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Research Article

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Posted Date: June 26th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10092647/v1

Additional Declarations: No competing interests reported.

UAV-Based Assessment of Pre- and Post-Harvest Water Stress Dynamics in Vineyards Using NDRE and GNDVI Spectral Responses

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Abstract
Climate change and increasing drought frequency are intensifying water stress risks in viticultural systems, particularly in semi-arid regions where water availability directly influences grapevine productivity and quality. This study investigated pre-harvest and post-harvest water stress dynamics in a commercial Ağın Beyazı vineyard located in Eastern Türkiye using UAV-based multispectral imagery. High-resolution orthomosaics (2.31 cm pixel^{-1}) were acquired with a DJI Mavic 3 Multispectral platform and used to generate Green Normalized Difference Vegetation Index (GNDVI) and Normalized Difference Red Edge Index (NDRE) maps for both phenological periods.
Water stress responses were evaluated through pixel-based change detection, descriptive statistics, spatial heterogeneity metrics (Local Mean and Local Standard Deviation), and Global Moran's I spatial autocorrelation analysis. Results revealed measurable spectral differences between pre-harvest and post-harvest periods, indicating changes in canopy physiological activity associated with water stress and post-harvest vine responses. GNDVI exhibited a higher relative change (+10.49%) and stronger standardized response ratio, suggesting greater sensitivity to overall canopy vigor and photosynthetic activity. In contrast, NDRE showed the highest heterogeneity response (+64.97%), demonstrating superior capability for identifying localized stress variability and fine-scale physiological differences within the vineyard.
Spatial heterogeneity analyses indicated increasing local variability after harvest, while consistently positive Moran's I values (≈0.257) revealed that stress patterns remained spatially organized rather than randomly distributed. These findings suggest that vineyard water stress is controlled not only by vine physiology but also by persistent spatial factors such as soil conditions, micro-topography, and water availability.
Overall, the combined use of GNDVI and NDRE provided complementary information for vineyard water stress assessment. The proposed framework demonstrates the potential of UAV-based multispectral monitoring for precision irrigation management, early stress detection, and climate-resilient viticulture in water-limited environments.

Keywords: UAV, water stress, precision viticulture, GNDVI, NDRE, spatial heterogeneity, vineyard monitoring, multispectral remote sensing.

1. INTRODUCTION

Global climate change is exerting increasing pressure on viticultural systems through rising temperatures, altered precipitation regimes, and more frequent drought events. These impacts are particularly pronounced in arid and semi-arid regions, where declining water availability adversely affects grapevine physiological processes, resulting in significant reductions in yield and fruit quality (Gambetta et al., 2020; Mirás-Avalos & Araujo, 2021). Under water-deficit conditions, reduced photosynthetic activity and limited carbon assimilation negatively influence key growth parameters, including shoot development, leaf area expansion, and berry growth (Damásio et al., 2023; Marty et al., 2022). Although moderate water stress can enhance certain grape quality attributes, severe water deficits may impair berry composition and phenolic accumulation, ultimately compromising wine quality (Keller, 2023; Morata et al., 2019; Rienth et al., 2021). Consequently, the development of efficient irrigation and water management strategies capable of maintaining the balance between yield and quality has become a primary objective in modern viticulture.

Deficit irrigation strategies, such as Regulated Deficit Irrigation (RDI) and Partial Root-Zone Drying (PRD), have demonstrated considerable potential for improving water-use efficiency in vineyards. However, the effectiveness of these approaches largely depends on the accurate and timely assessment of grapevine water status (Bellvert et al., 2021; Frioni et al., 2023). This necessity has accelerated the adoption of precision viticulture approaches that explicitly consider within-vineyard spatial variability.

Conventional methods used to monitor vine water status, including leaf water potential, stomatal conductance, and soil moisture measurements, remain widely employed. Nevertheless, these approaches are generally based on point measurements, are labor-intensive when applied across large areas, and often fail to adequately capture the spatial heterogeneity inherent within vineyard systems (Akkamış & Çalışkan, 2020; Pérez-Álvarez et al., 2021). As a result, remote sensing technologies, particularly unmanned aerial vehicles (UAVs), have emerged as powerful alternatives for vineyard monitoring and management.

UAV platforms offer significant advantages, including low operational costs, flexible data acquisition, and centimeter-level spatial resolution, enabling detailed characterization of vineyard conditions (Manfreda et al., 2018; Sassu et al., 2021). Multispectral imagery acquired by UAV-mounted sensors facilitates the indirect assessment of physiological traits such as chlorophyll content, photosynthetic activity, and plant water status (Matese et al., 2022; Passias et al., 2024). Furthermore, the integration of UAV-derived data with machine learning and advanced image-processing techniques has substantially improved the accuracy of stress detection, yield prediction, and site-specific vineyard management practices (Doğan & Güzel, 2025; Sharma et al., 2025).

Vegetation indices constitute one of the most widely used tools for remotely assessing plant water status. Although the Normalized Difference Vegetation Index (NDVI) provides valuable information regarding vegetation vigor and biomass, its tendency to saturate under dense canopy conditions may limit its sensitivity to subtle variations in chlorophyll content and plant stress levels (Marty et al., 2022; Sagan et al., 2019). Consequently, recent research has increasingly focused on red-edge and green-band-based vegetation indices, which exhibit greater sensitivity to chlorophyll concentration, nitrogen status, and water stress.

Among these indices, the Green Normalized Difference Vegetation Index (GNDVI) is highly responsive to changes in chlorophyll content and photosynthetic activity, whereas the Normalized Difference Red Edge Index (NDRE) more effectively captures physiological variations and chlorophyll saturation in dense canopies (Morata et al., 2019; Rienth et al., 2021). Owing to its sensitivity to the red-edge spectral region, NDRE enables the early detection of changes associated with plant nitrogen status and water stress (Galieni et al., 2021; Ku et al., 2023). The combined use of GNDVI and NDRE provides a more comprehensive understanding of spectral responses to water and nutrient stress across different growth stages of grapevines (Feizolahpour et al., 2023; Mimenbayeva et al., 2023).

With the widespread adoption of UAV-based multispectral imaging systems, NDRE and GNDVI can now be generated at extremely high spatial resolutions, allowing detailed mapping of within-vineyard stress variability (Acharya et al., 2021; Liu et al., 2022). Nevertheless, most existing studies have focused on specific phenological stages or on the general performance of vegetation indices. Comparative investigations of pre-harvest and post-harvest spectral dynamics and water stress patterns using NDRE and GNDVI remain relatively scarce (Goebel & Iwaszczuk, 2023; Yang et al., 2020).

Therefore, the primary objective of this study is to evaluate pre-harvest and post-harvest water stress dynamics in vineyards using UAV-based multispectral imagery and two stress-sensitive vegetation indices, NDRE and GNDVI. Specifically, the study aims to: (i) quantify spectral changes in NDRE and GNDVI between pre-harvest and post-harvest periods; (ii) compare the sensitivity of both indices to water stress; (iii) identify and map the spatial distribution of stress patterns; and (iv) analyze spatial heterogeneity within the vineyard. The novelty of this research lies in the integrated assessment of pixel-level spectral changes, spatial heterogeneity, and stress distribution patterns derived from centimeter-resolution UAV imagery. Unlike previous studies that primarily focus on average index values, this approach provides a spatially explicit evaluation of vineyard stress dynamics. The findings are expected to contribute to the optimization of irrigation management, the early identification of stress-prone zones, and the development of decision-support systems for sustainable vineyard management under climate change conditions.

