0.670 to 0.697 in GAM, from 0.510 to 0.625 in RF, and from 0.512 to 0.615 in SVM, with similar reductions in the RMSE and MAE. In Cabernet Sauvignon, although unmixed models achieved higher R^2 values in the GAM and SVM models, their effect was not as prominent for the RF model. In the case of Chardonnay, the unmixed indices only improved the GAM ($R^2 = 0.901$ vs. 0.877) and RF ($R^2 = 0.814$ vs. 0.787) models, but not the SVM model.

The predictions of the K_c showed varying improvement throughout the season, with similar patterns observed among different cultivars and models (Figure 5). The benefit of unmixed indices was most noticeable during the early stage (October) and late stage (February–March) of the season for all the cultivars (Figure 3). In the early season, when cover crops were greener, mixed models tended to overestimate the K_c . Conversely, in most models, mixed models underestimated the K_c in the late season when cover crops were absent or dry. These patterns were particularly evident for Shiraz and Chardonnay. During the mid-season, unmixed and mixed models exhibited similar performance and little difference in accuracy.

Model selection revealed that a core group of vegetation indices was consistently retained across cultivars and modelling approaches (Table 6). The GI and GNDVI were

present in almost every model, while the $RENDVI2$, $NDWI$, $CIred$, $NDRE$, and REP were also frequently selected, particularly in models using unmixed indices. Among the unmixed models, the indices most often retained were the $CIred$, GI , $GNDVI$, $NDRE$, $NDWI$, $RENDVI2$, and REP . Most of these indices considered the red-edge band as part of their calculation. In contrast, the mixed models presented a greater variety in indices. Most indices showed temporal agreement with the evolution of the K_c , with the exceptions of the $RECAI$, $NDWI$, and $SAVI$. The disagreement with the $RECAI$ could be associated with the chlorophyll content, which may remain relatively stable even after véraison and harvest. In the case of the $NDWI$ and $SAVI$ during the first months, the major exposure of soil underneath the vines (this area is mainly free of cover crops throughout the season) and the high soil moisture associated with rains and irrigation could have influenced the values of these two indices.

Table 6. Vegetation indices selected after the model selection process for the generalised additive model (GAM), random forest (RF), and support vector machine (SVM) classifier in relation to the use of the unmixed and mixed indices and the cultivars Shiraz, Cabernet Sauvignon, and Chardonnay.

Variety	Model	Unmixed	Mixed
Shiraz	RF	$CIred$, GI , $GNDVI$, $NDRE$, $NDVI$, $NDWI$, $RENDVI2$, REP	$CIred$, GI , $GNDVI$, $IRECI$, $NDWI$, $RECAI$, $RENDVI2$, $SAVIRED$
	GAM	GI , $GNDVI$, MSI , $NDRE$, $NDWI$, $RECAI$, $RENDVI2$, $SAVIRED$	EVI , GI , $IRECI$, $NDII$, $NDWI$, $RENDVI2$, REP , $SAVIRED$
	SVM	REP , $NDVI$, $RENDVI2$, $NDRE$, $CIred$, $NDWI$, $GNDVI$, GI	$IRECI$, GI , $RENDVI2$, $SAVIRED$, $CIred$, $GNDVI$, $NDRE$, $NDWI$
Cabernet Sauvignon	RF	$CIred$, GI , $GNDVI$, $MSAVI$, $NDWI$, $RECAI$, REP , $SAVI$	GI , $GNDVI$, MSI , $NDII$, $NDRE$, $NDWI$, $RECAI$, $RENDVI2$
	GAM	$CIred$, GI , $GNDVI$, MSI , $NDVI$, $NDWI$, $RECAI$, REP	$CIred$, GI , MSI , $NDII$, $RENDVI2$, REP
	SVM	$GNDVI$, $NDWI$, GI , $RECAI$, $SAVI$, REP , $CIred$, $MSAVI$	$IRECI$, GI , $RENDVI2$, $SAVIRED$, $CIred$, $GNDVI$, $NDRE$, $NDWI$
Chardonnay	RF	$CIred$, GI , $GNDVI$, $NDRE$, $NDVI$, $NDWI$, $RENDVI2$, REP	EVI , GI , $MSAVI$, MSI , $NDII$, $RENDVI2$, REP , $SAVI$
	GAM	$CIred$, EVI , $GNDVI$, $MSAVI$, MSI , $NDRE$, $SAVI$	GI , $GNDVI$, $IRECI$, MSI , $NDII$, $RECAI$, $SAVIRED$
	SVM	$NDII$, $RENDVI2$, $CIred$, $NDRE$, $NDWI$, REP , $MSAVI$, MSI	GI , MSI , $NDII$, EVI , REP , $RENDVI2$, $MSAVI$, $SAVI$

