Monitoring Long-Term Trends in Aglianico Vineyards Using a Mann-Kendall Test Approach, Sen's Slope Estimator, and Sentinel-2 Time Series

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Abstract. The vineyard sector is a key economic driver in the Mediterranean Basin, particularly in Italy, requiring a scientifically sound management plan to optimize yield and quality. Geomatic techniques provide a fast, cost-effective, and non-destructive way to collect data, with remote sensing excelling in long-term grape monitoring. The Sentinel-2 mission, launched by the European Space Agency in 2015, captures multispectral images with spatial resolutions of 10 m, 20 m, and 60 m, depending on the spectral band. While this resolution does not allow for detailed analysis at the scale of individual grape rows or leaves, it enables vineyard monitoring at the field scale with medium spatial resolution. This study explores the potential of Sentinel-2 data for analysing long-term trends using two non-parametric statistical methods: the Mann-Kendall test and Sen's slope estimator. The former detects monotonic trends, while the latter quantifies the magnitude of change over time. A time series of Sentinel-2 imagery, comprising 1,348 images spanning a ten-year period (2015–2025), was collected and pre-processed. After cloud masking and resampling all bands to a 10m spatial resolution, four vegetation indices were computed and subjected to statistical analysis. The resulting maps served as input for the aforementioned non-parametric tests. Findings highlight the effectiveness of a well-structured management plan, though certain areas require closer attention. In particular, all statistical tests consistently indicate negative long-term trends in the lower portion of the field. These results emphasize the necessity of integrating geospatial big data to enhance decision-making, surpassing the limitations of management strategies based solely on farmers' experience.

Keywords: Geospatial Big Data · Google Earth Engine (GEE) · Cloud Computing Analysis

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1 Introduction

The vineyard sector is a key component of the Mediterranean Basin economy and has gained increasing attention in recent years [1]. Traditionally, vineyard management has relied on farmers' experience and expertise [2]. However, this approach alone is insufficient. To optimize both yield and quality, a scientifically based management plan, adaptable to grape characteristics at the field scale, is essential.

Geomatic techniques offer a viable solution, providing non-destructive methods for rapid and accurate data acquisition. Among these, remote sensing has been widely used since 1972 to assess plant health and monitor vegetation changes over time [3]. However, as noted by [4], four main challenges persist: (i) a limited number of usable images due to weather conditions; (ii) the low spatial resolution of many satellite platforms, making them unsuitable for detailed field-scale analyses; (iii) the need for efficient platforms to process large datasets; and (iv) the challenge of extracting meaningful information from both single images and time series.

The first issue can be mitigated by selecting satellite missions with high temporal resolution, ensuring frequent image acquisitions. Similarly, the second challenge can be addressed by choosing appropriate satellite platforms. Although freely available satellite imagery generally has low to medium spatial resolution, Landsat (NASA) and Sentinel-2 (ESA) provide viable alternatives, offering 30 m and 10 m spatial resolution in visible bands, respectively, with revisit times of 16 and 10 days [5]. However, analyzing long-term trends requires processing vast amounts of data, exceeding the computational capacity of standalone software [6]. This limitation can be overcome through cloud-based platforms like Google Earth Engine (GEE) [7], designed to handle geospatial big data using parallel computing [8]. Additionally, GEE integrates an extensive and continuously updated dataset catalog, facilitating data selection and import via its Application Programming Interface (API) [8]. It also provides numerous tools for processing geospatial data [10, 11], enabling the implementation of various analytical approaches.

A widely used method for extracting information from vegetation is the application of Vegetation Indices (VIs). Among the numerous indices developed, Normalized Difference Vegetation Index (NDVI) [12], Optimized Soil Adjusted Vegetation Index (OSAVI) [13], Green Normalized Difference Vegetation Index (GNDVI) [14] and Normalized Difference Red Edge Index (NDRE) [15] are particularly effective for vineyard monitoring [16]. However, while these indices capture plant characteristics at a specific moment, they do not provide insights into long-term vegetation dynamics.

To analyze gradual and abrupt vegetation changes over time, specific statistical approaches are required [17]. Both parametric and non-parametric methods can be used, although the former require assumptions that limit their applicability [18], such as data following a Gaussian distribution and being sensitive to outliers. Non-parametric techniques overcome these limitations as they do not require prior distribution assumptions and are resistant to outliers. Additionally, they can handle missing values and detection limits, making them widely used in remote sensing for long-term trend analysis. Among them, the Mann-Kendall trend test [19, 20] detects monotonic trends, while Sen's slope estimator [21] quantifies changes over time.

This study evaluates the potential of Sentinel-2 medium-resolution imagery for monitoring long-term trends in an Aglianico vineyard located in the Campania region

(Southern Italy). A Sentinel-2 time series spanning ten years was analyzed using these non-parametric approaches to assess vineyard dynamics over time.

2 Material and Methods

This section provides an overview of the datasets and methodology used to achieve the research objectives. A Sentinel-2 time series covering a vineyard field dedicated to Aglianico in Campania was collected over a 10-year period (2015–2025) and imported into the cloud-based GEE platform. The pre-processing phase was then carried out to remove cloud contamination and resample the spectral bands to ensure a consistent spatial resolution across all images.