2. MATERIAL AND METHODS

2.1. Study Area

The research was carried out in a vineyard located in the Hoşköy district of Elazığ Province, Eastern Anatolia, Türkiye, a viticulturally important region characterized by unique microclimatic conditions. The area experiences a semi-arid continental climate, with hot, dry summers and limited rainfall, creating conditions conducive to the development of vine water stress during the growing season. These environmental characteristics make the study site particularly suitable for evaluating spatial patterns of canopy vigor and water stress dynamics using high-resolution UAV-based remote sensing approaches (Figure 1).

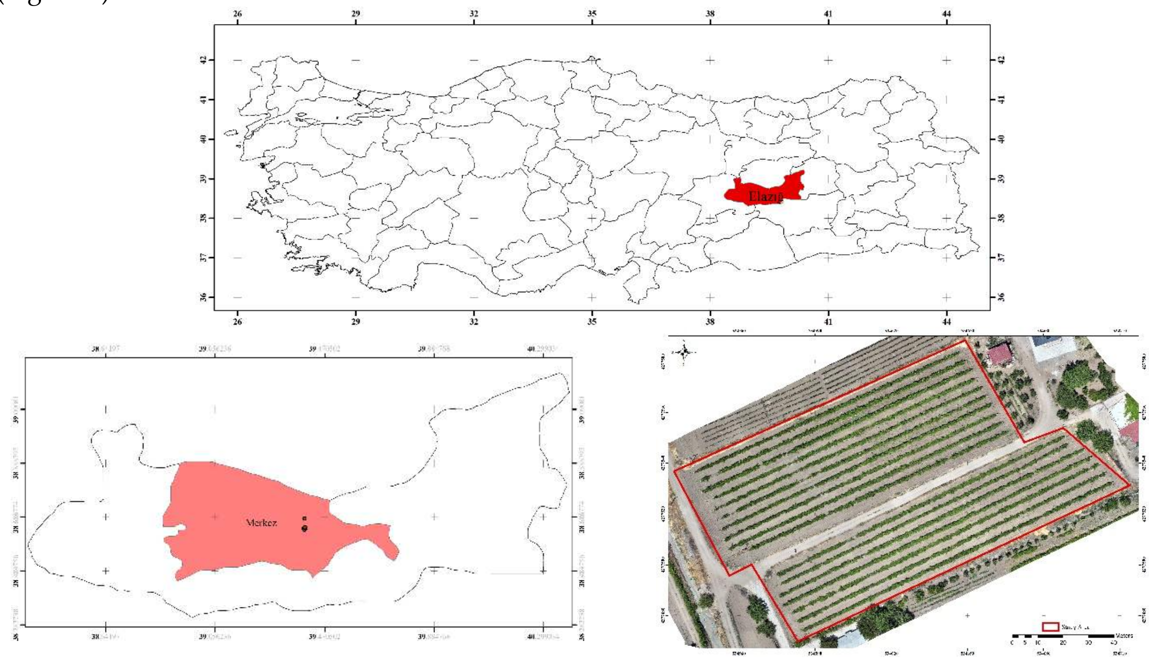


Figure 1. Study area

The study area is characterized by a mean annual temperature of 13.2 °C, an average daily sunshine duration of 7.1 h, an annual average of 94.8 rainy days, and a total annual precipitation of 420.3 mm (Turkish State Meteorological Service, 2025). These climatic conditions make vineyard water status monitoring particularly important during the ripening and harvest periods, when elevated temperatures and limited rainfall may intensify water stress in grapevines. The vineyard is situated on gently sloping terrain, which minimizes surface runoff and contributes to the acquisition of more homogeneous UAV-based observations across the study area.

A drip irrigation system is employed throughout the vineyard, and vines are arranged in a rectangular planting pattern. This configuration facilitates the discrimination of vine rows from inter-row soil surfaces in UAV-derived multispectral imagery, thereby enhancing the reliability of vegetation index-based analyses. The entire vineyard is planted with Ağın Beyazı, a local table grape cultivar characterized by large berries, thin skins, and a relatively late ripening period. Beyond its agricultural value, Ağın Beyazı represents an important regional genetic resource and constitutes a significant component of the local cultural heritage.

The research design was based on two key phenological periods: pre-harvest and post-harvest. This approach enabled a comparative assessment of harvest-induced canopy loss, changes in vegetative vigor, and spectral responses associated with vine water stress. The semi-arid climatic setting, combined with uniform irrigation management, relatively homogeneous topo-edaphic conditions, and the cultivation of a single grape cultivar, provided a suitable experimental framework for investigating the spatial dynamics of water stress using the NDRE and GNDVI vegetation indices.

Accordingly, the selected vineyard served as a representative model site under real-world production conditions for evaluating spectral changes, stress sensitivity, and spatial heterogeneity derived from UAV-based multispectral imagery during pre- and post-harvest periods. Particular emphasis was placed on the performance of NDRE and GNDVI indices in detecting canopy responses to water stress and harvest-related changes in vine condition.

2.2. UAV Data Acquisition and Image Precessing

A DJI Mavic 3 Multispectral (M3M) unmanned aerial vehicle (UAV) was employed for image acquisition. The platform integrates a multispectral sensor system consisting of four spectral bands, including Green (560 ± 16 nm), Red (650 ± 16 nm), Red Edge (730 ± 16 nm), and Near-Infrared (NIR; 860 ± 26 nm), in addition to a high-resolution RGB camera. This sensor configuration enables detailed monitoring of vegetation physiological status and canopy condition at very high spatial resolution.

Multispectral imagery was acquired during two distinct phenological stages. The first flight was conducted during the pre-harvest period, corresponding to the full ripening stage, whereas the second flight was performed immediately after harvest (post-harvest). This two-temporal acquisition strategy enabled the assessment of harvest-induced changes in canopy structure, vegetative vigor, and spectral responses associated with vine water stress.

All flights were performed at an altitude of 50 m above ground level and an average flight speed of approximately 3 m s^{-1}. To ensure high-quality photogrammetric reconstruction, image acquisition was conducted with 80% forward overlap and 70% side overlap. These flight parameters resulted in imagery with an approximate ground sampling distance (GSD) of 2.31 cm $pixel^{-1}$. To minimize radiometric variability caused by changing illumination conditions, all surveys were conducted under cloud-free weather conditions between 11:00 and 14:00 local time, when solar angle fluctuations were relatively limited.

The acquired multispectral datasets were processed using DJI Terra software. The photogrammetric workflow included image alignment, dense point cloud generation, surface reconstruction, and orthorectification procedures. Subsequently, high-resolution multispectral orthomosaics were generated for each acquisition period.

