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Interannual Variation in UAV Vegetation Index Relationships with Grapevine Yield and Quality: A Two-Year Case Study in Madeira

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Highlights

What are the main findings?

- NDRE and GNDVI were the most frequently involved in nominal associations with grapevine yield and quality parameters, particularly during the 2024 growing season.
- The two growing seasons showed contrasting exploratory patterns in spectral–agronomic relationships, but none of the tested associations remained statistically significant after FDR correction.

What are the implications of the main findings?

- Seasonal and environmental context should be considered when interpreting relationships between UAV-derived vegetation indices and grapevine productivity and quality.
- Single-season spectral–agronomic relationships require evaluation across multiple years and environmental conditions before temporal consistency or broader applicability is assumed.

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Abstract

Unmanned aerial vehicle (UAV)-derived vegetation indices are increasingly used to characterize vineyard canopy variability, yet their relationships with grapevine yield and grape quality may vary between growing seasons. This two-year case study evaluated associations between multispectral vegetation indices and grapevine productivity and quality parameters in a commercial Verdelho vineyard on Madeira Island during the 2024 and 2025 growing seasons, which differed markedly in accumulated precipitation (77.3 and 249.1 mm, respectively), while thermal accumulation increased from 1411 GDD to 1525 GDD in 2025. UAV multispectral imagery was acquired at key phenological stages using a MicaSense Altum sensor. NDVI, NDRE, GNDVI, GLI, and NGRDI were evaluated in relation to yield and grape-quality parameters using Spearman rank correlations based on nine independent experimental replicates per season. To support interannual comparison despite unequal

UAV survey availability, seasonal analyses were additionally based on four phenologically matched stages represented in both years. Statistical uncertainty and robustness were assessed using bootstrap confidence intervals, leave-one-out sensitivity analysis, Benjamini–Hochberg false discovery rate correction, and treatment-adjusted partial rank correlations. Relatively strong nominal associations were observed in 2024, particularly involving NDRE and GNDVI, whereas fewer nominal date-specific associations occurred in 2025. No nominal associations were detected for the phenologically matched seasonal means in 2025. However, none of the date-specific or seasonal-mean associations remained statistically significant after FDR correction. Treatment adjustment preserved the direction of all nominal associations but reduced their magnitude in most cases. The results indicate contrasting exploratory interannual patterns rather than statistically confirmed temporal instability. UAV-derived vegetation indices provided useful information on vineyard spectral variability, but relationships with yield and grape quality identified within a single season require validation across larger multi-year and multi-site datasets before broader temporal consistency or transferability can be established.

Keywords: precision viticulture; UAV; vegetation indices; grapevine yield; grape quality; climatic variability; interannual variation

1. Introduction

Precision viticulture (PV) has become an important approach for characterizing the spatial and temporal variability within vineyards and supporting more efficient management decisions. Vineyard variability is influenced by edaphoclimatic, topographic, and management-related factors, including soil properties, water availability, nutritional status, canopy development, pest and disease pressure, and agronomic practices [1–4]. Understanding this heterogeneity is essential for implementing site-specific strategies, such as selective harvesting, precision irrigation, and localized fertilization, to improve yield, grape quality, and resource-use efficiency.

Advances in remote and proximal sensing technologies have greatly improved vineyard monitoring by enabling rapid, non-destructive, and high-resolution assessments of crop conditions [5,6]. Among these technologies, unmanned aerial vehicles (UAVs) have become particularly useful in viticulture because they can provide detailed georeferenced imagery at the intra-plot scale using RGB, multispectral, hyperspectral, and thermal sensors [7]. This capability is especially relevant in fragmented vineyards and areas with irregular topography, such as Madeira Island, where satellite imagery may be limited by mixed pixels and insufficient spatial resolution [8].

UAV-derived vegetation indices are widely used to describe canopy spectral properties associated with vine vigor, biomass, leaf area, nutritional status, and plant physiological conditions [9,10]. The normalized difference vegetation index (NDVI) is one of the most commonly used indices in agricultural studies because of its relationship with photosynthetic activity and vegetation vigor [11,12]. In viticulture, NDVI and other spectral indices have been used to identify vigor zones, assess canopy development, describe spatial variability, and support vineyard management decisions [13,14]. However, NDVI may be affected by saturation under high canopy density and soil background effects in vineyards with low canopy cover [15,16]. Therefore, indices based on the red-edge and green spectral regions, such as NDRE and GNDVI, have gained increasing attention for vineyard monitoring.

Several studies have reported relationships between vegetation indices, vine vigor, and grapevine performance. High-vigor zones are often associated with greater canopy development and, in some cases, higher yield, whereas low-vigor zones may be associated with different ripening patterns and grape composition [17]. Spectral indices have also been evaluated at different phenological stages as indicators of yield-related variability, allowing growers to identify spatial differences within vineyards before the harvest [18]. Beyond yield, vegetation indices have been related to grape quality parameters, including soluble solids, acidity, phenolic compounds, anthocyanins, and other berry composition traits [19–21]. These studies indicate that spectral information can provide useful indirect information on vineyard variability and grape quality.

However, vegetation indices primarily describe canopy spectral properties and vine vigor, whereas grape yield and berry composition are also influenced by reproductive development, crop load, source–sink balance, and seasonal environmental conditions. Therefore, significant relationships observed between vegetation indices and yield or quality parameters in a single season may not be transferable to another season. This discrimination is important because a vigorous canopy does not always imply a proportional increase in yield or grape quality, particularly when climatic conditions modify the balance between vegetative growth and fruit development.

The temporal stability of the relationship between vegetation indices, grapevine yield, and grape quality remains poorly understood. Most studies are based on a single season or specific environmental conditions, making it difficult to determine whether vegetation indices consistently reflect grapevine performance under contrasting climatic scenarios. Variations in temperature, rainfall distribution, and water availability between growing seasons may alter vine physiology, canopy development, and berry composition, thereby affecting the extent to which canopy spectral responses are associated with harvest-related variables [22,23]. This represents an important limitation for the use of single-season relationships as transferable indicators in precision viticulture.

A growing body of recent research has addressed spatio-temporal vineyard variability through multi-temporal remote and proximal sensing, with UAV-based multispectral imagery emerging as one of the most widely used approaches for within-vineyard monitoring [24,25]. In the last five years, authors have mainly used vegetation indices to characterize canopy vigor, management zones, and temporal changes across phenological stages, while also relating these spatial patterns to yield and, less consistently, to grape composition [24,26]. NDVI remains the most frequently adopted index in viticulture, but recent studies increasingly combine it with NDRE, GNDVI, MSAVI, SAVI, NDWI, FAPAR, and fractional cover to reduce saturation effects, improve sensitivity to canopy structure and water status, and strengthen prediction across contrasting vineyard conditions.

Recent work also shows that robust assessment of vineyard variability increasingly depends on integrated workflows rather than on vegetation indices alone [26,27]. In row crops such as grapevine, segmentation of pure canopy pixels has become a key methodological step because soil, shadows, and inter-row vegetation can bias spectral responses, whereas canopy-only UAV products generally provide a more reliable representation of true vine variability than mixed-pixel or coarse-resolution imagery [25,28]. Beyond spectral indices, recent studies have combined thermal data, canopy height or thickness, crop surface models, soil electrical conductivity, fluorescence sensing, and machine-learning methods to improve the interpretation of water status, vigor, yield, berry chemistry, and harvest zoning [29]. At the same time, interannual studies indicate that vineyard vigor patterns can remain spatially stable across seasons, although the strength of relationships with yield, quality, and vine physiology varies with climate, cultivar, and phenological stage, which supports the need for multi-season validation before transferring empirical relationships

between years or sites [25,30]. Despite these advances in UAV-based monitoring, several methodological challenges remain. The fragmented layout of vineyards, characterized by rows of plants interspersed with bare soil and, in some cases, cover crops or spontaneous vegetation, complicates spectral data analysis. Although UAV imagery provides very high spatial resolution and can reduce the mixed-pixel problem commonly associated with satellite imagery, the extraction of vegetation index values must be carefully defined to ensure that the spectral information is meaningful in relation to field measurements [31–33]. This is particularly relevant when UAV-derived indices are compared with yield or grape quality measurements obtained at the plant or replicate level.

Madeira Island provides a relevant context for evaluating this question in this study. Vineyards on the island are often small, fragmented, and located on sloping terrain, with marked spatial heterogeneity and strong cultural and economic importance. Under these conditions, UAV-based monitoring may provide valuable information for precision viticulture; however, the transferability of spectral relationships between growing seasons still needs to be better understood.

Therefore, this study aimed to characterize interannual variation in the relationships between UAV-derived vegetation indices, grapevine yield, and grape quality parameters during two consecutive growing seasons, 2024 and 2025, under contrasting environmental conditions on Madeira Island. Rather than establishing long-term temporal stability or testing the causal effect of climatic conditions on grapevine development, the study examined whether the magnitude, direction, and consistency of spectral–agronomic relationships differed between the two seasons. Environmental variables were therefore used to characterize the seasonal context rather than as experimentally isolated causal drivers. To reduce potential bias associated with the unequal number of UAV acquisitions, interannual seasonal comparisons were additionally based on four phenologically matched survey stages available in both years.

2. Materials and Methods

2.1. Study Area

This study was conducted in a private vineyard of *Vitis vinifera* L. cv. Verdelho, located in the parish of Fajã da Ovelha, Madeira Island, Portugal, and covers an area of 330 m^2. According to the Köppen–Geiger climate classification, this area is classified as Csb, characterized by rainy winters and dry and moderately warm summers. Temperatures range from 12 °C to 24 °C, with an average annual temperature of 17.1 °C and total annual precipitation of approximately 620 mm [8].

