Comparison of Satellite-based Vegetation Indices for Grape Yield Estimation

by

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CANDIDATE DECLARATION

By submitting this declaration form, I, Kishun Ghalan

Hereby confirm that this report is completely my own work.

This report, or any portion of it, has never been submitted before for any evaluation, degree, or equivalent award, and I confirm that the work is original and properly cited.

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ACRONYMS AND ABBREVIATIONS

ANOVA	Analysis of Variance
ARVI	Atmospherically Resistant Vegetation Index
EVI	Enhanced Vegetation Index
GIS	Geographic Information System
Ha	hectare
Kg	Kilogram
LAI	Leaf Area Index
LIDAR	Light Detection and Ranging
m	meter
masl	meters above sea level
MODIS	Moderate Resolution Imaging Spectroradiometer
mt	Metric ton
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NIR	Near-Infrared
nm	nanometer
PA	Precision Agriculture
PV	Precision Viticulture
QGIS	Quantum Geographic Information System
SVI	Spectral Vegetation Index
UAV	Unmanned Aerial Vehicle
VI	Vegetation Index

ABSTRACT

Yield estimation of grapes is crucial for efficient and cost-effective management of vineyards. Presence of spatial variability within and across vineyards poses a great challenge for development of standard models to accurately predict grape yields. Traditional methods of yield prediction are highly costly and time-consuming, requiring a large amount of human labor. Precision Viticulture (PV) involves the use of remote sensing technologies that are non-invasive, time and cost-effective in defining the spatial variability of vineyards and estimating grape yields. Normalized Difference Vegetation Index (NDVI) is the most widely used satellite-based vegetation index whose relationship with crop vigor is well-defined. However, NDVI has inadequacies due to its susceptibility to atmospheric effect, saturation phenomenon, and sensor quality, due to which it gives unreliable prediction in many cases. To address this problem, this study attempted to compare the effectiveness of satellite imagery-derived vegetation indices namely, NDVI and Enhanced Vegetation Index (EVI) in predicting the yield of grapes (*Vitis vinifera* L.) vineyard in Western New York, USA. Sentinel-2 images were used to calculate NDVI and EVI values, which were correlated with ground-measured yield of grapes. Linear regression analysis showed no relationship of either index with yield of grapes. Pearson's correlation test resulted a correlation coefficient of -0.188 between NDVI and yield and -0.23 between EVI and yield and the correlation coefficients were statistically significant at $p<0.05$. The results revealed that Sentinel-2 remote sensing based vegetation indices do not effectively predict the yield of grape vineyards. Further study needs to be done to realize the best remote sensing platform and best vegetation index for reliable yield estimation of wine grapes. Identification of such a technology has great potential in revolutionizing the viticulture industry through increase in efficiency of vineyard management and yield estimation.

Keywords: *Precision Viticulture, Yield Prediction, Vitis vinifera, NDVI, EVI*

1 INTRODUCTION

1.1 Background

Precision Viticulture (PV) attempts to detect the temporal and spatial variation of grape yields and quality within a degree of stability, to discover the causes of such variability, and whether they are related to any site-specific management strategies (Bramley & Hamilton 2004). It aims to achieve adequate crop variability control with increased economic advantages and reduced environmental impact (Blackmore, 1999; Silverstoni, 2018). PV has brought several options for precise farming with a multitude of reliable data, allowing farmers and enterprises to make decisions that are advantageous both in terms of wine quality and economic viability.

Yield prediction is important in vineyard management to prevent an excess or deficit of fruit on vines and to optimize the amount of fruit in each growing season (Arab et al., 2021). This not only helps in prediction of grape production but also in management of time and human resources, especially during harvesting (Ballesteros et.al, 2020). In addition, it is critical for inventory planning in supply chain management, avoiding postharvest losses, and assisting vineyard producers during natural disasters through subsidies or insurance (Arab et al., 2021).