The resulting orthomosaics provided geometrically corrected and spatially comparable raster datasets for the study area. These products served as the primary data source for subsequent analyses, including canopy extraction, vegetation index computation, temporal change detection, and spatial heterogeneity assessment. The standardized acquisition and processing workflow ensured consistency between pre-harvest and post-harvest datasets, thereby improving the reliability of spectral comparisons related to vineyard water stress and canopy dynamics.

2.3. Vegetation Index Calculation

To evaluate vineyard water stress dynamics, the Green Normalized Difference Vegetation Index (GNDVI) and the Normalized Difference Red Edge Index (NDRE) were derived from multispectral orthomosaics generated from UAV imagery. Both indices were calculated on a pixel-by-pixel basis using DJI Terra software and subsequently analyzed across the entire vineyard area.

GNDVI was calculated using the near-infrared (NIR) and green spectral bands according to Equation (1) (Gitelson et al., 1996, 2003).

$$\frac{NIR - Green}{NIR + Green} \tag{1}$$

GNDVI is particularly sensitive to variations in chlorophyll concentration, nitrogen status, and photosynthetic activity due to its incorporation of the green spectral region. Compared with the conventional NDVI, GNDVI has been shown to provide enhanced sensitivity to physiological changes occurring during plant development and to more effectively capture reductions in chlorophyll content associated with water stress conditions (Abbatantuono et al., 2024; Vera-Esmeraldas et al., 2025).

NDRE was calculated using the near-infrared (NIR) and red-edge spectral bands according to Equation (2) (Barnes et al., 2003; Zarco-Tejada et al., 2004).

$$\frac{NIR - RedEdge}{NIR + RedEdge} \tag{2}$$

NDRE exploits the spectral sensitivity of the red-edge region and is therefore highly effective in detecting subtle variations in chlorophyll content and early signs of physiological stress under dense canopy conditions. Because the red-edge region represents the transition between chlorophyll absorption and near-infrared reflectance, NDRE is particularly responsive to small changes in plant health. Furthermore, it is less affected by the saturation problems commonly associated with NDVI in high-biomass vineyards, providing more reliable estimates of vine condition and water status (Abbatantuono et al., 2024; Berry et al., 2025).

The selection of GNDVI and NDRE was motivated by their complementary ability to characterize chlorophyll-related responses to vine water status through different spectral regions. While GNDVI primarily reflects variations in photosynthetic activity and chlorophyll abundance, NDRE provides enhanced sensitivity to early stress signals through the red-edge spectrum. In addition, both indices have been widely adopted in precision viticulture applications for monitoring spatial variability associated with irrigation management and vineyard health.

In this study, vegetation indices were evaluated across the entire vineyard surface rather than being restricted solely to vine canopy pixels. This whole-field approach enabled the characterization of spatial patterns arising from interactions among vine rows, inter-row spaces, exposed soil surfaces, and harvest-induced canopy changes. Consequently, the combined use of GNDVI and NDRE provided a comprehensive framework for assessing water stress dynamics, canopy vigor variations, and spatial heterogeneity between the pre-harvest and post-harvest periods.

2.4. Pixel-Based Change Detection Analysis

Pixel-based change detection analysis was performed to quantify spectral variations between the pre-harvest and post-harvest periods. For this purpose, change rasters were generated from the GNDVI and NDRE datasets by calculating the difference between the two acquisition dates for each pixel. The change indices were computed as follows (Equation 3-4):

$$\Delta GNDVI = GNDVI_{post} - GNDVI_{pre} \tag{3}$$

$$\Delta NDRE = NDRE_{post} - NDRE_{pre} \tag{4}$$

Positive values indicate an increase in vegetation index values, whereas negative values represent a decline in spectral response between the two observation periods. These change maps enabled the spatial identification of canopy alterations and potential water stress patterns associated with vineyard management and harvest-related processes.

Unlike many vineyard remote sensing studies that focus exclusively on vine canopy pixels, the present analysis was conducted across the entire vineyard surface. This approach was adopted because water stress dynamics are influenced not only by vine physiological responses but also by interactions among canopy cover, exposed soil surfaces, inter-row spaces, and the overall spatial heterogeneity of the vineyard system. Recent precision viticulture studies have emphasized the importance of evaluating vineyard conditions at the whole-field scale to support irrigation management and site-specific decision-making processes (Abbatantuono et al., 2024; Passias et al., 2024).

Furthermore, canopy reduction and increased vegetation gaps following harvest were considered integral components of the vineyard's spectral response. Consequently, no canopy mask was applied, and all pixels within the vineyard boundary were included in the analysis. This strategy allowed the assessment of not only vine-related physiological changes but also broader spatial stress patterns emerging across the vineyard landscape. Similar whole-field approaches have been successfully applied in vineyard water status monitoring and precision irrigation studies, where both vegetation and soil-related spectral signals contribute to the characterization of spatial variability (Berry et al., 2025; Giannico et al., 2024).

2.5. Spatial Heterogeneity Analysis

To characterize the spatial variability of vineyard water stress and vegetation condition, local spatial statistics and spatial autocorrelation analyses were applied to the GNDVI and NDRE raster datasets. In vineyard ecosystems, water status, vegetation vigor, and chlorophyll content rarely exhibit homogeneous spatial distributions. Instead, they are influenced by variations in soil properties, micro-topography, irrigation efficiency, and plant physiological responses, resulting in complex spatial patterns across the vineyard landscape (Hall et al., 2002; Zarco-Tejada et al., 2004). Consequently, analyses based solely on mean vegetation index values may fail to capture fine-scale spatial variability associated with stress dynamics.

Local spatial statistics were first calculated using a moving-window approach. Specifically, Local Mean and Local Standard Deviation (Local SD) were derived from the GNDVI and NDRE rasters using a 15 × 15 pixel neighborhood window, corresponding to an area of approximately 34.7 × 34.7 cm at the image spatial resolution. Local Mean represents the average index value within the neighborhood of each pixel and provides information on the local trend of vegetation vigor and photosynthetic activity (Woodcock & Strahler, 1987). Local Mean was calculated as follows Equation 5.

$$\mu_i = \frac{1}{n}\sum_{j=1}^{n} x_j \tag{5}$$

where μ_i denotes the local mean value for pixel, x_j represents neighboring pixel values, and n is the total number of pixels within the moving window.

To quantify local spatial variability and heterogeneity, Local Standard Deviation (Local SD) was subsequently calculated. This metric measures the magnitude of variation among neighboring pixels and is particularly useful for identifying fragmented or spatially heterogeneous patterns associated with differential water stress conditions (Cohen et al., 1990; Johansen et al., 2011). Local SD was computed as Equation 6.

$$\sigma_i = \sqrt{\frac{\sum_{j=1}^{n}(x_j - \mu_i)^2}{n}} \tag{6}$$

where σ_i represents the local standard deviation, x_j denotes neighboring pixel values, μ_i is the local mean, and n is the number of pixels within the analysis window. Higher Local SD values indicate greater spatial heterogeneity, whereas lower values reflect more homogeneous spatial organization.