3.6. Projection to Sentinel-2 Rasters

Applying the random forest model with unmixed data to the Sentinel-2 stacks and consecutive post hoc calibration produced spatially coherent maps (10 m resolution) in accordance with the K_c expected in the mid- and late-season stages (Figure 6). In January (Figure 6A), the K_c showed higher values ranging between 0.55 and 0.60, whereas in March (Figure 6B), a decline in K_c was observed, with values ranging from 0.42 to 0.5. These results closely align with the Paso Panel's K_c registered in January (0.589 ± 0.067) and March (0.443 ± 0.086), demonstrating that r-pixel projections capture both the phenological patterns at the block scale.

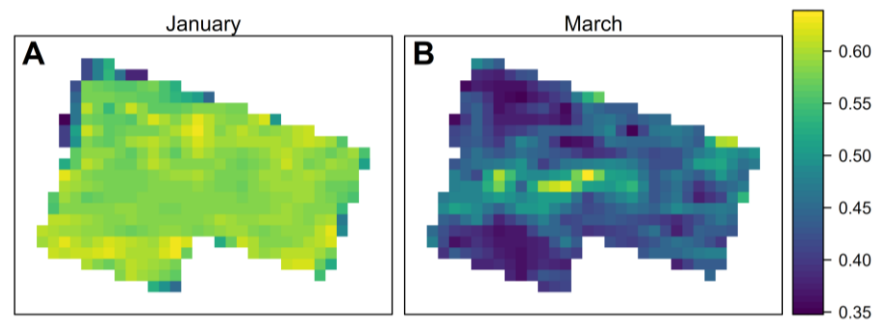


Figure 6. Vineyard-level spatial patterns of Shiraz K_c on 9 January (A) and 23 March (B) predicted using the random forest model.

Computations for Cabernet Sauvignon's K_c on November 30 showed coherent spatial structure for both approaches, with predictions from the RF model being closer to the LI-710 data registration on that date (0.64). Both approaches highlighted high K_c s toward the east sector, showing lower values to the west, an area that was affected by frost in 2023. However, our approach predicted K_c in the range of 0.54 to 0.68 (Figure 7A), which were closer to LI-710 sensor results than the calculations made with the empirical relationship provided in [24], which showed a broader range from 0.24 to 0.81 (Figure 7B)

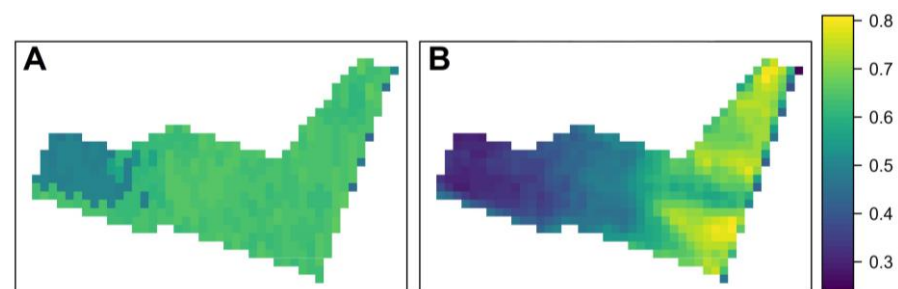


Figure 7. Spatial patterns of Cabernet Sauvignon K_c predicted for 30 November 2023 using a random forest model with: (A) unmixed indices and (B) the equation proposed in [24].