Following pre-processing, the resulting images were averaged and used as input for the subsequent analytical steps: i) computation of VIs; ii) analysis of annual VIs distribution using basic statistical metrics; iii) comparison of VIs performance; and iv) assessment of VIs trends through non-parametric statistical tests.

Further details on the input datasets and processing methods are provided in the following sections.

2.1 Study Area

The experiment was conducted in a vineyard located in Avellino, a small town in the Campania Region (Southern Italy), provided by Cantina Di Prisco. The study area (41° 0′3.25″N; 15° 1′48.85″E) covers approximately 21000 m^2 and is dedicated to the cultivation of Aglianico grapes (Fig. 1). Aglianico is one of the most renowned wines produced in Southern Italy, particularly in the Campania and Basilicata regions. It comprises three distinct biotypes: Taurasi, Taburno, and Vulture [22]. However, the vineyard selected for this study exclusively cultivates the Taurasi variety.

Aglianico is a late-ripening grape variety that requires a long growing season to reach full maturity. Budburst typically occurs in early April, followed by flowering between late May and early June [22]. Veraison, the stage when grapes begin to change color and accumulate sugars, takes place between mid-August and early September. Due to its thick skin and high tannin content, Aglianico requires an extended ripening period, with harvest usually occurring between late October and early November. This prolonged maturation enhances the grape's deep color, firm structure, and high acidity, making it well-suited for aging [22].

The vineyard installation began in 2007 and was completed in 2015. Consequently, 2015 was considered the starting point for this research analysis. By Aglianico's phenological cycle, the growing season for this study was defined as spanning from April to October..

2.2 Data Collection and Pre-processing Analysis

GEE, the cloud-based platform developed by Google in 2017 for handling geospatial big data, was selected in this study as the most reliable environment for implementing customized code and overcoming the limitations of traditional standalone software [8, 9].

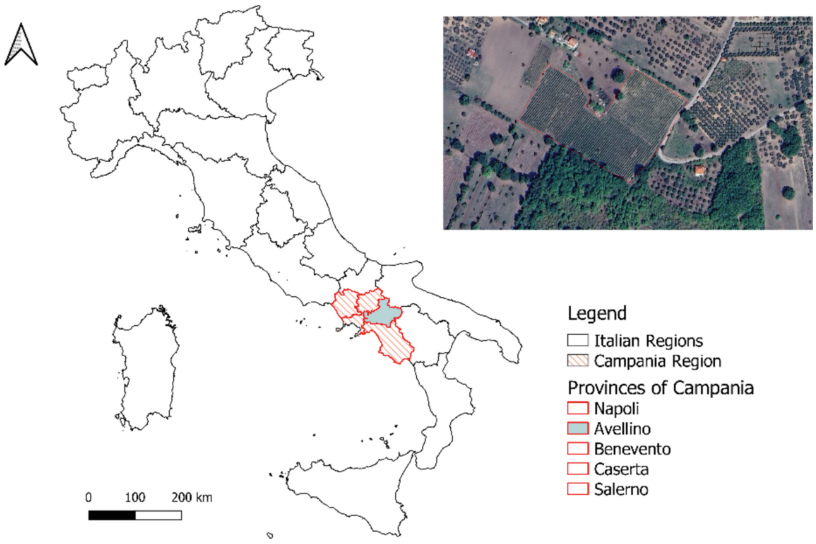

Fig. 1. Study area location.

Indeed, GEE offers innovative features that significantly accelerate both data acquisition and management processes.

Firstly, it leverages multiple processors working in parallel and provides access to an integrated data catalog, which is updated daily with 6,000 freely available scenes. These characteristics enable the processing of vast amounts of data in a relatively short time and reduce data collection efforts, as users can access raw and pre-processed datasets directly from a single platform. Additionally, users can import their own datasets. The platform also includes an integrated API that supports code development in both JavaScript and Python. In this study, customized scripts were implemented using JavaScript.

The integrated data catalog was used to select and import monthly Sentinel-2 images spanning the period from 2015 to 2025 into the GEE API. Sentinel-2 imagery consists of multiple spectral bands, each acquired at different spatial resolutions. Specifically, the four visible and Near-InfraRed bands (Blue, Green, Red, and NIR) have a native resolution of 10 m. The Red Edge (RE), ShortWave InfraRed (SWIR), and some additional bands are available at 20 m, while atmospheric and cirrus bands are provided at a coarser resolution of 60 m. The time frame was chosen to align with vineyard installation timelines. As mentioned in the previous section, the Aglianico grapevine plantation was completed in 2015. Therefore, this year was set as the starting point of the investigation to monitor the vineyard's development over time.

To maximize data availability, no cloud cover threshold was imposed during image selection. However, when necessary, images were corrected using a cloud-masking procedure based on the Quality Assessment (QA) band, as recommended by [23].

A total of 1,348 images, projected in the Universal Transverse Mercator (UTM) coordinate system and referenced to the World Geodetic System (WGS84) datum, were collected. Since their geometric accuracy was deemed satisfactory, no orthorectification

was applied. Additionally, to enhance the usability of the RE band in vegetation index calculations, it was resampled from 20 m to 10 m.

Finally, the processed data were aggregated on a monthly basis by computing their mean values, and the resulting datasets were used as input for subsequent processing steps.