Agricultural activities on Madeira Island predominantly occur in mountainous regions within a geographically limited area influenced by both subtropical and Mediterranean climates. Traditional agroecosystems, locally referred to as fazendas, typically span less than one hectare and are arranged into narrow terraces (poios) bordered by dry-stone walls. Irrigation is supported by an extensive historical network of channels (levadas) that convey water from higher elevations [34]. The combination of mountainous terrain and favorable climatic conditions supports the cultivation of a wide variety of crops, including bananas, sugarcane, avocados, exotic fruits, and various horticultural species [35]. Among the cultivated crops, vineyards hold particular significance because of their role in producing internationally acclaimed Madeira wine.

The experimental vineyard was managed under rainfed conditions during both the 2024 and 2025 growing seasons, and no supplemental irrigation was applied to the study area. The traditional "levada" irrigation network described above represents the broader agricultural context of Madeira Island and was not used for irrigation of the experimental vineyard.

2.2. Experimental Trial

The study was conducted within a pre-existing field experiment established as part of the AGROSUS project. The experimental area comprised three weed-management treatments: (i) sowing a mixture of legumes and grasses, (ii) mechanical control, and (iii) conventional herbicide application using glyphosate (Figure 1). Each treatment replicate was considered the independent statistical unit, resulting in nine independent units per growing season (three treatments x three replicates). Each treatment included 15 plants. The present study was not designed to compare the agronomic effectiveness of the weed-management treatments. However, the treatment structure was retained because it defined the experimental units from which both UAV-derived vegetation indices and harvest measurements were obtained and could potentially contribute to variation in the spectral–agronomic relationships.

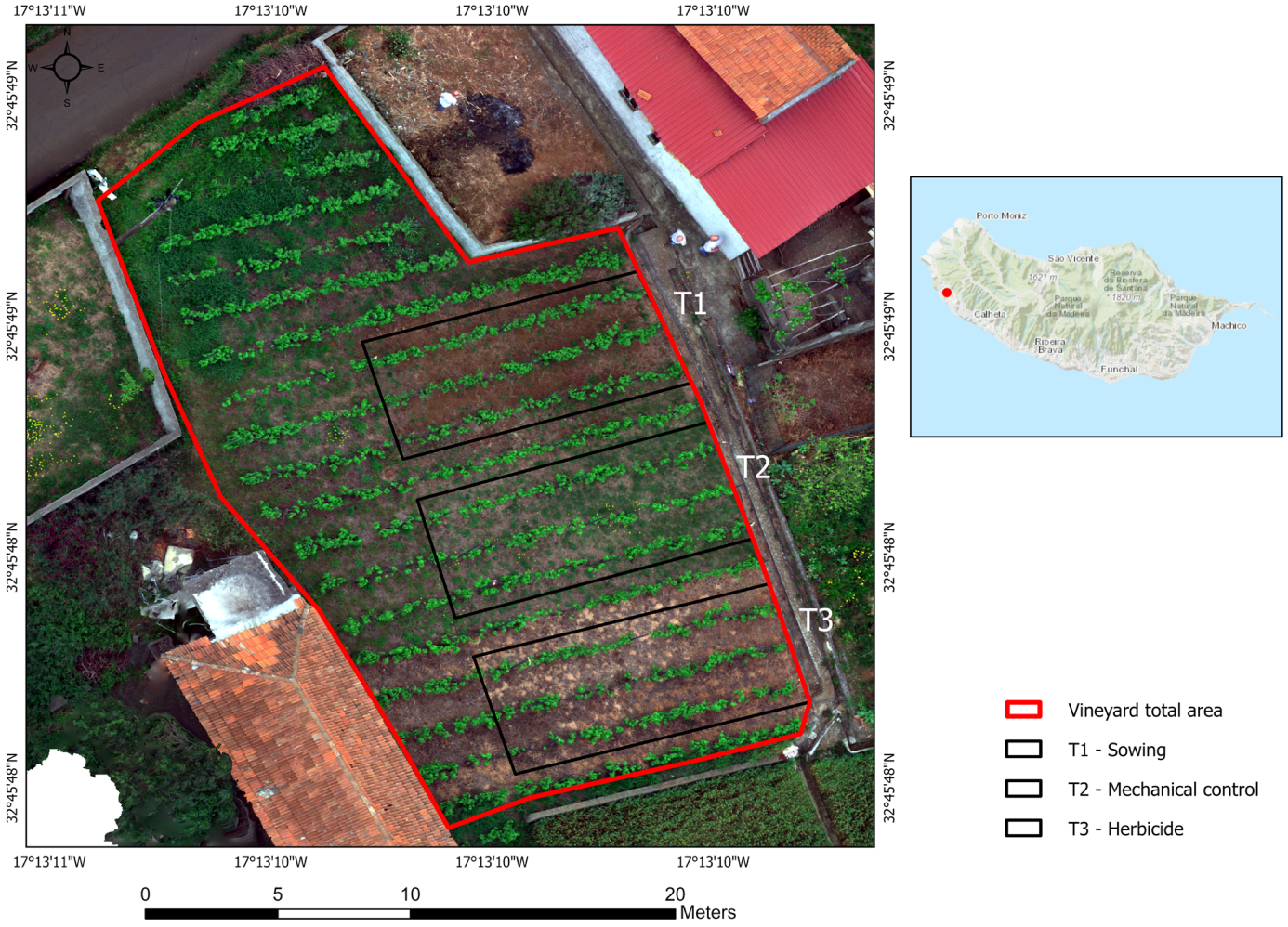


Figure 1. Location of the experimental vineyard and spatial layout of three weed-management treatments.

2.3. Climatic Characterization

Climatic conditions during the 2024 and 2025 growing seasons were characterized using meteorological data obtained from stations operated by the Portuguese Institute for Sea and Atmosphere (IPMA) on Madeira Island. Because no individual meteorological station was considered sufficiently representative of the experimental vineyard, spatialization procedures were applied to estimate temperature and precipitation for the study site. Monthly maximum and minimum air temperatures (°C) corresponded to the monthly means of daily

maximum and daily minimum temperatures, respectively, while accumulated precipitation (mm) was obtained for each growing season.

Air temperature at the experimental site was estimated using an altitude-based spatialization approach previously applied to Madeira Island [35] and based on established procedures for the spatial estimation of air temperature as a function of elevation [36,37]. Precipitation was spatialized using the Inverse Distance Weighting (IDW) method, following the approach previously applied to the characterization of vineyard agroecosystems on Madeira Island [34]. The same station network and spatialization procedures were applied independently to the 2024 and 2025 datasets. The geographic coordinates and elevation of the 18 IPMA meteorological stations used in these procedures are provided in Table 1.

Table 1. Geographic coordinates and elevation of the IPMA meteorological stations used for the spatial interpolation of temperature and precipitation during the 2024 and 2025 growing seasons.

Meteorological Station	Latitude (°)	Longitude (°)	Elevation (m.a.s.l.)
Funchal/Observatório	32.65	−16.89	58
Funchal/Lido	32.64	−16.93	25
Santa Catarina/Aeroporto	32.69	−16.77	58
Lugar de Baixo/Ponta do Sol	32.68	−17.09	40
Calheta/ponta do Pargo	32.81	−17.26	298
Santana/São Jorge	32.83	−16.91	257
Chão do Areeiro	32.72	−16.92	1590
Caniçal/Ponta de São Lourenço	32.75	−16.71	133
Santana	32.81	−16.89	380
São Vicente	32.80	−17.05	97
Santo da Serra	32.73	−16.82	660
Quinta Grande	32.66	−17.00	580
Pico Alto	32.69	−16.90	1118
Pico do Areeiro	32.74	−16.93	1799
Porto Moniz	32.87	−17.17	35
Cancela	32.65	−16.86	260
Monte	32.68	−16.90	593
Prazeres	32.75	−17.20	635

Note: elevation is expressed in meters above sea level (m.a.s.l.).

Mean monthly air temperature ($T_{mean,m}$) was estimated from the spatialized monthly means of daily maximum and minimum air temperatures as:

$$T_{mean,m} = \frac{T_{max,m} + T_{min,m}}{2}$$

where ($T_{max,m}$) and ($T_{min,m}$) represent the monthly means of daily maximum and daily minimum air temperatures, respectively. Monthly growing degree-day accumulation was then estimated using a base temperature (T_{base}) of 10 °C for grapevine development:

$$GDD_m = (T_{mean,m} - T_{Base}) \times n$$

where n represents the number of days included in the corresponding monthly period. Seasonal thermal accumulation was calculated as:

$$GDD_{season} = \sum GDD_m$$

with monthly GDD values summed from 1 April to the corresponding harvest date in each growing season. All monthly mean temperatures during the evaluated growing-season periods were above the adopted base temperature. Because the spatialized climatic dataset

was analyzed at monthly resolution, GDD was used as an approximation of seasonal thermal accumulation for descriptive comparison between the two growing seasons rather than as a daily phenological or physiological model.

2.4. Experimental Years

The two growing seasons were characterized by contrasting environmental conditions, particularly in terms of accumulated precipitation and thermal accumulation. These differences provided an opportunity to examine the temporal consistency of the relationships between UAV-derived vegetation indices and grapevine productivity and quality attributes across two consecutive seasons. UAV surveys were performed at key phenological stages throughout both growing seasons, from vegetative development to harvest. Detailed information regarding the flight and harvest dates is provided in Table 2.