However, the presence of spatial variability within and across vineyards poses a great challenge for development of standard models to accurately predict grape yields. With different topography, each vine reacts differently due to differences in environment and nutrient availability. For the best management of grapes, daily monitoring of the vineyard is necessary, but ground-based measures are expensive to install and maintain, especially for large-scale and distributed production systems, and are not likely to be reflective of whole-field conditions (Sun et al., 2017). Moreover, the traditional methods are highly costly and time-consuming, requiring a large amount of human labor for manual harvesting and weighing of the crop yield (Aquino et al. 2018; Bramley & Hamilton 2005).

Thanks to the development and proliferation of remote sensing technologies in agriculture, several non-invasive, time and cost-effective imaging methods are available which can be used to accurately capture data from vines by detecting spatial variability over the entire crop cycle, allowing the identification of micro-zones in the experimental fields (Acevedo-Opazo et al., 2008; Dorigo et al., 2007). These techniques include sensors, onboard ground vehicles, unmanned aerial vehicles (UAV) and satellites (Herrero-Huerta et al. 2015; Li et al. 2014;

Spalding & Miller 2013). UAV and satellite-based methods benefit from the relationship between surface reflectance and vine yield, e.g., vegetation indices (Jaafar & Ahmad 2015; Panda et al. 2010). Since the late 1970s, satellite-based remote sensing has been widely used for yield predictions (Prasad et al., 2006). Various satellite data sources like Landsat, Sentinel, MODIS, Gaofen, Aster, SPOT, etc. provide free access to satellite images of required locations which can be used for yield estimation in viticulture.

Normalized Difference Vegetation Index (NDVI) is the most commonly used and well-adopted remote sensing analytical product used to simplify the complexities of multi-spectral satellite imagery (Huang et al., 2020). Its correlation with crop vigor and ground-measured yield values has been proven by a number of studies (Ballesteros et al., 2020; Khaliq et al., 2019; Latrou et al., 2017; Pastonchi et al., 2020; Sun et al., 2017). Despite its popularity, NDVI is found to have several shortcomings due to its vulnerability to atmospheric effect, saturation phenomenon, and sensor factors (Huang et al., 2020). Even though the vigor and health of the vines haven't changed, NDVI provides significantly different results throughout the day since it doesn't account for variations in the solar incidence angle. It is also susceptible to background noise and produces erroneous data due to a variety of factors such as shading, air moisture, and differences in the soil. To overcome these drawbacks of NDVI, a more accurate vegetation index has been developed, called Enhanced Vegetation Index (EVI) which is calculated similarly to NDVI but uses different light wavelengths to make up for NDVI's inadequacies (Somvanshi & Kumari, 2020). It corrects for variations in the sun incidence angle, meteorological factors including distorted reflected light from airborne particles, and signals from the ground cover beneath the vegetation.

This paper aims to compare the efficacies of the two aforementioned vegetation indices i.e., NDVI and EVI in mapping the yield variability of grape vineyards. It analyzes the relationship between satellite image-derived indices and ground-measured data of grape yield and helps to identify the superior vegetation index for grape yield estimation.

1.2 Problem Statement and Rationale

Grapes vineyards are highly heterogeneous with macroscopic eco-physical response to pedo-morphological and climatic conditions (Matese et al., 2015). Significant spatial variability exists among vineyards in different countries and regions, and even in the same field, spatial variability occurs among vines in different growth stages (Tisseyre et al., 2007).