2.3 Index-Based Approach

The index-based approach relies on the mathematical combination of multiple spectral bands to extract information about various elements. Each object exhibits a characteristic spectral response across different wavelengths [24]. Based on these spectral signatures, specific indices have been developed to enhance the extraction of relevant features.

Indices designed for vegetation analysis are commonly referred to as VIs. Among these, the NDVI [12], OSAVI [13], GNDVI [14], and NDRE [15] have been recognized in the literature as particularly effective for monitoring vegetation in vineyards [16] (Eqs. 1–4).

$$NDVI = \frac{NIR - RED}{NIR + RED}, \tag{1}$$

$$OSAVI = \frac{NIR - RED}{NIR + RED + 0.16}, \tag{2}$$

$$GNDVI = \frac{NIR - GREEN}{NIR + GREEN} \tag{3}$$

$$NDRE = \frac{NIR - RE}{NIR + RE}. \tag{4}$$

These indices primarily combine RGB, NIR, and RE bands. RGB bands are useful for detecting pigments such as carotenoids and anthocyanins [25], while the inclusion of NIR allows for the estimation of biophysical parameters [26]. Additionally, integrating the RE band enables the assessment of chlorophyll concentration [27].

To compute these four vegetation indices within the GEE environment, a JavaScript script was developed. The computed indices were added as additional bands to each image. As with the other spectral bands, a monthly composite was generated by averaging all available images for each month.

2.4 Statistical Analysis of Spectral Indices Outcomes

Before analyzing VIs trends throughout the grapevine growing seasons using a non-parametric statistical approach, their annual variations were first assessed. This was done by computing the monthly mean, median, standard deviation (SD), minimum (min), and maximum (max) values. These statistical measures provide insights into the distribution, central tendency, and variability of the indices over time.

Additionally, the performance of different VIs was compared by calculating the Pearson correlation coefficient. This metric quantifies the strength and direction of the linear

relationship between VIs, helping to identify which indices exhibit similar temporal patterns and how they relate to each other. A strong positive correlation suggests that two indices respond similarly to vegetation dynamics, while a weaker or negative correlation may indicate differences in their sensitivity to specific physiological or environmental factors.

2.5 Trend Analysis

Significant positive and negative trends in the annual VI time series can be identified using both parametric and non-parametric approaches. However, parametric methods require data to be independent and normally distributed, whereas non-parametric methods are more flexible and robust, as they only assume data independence [17].

For this reason, the Mann-Kendall test and Sen's slope estimator, two widely used non-parametric methods, were selected and combined to identify significant trends. Specifically, the Mann-Kendall test was applied to detect the presence of monotonic trends, while Sen's slope estimator quantified the rate of change over time. Both methods were applied just on vineyard growing seasons. A detailed description of both methods is provided in the following sections.

2.6 Mann-Kendall Test

The Mann-Kendall test, introduced by Mann (1945) and later expanded by Kendall [19, 20], is widely used for analyzing satellite time series due to its robustness against a small number of outliers, which have minimal impact on the results [28]. In this study, the test was applied to identify positive and negative trends in VI values at the pilot site. However, rather than considering the entire time series, the analysis was restricted to the Aglianico growing season, as previously explained. The test statistic S is computed using the following equation:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(x_j - x_i), \tag{5}$$

where x_i and x_j represent valid observations at two different time points ($j > i$), and n is the total number of observations. The function sgn $(x_j - x_i)$ is defined as follows:

$$sgn(x_j - x_i) = \begin{cases} 1, & if \ x_j - x_i > 0 \\ 0, & if \ x_j - x_i = 0 \\ -1, & if \ x_j - x_i < 0 \end{cases}, \tag{6}$$

This function detects increases and decreases in the time series: a positive value indicates an increasing trend, a negative value a decreasing trend, and zero signifies no change. The results were analyzed at both the local and overall levels to assess trends at specific points and their impact on the entire dataset [29]. Assuming the observations are independent, the expected value and variance of S are calculated as follows [30].

$$E(S) = 0. \tag{7}$$

$$VAR(S) = \frac{n * (n-1) * (2n+5)}{18}. \tag{8}$$

The test statistic S is then used to compute t, an estimator of Kendall's τ, which measures the probability of concordance between two observed variables:

$$t = \frac{2S}{n(n-1)}. \tag{9}$$

$$\tau = P\Big(y_i < y_j | x_i < x_j\Big) - P\big(y_i > | x_i < x_j\big). \tag{10}$$

The expected value and variance of t are given by:

$$E(t) = 0. \tag{11}$$

$$VAR(S) = \frac{2n * (2n+5)}{9n(n-1)}. \tag{12}$$

Finally, the standardized test statistic Z, which follows a normal distribution, is computed as follows:

$$Z = \begin{cases} \frac{S-1}{\sqrt{VAR(S)}}, & if\ S > 0 \\ 0, & if\ S = 0 \\ \frac{S+1}{\sqrt{VAR(S)}}, & if\ S < 0 \end{cases} \tag{13}$$

The test was conducted at a significance level of $\alpha = 0.05$. A trend is considered significant when $|Z| > Z_{1-\alpha/2}$, where $Z_{1-\alpha/2}$ is derived from the standard normal distribution table. In this study, a significant trend was identified when $|Z|$ exceeded 1.96.