Table 2. UAV flight schedule and associated grapevine phenological stages in the 2024 and 2025 seasons.

Season	Flight Date	Phenological Stage
2024	08 May	Inflorescence development
2024	28 May	Flowering onset
2024	25 June	Berry development
2024	02 August	Veraison/Beginning of Ripening
2024	03 September	Harvest
2025	06 May	Inflorescence development
2025	03 June	Flowering onset
2025	09 July	Berry development
2025	17 September	Harvest

At harvest, grapevine yield and grape quality measurements were obtained for each experimental replicate. Total yield per replicate was calculated as the combined production of the five vines within each replicate, and mean yield per plant was obtained by dividing total replicate yield by the number of vines evaluated. Berry diameter was assessed using one randomly selected bunch per vine, with measurements taken at the basal, middle, and apical portions of each bunch. Grape quality parameters included ash content, pH, electrical conductivity, and titratable acidity (TA). Grape juice pH was determined according to AOAC method 943.02. Titratable acidity was determined by volumetric titration according to AOAC method 962.19 and expressed as a percentage of tartaric acid. Ash content was determined gravimetrically after incineration at 550 °C according to AOAC method 923.03. Total soluble solids (TSS) were not included because corresponding analytical data were not available for the dataset used in the present study. These variables were subsequently related to the vegetation indices derived from the UAV imagery.

Yield and grape quality parameters were measured once at harvest and were not independently determined at each UAV survey date. For each phenological-stage UAV survey, replicate-level vegetation index values were paired with the corresponding replicate-level harvest measurements. Thus, the date-specific analyses evaluated whether canopy spectral characteristics observed at different phenological stages were associated with final yield and grape quality attributes.

Each growing season was analyzed independently and comparatively to assess interannual differences in the relationships between vegetation indices and grapevine productivity and quality parameters.

For the interannual comparison of seasonal vegetation index values, only UAV surveys corresponding to phenologically comparable stages in both growing seasons were used. These stages were inflorescence development, flowering onset, berry development, and

harvest. A UAV survey at veraison was successfully conducted on 2 August 2024, whereas the corresponding veraison survey could not be completed in 2025 due to technical problems during the planned data acquisition period. Therefore, the 2024 version survey was retained for the date-specific analysis of the 2024 season but excluded from the calculation of the seasonal mean used for interannual comparison. Seasonal mean vegetation index values were consequently calculated from four phenologically matched UAV surveys in each growing season.

2.5. UAV Image Acquisition and Processing

UAV multispectral imagery was acquired using a DJI Matrice 210 RTK V2 multirotor platform (DJI, Shenzhen, China) equipped with a MicaSense Altum multispectral thermal sensor (MicaSense, Seattle, WA, USA). UAV surveys were conducted during the 2024 and 2025 growing seasons at key phenological stages, from inflorescence development to harvest. Flights were performed close to solar noon under clear-sky conditions, low wind speed, and stable illumination to minimize shadow effects and radiometric variability.

Image alignment, dense point cloud generation, and orthomosaic production were performed using Agisoft Metashape Professional 2.1.1 (Agisoft LLC, St. Petersburg, Russia, 2024) [38]. For each UAV survey, the main acquisition and photogrammetric processing parameters, including the number of images, point density, and ground sampling distance (GSD), were obtained from the Agisoft Metashape processing reports and are summarized in Table 3. The resulting orthomosaics had approximately centimetric spatial resolution, which supported the separation of grapevine canopy pixels from bare soil and inter- row vegetation prior to vegetation index extraction. Radiometric calibration was performed for all UAV surveys conducted during the 2024 and 2025 growing seasons using images of a calibrated reflectance panel, acquired in conjunction with the MicaSense Altum multispectral camera. The calibration procedure was applied during image processing in Agisoft Metashape Professional 2.1.1 (Agisoft LLC, 2024) [38] to convert the raw multispectral image data into reflectance values prior to vegetation-index calculation. The same radiometric calibration procedure was consistently applied across both growing seasons to improve the comparability of spectral measurements between acquisition dates.

Table 3. UAV flight characteristics and photogrammetric ground resolution for the 2024 and 2025 surveys.

Flight	Date	No of Images	Point Density (pt cm^{-2})	GSD (mm $Pixel^{-1}$)
1	8 May 2024	726	0.253	9.94
2	28 May 2024	738	0.272	9.59
3	25 June 2024	726	0.277	9.51
4	2 August 2024	732	0.279	9.47
5	3 September	726	0.233	10.4
6	6 May 2025	726	0.259	9.83
7	3 June 2025	732	0.271	9.61
8	9 July 2025	738	0.291	9.28
9	17 September 2025	732	0.266	9.69

2.6. Vegetation Index Extraction and Spatial Aggregation

Following orthomosaic generation, vegetation index values were extracted from UAV-derived raster layers using a vine canopy mask. Bare soil, inter-row vegetation, and weed-covered areas were removed before index extraction so that the spectral values used in the analysis corresponded only to pixels as grapevine canopies. This procedure was adopted to minimize the influence of non-vine elements on vegetation index val-

ues, which is particularly important in vineyards with discontinuous canopy cover and inter-row vegetation.

The vine-canopy pixels were spatially aggregated at the experimental-replicate level in Section 2.2. For each UAV survey, the mean value of each vegetation index was calculated from all canopy pixels associated with each of the nine independent experimental replicates. These replicate-level vegetation index values were paired with the corresponding field measurements obtained at harvest, including total yield, mean yield per plant, and grape quality parameters. Statistical analyses were performed using nine replicate-level observations per growing season.

This aggregation procedure ensured consistency between the spatial scale of the UAV-derived spectral information and field measurements. Because grape yield and grape quality parameters were determined at the replicate level, vegetation index values were also aggregated at the same experimental scale rather than analyzed at the individual pixel level, thereby reducing potential spatial mismatch between UAV-derived spectral information and harvest measurements.

For each growing season, the statistical database therefore consisted of nine rows representing the independent experimental replicates. Each row contained the replicate-level vegetation index values for the corresponding UAV survey together with the replicate-level yield and grape quality measurements obtained at harvest. Separate datasets were generated for each survey date and growing season, while phenologically matched seasonal means were calculated separately for the interannual comparison.

2.7. Vegetation Indices Used

To characterize the canopy spectral response and assess its relationship with grapevine yield and grape quality, the same five indices employed in previous studies by Macedo et al. [39] were used (Table 4). These vegetation indices were generated using Agisoft Metashape Professional 2.1.1 (2024) [38] and subsequently processed using ArcGIS Pro 3.3.2 software (2024) [40].

Table 4. Spectral vegetation indices employed for vineyard monitoring and their mathematical formulations.

Index	Formula	Reference
Normalized Difference Vegetation Index	$NDVI = \frac{(Nir-Red)}{(Nir+Red)}$	[11]
Green Leaf Index	$GLI = \frac{(2\ x\ Green-Red-Blue)}{(2\ x\ Green+Red+Blue)}$	[41]
Green Normalized Vegetation Index	$GNDVI = \frac{(Nir-Green)}{(Nir+Green)}$	[42]
Normalized Difference Red Edge	$NDRE = \frac{(Nir-Re)}{(Nir+Re)}$	[43]
Normalized Green Red Difference Index	$NGRDI = \frac{(Green-Red)}{(Green+Red)}$	[44]

For each UAV acquisition date, vegetation index values were spatially summarized within the grapevine canopy areas corresponding to each experimental replicate. The resulting replicate-level mean was used as the spectral observation in the subsequent statistical analyses, ensuring correspondence with the independent experimental unit adopted for harvest-related measurements. This spatial aggregation avoided treating individual image pixels or multiple vines within the same replicate as independent statistical observations. Consequently, spatial averaging was used to align the spectral and agronomic measurement scales rather than to increase the effective sample size.

2.8. Statistical Analyses

Statistical analyses were performed using Jamovi software version 2.6.26 [45]. The experimental replicate was considered the independent statistical unit, consistent with the spatial aggregation of UAV-derived vegetation indices and field measurements. The experimental design therefore provided nine independent observations per growing season (three weed-management treatments × three replicates; n = 9). Individual vines within each replicate were not treated as independent statistical observations. Given the limited number of independent experimental units, the statistical analyses were considered exploratory, and emphasis was placed on the magnitude, uncertainty, and robustness of the observed associations rather than on statistical significance alone.

Data normality was assessed using the Shapiro–Wilk test. Given the limited number of independent experimental units and the exploratory objective of the study, Spearman's rank correlation coefficient (ρ) was used to evaluate monotonic relationships between UAV-derived vegetation indices and replicate-level grapevine yield and quality parameters. This non-parametric approach does not require the assumption of a linear relationship or normally distributed variables. Spearman's ρ ranges from -1 to $+1$, with positive and negative values indicating the direction of the association, respectively, and its absolute magnitude reflecting the strength of the monotonic relationship.

Correlations were analyzed separately for each growing season and UAV survey date. All available vegetation indices were systematically evaluated against the corresponding replicate-level agronomic and grape-quality variables, rather than being selected a priori according to phenological stage or correlation strength. Five indices were evaluated in the 2024 dataset (NDVI, NDRE, GNDVI, GLI, and NGRDI), whereas four indices were available in the 2025 date-specific inferential dataset (NDRE, GNDVI, GLI, and NGRDI).