As this variability has direct consequences on grape quality and yield, it has long stood as a major challenge for wine growers around the world to estimate yields and to apply management strategies for obtaining high yield of good quality produce. Traditionally, most methods for vineyard yield estimation are based on ground measurements which involves tedious work that is labor intensive and time consuming with low economic viability (Arab et al., 2021; Bramley & Hamilton, 2004). In absence of proper yield estimation, the production capacity of vineyards is not known, which negatively affects the yield as well as market security of grapes. Although recent advances in precision viticulture including remote sensing platforms such as satellite imagery and the well-adapted Normalized Difference Vegetation Index (NDVI) are widely being used for vineyard variability assessment and yield estimation, many studies have demonstrated the ineffectiveness of NDVI in reliably describing vineyard variability. The major problems in NDVI, as reported by several authors, include its susceptibility to atmospheric effect, ease for saturation, and sensor quality (Huang et al., 2020; Khaliq et al., 2019). Such shortcomings of NDVI have created the need for identification of a better, more reliable vegetation index which would show greater correlation with ground yield data so that grape yield estimation can be done more accurately. The decametric resolution satellite i.e. Sentinel-2 based vineyard multispectral imagery used in this study will help to understand the intra-parcel spatial variability present in the Rail road block at Portland vineyard, which will assist in designing site-specific vineyard management strategies for higher productivity. The findings of this study can be applied to other similar ecosystems as well. Similarly, this study helps in further validation of the relationship between vegetation indices like NDVI and EVI with crop vigor and yield. The findings of this research will help to identify the superior satellite based vegetation index in yield mapping and yield estimation of vineyards. Hence, this study provides valuable information to different stakeholders including farmers, researchers, technicians, wine-growers, and policy-makers for improving the productivity and marketability of grapes through better yield estimation and vineyard management.

1.3 Objectives

1.3.1 General Objective

To compare the efficacy of satellite-derived vegetation indices in estimating yield of grape vineyard.

1.3.2 Specific Objectives

- To study the intra-parcel spatial variability in a grape vineyard using Sentinel-2 satellite imagery
- To compare NDVI and EVI for their effectiveness in yield estimation of grapevines.

2 LITERATURE REVIEW

One of the major problems for vine producers is to increase vineyard production and grape quality by a proper understanding of the spatial variability of the vineyard while consequently lowering costs and environmental effects (Song et al., 2014; Silvestroni et al., 2018; Khaliq et al., 2019; Pastonchi et al., 2020). Although a wide range of research has been conducted for the purpose of understanding yield variability in grape vineyards, an accurate model for the prediction of grape yields has not been defined so far. Over the years, techniques of grape yield estimation have developed from traditional, ground-based manual methods to newer, remote sensing-based satellites and UAVs.

Multi-spectral imaging technologies have been used for many agricultural applications, such as yield estimation, crop identification and classification, plant health assessment, disease forecasting, water stress detection, optimal harvest time prediction, etc. (He et al., 2018; Pôças et al., 2014; Robinson et al., 2017; Simms & Ward, 2013; Yang, Chen, & Tsai, 2017). Unmanned aerial vehicles (UAV), airborne sensors, and satellites are the most popular remote sensing platforms used in viticulture (Pastonchi et al., 2020). These platforms can be fitted with various optical sensors to analyze plant response over a broad spectral range, including RGB, multi- and hyper-spectral, thermal infrared, and LiDAR (Hall et al., 2002; Mathews and Jensen, 2012; Matese et al., 2015; Pádua et al., 2019; Sozzi et al., 2020). Landsat, MODIS, Gaofen, Aster, SPOT, Sentinel-1, Sentinel-2, etc. are popular satellite programmes providing free datasets, which are promoting the exploitation of satellite imagery for applications in viticulture (Khaliq et al., 2019; Shao, Tang, & Liao, 2015). These satellite images improve representations of terrestrial features like vegetation. Vegetation indices are sensitive to different characteristics of the plant such as chlorophyll, pigments, biomass or water content on the leaves (Giovos et al., 2021). So far, more than a hundred vegetation indices have been created from multispectral imagery (Xue & Su, 2017). Among these indices, Normalized Difference Vegetation Index (NDVI) is found to be the most appealing in commercial viticulture, especially because of its rapid delineation of vegetation and vegetative stress. Literature has demonstrated that NDVI can distinguish between savannah, dense forest, non-forest, and agricultural fields, as well as determine whether a forest is evergreen or seasonal (Pettorelli et al., 2005). It can also be used to estimate a variety of vegetation properties, such as the LAI (Tian et al., 2017), biomass (Zhu &Liu, 2015), chlorophyll concentration in leaves (Pastor-Guzman et al., 2015), productivity (Vicente-Serrano et al., 2016), plant stress (Chavez et al., 2016), and fractional vegetation cover (Dutrieux et al., 2015). NDVI makes use of the different response of vegetation to the visible (red) and near-infrared spectral bands that are closely related to crop status (Rouse et al., 1973).