2.7 Sen's Slope Estimator

The magnitude of statistically significant trends detected through the Mann-Kendall test was evaluated using Sen's slope estimator [21]. The slope (Q_i) was calculated by using the following formula:

$$Q_i = \frac{(X_j - X_k)}{j-k} \quad \text{for i} = 1, 2, \ldots \text{N}. \tag{14}$$

where Xj and Xk are data values at times j and k ($j > k$), and N is the total number of observations in the time series. Sen's estimator B is then given by the median of all computed slopes:

$$B = \begin{cases} Q * \frac{N+1}{2}, & if\ N\ is\ odd \\ \frac{1}{2}\big(Q * \frac{N}{2} + Q * \frac{N+1}{2}\big), & if\ N\ is\ even \end{cases} \tag{15}$$

3 Results and Discussion

This study aims to analyze long-term trends in an Aglianico vineyard located in Avellino, a small municipality in the Campania Region, over a 10-year period (2015–2025). The starting year was chosen based on the vineyard's installation timeline. Although planting began in 2007, it was completed in 2015, making this the ideal starting point for a comprehensive analysis of vineyard development.

A Sentinel-2 time series covering the entire period was selected and processed within GEE, the cloud-based geospatial analysis platform developed by Google in 2017. Sentinel-2 imagery was preferred over other freely available datasets due to its higher spatial resolution. Likewise, GEE was chosen over traditional standalone software because of its ability to streamline data acquisition and processing. The platform benefits from an integrated data catalog, updated daily with 6,000 freely accessible scenes, which can be directly imported into its API without requiring manual downloads. Additionally, GEE's cloud computing infrastructure, leveraging multiple parallel processors, enables efficient storage and processing of large-scale geospatial datasets [8, 9].

A total of 1,348 Sentinel-2 images were collected and pre-processed. This included cloud removal where necessary and resampling of the RE band to 10 m to ensure consistency in spatial resolution and prevent errors in VI calculations. Four VIs, NDVI, OSAVI, GNDVI, and NDRE, were selected based on their proven effectiveness in vineyard monitoring [16]. These indices leverage different spectral combinations: NDVI, OSAVI, and GNDVI integrate NIR with RGB bands, allowing the estimation of biophysical parameters [26], while NDRE incorporates the RE band, making it particularly useful for assessing chlorophyll concentration [27].

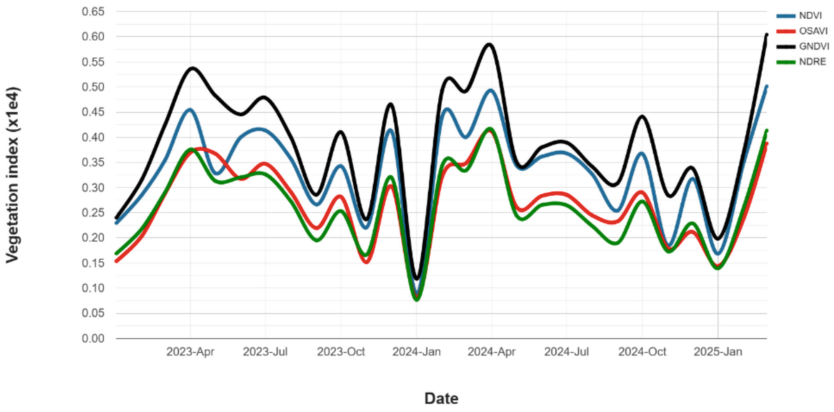

Fig. 2. Monthly mean of computed VIs over the 2015–2025 period.

Each index was computed for all available images, and basic statistical metrics (mean, median, standard deviation, minimum, and maximum) were extracted on a monthly basis to analyze their distribution over time. Figures 2, 3, 4, 5 and 6 illustrate the results.

The computed indices exhibit consistent seasonal trends across all statistical metrics, which aligns with the expected phenological cycle of grapevines. Vineyards typically

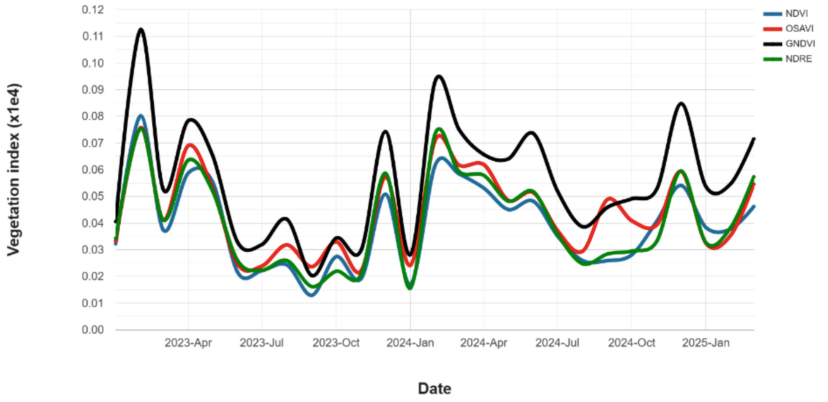

Fig. 3. Monthly standard deviation of computed VIs over the 2015–2025 period.