Nominal statistical significance was initially assessed using a two-sided threshold of $p < 0.05$. To account for multiple testing, the resulting p-values were subsequently adjusted using the Benjamini–Hochberg false discovery rate (FDR) procedure. The FDR correction was applied across the complete family of 400 correlation tests conducted in the date-specific and phenologically matched seasonal analyses. Associations with an FDR-adjusted p-value (q-value) < 0.05 were considered statistically significant after correction. Associations with an unadjusted $p < 0.05$ that did not meet the FDR-adjusted threshold were classified as nominal associations and interpreted as exploratory evidence rather than statistically confirmed relationships.

For transparency, the main results tables report all associations reaching the nominal unadjusted $p < 0.05$ threshold, whereas the complete set of correlation tests, including weak and non-nominal associations, is provided in Table S1. Consequently, the vegetation indices appearing in the main tables reflect the nominal reporting criterion rather than a stage-specific index selection procedure.

Because the experimental area comprised three weed-management treatments, an additional treatment-adjusted sensitivity analysis was performed to evaluate whether the pooled spectral–agronomic correlations were primarily driven by between-treatment differences. For this analysis, the vegetation index and response variables were rank-transformed, and the effects of weed-management treatment were removed from each ranked variable using indicator variables representing the three treatment groups. Spearman-type partial correlations were then calculated between the resulting residuals. Treatment-specific correlations were not estimated because only three independent replicates were available within each treatment.

Given the limited overall sample size (n = 9), the treatment-adjusted analysis was considered a sensitivity analysis rather than an independent confirmatory test. To characterize the uncertainty associated with the correlation estimates, 95% percentile bootstrap

confidence intervals were calculated for Spearman's ρ using 10,000 paired resamples of the experimental units. In addition, a leave-one-out sensitivity analysis was performed by sequentially excluding each experimental replicate and recalculating Spearman's ρ using the remaining eight observations. This analysis was used to determine the extent to which the magnitude and direction of the observed associations were influenced by individual experimental units.

For the interannual seasonal analysis, mean vegetation index values were calculated at the replicate level using the four phenologically matched UAV surveys available in both years: inflorescence development, flowering onset, berry development, and harvest. For each available vegetation index, the four replicate-level observations obtained at these phenological stages were combined using an unweighted arithmetic mean to generate one seasonal mean value per experimental replicate. The additional veraison survey conducted in 2024 was excluded from this calculation to ensure equivalent temporal and phenological sampling between growing seasons. This complementary analysis was performed to examine whether summarizing canopy spectral characteristics across the four sampled phenological stages provided associations with harvest-related variables that differed from those observed at individual acquisition dates. These seasonal means were considered exploratory descriptors of the sampled canopy spectral response rather than estimates of cumulative physiological activity or continuous seasonal canopy development, and were not regarded as independent validation of the date-specific results. Seasonal-mean correlations were calculated using the same nine independent experimental replicates per growing season (n = 9); therefore, temporal averaging did not increase the effective sample size.

3. Results

3.1. Climatic Conditions

The two growing seasons differed in both rainfall amount and thermal accumulation. Total precipitation from April to harvest reached 77.32 mm in 2024 and 249.05 mm in 2025. The temporal distribution of rainfall also differed markedly between years. In 2025, precipitation was strongly concentrated at the beginning of the growing season, with 122.56 mm in April and 104.27 mm in May, corresponding to approximately 91% of the seasonal total. In contrast, rainfall in 2024 was substantially lower and more dispersed throughout the season, with the highest monthly values recorded in April (39.26 mm) and June (23.59 mm) (Figure 2).

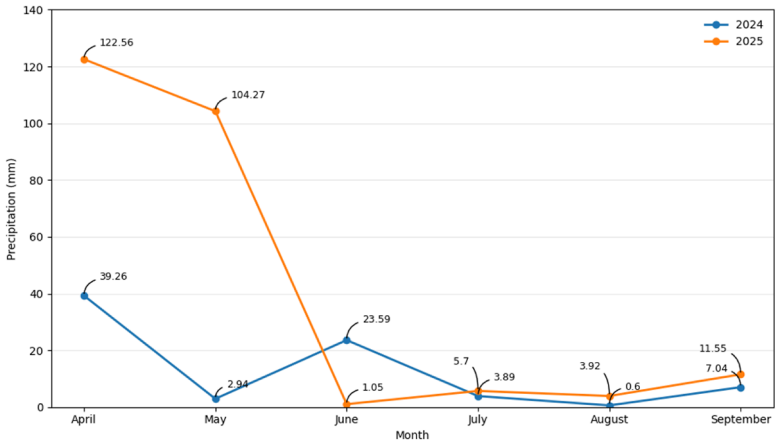


Figure 2. Monthly accumulated precipitation (mm) from April to harvest during the 2024 and 2025 growing seasons at the experimental vineyard.

Thermal accumulation also showed distinct within-season patterns (Figure 3). Total growing degree days (GDD) reached 1411.04 °C day in 2024 and 1525.11 °C day in 2025. In 2024, monthly GDD increased progressively from April (207.45 °C day) to August (354.49 °C day), with the highest accumulation occurring in July and August. In 2025, lower GDD values were recorded in April and May, followed by higher accumulation from June onward, reaching 359.29 °C day in August. July showed similar thermal accumulation in both years, with 353.56 °C day in 2024 and 342.40 °C day in 2025. The apparent difference in September GDD should be interpreted in relation to the different harvest dates, because thermal accumulation was calculated only until 3 September in 2024 and until 17 September in 2025. Therefore, the September values of 30.54 and 184.71 °C day, respectively, reflect both climatic conditions and the different duration of the accumulation period. Overall, seasonal GDD was approximately 8% higher in 2025, while the main climatic contrast between the two growing seasons was the markedly different amount and temporal distribution of precipitation.

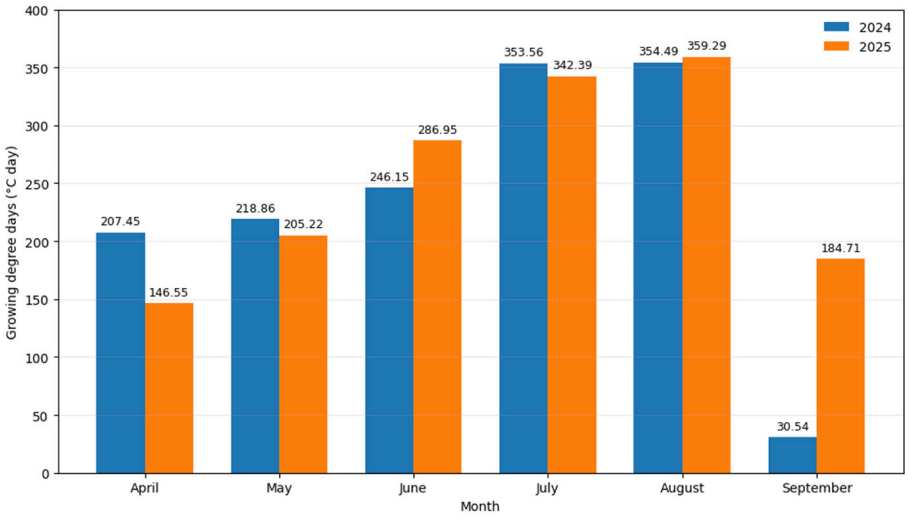


Figure 3. Monthly growing degree days (GDD) during the 2024 and 2025 growing seasons. GDD values were calculated using a base temperature of 10 °C and accumulated from April to harvest.

3.2. Descriptive Characterization of Grapevine Yield and Grape Quality at Harvest

The descriptive statistics of grapevine yield and grape quality parameters measured at harvest during the 2024 and 2025 growing seasons are presented in Table 5. All values were summarized at the experimental-replicate level, corresponding to nine independent observations per growing season (n = 9), consistent with the statistical unit adopted in the correlation analyses. Mean total yield was 15.19 ± 4.06 kg per replicate in 2024 and 14.89 ± 2.87 kg per replicate in 2025, corresponding to mean yields per vine of 3.03 ± 0.81 and 2.98 ± 0.57 kg, respectively. Mean berry diameter was 14.15 ± 0.64 mm in 2024 and 12.84 ± 0.43 mm in 2025.

Regarding grape quality-related parameters, mean biomass was 22.06 ± 1.05% DW in 2024 and 23.10 ± 1.44% DW in 2025, whereas ash content averaged 21.69 ± 0.91 and 19.02 ± 2.24 g/100 g DW, respectively. Grape juice pH exhibited relatively similar mean values between seasons (3.63 ± 0.08 in 2024 and 3.60 ± 0.09 in 2025).

These descriptive results provide the agronomic context for the subsequent analyses of associations between UAV-derived vegetation indices and harvest-related variables. They are presented to characterize the measured responses and improve data transparency, rather than to establish statistically significant differences between growing seasons.

Table 5. Descriptive statistics of grapevine yield and grape quality parameters measured at harvest during the 2024 and 2025 growing seasons.