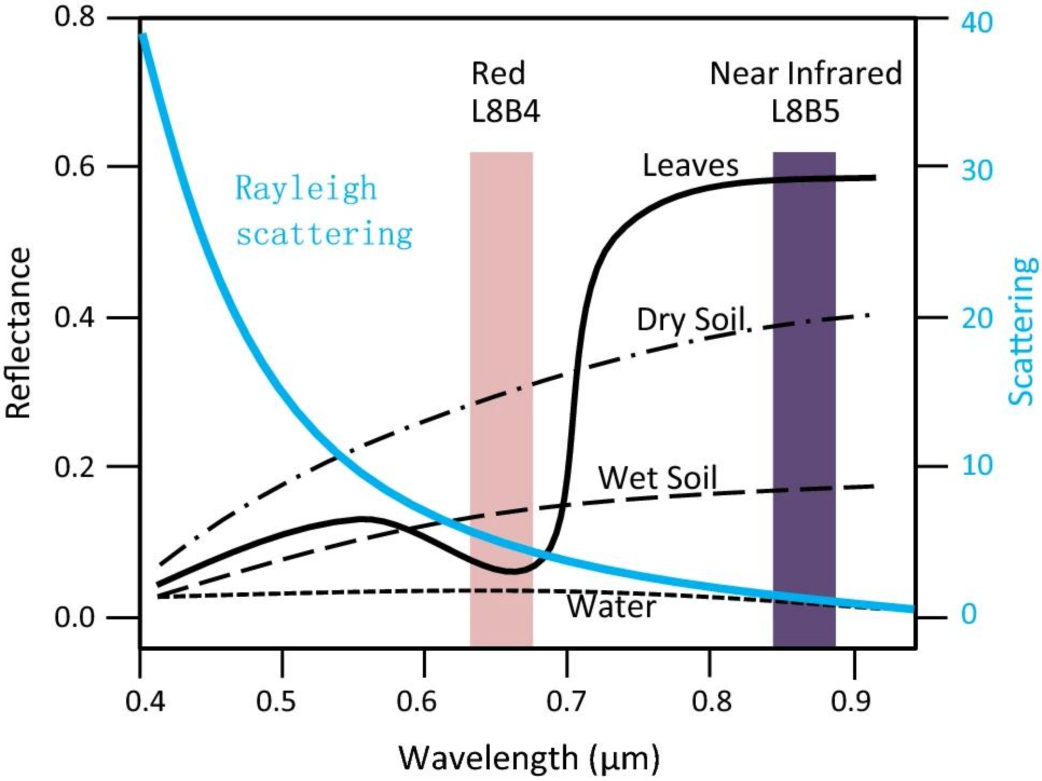

Figure 1 An illustration of spectral response curves and their intersections with red and near infrared bands as well as the wavelength-dependent scattering (Huang et al., 2020)