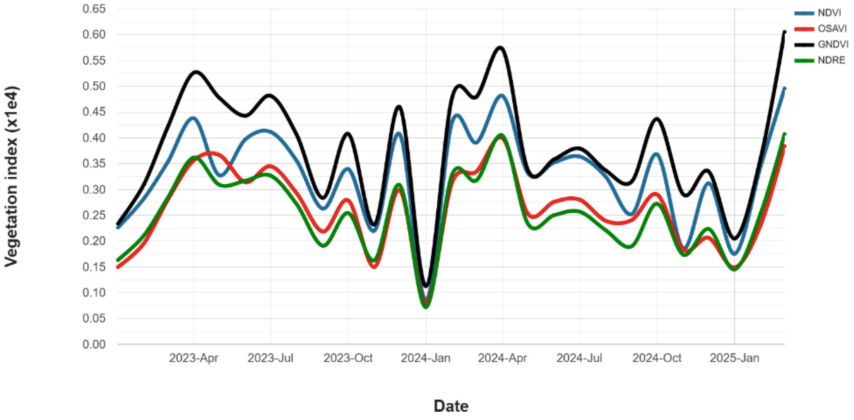

Fig. 4. Monthly median of computed VIs over the 2015–2025 period.

experience a progressive increase in vegetation indices from early spring to summer, corresponding to canopy development, followed by a decline in late summer and autumn due to senescence and harvest activities [16].

However, some notable differences emerge. OSAVI and NDRE display almost identical temporal patterns, with consistently lower values compared to NDVI and GNDVI. This suggests that these indices are more sensitive to soil background effects and canopy structure. OSAVI includes a correction factor (0.16) to minimize soil influence, which may explain its lower values [13], while NDRE incorporates the RE band, making it more responsive to subtle chlorophyll variations rather than overall vegetation cover [15]. GNDVI shows a distinct behavior, often diverging from the other indices. This could be attributed to its reliance on the green band, making it more responsive to variations in leaf pigment concentration, particularly chlorophyll content [14]. NDVI, widely recognized as a robust vegetation indicator, follows a trend similar to GNDVI but with

slightly lower values, likely due to its greater sensitivity to overall vegetation density rather than specific leaf properties [25, 31].

These differences highlight the importance of selecting appropriate indices based on the specific characteristics of vineyard monitoring. The integration of RE-based indices (NDRE) and traditional NIR-based indices (NDVI, OSAVI, GNDVI) provides a more comprehensive understanding of vineyard health, balancing canopy vigor assessment with chlorophyll concentration analysis [32].

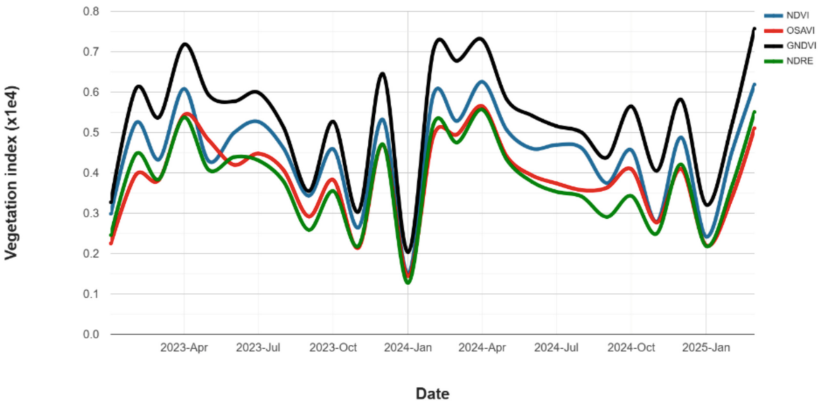

Fig. 5. Monthly maximum of computed VIs over the 2015–2025 period.

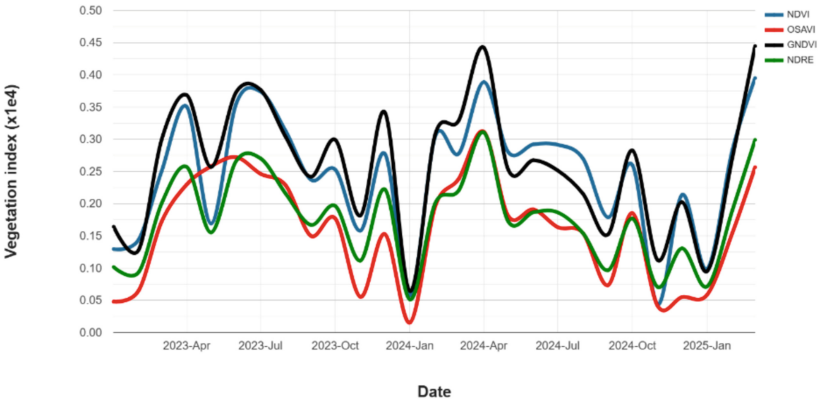

Fig. 6. Monthly minimum of computed VIs over the 2015–2025 period.

To gain deeper insight into the relationships among the four computed indices, the Pearson correlation coefficient was also calculated. The results are illustrated in Fig. 7, which presents a radial diagram depicting the strength and direction of the linear relationships between the indices over time.