Parameter	2024. (n = 9)	2025. (n = 9)
Total yield (kg/replicate)	15.19 ± 4.06 (9.70–22.43)	14.89 ± 2.87 (10.35–19.40)
Yield per vine (kg/vine)	3.03 ± 0.81 (1.94–4.49)	2.98 ± 0.57 (2.07–3.88)
Berry diameter (mm)	14.15 ± 0.64 (13.34–15.20)	12.84 ± 0.43 (12.01–13.41)
Biomass (% DW)	22.06 ± 1.05 (20.03–23.27)	23.10 ± 1.44 (21.46–25.20)
Ash content (g/100 g DW)	21.69 ± 0.91 (19.65–22.97)	19.02 ± 2.24 (15.98–22.20)
pH	3.63 ± 0.08 (3.51–3.75)	3.60 ± 0.09 (3.45–3.76)
Electrical conductivity (mV)	206.67 ± 5.99 (196.67–212.67)	210.85 ± 4.35 (204.00–218.33)
Titratable acidity (%)	21.81 ± 1.90 (19.33–25.25)	21.78 ± 3.32 (18.08–27.92)

3.3. Relationships Between Vegetation Indices and Grapevine Parameters During the 2024 Season

Thirty-seven date-specific associations reached the nominal $p < 0.05$ threshold during the 2024 growing season (Table 6). Two nominal associations were observed on 8 May, seven on 28 May, six on 25 June, seven on 2 August, and fifteen at the harvest survey on 3 September. Thus, nominal associations occurred throughout the growing season but were most numerous at harvest. Nevertheless, none remained statistically significant after Benjamini–Hochberg false discovery rate correction ($q < 0.05$). For transparency, Table 5 reports all date-specific associations reaching the nominal threshold, whereas the complete set of tested correlations, including non-nominal associations, is provided in Supplementary Table S2.

Table 6. Date-specific nominal Spearman rank correlations (unadjusted $p < 0.05$) between UAV-derived vegetation indices and grapevine productivity and quality parameters during the 2024 growing season.

Date	Vegetation Index	Variable	ρ	*p*-Value	FDR-Adjusted q-Value	95% Bootstrap CI
08 May	GNDVI	Yield per plant	0.800	0.014	0.191	0.182 to 1.000
08 May	GLI	Electrical conductivity	0.783	0.017	0.197	0.232 to 1.000
28 May	NDVI	Ash content	0.733	0.031	0.215	0.105 to 1.000
28 May	NDRE	Ash content	0.733	0.031	0.215	0.061 to 1.000
28 May	NDRE	Berry diameter	−0.867	0.005	0.150	−1.000 to −0.339
28 May	NDRE	pH	0.783	0.017	0.197	0.263 to 1.000
28 May	GNDVI	Ash content	0.867	0.0051	0.150	0.448 to 1.000
28 May	GNDVI	Electrical conductivity	−0.750	0.025	0.215	−1.000 to −0.086
28 May	GNDVI	pH	0.733	0.031	0.215	0.178 to 1.000
25 Jun	NDRE	Total yield	0.750	0.025	0.215	0.077 to 1.000
25 Jun	NDRE	Ash content	0.800	0.014	0.191	0.123 to 1.000
25 Jun	NDRE	pH	0.733	0.031	0.215	0.229 to 0.982
25 Jun	NDRE	Electrical conductivity	−0.917	0.001	0.101	−1.000 to −0.565
25 Jun	GNDVI	Ash content	0.850	0.006	0.152	0.257 to 1.000
25 Jun	GNDVI	Electrical conductivity	−0.850	0.006	0.152	−1.000 to −0.368
02 Aug	NGRDI	Ash content	0.867	0.005	0.150	0.464 to 1.000
02 Aug	NGRDI	Berry diameter	−0.767	0.037	0.242	−0.983 to 0.026
02 Aug	NDVI	Ash content	0.900	0.002	0.101	0.518 to 1.000
02 Aug	NDRE	Ash content	0.733	0.031	0.215	0.077 to 1.000
02 Aug	NDRE	Electrical conductivity	−0.933	<0.001	0.100	−1.000 to −0.583
02 Aug	NDRE	Total yield	0.717	0.037	0.242	0.128 to 0.983
02 Aug	NDRE	pH	0.800	0.014	0.191	0.263 to 1.000
03 Sep	NDVI	Ash content	0.833	0.008	0.165	0.236 to 1.000
03 Sep	NDVI	Electrical conductivity	−0.917	0.001	0.101	−1.000 to −0.565

Table 6. *Cont.*

Date	Vegetation Index	Variable	ρ	*p*-Value	FDR-Adjusted q-Value	95% Bootstrap CI
03 Sep	NDVI	Total yield	0.717	0.037	0.242	−0.071 to 1.000
03 Sep	NDVI	pH	0.817	0.011	0.191	0.270 to 1.000
03 Sep	NDRE	Ash content	0.700	0.043	0.275	−0.086 to 1.000
03 Sep	NDRE	Electrical conductivity	−0.950	0.071	< 0.001	−1.000 to −0.722
03 Sep	NDRE	Total yield	0.883	0.003	0.137	0.402 to 1.000
03 Sep	NDRE	Yield per plant	0.833	0.008	0.165	0.174 to 1.000
03 Sep	NDRE	pH	0.783	0.017	0.197	0.270 to 1.000
03 Sep	GNDVI	Ash content	0.733	0.031	0.215	−0.053 to 1.000
03 Sep	GNDVI	Total yield	0.800	0.014	0.191	0.179 to 1.000
03 Sep	GNDVI	pH	0.833	0.008	0.165	0.381 to 1.000
03 Sep	GNDVI	Yield per plant	0.750	0.025	0.215	0.096 to 1.000
03 Sep	GNDVI	Electrical conductivity	−0.967	<0.001	0.066	−1.000 to −0.737
03 Sep	GLI	Ash content	0.800	0.014	0.191	0.250 to 1.000

Correlations were based on nine independent experimental replicates (n = 9). The 95% percentile bootstrap confidence intervals were estimated from 10,000 paired resamples of the experimental units. Unadjusted *p*-values and Benjamini–Hochberg false discovery rate (FDR)-adjusted q-values are reported. None of the associations remained statistically significant after FDR correction (q < 0.05). Additional uncertainty and sensitivity analyses are provided in Table S1, and the complete set of correlation tests is provided in Table S2.

Among the vegetation indices systematically evaluated, NDRE and GNDVI emerged as those most frequently involved in nominal associations during the 2024 growing season, accounting for 16 and 11 date-specific associations, respectively. This pattern arose from the exploratory analysis and did not reflect an a priori selection of these indices. The observed relationships involved both yield-related and grape-quality variables, including total yield, yield per plant, berry diameter, ash content, pH, and electrical conductivity. The largest absolute correlation coefficients were observed for electrical conductivity, particularly with GNDVI at harvest ($\rho = -0.967$), NDRE at harvest ($\rho = -0.950$), and NDRE at veraison ($\rho = -0.933$). NDRE was also positively associated with total yield at harvest ($\rho = 0.883$). However, these relationships should be interpreted as exploratory nominal associations because none remained statistically significant after FDR correction.

The analysis based on phenologically matched seasonal mean vegetation index values identified 14 additional nominal associations in 2024 (Table 7). Seasonal means were calculated using the four UAV surveys corresponding to phenological stages represented in both growing seasons: inflorescence development, flowering onset, berry development, and harvest. NDRE was positively associated with total yield ($\rho = 0.767$), yield per plant ($\rho = 0.850$), and pH ($\rho = 0.783$), and negatively associated with electrical conductivity ($\varrho = -0.817$). GNDVI showed positive nominal associations with total yield ($\rho = 0.750$), yield per plant ($\rho = 0.800$), ash content ($\rho = 0.783$), and pH ($\rho = 0.850$), together with negative associations with berry diameter ($\rho = -0.700$) and electrical conductivity ($\rho = -0.900$). NDVI was negatively associated with berry diameter ($\rho = -0.800$) and electrical conductivity ($\rho = -0.733$) and positively associated with ash content ($\rho = 0.767$) and pH ($\rho = 0.783$). None of the phenologically matched seasonal-mean associations remained statistically significant after FDR correction. Therefore, these results should also be interpreted as exploratory spectral–agronomic patterns rather than statistically confirmed associations after adjustment for multiple comparisons.

Table 7. Nominal Spearman rank correlations (unadjusted $p < 0.05$) between phenologically matched seasonal mean UAV-derived vegetation indices and grapevine productivity and quality during the 2024 growing season.

Vegetation Index	Variable	ρ	p-Value	FDR-Adjusted q-Value	95% Bootstrap CI
NDRE	Total yield	0.767	0.021	0.215	0.113 to 1.000
NDRE	Yield per plant	0.850	0.006	0.152	0.282 to 1.000
NDRE	pH	0.783	0.017	0.197	0.179 to 1.000
NDRE	Electrical conductivity	−0.817	0.001	0.191	−1.000 to −0.270
GNDVI	Total yield	0.750	0.025	0.215	0.096 to 1.000
GNDVI	Yield per plant	0.800	0.014	0.191	0.179 to 1.000
GNDVI	Berry diameter	−0.700	0.043	0.275	−0.947 to −0.034
GNDVI	Ash content	0.783	0.017	0.197	0.143 to 1.000
GNDVI	pH	0.850	0.006	0.152	0.448 to 1.000
GNDVI	Electrical conductivity	−0.900	0.002	0.101	−1.000 to −0.514
NDVI	Berry diameter	−0.800	0.014	0.191	−1.000 to −0.217
NDVI	Ash content	0.767	0.021	0.215	0.222 to 1.000
NDVI	pH	0.783	0.017	0.197	0.248 to 1.000
NDVI	Electrical conductivity	−0.733	0.031	0.215	−0.949 to −0.143

As a complementary analysis to the date-specific correlations presented in Table 6, phenologically matched seasonal mean vegetation index values were calculated to summarize the spectral response of each experimental replicate across the four survey stages represented in both growing seasons. This approach allowed the evaluation of associations based on a common phenological sampling framework rather than on individual acquisition dates. Fourteen associations reached the nominal $p < 0.05$ threshold in 2024 (Table 6), although none remained statistically significant after FDR correction.