4. Discussion

Our results showed that spectral unmixing of Sentinel-2 VIs can improve the accuracy of K_c in vineyards, facilitating an approach that can be applied to different cultivars and time frames. The importance of our approach is most critical when cover crops confound early- and late-season spectral signals. Below, we discuss the steps taken, together with practical limitations and avenues for improvement.

4.1. Canopy Area Model

Estimating the canopy area based on the NDVI showed consistent results for Shiraz and Cabernet Sauvignon and proved to be reliable for Chardonnay. These results suggest that the canopy area models developed in this study may be applicable to other winegrape cultivars, provided that their canopy growth and NDVI time series follow similar patterns. However, predictions during winter and spring months, when cover crops are growing at their peak rates (e.g., October in our case), require special attention. The logistic model developed to correct the overprediction of canopy area effectively lowered the predictions for this initial growth stage. Unfortunately, we lacked image or field data to validate the predictions. Acquiring early-season canopy area data could improve the accuracy of the cover area model and enhance the subsequent spectral unmixing procedure.

4.2. Crop Coefficient Model

Random forest and SVM models could be considered more reliable options than GAM, despite the high accuracies achieved by GAM models in all cultivars. Both the RF and SVM models showed accurate predictions, with RF exhibiting greater stability across the time series, particularly during the late season. This pattern may be due to RF's robustness to outliers, achieved through the averaging of multiple decision trees [72]. This averaging also makes them less sensitive to overfitting [73]. The SVM models performed comparably to RF in most cases, reinforcing their value as complementary approaches. While the GAM models demonstrated the highest apparent accuracies, particularly for Chardonnay, these values appeared inflated. The flexibility of the GAM models in capturing nonlinear relationships can lead to overfitting, especially when predictors are collinear or small sample sizes are used, resulting in high R^2 values that do not necessarily reflect genuine improvements in predictive accuracy.

Importantly, the indices most frequently selected in the RF and SVM models were based on red-edge bands, reflecting their strong sensitivity to chlorophyll content. Nevertheless, indices based only on RGB and NIR bands also proved relevant, likely because their finer spatial resolution (10 m) allowed for more detailed detection of pigment concentration patterns. Moreover, the inclusion of SWIR bands is indicative of the presence of moisture within vegetation, highlighting the importance of vegetation water status in explaining K_c variability.

4.3. Effectiveness of Spectral Unmixing

The application of linear spectral unmixing improved model performance by separating the spectral responses of the grapevine canopy and background elements. This separation mitigated the distorting effect of cover crops on vegetation indices. Cover crops in South Australia inflate vegetation indices at early phenological stages, when vines are developing and cover crops are greener, and depress indices during late stages and senescence, when cover crops become dry or absent. By isolating the canopy signal, unmixing enabled the use of indices more closely related to grapevines than cover crops, especially in the early- and late-season stages, yielding more robust and consistent K_c predictions across phenological stages. This advantage could be observed when compared to the results obtained using the equation provided by Campos et al. [24] in the early season, which tended to overinflate K_c values. Importantly, we note that the same (Campos) study was conducted in vineyards with bare soil inter-rows, using data from days with minimal soil evaporation when no vine water stress was observed, thereby reducing noise and mixed-pixel effects. Hence, it is plausible that our approach can handle scenarios with greater vineyard variability.

The application of spectral unmixing improved model performance to varying degrees across different cultivars. In Shiraz, unmixing was especially effective, resulting in unmixed indices consistently lower than mixed values in October. This response separation produced a canopy signal that better tracked the K_c evolution, explaining the higher accuracy achieved by the unmixed GAM, RF, and SVM models. In Chardonnay, the effect of unmixing was weaker than in Shiraz. Although unmixed indices were lower than mixed values in October, later dates were not always lower compared to predictions from the mixed models. Nevertheless, the GAM and RF models still achieved higher accuracy with unmixed inputs over the season. Both the unmixed and mixed model predictions for Cabernet Sauvignon were similar. In the case of the SVM model, higher values in October were observed for unmixed indices, which may be related to the more vigorous and greener canopy of Cabernet Sauvignon compared to the understory. In this situation, unmixing elevated NDVI values leads to only moderate improvements in model performance.