A strong positive correlation (values close to +1) indicates that two indices follow similar temporal trends, suggesting that they respond similarly to vegetation changes.

Conversely, lower correlation values imply differences in sensitivity to specific vegetation properties. The high correlation between NDVI and OSAVI suggests that both indices are primarily influenced by vegetation density as they incorporate similar spectral bands in their formulation. On the other hand, NDRE shows a moderate correlation with the other indices, reflecting its unique sensitivity to chlorophyll content, which is particularly relevant in assessing plant health.

It is important to highlight that the Pearson coefficient measures the strength of linear relationships between two indices but does not describe their absolute values or distribution. While NDVI, OSAVI, GNDVI, and NDRE may exhibit different means, medians, minimum, and maximum values, their correlation coefficients remain high if they follow similar seasonal trends. This distinction is crucial: an index can have a lower or higher absolute value but still be strongly correlated with another if both increase and decrease in sync over time. Thus, correlation analysis complements the statistical metrics previously examined, providing a broader perspective on how these indices interact in vineyard monitoring.

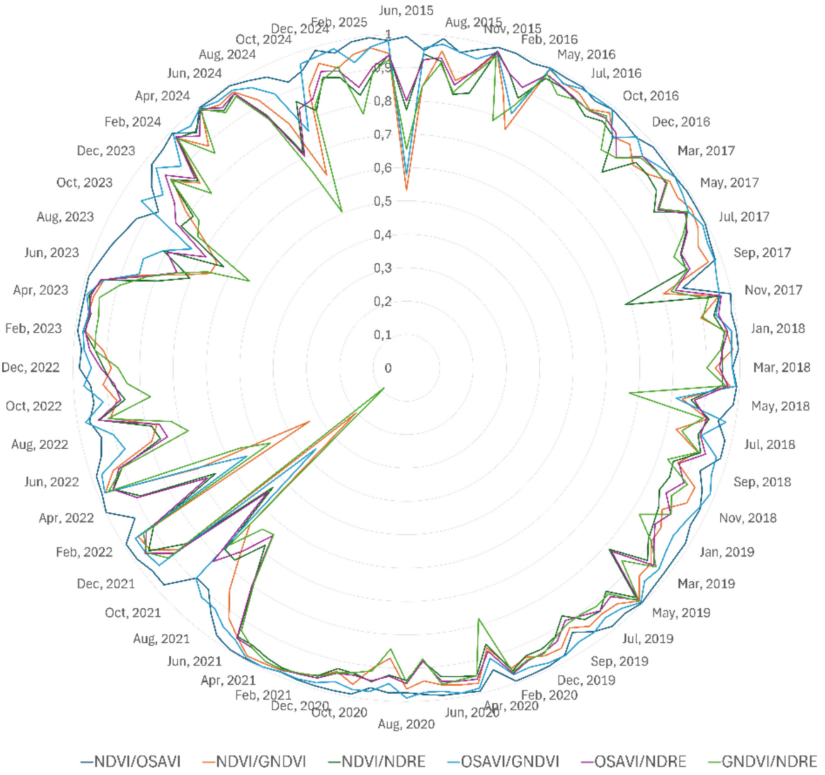

Fig. 7. Radial diagram of Pearson correlation coefficients among different vegetation indices.

However, these analyses do not provide direct insights into the long-term trends of the Aglianico vineyard. To address this, the non-parametric Mann-Kendall test and the

Sen's slope test were applied. The Mann-Kendall test was used to detect the presence of monotonic trends, while Sen's slope test quantified the rate of change over time. Both tests were performed on the results of the four computed vegetation indices.

Figures 8 and 9 present the results of the Mann-Kendall τ correlation and the Mann-Kendall Z-Test, respectively, applied to the four vegetation indices (NDVI, OSAVI, GNDVI, and NDRE) over the period 2015–2025. These analyses provide a comprehensive assessment of both the direction and statistical significance of the observed trends.

Figure 8 illustrates the Mann-Kendall τ correlation, which quantifies the strength and direction of monotonic trends in the computed vegetation indices. The τ values range from negative (blue tones) to positive (red tones), where: i) positive τ values indicate an increase in vegetation health or coverage over time; ii) negative τ values suggest a declining trend, though the intensity is generally low, with a minimum around −0.3.

The results reveal that most of the vineyard exhibits a positive trend, suggesting progressive improvement in vegetative conditions. This could be attributed to vine maturation, favorable environmental conditions, or effective agronomic practices. However, a localized area in the lower part of the field shows a weak negative trend, potentially indicating localized stress factors such as soil degradation, waterlogging, or nutrient deficiencies.