Seasonal vegetation index means were calculated from four phenologically matched UAV surveys available in both growing seasons: inflorescence development, flowering onset, berry development, and harvest. Correlations were based on nine independent experimental replicates (n = 9). The 95% percentile bootstrap confidence intervals were estimated from 10,000 paired resamples. Unadjusted p-values and Benjamini–Hochberg FDR-adjusted q-values are reported. None of the associations remained statistically significant after FDR correction ($q < 0.05$). Additional uncertainty and sensitivity analyses are provided in Table S1, and the complete correlation results are provided in Table S2.

3.4. Relationships Between Vegetation Indices and Grapevine Parameters During the 2025 Season

Twelve date-specific associations reached the nominal $p < 0.05$ threshold during the 2025 growing season (Table 8). Three nominal associations were observed on 6 May, one on 3 June, three on 9 July, and five at the harvest survey on 17 September. During the early-season survey, NGRDI was negatively associated with total yield and yield per plant ($\rho = -0.767$ for both), while GLI was negatively associated with berry diameter ($\rho = -0.733$). In June, GNDVI showed a negative nominal association with ash content ($\rho = -0.733$). None of these associations remained statistically significant after FDR correction.

The largest absolute correlation coefficients in 2025 were observed during the July survey, when NDRE and GNDVI were negatively associated with ash content ($\rho = -0.900$ and $\rho = -0.833$, respectively), whereas GLI showed a positive association with the same variable ($\rho = 0.750$). At harvest, NDRE and NGRDI were positively associated with both total yield and yield per plant ($\rho = 0.733$), while GLI was positively associated with ash content ($\rho = 0.750$). These relationships represent nominal exploratory associations because none remained statistically significant after FDR correction.

Table 8. Date-specific nominal Spearman rank correlations (unadjusted $p < 0.05$) between UAV-derived vegetation indices and grapevine productivity and quality parameters during the 2025 growing season.

Date	Vegetation Index	Variable	ρ	*p*-Value	FDR-Adjusted q-Value	95% Bootstrap CI
06 May	NGRDI	Total yield	−0.767	0.021	0.215	−1.000 to −0.174
06 May	NGRDI	Yield per plant	−0.767	0.021	0.215	−1.000 to −0.174
06 May	GLI	Berry diameter	−0.733	0.031	0.215	−1.000 to 0.065
03 Jun	GNDVI	Ash content	−0.733	0.031	0.215	−0.947 to −0.105
09 Jul	NDRE	Ash content	−0.900	0.002	0.101	−1.000 to −0.478
09 Jul	GNDVI	Ash content	−0.833	0.008	0.165	−1.000 to −0.374
09 Jul	GLI	Ash content	0.750	0.025	0.215	0.105 to 0.982
17 Sep	NDRE	Total yield	0.733	0.031	0.215	−0.009 to 1.000
17 Sep	NDRE	Yield per plant	0.733	0.031	0.215	−0.009 to 1.000
17 Sep	NGRDI	Total yield	0.733	0.031	0.215	−0.009 to 1.000
17 Sep	NGRDI	Yield per plant	0.733	0.031	0.215	−0.009 to 1.000
17 Sep	GLI	Ash content	0.750	0.025	0.215	0.105 to 0.982

Correlations were based on nine independent experimental replicates (n = 9). The 95% percentile bootstrap confidence intervals were estimated from 10,000 paired resamples of the experimental units. Unadjusted *p*-values and Benjamini–Hochberg FDR-adjusted q-values are reported. None of the associations remained statistically significant after FDR correction (q < 0.05). Additional uncertainty and sensitivity analyses are provided in Table S1, and the complete set of 2025 correlations is provided in Table S2.

In contrast to 2024, no associations reached the nominal $p < 0.05$ threshold between the phenologically matched seasonal mean vegetation indices and grapevine productivity or grape-quality parameters in 2025. The complete set of 2025 date-specific and seasonal-mean correlations, including associations that did not reach the nominal threshold, is provided in Table S2.

3.5. Uncertainty and Sensitivity Analysis

The uncertainty and robustness of the 63 associations reaching the nominal $p < 0.05$ threshold were further evaluated using 95% percentile bootstrap confidence intervals and leave-one-out sensitivity analysis (Table S1). These analyses were used to characterize the precision of the correlation estimates and their sensitivity to individual experimental units rather than to establish statistical significance after correction for multiple comparisons.

Across all 63 nominal associations, the direction of Spearman's ρ was preserved in every leave-one-out iteration. Fifty-four of the 63 bootstrap confidence intervals excluded zero, whereas nine included zero. However, because these associations were selected based on the nominal $p < 0.05$ threshold and none remained statistically significant after Benjamini–Hochberg FDR correction, exclusion of zero from the bootstrap interval should not be interpreted as independent confirmatory evidence.

The potential influence of the weed-management treatments was additionally evaluated using treatment-adjusted partial rank correlations. Adjustment for treatment preserved the direction of the original pooled correlation in all 63 associations. However, the absolute magnitude of the correlation coefficient decreased in 53 of the 63 associations and increased in 10. The median absolute correlation coefficient decreased from $|\rho| = 0.783$ in the pooled analyses to $|\text{partial } \rho| = 0.664$ after treatment adjustment. These results indicate that treatment structure contributed to the magnitude of several spectral–agronomic relationships, although it did not reverse their overall direction. Given the limited number of independent experimental units, these treatment-adjusted results should be interpreted as exploratory sensitivity evidence.

In 2024, all 37 date-specific nominal associations retained their direction throughout the leave-one-out analysis. The minimum absolute leave-one-out correlation coefficient across these associations ranged from 0.571 to 0.952, and 33 of the 37 bootstrap confidence intervals excluded zero. The 14 phenologically matched seasonal-mean associations observed in 2024 also retained their direction in all leave-one-out iterations, and their bootstrap confidence intervals excluded zero. For example, the association between NDRE and total yield at harvest ($\rho = 0.883$) had a 95% bootstrap confidence interval of 0.402 to 1.000 and ranged from $\rho = 0.833$ to 0.976 across the leave-one-out iterations. Similarly, the association between GNDVI and electrical conductivity at harvest ($\rho = -0.967$) had a 95% bootstrap confidence interval of -1.000 to -0.737 and ranged from $\rho = -0.976$ to -0.952 after sequential removal of individual experimental units.

In 2025, all 12 date-specific nominal associations also preserved their direction throughout the leave-one-out analysis, with minimum absolute leave-one-out coefficients ranging from 0.619 to 0.857. Seven of the 12 bootstrap confidence intervals excluded zero. For example, the July association between NDRE and ash content ($\rho = -0.900$) had a 95% bootstrap confidence interval of -1.000 to -0.478 and remained between $\rho = -0.929$ and -0.857 across the leave-one-out iterations.

Overall, the sensitivity analyses indicate that the direction of the nominal associations was not determined by a single experimental replicate. Nevertheless, the relatively wide bootstrap confidence intervals observed for several relationships, the attenuation of many correlation coefficients after adjustment for treatment, the small number of independent experimental units, and the absence of FDR-adjusted significance highlight the uncertainty of the estimates. The observed relationships should therefore be interpreted as exploratory evidence of effect magnitude and directional consistency rather than as statistically confirmed associations.

3.6. Interannual Comparison

The 2024 and 2025 growing seasons showed contrasting exploratory patterns in the relationships between UAV-derived vegetation indices and grapevine productivity and quality parameters. Across all analyses, 51 associations reached the nominal $p < 0.05$ threshold in 2024, comprising 37 date-specific and 14 phenologically matched seasonal-mean associations, whereas 12 nominal associations were observed in 2025, all of which were date-specific. However, these raw counts are not directly comparable because the 2024 dataset included an additional veraison survey and NDVI was not available in the 2025 date-specific inferential dataset.

To provide a more comparable descriptive assessment, the date-specific results were also considered using only the four phenologically matched survey stages and the four vegetation indices available in both years (NGRDI, NDRE, GNDVI, and GLI). Under this common analytical framework, 25 nominal associations were observed in 2024 and 12 in 2025. This difference should nevertheless be interpreted descriptively, because none of the associations remained statistically significant after Benjamini–Hochberg FDR correction.

In 2024, nominal associations involved a broader range of productivity and grape-quality variables, with NDRE and GNDVI frequently associated with total yield, yield per plant, berry diameter, ash content, pH, and electrical conductivity. In 2025, the nominal associations were more restricted and primarily involved yield-related variables, ash content, and berry diameter at specific survey dates.

The phenologically matched seasonal-mean analysis provided an additional interannual contrast. Fourteen nominal associations were identified in 2024, involving NDRE, GNDVI, and NDVI, whereas no seasonal-mean association reached the nominal $p < 0.05$

threshold in 2025. Nevertheless, none of the seasonal-mean associations observed in 2024 remained statistically significant after FDR correction.

Overall, the results indicate differences between the two growing seasons in the magnitude, direction, and temporal consistency of the spectral–agronomic relationships. These differences represent exploratory interannual patterns rather than statistically confirmed temporal instability and therefore require validation using larger datasets encompassing additional growing seasons and vineyard sites.