In addition to local statistics, Global Moran's I spatial autocorrelation analysis was employed to evaluate the overall spatial organization of vegetation index values across the vineyard. Moran's I quantifies the degree to which similar values are spatially clustered and enables the identification of structured, random, or dispersed spatial patterns associated with vineyard water stress (Moran, 1950; Anselin, 1995). The statistic was calculated as Equation 7.

$$I = \frac{N}{W}\frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{7}$$

where N is the total number of observations, x_i and x_j are vegetation index values at locations i and j, $\bar{x}$ is the mean index value, w_{ij} denotes the spatial weight between observations, and W is the sum of all spatial weights. Moran's I values approaching +1 indicate strong positive spatial clustering, values near 0 indicate random spatial distributions, and negative values indicate spatial dispersion.

All analyses were performed independently for the pre-harvest and post-harvest datasets. Subsequently, Local Mean, Local SD, and Global Moran's I results were compared between acquisition periods to evaluate changes in vineyard spatial organization. This framework enabled not only the assessment of spectral changes associated with harvest and water stress but also the quantification of shifts in spatial heterogeneity and autocorrelation patterns across the vineyard landscape.

2.6. Comparative Sensitivity Analysis

A comparative sensitivity analysis was performed to quantify the magnitude of spectral changes between the pre-harvest and post-harvest periods and to evaluate the responsiveness of different vegetation indices to vineyard water stress dynamics. In this framework, GNDVI and NDRE were assessed in terms of relative change magnitude, standardized response intensity, spatial heterogeneity variation, and spatial organization dynamics. This multi-dimensional approach enabled the comparison of not only temporal changes in vegetation index values but also shifts in the spatial behavior of stress-related patterns across the vineyard (Abbatantuono et al., 2024; Berry et al., 2025).

First, the Relative Change (RC) was calculated to quantify the percentage change in mean vegetation index values between acquisition periods (Equation 8).

$$RC(\%) = \frac{\bar{X}_{post} - \bar{X}_{pre}}{\bar{X}_{pre}} \times 100 \quad (8)$$

where $\bar{X}_{pre}$ and $\bar{X}_{post}$ represent the mean vegetation index values before and after harvest, respectively.

To compare the sensitivity of the vegetation indices independently of their original measurement scales, the Standardized Response Ratio (SRR) was calculated following effect-size approaches commonly used in ecological and environmental studies (Equation 9). (Hedges et al., 1999; Nakagawa & Cuthill, 2007).

$$SRR = \frac{\bar{X}_{post} - \bar{X}_{pre}}{SD_{pooled}} \quad (9)$$

where the pooled standard deviation was computed as Equation 10.

$$SD_{pooled} = \sqrt{\frac{SD_{pre}^2 + SD_{post}^2}{2}} \quad (10)$$

Higher absolute SRR values indicate stronger responses of a vegetation index to harvest-related changes and potential water stress conditions.

To evaluate changes in spatial heterogeneity, a study-specific Heterogeneity Response (HR) indicator was derived from the Local Standard Deviation (Local SD) statistics (Equation 11).

$$HR = \frac{LocalSD_{post}}{LocalSD_{pre}} \quad (11)$$

This metric quantifies the relative change in local spatial variability between observation periods. HR values greater than 1 indicate an increase in spatial heterogeneity, whereas values below 1 suggest a more homogeneous spatial structure following harvest.

Similarly, changes in overall spatial organization were evaluated using a Spatial Organization Response (SOR) indicator based on Global Moran's I statistics (Equation 12).

$$SOR = \frac{Moran's\ I_{post}}{Moran's\ I_{pre}} \quad (12)$$

SOR values greater than 1 indicate stronger spatial clustering of similar vegetation index values after harvest, while values below 1 reflect a reduction in spatial organization and clustering intensity.

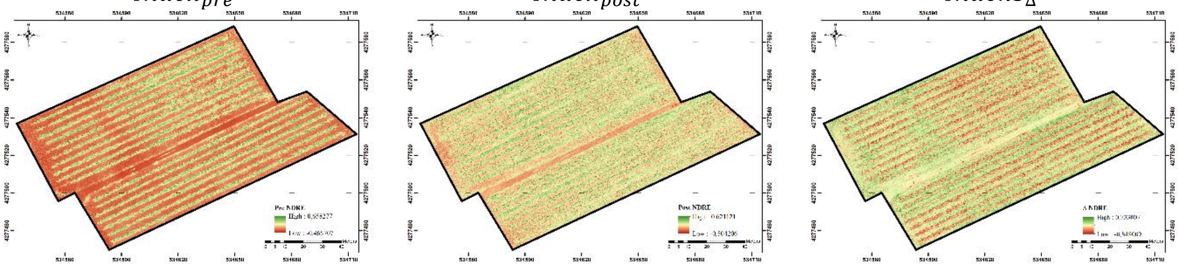
The combined interpretation of RC, SRR, HR, and SOR provided a comprehensive framework for comparing the sensitivity of GNDVI and NDRE to harvest-induced canopy modifications and water stress dynamics. By integrating spectral, spatial variability, and spatial autocorrelation metrics, the analysis enabled the identification of the vegetation index that most effectively captured both physiological changes and evolving spatial stress patterns within the vineyard.

3. RESULTS AND DISCUSSION

3.1. Temporal Changes in GNDVI and NDRE

The spatial distribution maps revealed a general decline in vegetation index values across the vineyard following harvest (Figure 2). Negative values dominated both ΔGNDVI and ΔNDRE maps, indicating a widespread reduction in vegetation vigor, chlorophyll activity, and overall canopy condition. The concentration of negative change values was particularly evident in areas characterized by dense pre-harvest vegetation cover, suggesting that harvest-related canopy modifications and late-season water limitations substantially influenced the spectral response of the vineyard.

$Index_{pre}$ $Index_{post}$ $Indeks_{\Delta}$



a *b* *c*

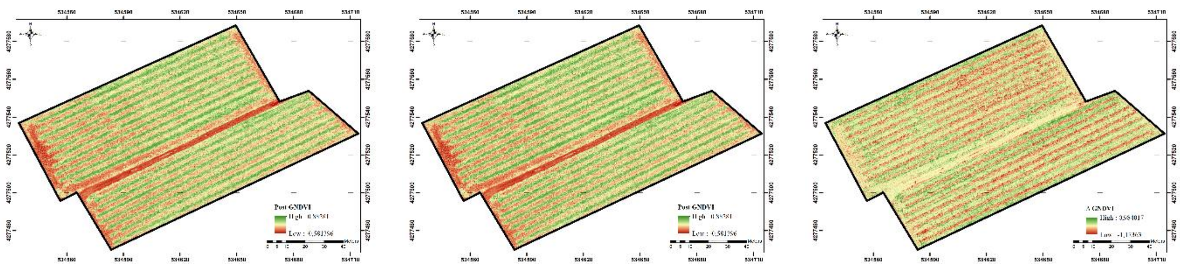


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Figure 2. Spatial distribution of vegetation indices derived from UAV multispectral imagery during the pre-harvest, post-harvest, and change-detection periods. (a–c) NDRE and (d–f) GNDVI.