The unmixed vegetation indices were subject to several outliers, especially during the early season when the cover crops were substantial. The variability in the composition of cover crops likely affected the unmixing procedure since the vineyard mid-rows occasionally contained vegetation different to that present at the cover crop reference points. Annual grasses primarily dominated the cover crops but were occasionally accompanied by broad-leaf weeds or more vigorous grass species with denser or greener biomass, potentially influencing the spectral signal of the mid-rows. Furthermore, bare soil was not included as an endmember in the present study; however, its influence should be considered in vineyards without cover crops or during late-season periods when cover crops have fully senesced. Future studies should carefully assess patterns of mid-row vegetation, considering the mix of species, and the influence of bare soil and other potential endmembers.

Future improvements to our analysis may involve advanced separation techniques. For example, [20] proposed combining multispectral and structural masking from high-resolution UAV imagery, using canopy height and NDVI thresholds to effectively isolate pure vine canopy pixels, while excluding soil, inter-row vegetation, and underperforming vines. Similar approaches could be applied to high-resolution commercial satellite RGB imagery (Airbus, Jilin/Gaofen). Another promising tool is the Latent Diffusion Super Resolution model for Sentinel-2 (LDSR-S2) [81], which enhances spatial resolution from 10 m to 2.5 m while preserving spectral consistency, and provides pixel-wise uncertainty maps. In contrast to traditional pan-sharpening, LDSR-S2 supports spectrally consistent super-resolution across all bands, enabling more accurate VI computation directly from Sentinel products. This approach would allow vineyard endmembers to be accurately classified, and their specific spectral reflectance determined.

5. Conclusions

This study demonstrates that machine learning models based on vegetation indices derived through spectral unmixing can effectively predict crop coefficients (K_c) in vineyards. Random forest models provided the most stable and reliable performance, while SVM models were less stable with independent data, and GAM models achieved higher but potentially inflated accuracies. The application of spectral unmixing improved model accuracy, especially in Shiraz and Chardonnay during the early and late canopy stages when pixel variability was greater due to inter-row variability in terms of cover crop and bare soil. Red-edge and SWIR indices proved relevant in model selection due to their capacity to capture canopy chlorophyll and moisture dynamics. These findings highlight the potential of open-source remote sensing and machine learning to provide scalable, cost-effective tools for irrigation scheduling and sustainable vineyard management.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs17193365/s1>, Figure S1: Season trajectories for mixed (blue) and unmixed (red) NDVI and NDRE indices in Shiraz (A,B), Cabernet Sauvignon (C,D), and Chardonnay (E,F).

Author Contributions: V.P. conceived the initial concept of the research. V.P. and D.R.G.-T. designed the research. D.R.G.-T. and V.P. acquired the UAV remote sensing data. D.R.G.-T. processed and analysed the data, and, together with V.P., interpreted the results. D.R.G.-T. and H.L. prepared the manuscript. All authors contributed to the review and editing of the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: The authors acknowledge the funding contribution of Primary Industries and Regions South Australia (PIRSA; Grant ID: AGF-17639418) and Athena IR-Tech. We also thank Treasury Wine Estates for their in-kind support and access to their vineyards used in this trial.

Data Availability Statement: The dataset is available on request from the authors.

Acknowledgments: The authors are grateful to Sami Rifai for providing technical information about Google Earth Engine. We are grateful to the vineyard growers and managers who facilitated the data collection, as well as members of the Pagay lab who assisted with the fieldwork, with special thanks to Caoyang (Wesley) Wang.

Conflicts of Interest: The authors declare no conflicts of interest.

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