In a research carried out by Ballesteros et al. in 2020 for yield estimation of vineyard by combination of remote sensing, computer vision, and artificial neural network, it was concluded that, receiving accurate plot information, including geometric characterisation of the canopy as well as spectral information, is made easier by high-resolution multispectral data taken with UAVs. Pastonchi et al. (2020) compared Sentinel-2 and UAV data with ground data to analyze the spatio-temporal variability of vineyard and came to the conclusion that Sentinel-2 photos and UAV-derived information would provide meaningful decision support for the stakeholders to define in-field management zones to manage vineyard vigor. However, they recognized the need to take into account the fact that 10 m resolution of S2 cannot be used for any vine-specific application because it is only appropriate for larger scale uses. Sun et al. (2017) mapped the 30 m LAI and NDVI for yield prediction of grapes in California vineyards using satellite data from Landsat and concluded that NDVI demonstrated a strong connection with yield, making it an effective predictor of spatial yield variability. However, the correlations changed across seasons over the growing period. Di Gennaro et al. (2019) in their experiment to validate Sentinel-2's performance in assessment of spatial variability also observed strong correlation of NDVI and ground data for yield and biomass of vineyards. In a study conducted to predict grape yields from different satellite remote sensing-based time-series vegetation indices, NDVI was found to have the highest accuracy in yield estimation as compared to other indices like LAI and NDWI (Arab et al., 2021). Meyers et al. (2020) reported NDVI based sampling protocol to be effective in estimation of physiological parameters like TSS, TA, pH, and anthocyanin content of grapes, which determine fruit quality.

Nevertheless, because of its susceptibility to atmospheric effect, saturation phenomena, and sensor quality, NDVI has displayed unprofessional inadequacies (Huang et al., 2020). In a study conducted by Khaliq et al. (2019), the relationship between the enhanced NDVI map and the satellite NDVI map was found to be weak when simply taking into account the UAV imagery's pixels that represented vine canopies. This analysis demonstrated that the radiometric data collected by decametric spatial resolution satellite platforms were insufficient to accurately assess crop status and variability in the case of crops where the inter-row surfaces and paths involved a significant portion of the cropland, such as vineyards. Since it was discovered that the in-field crop vigor evaluation did not agree with the NDVI maps produced from the satellite imagery, it can be understood that the inter-row surfaces' contribution to the remotely sensed data set may influence the NDVI computation, producing biased crop descriptors.

In order to address these shortcomings of NDVI, several corrected vegetation indices have been derived, among which, Enhanced Vegetation Index (EVI) is gaining popularity. EVI is an improved vegetation index created to improve vegetation monitoring by decoupling the canopy background signal and reducing atmospheric impacts, as well as to improve the sensitivity of the vegetation signal in high biomass regions (Somvanshi & Kumari, 2020). This index is more receptive to canopy variations, canopy type and architecture. EVI can also be linked to stress and changes related to drought (Huete et al., 2002). In a study conducted in India, EVI showed a better result with a greater value of correlation of the enhanced image with original multispectral image as compared to NDVI and ARVI (Somvanshi & Kumari, 2020). Similarly, Fraga et al. (2014) in their experiment for examining the relationship between EVI and phenology of grape vines reported the usefulness of EVI in monitoring of grapevines as it significantly decreased the need for intensive ground-based observations. The study concluded that vine growers would be able to efficiently use EVI data to optimize vineyard management and field intervention needs by combining remote sensing with traditional agricultural techniques. Hall and Wilson (2013) found that spectral vegetation indices (SVIs), like the EVI (Enhanced Vegetation Index), perform better than NDVI in estimating wine grape yield characteristics, thus supporting the findings of Anastasiou et al. (2018).

As no research had been done to map the yield of vineyards of Portland, New York by using satellite-based vegetation indices, the necessity to conduct such a study was identified. Moreover, the existing literature shows conflicting results regarding the relationship of NDVI and yield of grapes as varying degrees of correlation have been observed in different locations across different seasons. Therefore, the gap in research was identified and hence, this study was specially focused on comparing the effectiveness of NDVI and EVI to predict yield of wine grapes in Portland, New York as an attempt to further validate previous findings and to fill the gap existing in viticulture research.