Descriptive statistics further confirmed the decline in vegetation condition after harvest (Table 1). GNDVI values ranged from −0.53 to 0.91 during the pre-harvest period and decreased to −0.58–0.88 after harvest. Similarly, NDRE values declined from −0.46–0.65 to −0.50–0.62. Although the overall ranges remained relatively stable, the reduction in maximum index values indicates a decline in chlorophyll content, photosynthetic activity, and vine water status during the post-harvest period.

Table 1. Descriptive statistics of GNDVI and NDRE values derived from UAV multispectral imagery during pre-harvest and post-harvest periods.

Index	Period	Minimum	Maximum	Range
GNDVI	Pre-harvest	-0.53	0.91	1.44
GNDVI	Post-harvest	-0.58	0.88	1.46
NDRE	Pre-harvest	-0.46	0.65	1.11
NDRE	Post-harvest	-0.50	0.62	1.12

The observed reductions are consistent with physiological changes typically occurring after harvest. Removal of grape clusters alters source–sink relationships within the vine, while leaf senescence and increasing late-season water deficits contribute to reductions in photosynthetic performance and chlorophyll concentration. Previous studies have demonstrated that decreases in plant water potential are often accompanied by reductions in vegetation index values, particularly those associated with chlorophyll-sensitive spectral regions (Gambetta et al., 2020; Tang et al., 2022).

Spatially, the ΔGNDVI and ΔNDRE maps revealed that these changes were not uniformly distributed across the vineyard. Instead, distinct zones of stronger negative responses were observed, reflecting localized variations in water availability, soil conditions, irrigation effectiveness, and plant physiological status. Similar patterns of intra-vineyard spatial variability have been reported in precision viticulture studies, where water stress frequently develops in heterogeneous patches rather than uniformly across the field (Yu et al., 2020; Giannico et al., 2024).

The two vegetation indices exhibited complementary responses. GNDVI captured broader changes in chlorophyll concentration and photosynthetic activity through its sensitivity to the green spectral region, whereas NDRE provided enhanced sensitivity to subtle physiological stress signals associated with the red-edge spectrum. The persistence of localized negative NDRE responses suggests that stress-related changes remained detectable even under relatively dense vegetation conditions, where conventional vegetation indices may experience saturation effects. This finding supports previous research indicating that NDRE is particularly effective for monitoring vineyard water status and early stress responses in high-biomass environments (Abbatantuono et al., 2024; Berry et al., 2025).

Overall, the results demonstrate that both GNDVI and NDRE are effective indicators for monitoring harvest-related changes and water stress dynamics in vineyards. The high spatial resolution of UAV-derived multispectral imagery enabled the identification of fine-scale stress patterns that would be difficult to detect through conventional field observations, highlighting the potential of UAV-based monitoring systems to support precision irrigation management and site-specific viticultural decision-making.

3.2. Descriptive Statistics of Vegetation Indices

Table 2 presents the descriptive statistics of GNDVI and NDRE derived from UAV multispectral imagery acquired during the pre-harvest and post-harvest periods. Both vegetation indices exhibited slight increases in mean values after harvest. Mean GNDVI increased from 0.388 to 0.429, while mean NDRE increased from 0.094 to 0.097. At first glance, this trend may appear inconsistent with the reductions observed in the change maps and maximum index values. However, because the analysis was performed across the entire vineyard surface rather than being restricted to vine canopy pixels, the observed increase in mean values likely reflects changes in the overall spectral composition of the vineyard following harvest rather than an improvement in vine physiological condition.

Table 2. Descriptive statistics of GNDVI and NDRE indices during pre-harvest and post-harvest periods.

Index	Period	Mean	SD	Min	Max
GNDVI	Pre-harvest	0.3879	0.1954	-0.5368	0.9189
GNDVI	Post-harvest	0.4286	0.1426	-0.5814	0.8828
NDRE	Pre-harvest	0.0935	0.0906	-0.4657	0.6583
NDRE	Post-harvest	0.0971	0.0768	-0.5042	0.6211

In contrast to the increase in mean values, maximum index values decreased in both vegetation indices. GNDVI declined from 0.919 to 0.883, while NDRE decreased from 0.658 to 0.621. These reductions indicate that the most vigorous portions of the vineyard, characterized by high chlorophyll content and photosynthetic activity before harvest, experienced a measurable decline during the post-harvest period. Similar decreases in vegetation index maxima have been associated with harvest-induced physiological adjustments, chlorophyll degradation, leaf senescence, and increasing water limitations during late-season vineyard development (Gambetta et al., 2020; Abbatantuono et al., 2024).

Standard deviation values decreased substantially after harvest, from 0.195 to 0.143 for GNDVI and from 0.091 to 0.077 for NDRE. This reduction suggests a decline in spatial variability across the vineyard and indicates a tendency toward a more homogeneous spectral structure. The simultaneous occurrence of lower standard deviations and reduced maximum values suggests that highly vigorous zones became less pronounced following harvest, while differences among vineyard sectors diminished. Such homogenization has been reported in vineyards undergoing post-harvest physiological transitions, where reductions in canopy complexity and convergence in vegetation condition lead to more uniform spectral responses (Giannico et al., 2024; Vera-Esmeraldas et al., 2025).

Minimum values became slightly lower during the post-harvest period, particularly for NDRE, indicating that localized areas of physiological stress persisted within the vineyard. These localized declines likely reflect spatial differences in soil moisture availability, plant water status, and micro-environmental conditions. Previous studies have shown that water stress rarely develops uniformly across vineyard systems and instead manifests as spatially heterogeneous patterns driven by variations in soil properties, topographic conditions, and irrigation efficiency (Yu et al., 2020; Passias et al., 2024).

The combined interpretation of mean values, extrema, and variability metrics indicates that harvest did not simply result in a uniform decline in vegetation condition. Rather, the vineyard underwent a process of spatial reorganization characterized by reduced high-vigor zones, lower overall variability, and a more homogeneous spectral structure. This finding highlights the limitations of relying solely on mean vegetation index values when assessing vineyard water stress and canopy dynamics. While average GNDVI and NDRE values increased slightly, the concurrent reductions in maximum values and spatial variability demonstrate that important physiological and structural changes occurred following harvest.

Overall, GNDVI and NDRE provided complementary information regarding vineyard condition. GNDVI effectively captured broad changes in chlorophyll concentration and photosynthetic activity, whereas NDRE demonstrated greater sensitivity to subtle physiological variations associated with chlorophyll dynamics in the red-edge region. Together, these indices offer a robust framework for monitoring vineyard water status and post-harvest canopy responses using UAV-based multispectral imagery.

3.3. Pixel-Based Change Detection Analysis

Pixel-based change detection analysis was performed to quantify spectral responses between the pre-harvest and post-harvest periods using GNDVI and NDRE raster datasets (Figure 3, Table 3). The results revealed positive mean changes for both vegetation indices, although the magnitude of change differed considerably between them.