4. Discussion

4.1. Climatic Conditions and Growing Season Contrasts

The two growing seasons evaluated in this study were characterized by distinct climatic conditions, particularly regarding the amount and temporal distribution of precipitation. Thermal accumulation was moderately higher in 2025 (1525 GDD) than in 2024 (1411 GDD), whereas accumulated precipitation increased from 77.3 mm in 2024 to 249.1 mm in 2025. In addition to this difference in seasonal totals, rainfall distribution also differed markedly between years, with approximately 91% of the precipitation recorded in 2025 occurring during April and May. Thus, the principal climatic contrast between the two seasons was associated with precipitation amount and distribution rather than with large differences in thermal accumulation.

Previous studies have demonstrated that vine water status can substantially influence grapevine growth, canopy development, yield information, and berry composition [22,46]. Water conditions during spring may be particularly relevant because this period coincides with early vegetative development, when shoot growth, leaf expansion, and canopy establishment occur [22,46]. Likewise, temperature is a major environmental factor controlling grapevine phenological development, and thermal accumulation expressed as growing degree days (GDD) is widely used to characterize growing-season conditions and phenological progression [46,47].

The experimental vineyard was managed under rainfed conditions during both growing seasons, and no supplemental irrigation was applied. Consequently, precipitation represented the main direct external water input during the study period. However, precipitation should not be interpreted as equivalent to soil water availability or vine water status. Plant water conditions also depend on soil water storage, rooting depth, evapotranspiration, atmospheric demand, and soil hydraulic properties. Direct measurements of soil moisture, vine water potential, or other indicators of vine water status were not available in the present study. Previous research has shown that differences in vine water status can influence vegetative growth, photosynthetic activity, yield formation, and berry composition [22,46,48], but these mechanisms were not directly assessed here.

Accordingly, the contrasting precipitation regimes observed in 2024 and 2025 are interpreted as components of the environmental context of the two growing seasons rather than as evidence of a specific water-status mechanism. Because only two consecutive growing seasons were evaluated, year and environmental conditions are intrinsically confounded, and the individual effects of precipitation, thermal conditions, and other unmeasured annual factors cannot be statistically separated. Therefore, the present results do not allow the observed interannual differences in spectral–agronomic relationships to be causally attributed to rainfall or vine water status.

This distinction is particularly important because previous studies have reported that vine water status and water deficits can modify vegetative growth and grape composition [22,48]. Such findings provide a relevant physiological context for interpreting the contrasting growing seasons, but they should not be considered direct evidence of the mechanisms operating in the present vineyard. The climatic contrast observed between

2024 and 2025 therefore provides an environmental framework within which the interannual variation in UAV-derived spectral–agronomic relationships can be discussed, while mechanistic interpretation requires direct measurements of soil and plant water status in future studies.

4.2. Relationships Between Vegetation Indices and Grapevine Productivity and Quality During the 2024 Season

The 2024 growing season exhibited several relatively strong nominal relationships between UAV-derived vegetation indices and grapevine productivity and quality parameters. Date-specific associations reaching the nominal $p < 0.05$ threshold were observed throughout the growing season but were most numerous at the harvest survey, when 15 associations were identified. Some of the largest absolute correlation coefficients were also observed at harvest, particularly for relationships involving NDRE and GNDVI. However, none of these associations remained statistically significant after Benjamini–Hochberg FDR correction. Therefore, the 2024 results should be interpreted as exploratory patterns in the magnitude and direction of spectral–agronomic relationships rather than as statistically confirmed associations.

The observed patterns are consistent with previous studies demonstrating the sensitivity of red-edge and near-infrared spectral information to variation in chlorophyll content, canopy vigor, and vegetation biomass [49], as well as its application in vineyard monitoring and precision viticulture [2]. Macedo et al. [39] also identified NDRE and GNDVI as informative vegetation indices for characterizing crop productivity and aboveground biomass under the environmental conditions of Madeira Island, Portugal. Although that study was conducted on a different crop, it provides relevant local evidence that indices incorporating red-edge, near-infrared, and green spectral information can respond to spatial variation in vegetation condition. In the present study, the relatively large correlation coefficients involving NDRE and GNDVI suggest that these indices may capture components of canopy variability associated with grapevine productivity, although this interpretation requires confirmation using larger datasets.

Nominal positive relationships were observed between NDRE, GNDVI, and yield-related variables during 2024. These patterns indicate that higher values of these canopy-sensitive indices tended to occur in experimental units with greater productivity. Such a relationship is biologically plausible because canopy development, light interception, and photosynthetic activity contribute to biomass accumulation and fruit production [46,50]. Nevertheless, these physiological processes were not directly measured in the present study, and the observed correlations should not be interpreted as evidence of a specific causal mechanism. The relatively large effect sizes observed at harvest instead indicate that later-season spectral measurements warrant further investigation as potential indicators of harvest-related spatial variability.

Nominal associations were also observed between the vegetation indices and grape-quality parameters, particularly ash content, berry diameter, pH, and electrical conductivity. NDRE and GNDVI showed positive relationships with pH and strong negative relationships with electrical conductivity at several survey dates, while additional associations with ash content and berry diameter were observed for NDVI, NGRDI, and GLI. Previous studies have reported relationships between vine vigor and grape composition, although the magnitude and direction of these relationships are not necessarily consistent across vineyard conditions [12,14]. The present findings therefore suggest that UAV-derived vegetation indices may contain information related to spatial variation in grape composition, but the absence of FDR-adjusted significance indicates that these relationships should be considered exploratory rather than definitive.

The analysis based on phenologically matched seasonal mean vegetation index values showed a broadly similar pattern. Fourteen nominal associations were identified in 2024, involving NDRE, GNDVI, and NDVI and including total yield, yield per plant, berry diameter, ash content, pH, and electrical conductivity. However, none of these seasonal-mean relationships remained statistically significant after FDR correction. Taken together, the 2024 results identify potentially relevant spectral–agronomic patterns, particularly involving NDRE and GNDVI, but do not provide confirmatory statistical evidence that these relationships are transferable beyond the conditions observed in this growing season. These patterns should therefore be regarded as hypotheses for further evaluation using larger, independently replicated, multi-year datasets.

4.3. Relationships Between Vegetation Indices and Grapevine Productivity and Quality During the 2025 Season

The 2025 growing season showed 12 date-specific associations reaching the nominal $p < 0.05$ threshold. These associations were restricted to specific survey dates and involved total yield, yield per plant, berry diameter, and ash content. In contrast to 2024, no nominal associations were detected between the phenologically matched seasonal mean vegetation indices and the evaluated productivity or grape-quality parameters. Importantly, none of the date-specific associations observed in 2025 remained statistically significant after Benjamini–Hochberg FDR correction. The 2025 results should therefore be interpreted as exploratory patterns rather than statistically confirmed spectral–agronomic relationships.

The environmental conditions during 2025 differed markedly from those observed in 2024, particularly in terms of precipitation amount and temporal distribution. Accumulated precipitation was more than three times higher in 2025, with most rainfall concentrated in April and May, whereas thermal accumulation differed more moderately between years. Previous studies have shown that seasonal environmental conditions and vine water status can influence canopy development, shoot growth, leaf area, and berry composition [46,48]. These processes provide a plausible physiological context for interpreting seasonal variation in spectral–agronomic relationships. However, because soil moisture, vine water status, and related physiological variables were not directly measured in the present study, the differences observed in 2025 cannot be causally attributed to precipitation or plant water availability.

The date-specific results further illustrate the temporal variability of the relationships observed in 2025. Early in the season, NGRDI showed negative nominal associations with total yield and yield per plant, while GLI was negatively associated with berry diameter. In July, the largest absolute correlation coefficients were observed between ash content and NDRE, GNDVI, and GLI. At harvest, NDRE and NGRDI were positively associated with total yield and yield per plant, while GLI was positively associated with ash content. Although some of these effect sizes were relatively large, their occurrence at specific survey dates and the absence of FDR-adjusted significance indicate that they should not be interpreted as temporally consistent relationships.

The absence of nominal associations in the phenologically matched seasonal-mean analysis indicates that the spectral–agronomic patterns identified in 2024 were not reproduced in the same way in 2025. This observation does not imply that the vegetation indices lacked sensitivity to canopy variation; rather, it suggests that relationships between canopy spectral characteristics and harvest-related variables may depend on the seasonal and phenological context. Previous studies have similarly reported that vine water status and environmental conditions can modify the relationships among canopy development, vine vigor, and berry composition [22]. Nevertheless, these physiological mechanisms were not directly evaluated in the present experiment and should therefore be considered hypotheses rather than demonstrated explanations for the interannual differences.

More broadly, previous studies have reported that relationships between spectral indicators, vine vigor, yield, and fruit composition may vary with environmental conditions and the timing of image acquisition [22,46,48,50,51]. Such findings support the need to interpret UAV-derived vegetation indices within their seasonal and phenological context. The 2025 results therefore reinforce the importance of evaluating spectral–agronomic relationships across multiple growing seasons before temporal consistency or broader transferability is assumed [50,51].

4.4. Interannual Variation and Limitation of UAV-Derived Vegetation Index Relationships

The two growing seasons showed contrasting exploratory patterns in the relationships between UAV-derived vegetation indices, grapevine productivity, and grape-quality parameters. In 2024, nominal associations involved a broader range of response variables and were observed both at individual survey dates and in the phenologically matched seasonal-mean analysis. In 2025, nominal associations were restricted to individual survey dates, and no association reached the nominal $p < 0.05$ threshold in the seasonal-mean analysis. However, none of the date-specific or seasonal-mean associations remained statistically significant after Benjamini–Hochberg false discovery rate correction. Consequently, the observed interannual differences should be interpreted as exploratory variation in effect magnitude, direction, and temporal consistency rather than as statistically confirmed evidence of temporal instability.