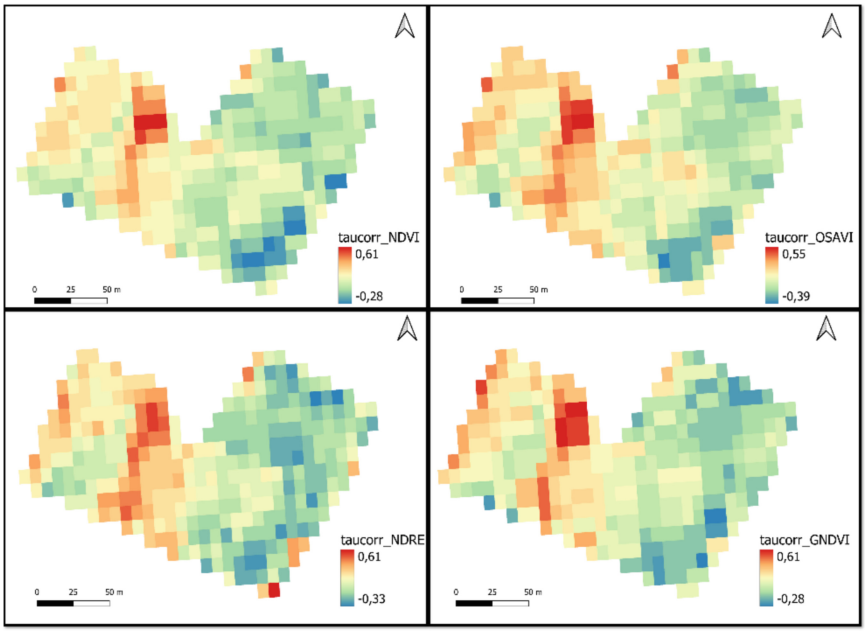

Fig. 8. Mann-Kendall's τ correlation of the four calculated vegetation indices (NDVI, OSAVI, GNDVI, and NDRE).

Figure 9 represents the results of the Mann-Kendall Z-Test, which evaluates the statistical significance of the trends identified in Fig. 8. The Z values range from −1.4

to 2.2, with: i) blue tones corresponding to negative trends, though limited in extent; ii) red tones indicating statistically significant positive trends across most of the vineyard.

The spatial pattern in Fig. 9 closely aligns with Fig. 8, confirming that the positive trends detected in the vineyard are statistically significant. Conversely, the negative values in the lower portion of the field remain relatively low, suggesting that while some declines are present, it is not severe.

The consistency between the two analyses reinforces the reliability of the detected trends. The general increase in vegetation indices supports the hypothesis of vineyard improvement, potentially due to i) canopy development and grapevine maturation over time; ii) sustainable management practices improving plant health; iii) favorable climatic conditions contributing to stable or increasing vegetation indices.

However, the localized negative trend observed in both figures suggests an area that may require further investigation. Potential causes could include soil degradation, water stress, or microclimatic variability. While the decline is not drastic, monitoring and targeted agronomic interventions may help mitigate any long-term impact.

By using the same color scale across both figures, the analysis ensures visual consistency, making it easier to compare the strength and statistical significance of detected trends. This reinforces the study's findings and provides valuable insights into the vineyard's long-term vegetation dynamics.

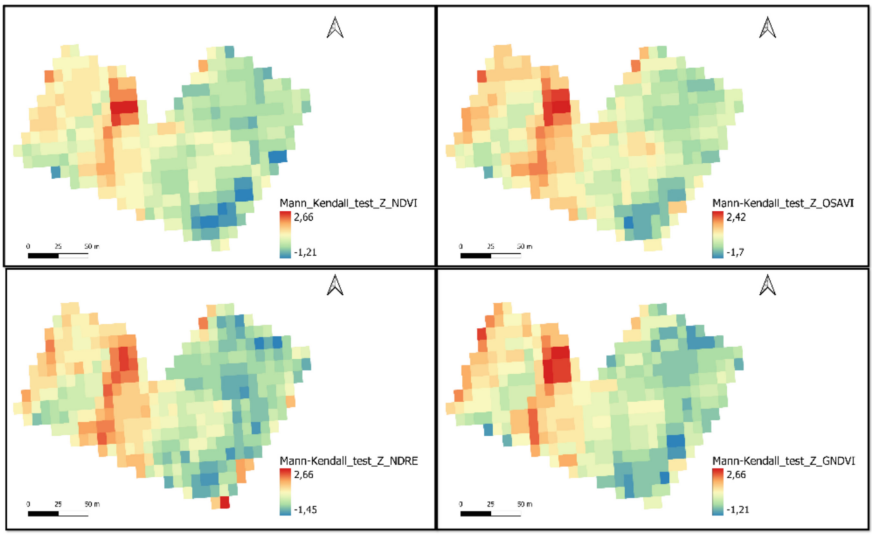

Fig. 9. Mann-Kendall's Z-Test of the four calculated vegetation indices (NDVI, OSAVI, GNDVI, and NDRE).

Unlike the Mann-Kendall τ correlation (Fig. 8) and Z-Test (Fig. 9), which identify the presence and significance of trends, Sen's Slope provides an estimate of their magnitude, indicating how rapidly vegetation indices are increasing or decreasing over time [21]. Sen's slope result is depicted in Fig. 10, which quantifies the rate of change in the four computed vegetation indices (NDVI, OSAVI, GNDVI, and NDRE) over the period

2015–2025. The color scale remains consistent with Figs. 8 and 9, ranging from blue (negative trends) to red (positive trends). This ensures visual coherence and facilitates comparison across analyses.