$Local\ index_{pre}$ $Local\ index_{post}$ $Local\ indeks_{\Delta}$

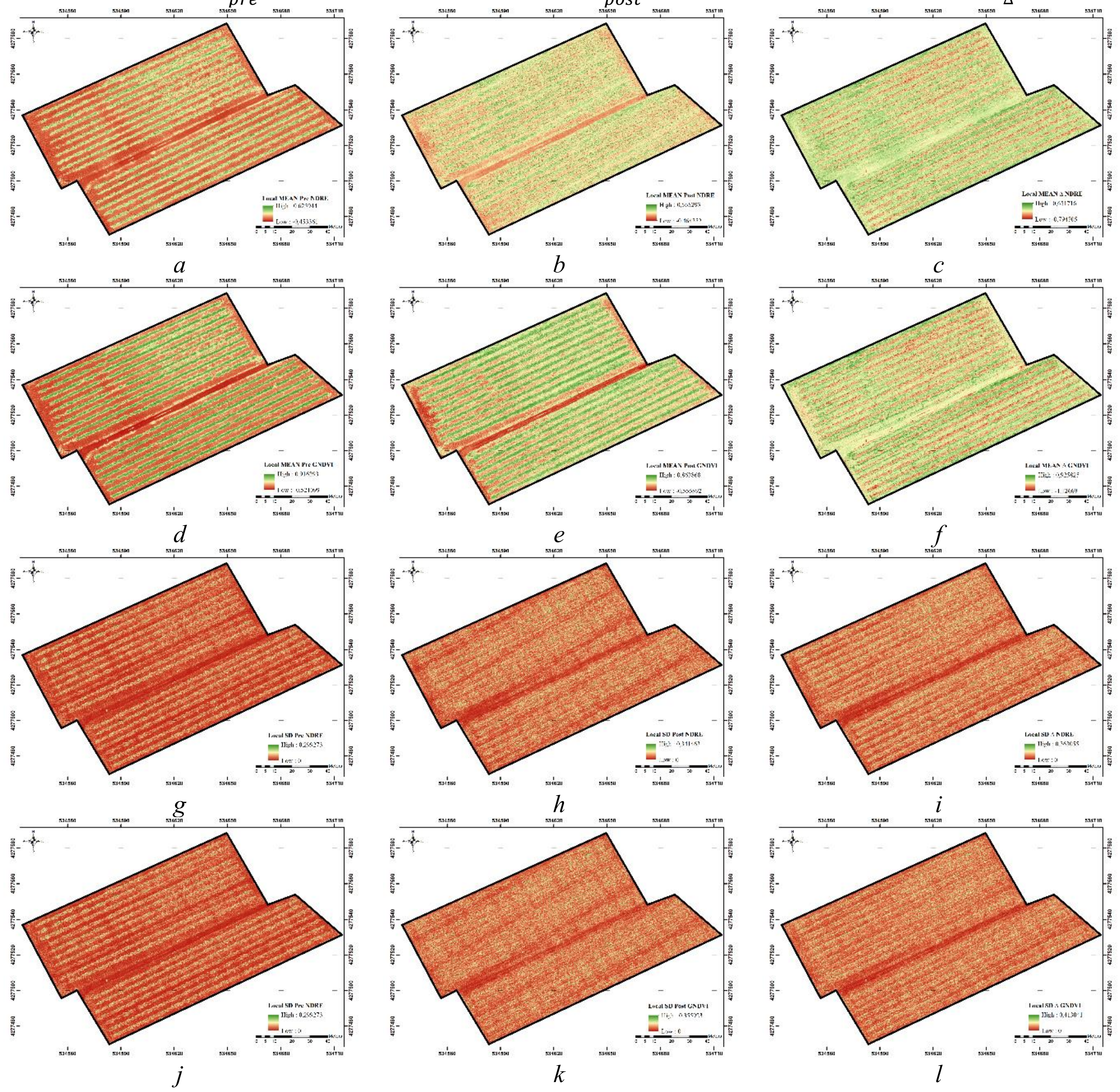

Figure 3. Spatial heterogeneity patterns derived from GNDVI and NDRE focal statistics before and after harvest. (a–c) Local Mean NDRE, (d–f) Local Mean GNDVI, (g–i) Local SD NDRE, and (j–l) Local SD GNDVI.

Table 3. Pixel-based change statistics of vegetation indices between pre-harvest and post-harvest periods.

Index	Mean Δ	SD Δ	Min Δ	Max Δ
ΔGNDVI	0.0408	0.0314	-1.1267	0.9840
ΔNDRE	0.0036	0.0322	-0.4657	0.7330

The mean change value of ΔGNDVI was calculated as 0.0408, whereas ΔNDRE exhibited a substantially smaller mean increase of 0.0036. The stronger response observed in GNDVI suggests that post-harvest spectral changes were more pronounced within the green spectral region, which is closely associated with chlorophyll activity and photosynthetic functioning. This result indicates that harvest-related modifications altered the overall spectral composition of the vineyard surface, producing a stronger response in GNDVI than in NDRE.

The relatively limited change observed in NDRE suggests that red-edge reflectance characteristics remained comparatively stable throughout the study area. Because NDRE is less susceptible to saturation effects and is strongly linked to chlorophyll dynamics in moderate-to-dense vegetation canopies, the low mean ΔNDRE value indicates that structural vegetation characteristics were largely maintained despite harvest-related modifications. Similar findings have been reported in vineyard monitoring studies, where NDRE exhibited greater temporal stability while remaining sensitive to localized physiological stress responses (Berry et al., 2025; Giannico et al., 2024).

Although mean changes were positive, the broad ranges observed in both change rasters demonstrate substantial spatial variability. ΔGNDVI values ranged from −1.1267 to 0.9840, whereas ΔNDRE values varied between −0.4657 and 0.7330. These wide distributions indicate that vineyard responses were highly heterogeneous, with some locations exhibiting substantial declines while others showed positive spectral changes. Such variability is consistent with the spatially heterogeneous nature of vineyard environments, where soil moisture availability, root-zone conditions, micro-topography, and irrigation effectiveness can generate contrasting physiological responses within the same field (Tang et al., 2022; Yu et al., 2020).

The standard deviation values of the change rasters were remarkably similar (0.0314 for ΔGNDVI and 0.0322 for ΔNDRE), indicating that both indices captured comparable levels of spatial variability despite differences in their mean responses. This finding suggests that vineyard stress dynamics were not uniformly distributed but instead occurred as localized spatial patterns. Consequently, the results reinforce the importance of site-specific management strategies and support the use of precision irrigation approaches that account for within-vineyard variability.

Overall, the pixel-based change analysis revealed that GNDVI was more responsive to harvest-induced spectral modifications, whereas NDRE exhibited greater temporal stability while remaining sensitive to localized physiological variability. The complementary behavior of the two indices highlights the value of integrating both green and red-edge spectral information when monitoring vineyard condition and spatially variable water stress dynamics. Furthermore, the coexistence of positive mean changes and broad spatial variability suggests that harvest primarily induced a reorganization of vineyard spectral patterns rather than a uniform deterioration of vegetation condition across the entire field.

3.4. Spatial Heterogenety Analysis

To further evaluate vineyard water stress dynamics beyond mean vegetation index responses, Local Mean, Local Standard Deviation (Local SD), and Global Moran's I analyses were performed using the GNDVI and NDRE datasets (Tables 4 and 5). These metrics provide complementary information regarding both the magnitude of local variability and the spatial organization of vineyard spectral patterns.