Previous studies have demonstrated substantial spatial and temporal variability in vineyard vigor and yield and have shown that relationships between UAV-derived vegetation indices and agronomic variables may vary according to image-acquisition timing and phenological stage [17,51]. Vegetation indices such as NDRE and GNDVI can provide useful information on canopy condition, but their relationships with productivity and grape composition are not necessarily constant across environmental conditions, vineyard characteristics, or phenological stages [50]. Consequently, empirical relationships identified during a single growing season should not automatically be assumed to be transferable to other years without further evaluation.

Similar relationships between remotely sensed canopy characteristics and vineyard productivity have been reported previously. López-Gárcia et al. [18] demonstrated the potential of high-resolution UAV imagery for vineyard yield estimation, whereas González-Flor et al. [21] reported relationships between reflectance-based indices, grape yield, and grape composition in rainfed vineyards. Nevertheless, relationships among canopy vigor, yield, and grape composition are not necessarily proportional or constant across vineyard conditions [12,17,21]. The present results are consistent with this broader variability, although they do not establish the environmental mechanisms responsible for the differences observed between 2024 and 2025.

The descriptive interannual differences coincided with contrasting environmental conditions, particularly in the amount and temporal distribution of precipitation and, to a lesser extent, thermal accumulation. Previous studies have shown that grapevine growth, canopy development, vine water status, and berry composition can respond to environmental conditions, particularly temperature and plant water status [22,46,48]. These physiological responses provide a plausible biological context for interpreting interannual variation in spectral–agronomic relationships [50]. However, year and environmental conditions were intrinsically confounded in the present two-year study, and direct measurements of soil moisture, vine water status, canopy water content, chlorophyll concentration, or vegetative–reproductive allocation were not available. Therefore, the observed interannual differences cannot be attributed specifically to rainfall, plant water status, or changes in source–sink relationships.

These findings have practical implications for precision viticulture. UAV-derived vegetation indices provide high-resolution information on vineyard canopy variability, but grapevine yield and quality also depend on reproductive development, crop load, source–sink relationships, berry development, and other environmental and management factors. Accordingly, relatively strong spectral–agronomic relationships identified in one growing season may not necessarily be reproduced under different seasonal conditions. Multi-year datasets encompassing a broader range of environmental conditions are therefore required before temporal consistency or transferability can be established [18,51,52]. More broadly, remotely sensed canopy characteristics can provide valuable information for vineyard monitoring, but their relationships with agronomic variables depend on vineyard structure, phenological stage, environmental conditions, and the variable under consideration [17,21,50–52].

The present study should therefore be interpreted as an assessment of interannual variation in spectral–agronomic associations rather than as a predictive validation study. No predictive models were developed or independently validated. Although cross-year calibration and validation would be valuable for evaluating predictive transferability, each growing season contained only nine independent experimental units. Developing a predictive model from nine observations in one season and evaluating it using nine observations from the other would provide highly uncertain estimates of model performance and would not constitute a robust assessment of broader transferability. Studies specifically designed for prediction should therefore include larger calibration and independent validation datasets collected across multiple growing seasons and, preferably, multiple vineyards [18,51,52].

An important limitation of the present study is the relatively small number of independent experimental units within each growing season (n = 9). Although each experimental replicate comprised five vines, the replicate, rather than the individual vine, represented the independent statistical unit. This sample size provides limited statistical power, particularly for detecting small-to-moderate associations. With nine observations, relatively large Spearman correlation coefficients are required to reach a nominal two-sided $p < 0.05$ threshold, emphasizing the uncertainty associated with individual effect estimates and the need to interpret nominal associations cautiously.

The experimental units were distributed across three weed-management treatments (cover crop, mechanical weed control, and herbicide application), and pooling replicates across treatments could contribute to the observed spectral–agronomic relationships. In the treatment-adjusted sensitivity analysis, the direction of all 63 nominal associations was preserved after accounting for the weed-management structure. However, the absolute magnitude of the correlation coefficient decreased in 53 of the 63 associations and increased in 10, with the median absolute coefficient decreasing from $|\rho| = 0.783$ in the pooled analysis to $|\text{partial } \rho| = 0.664$ after treatment adjustment. These results indicate that between-treatment differences contributed to the magnitude of several relationships without reversing their direction. Nevertheless, only three independent replicates were available within each treatment, precluding reliable treatment-specific correlation analyses. Future studies with greater replication within management treatments are therefore required to distinguish within-treatment spectral–agronomic relationships from between-treatment effects.

Uncertainty associated with the small sample size was further characterized using bootstrap confidence intervals and leave-one-out sensitivity analysis. Across the 63 nominal associations, the direction of the correlation was preserved in all leave-one-out iterations, indicating that the direction of the observed patterns was not determined by a single experimental replicate. Nevertheless, several bootstrap confidence intervals were relatively wide, and nine of the 63 intervals included zero. These sensitivity analyses therefore characterize robustness and uncertainty but do not overcome the limitations imposed by

the small number of experimental units or the absence of FDR-adjusted significance. The results should consequently be interpreted with greater emphasis on effect magnitude, uncertainty, and directional consistency than on nominal statistical significance alone.

A further limitation is that the study was conducted in a single commercial vineyard over only two growing seasons. The findings should therefore be interpreted as site-specific evidence of interannual variation in spectral–agronomic relationships rather than as definitive estimates of broad temporal stability or transferability. The substantial spatio-temporal variability reported in previous vineyard remote-sensing studies further supports the need for validation across multiple sites and growing seasons [50–52].

Site-specific soil texture was not determined in the present study. Consequently, potential effects of soil physical properties on vine development and spectral–agronomic relationships could not be explicitly evaluated. Future studies should incorporate detailed soil characterization, including particle-size distribution and relevant soil hydraulic properties, together with direct measurements of soil and vine water status, to better account for edaphic and physiological variability.

The assessment of grape quality was also limited by the analytical parameters available in the present dataset. Although titratable acidity was included, total soluble solids (TSS) were not available and therefore could not be evaluated in relation to the UAV-derived vegetation indices. Consequently, the quality assessment does not encompass the complete set of conventional indicators of grape technological maturity. Future studies should incorporate TSS together with titratable acidity and other ripening-related variables to provide a more comprehensive assessment of the relationships between canopy spectral characteristics and grape composition.

Future research should therefore combine multi-year and multi-site datasets with climatic, soil, spectral, and direct physiological measurements and include different cultivars, vineyard structures, and management conditions. Where prediction is the objective, larger independent calibration and validation datasets will also be necessary to determine whether UAV-derived spectral–agronomic relationships can be transferred reliably across growing seasons and vineyard environments.

5. Conclusions

This study evaluated the relationships between UAV-derived vegetation indices and grapevine yield and quality parameters over two consecutive growing seasons, 2024 and 2025, in a commercial vineyard on Madeira Island. The two seasons were characterized by contrasting environmental conditions and showed different exploratory patterns in the magnitude, direction, and temporal consistency of spectral–agronomic relationships. Among the evaluated vegetation indices, NDRE and GNDVI were most frequently involved in relatively strong nominal associations with grapevine productivity and quality parameters. In 2024, numerous date-specific associations reached the nominal $p < 0.05$ threshold, and additional nominal relationships were identified using phenologically matched seasonal mean vegetation indices. In 2025, fewer nominal date-specific associations were observed, and no nominal relationships were detected for the phenologically matched seasonal means. However, none of the date-specific or seasonal-mean associations remained statistically significant after Benjamini–Hochberg false discovery rate correction.

Accordingly, the differences observed between the two growing seasons should not be interpreted as definitive statistical evidence of temporal instability. Rather, the results provide exploratory, site-specific evidence of interannual variation in spectral–agronomic association patterns. Because only two growing seasons were evaluated and year was intrinsically confounded with environmental conditions, the observed differences cannot be attributed to a specific climatic or physiological mechanism. In particular, precipitation

should not be considered a direct proxy for vine water status, and the present study does not provide experimental evidence of water-induced changes in vine physiology or vegetative–reproductive allocation.

UAV-derived vegetation indices nevertheless provided useful information for characterizing vineyard spectral variability and identifying potentially relevant relationships with agronomic and grape-quality attributes. However, relationships observed during a single growing season should not be assumed to persist across subsequent seasons without further validation. The present findings should therefore be regarded as those of an exploratory two-year case study rather than as predictive validation or definitive evidence of temporal stability or transferability.

Future research should incorporate larger multi-year and multi-site datasets encompassing different cultivars, training systems, management conditions, and environmental scenarios. Integrating UAV-derived spectral information with direct measurements of soil and vine water status, canopy structural and physiological traits, and reproductive development would help clarify the mechanisms underlying interannual variation. Where prediction is the objective, larger independent calibration and validation datasets will be required to develop and evaluate robust and transferable remote-sensing approaches for precision viticulture.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/rs18213650/s1, Table S1—FDR correction, bootstrap uncertainty, leave-one-out sensitivity, and treatment-adjusted partial rank correlations for all nominal ($p < 0.05$) spectral–agronomic associations in 2024 and 2025; Table S2—Complete Spearman correlation results between UAV-derived vegetation indices and grapevine yield and quality parameters for the 2024 and 2025 growing seasons.

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Data Availability Statement: The field-collected data and the datasets supporting the findings of this study are available from the corresponding author upon reasonable request. These data include replicate-level grapevine yield and grape quality measurements, UAV-derived vegetation index values, and the datasets used in the statistical analyses.

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