The findings confirm a predominant positive trend across most of the vineyard, suggesting an overall improvement in vegetation health and coverage. This trend is likely influenced by factors such as vine maturation, favorable climatic conditions, and effective agronomic management. However, a localized negative trend is evident in the lower portion of the vineyard, mirroring the patterns observed in the Mann-Kendall analyses. Although the magnitude of this decline remains relatively low, it indicates a gradual rather than abrupt deterioration, which may be linked to localized factors such as soil conditions, water stress, or microclimatic variability. Additionally, the asymmetry in the range, with a slightly higher maximum positive value than the minimum negative value, suggests that the overall trend is more inclined towards improvement rather than decline. However, the presence of negative slopes, even if limited, warrants attention to prevent further deterioration. This reinforces the importance of integrating statistical analyses with field observations to identify the underlying causes of such variations.

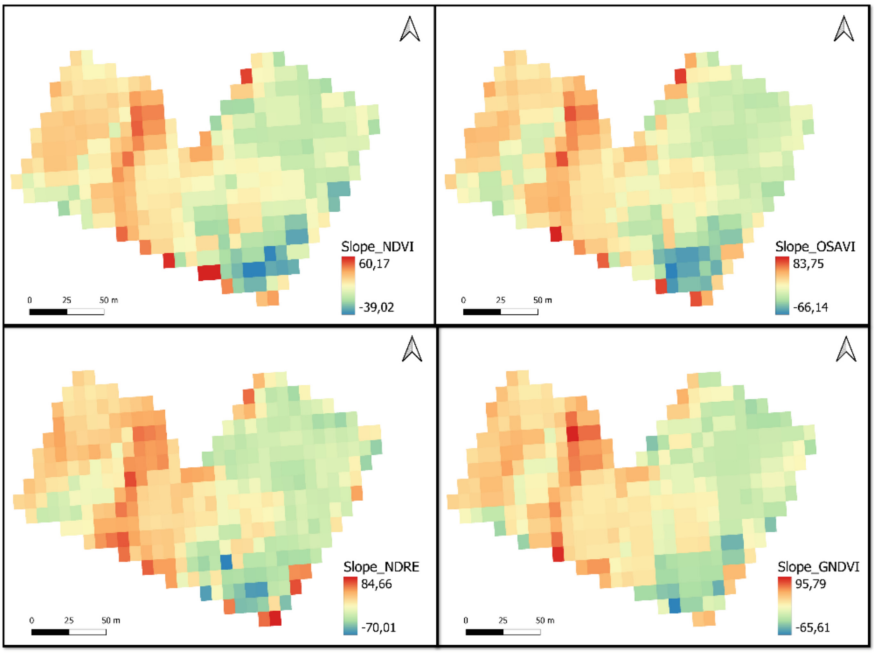

Fig. 10. Sen's slopes of the four calculated vegetation indices (NDVI, OSAVI, GNDVI, and NDRE).

The strong agreement among the results of the Mann-Kendall τ test, the Z-Test, and Sen's Slope strengthens the reliability of the observed trends. The overall positive trajectory suggests that the vineyard is experiencing stable or improving conditions, while the localized negative area highlights the need for further monitoring and potential

intervention. Understanding the factors driving these trends can help optimize vineyard management strategies, ensuring long-term sustainability and productivity.

4 Conclusion

The vineyard ecosystem is a key component of the Mediterranean Basin, serving as a major economic driver, particularly in Italy, France, and Spain, which lead global wine production. In Italy, the Campania region is especially notable for its viticulture, with Aglianico standing out as one of its most renowned grape varieties. Given its economic and agricultural significance, the cultivation of Aglianico requires a precise and data-driven management approach that extends beyond traditional farming expertise. In this context, geospatial big data and remote sensing techniques play a crucial role in monitoring vine health and extracting valuable vineyard information.

This study aimed to detect long-term trends in Aglianico vineyards by analyzing a case study provided by Cantina Di Prisco. A 10-year Sentinel-2 time series was selected and processed using two non-parametric statistical methods: the Mann-Kendall test and Sen's slope estimator, applied to four spectral indices (NDVI, OSAVI, GNDVI, and NDRE). Sentinel-2 was chosen for its superior spatial resolution compared to other freely available satellite missions. However, despite its 10-m resolution, it does not capture changes at the grapevine row or leaf level but rather provides an integrated view of all elements within a 10×10 m^2 area.

The results indicate that all indices follow similar distribution patterns, with NDRE showing a moderate correlation with the others due to its reliance on the Red Edge (RE) band. Long-term trends were assessed using the Mann-Kendall τ test, the Z-Test, and Sen's Slope, all of which yielded consistent findings. The analysis reveals that most of the vineyard exhibits a positive trend, suggesting an overall improvement in vegetative conditions, while a small portion displays a negative trend, likely influenced by localized factors such as soil conditions, water stress, or microclimatic variability. Additionally, the asymmetry in the Sen's Slope range, with slightly higher positive values than negative ones, suggests a net tendency toward vegetation enhancement rather than decline. However, the presence of even limited negative slopes underscores the importance of targeted monitoring to prevent further deterioration.

These findings highlight the effectiveness of integrating satellite-based time series analysis with statistical trend assessments for vineyard monitoring. The approach provides valuable insights into vine health evolution over time, supporting more informed agronomic decisions. Future research could benefit from higher-resolution imagery and ground-based validation to refine the detection of fine-scale variations and better understand the driving factors behind vineyard dynamics.

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