Table 4. Spatial heterogeneity metrics derived from focal statistics.

Index	Metric	Pre-harvest	Post-harvest	Change (%)
GNDVI	Local Mean	0.3879	0.4286	+10.49
GNDVI	Local SD	0.0169	0.0242	+43.43
NDRE	Local Mean	0.0935	0.0971	+3.86
NDRE	Local SD	0.0157	0.0259	+64.89

Table 5. Global Moran's I statistics.

Index	Period	Moran's I	Z-score	p-value
GNDVI	Pre-harvest	0.2572	25.87	<0.001
GNDVI	Post-harvest	0.2572	25.87	<0.001
NDRE	Pre-harvest	0.2572	25.87	<0.001
NDRE	Post-harvest	0.2572	25.87	<0.001

Local Mean values increased after harvest for both vegetation indices, consistent with the slight increases observed in the overall mean index values. GNDVI Local Mean increased from 0.3879 to 0.4286 (+10.49%), whereas NDRE Local Mean increased from 0.0935 to 0.0971 (+3.86%). These results suggest that photosynthetically active vegetation remained present throughout the vineyard after harvest and that physiological activity was not uniformly suppressed. Previous studies have demonstrated that grapevine leaves can continue to contribute to carbon assimilation and reserve accumulation during the post-harvest period, particularly under favorable environmental conditions (Gambetta et al., 2020; Abbatantuono et al., 2024).

More substantial changes were observed in Local SD values. GNDVI Local SD increased from 0.0169 to 0.0242 (+43.43%), while NDRE Local SD increased from 0.0157 to 0.0259 (+64.89%). The marked increase in local variability indicates that post-harvest spectral responses became considerably more heterogeneous across the vineyard. In particular, the stronger response observed in NDRE suggests that red-edge reflectance was more sensitive to localized physiological differences associated with chlorophyll dynamics, leaf senescence, and spatially variable water availability. Previous research has shown that red-edge-based vegetation indices are highly responsive to subtle physiological changes and often provide enhanced sensitivity to spatially heterogeneous stress conditions in vineyard ecosystems (Berry et al., 2025; Vera-Esmeraldas et al., 2025).

Despite the substantial increase in local heterogeneity, Global Moran's I analysis revealed persistent and statistically significant positive spatial autocorrelation during both periods ($p < 0.001$). Moran's I values remained constant at approximately 0.257 for both GNDVI and NDRE, indicating that vineyard spectral patterns continued to exhibit clustered rather than random spatial distributions. The consistently high Z-scores further confirm the robustness of these clustering patterns across the study area.

The combination of increasing Local SD and unchanged Moran's I values provides important insight into vineyard spatial dynamics. While local variability intensified after harvest, the overall spatial configuration of vineyard stress patterns remained remarkably stable. In other words, the locations of major clusters were preserved, whereas the magnitude of differences within and among those clusters became more pronounced. This finding suggests that harvest-induced physiological responses primarily altered the intensity of spatial variability rather than the underlying spatial organization of the vineyard.

The persistence of spatial clustering likely reflects the influence of relatively stable environmental controls, including soil properties, micro-topography, irrigation distribution, and root-zone water availability. These factors are known to generate long-term spatial patterns in vineyard water status and vegetation performance, particularly under semi-arid conditions where small differences in water accessibility can produce significant physiological responses (Tang et al., 2022; Yu et al., 2020). Consequently, the post-harvest increase in heterogeneity appears to represent an amplification of existing spatial contrasts rather than the emergence of new spatial structures.

Overall, the spatial analyses demonstrate that post-harvest vineyard dynamics were characterized by increased local heterogeneity within a stable spatial framework. Among the evaluated indices, NDRE exhibited the strongest response in Local SD, indicating superior sensitivity to fine-scale spatial variability associated with vineyard physiological condition and water stress. This finding highlights the potential of NDRE for identifying management zones and supporting site-specific irrigation strategies in precision viticulture applications. Furthermore, the combined use of Local Mean, Local SD, and Moran's I proved valuable for distinguishing changes in stress intensity from changes in spatial organization, providing a more comprehensive assessment of vineyard water stress dynamics than conventional mean-based analyses alone.

3.5. Comparative Sensitivity Analysis of Vegetation Indices

To compare the performance of vegetation indices in detecting post-harvest water stress dynamics, Relative Change (RC), Standardized Response Ratio (SRR), Heterogeneity Response (HR), and Spatial Organization Response (SOR) analyses were performed (Table 6).

Table 6. Comparative sensitivity metrics of vegetation indices for assessing post-harvest water stress dynamics

Index	RC (%)	SRR	HR (%)	SOR (%)
GNDVI	10.49	0.208	43.20	-0.003
NDRE	3.85	0.040	64.97	-0.002

The results demonstrated that GNDVI and NDRE responded to vineyard water stress dynamics at different scales. GNDVI exhibited the highest response to overall spectral change, with an RC value of 10.49%. Consistent with this finding, the higher SRR value observed for GNDVI (0.208) indicates that post-harvest physiological changes were more clearly detected at the overall vineyard scale. Due to its sensitivity to the green spectral region, GNDVI effectively reflects variations in leaf chlorophyll content and photosynthetic activity. In particular, post-harvest senescence processes, reductions in leaf physiological activity, and changes in water-use efficiency may result in substantial alterations in GNDVI values (Abbatantuono et al., 2024; Passias et al., 2024).

In contrast, NDRE exhibited lower RC (3.85%) and SRR (0.040) values. At first glance, this may suggest lower sensitivity; however, a different pattern emerged when spatial heterogeneity metrics were considered. NDRE achieved the highest HR value among all evaluated indices (64.97%), whereas the HR value for GNDVI was 43.20%. This result indicates that NDRE was more effective in capturing localized physiological variability and spatial heterogeneity associated with vineyard water stress.

The red-edge-based structure of NDRE enables the detection of subtle variations in chlorophyll concentration, particularly in vineyards characterized by moderate to high biomass. Recent studies have reported strong relationships between NDRE and leaf water potential, chlorophyll concentration, and moderate water stress responses (Berry et al., 2025; Giannico et al., 2024). Likewise, recent reviews of UAV-based vineyard monitoring have highlighted the superior discriminatory capability of NDRE compared with conventional vegetation indices under dense canopy conditions (Sharma et al., 2025; Vera-Esmeraldas et al., 2025).

The Spatial Organization Response (SOR) values were close to zero for both indices. SOR values of −0.003% for GNDVI and −0.002% for NDRE indicate that the overall spatial organization of vineyard stress patterns remained largely unchanged following harvest. This finding is consistent with the Global Moran's I analysis, which revealed strong positive spatial autocorrelation during both observation periods. In other words, although stress intensity and local heterogeneity increased after harvest, the spatial distribution of stress-prone zones remained largely stable. This pattern is likely associated with persistent environmental controls, including soil characteristics, micro-topography, and root-zone water availability, which generate relatively stable spatial structures within semi-arid vineyard ecosystems (Tang et al., 2022; Yu et al., 2020).

Overall, GNDVI exhibited greater sensitivity to broad-scale physiological responses and average vineyard condition, whereas NDRE proved more effective in identifying spatial heterogeneity and localized stress responses. These findings suggest that relying on a single vegetation index may not be sufficient for comprehensive vineyard water stress assessment and that different indices provide complementary information. From a vineyard management perspective, GNDVI appears particularly useful for evaluating overall stress levels, whereas NDRE offers greater potential for delineating management zones and supporting variable-rate irrigation strategies. Under increasing drought pressure associated with climate change, high-resolution NDRE-based monitoring approaches may provide valuable support for the early detection of vineyard water stress hotspots (Abbatantuono et al., 2024; Bahat et al., 2024; Gao et al., 2026).

This study evaluated water stress-related spectral responses occurring between pre-harvest and post-harvest periods in the local grape cultivar Ağın Beyazı using UAV-based multispectral imagery and the GNDVI and NDRE vegetation indices. The results demonstrated that both indices successfully captured temporal physiological changes; however, they exhibited different levels of sensitivity to specific stress-related components.

Pixel-based change analyses revealed measurable post-harvest variations in both GNDVI and NDRE values. The stronger mean response observed in GNDVI indicates that this index is more sensitive to changes in canopy vigor, chlorophyll activity, and overall photosynthetic performance. In contrast, NDRE provided enhanced sensitivity to chlorophyll concentration and early physiological stress signals due to its reliance on the red-edge spectral region. Recent studies have similarly demonstrated that NDRE frequently outperforms conventional vegetation indices under dense canopy conditions and serves as a reliable indicator of vineyard water status (Abbatantuono et al., 2024; Berry et al., 2025; Vera-Esmeraldas et al., 2025).

Spatial heterogeneity analyses revealed substantial increases in Local SD values following harvest, indicating enhanced physiological variability throughout the vineyard. In contrast, the consistently high and positive Moran's I values observed in both periods demonstrated that the spatial organization of stress patterns remained largely unchanged. These findings suggest that vineyard water stress patterns do not develop randomly but are instead governed by relatively persistent environmental controls, including soil properties, micro-topography, root-zone water availability, and management practices. Similar observations have been reported by Yu et al. (2020), Bahat et al. (2024), and Giannico et al. (2024).

The comparative sensitivity analysis further demonstrated that GNDVI was more effective in detecting broad-scale spectral changes, whereas NDRE provided superior sensitivity to spatial heterogeneity and localized stress responses. This finding indicates that water stress assessments based on a single vegetation index may overlook important dimensions of vineyard variability. Recent advances in precision viticulture similarly emphasize the advantages of multi-index approaches, highlighting the complementary roles of GNDVI and NDRE in supporting vineyard management and decision-making processes (Ferro & Catania, 2023; Passias et al., 2024; Sharma et al., 2025).

Although direct measurements of leaf water potential or soil moisture were not included in this study, the observed spectral responses can be considered indirect indicators of physiological processes associated with vineyard water status. Recent studies have demonstrated that the integration of UAV-based multispectral imagery with thermal sensors, meteorological observations, and machine-learning algorithms can significantly improve the accuracy of vineyard water stress assessments (Choi et al., 2025; Gao et al., 2026; Tang et al., 2022). Therefore, future research should focus on combining multispectral and thermal datasets with field-based physiological measurements to enhance the interpretation and prediction of vineyard water stress dynamics.

In conclusion, UAV-based multispectral imaging represents an effective and operationally feasible tool for characterizing water stress-related spatial variability in vineyards at centimeter-level resolution. While GNDVI proved effective in capturing overall canopy responses, NDRE demonstrated superior performance in identifying fine-scale stress heterogeneity. The combined use of these indices offers considerable potential for precision irrigation management, variable-rate irrigation applications, and climate change adaptation strategies. Furthermore, this study contributes to the limited body of literature investigating UAV-based water stress assessment, spatial heterogeneity, and vegetation-index sensitivity in the local Ağın Beyazı grape cultivar under semi-arid environmental conditions.

4. CONCLUSSION AND REMCOMMENDATIONS

This study aimed to evaluate the spatial and temporal variations associated with vineyard water stress between pre-harvest and post-harvest periods using UAV-based multispectral imagery and the GNDVI and NDRE vegetation indices. The findings demonstrated that both indices were capable of detecting physiological changes occurring within the vineyard canopy; however, they reflected different dimensions of water stress dynamics.

Pixel-based change analyses revealed substantial spectral variations across the vineyard following harvest. These changes can be associated with alterations in vine water use, photosynthetic activity, and chlorophyll dynamics. In particular, the stronger spectral response observed in GNDVI indicates that this index is a valuable indicator of changes in photosynthetic capacity and vegetative activity under water stress conditions. Although NDRE exhibited lower absolute changes, it proved more effective in capturing fine-scale physiological variability and localized stress patterns within the vineyard.

Spatial heterogeneity analyses demonstrated that post-harvest variability increased across the vineyard and that water stress became more spatially differentiated. The increase in Local SD values indicated that water stress was not uniformly distributed but instead exerted stronger effects in specific areas of the vineyard. In contrast, the Moran's I results showed that stress patterns remained spatially clustered throughout both observation periods. This finding suggests that vineyard water stress should not be interpreted solely as a temporal physiological response but also as a spatial process influenced by environmental factors such as topography, soil properties, root-zone conditions, and irrigation efficiency.

Comparative sensitivity analyses further revealed that GNDVI and NDRE were responsive to different components of vineyard water stress. While GNDVI more effectively represented overall canopy responses and water stress-related changes in photosynthetic activity, NDRE provided superior sensitivity to spatial heterogeneity and early-stage stress differentiation within the vineyard. These findings indicate that water stress assessments based on a single vegetation index may overlook important aspects of vineyard variability and that multi-index approaches can provide more reliable and comprehensive information.

The results also demonstrated that evaluating water stress solely through average vegetation index values may be insufficient. The spatial organization and heterogeneity of stress patterns should likewise be considered, as water stress often develops unevenly across vineyard systems. The identification of stress hotspots within specific vineyard zones offers valuable information for variable-rate irrigation applications and site-specific management strategies. Such approaches may allow growers to target interventions only where stress is concentrated, thereby improving water-use efficiency and reducing unnecessary water consumption.

Overall, UAV-based multispectral imaging proved to be an effective and practical tool for characterizing vineyard water stress dynamics at high spatial resolution. The combined use of GNDVI and NDRE enabled the simultaneous assessment of overall canopy condition and within-vineyard spatial stress variability. Consequently, this approach has considerable potential to support precision irrigation management, early stress detection, improved water-use efficiency, and decision-support systems aimed at mitigating the impacts of climate change on viticulture.

Future studies should integrate multispectral imagery with direct indicators of plant water status, including thermal imagery, soil moisture measurements, and leaf water potential assessments. Furthermore, investigations involving different grape cultivars, phenological stages, and climatic conditions would contribute to a more comprehensive understanding of vineyard water stress dynamics. The integration of artificial intelligence and machine-learning approaches with UAV-derived datasets may also facilitate the prediction of water stress risk and support the development of more sustainable and adaptive vineyard water-management strategies.

Funding Declaration

This research received no external funding.

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