3 MATERIALS AND METHODS

3.1 Research Framework

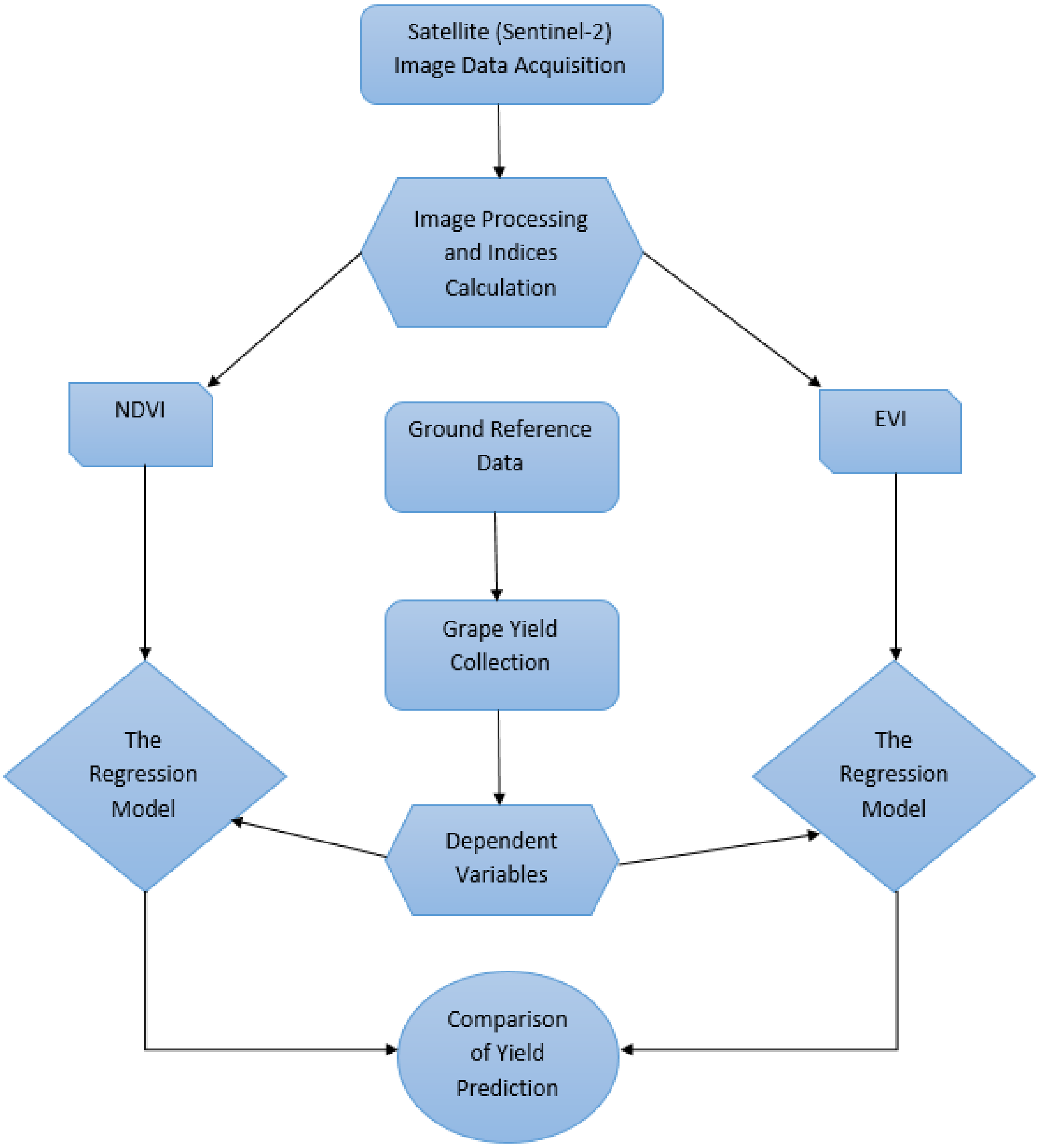

Figure 2 Research methodology flow chart for comparison of Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) for yield estimation of grapes.

3.2 Experimental Details

The research took place in an experimental vineyard at the Cornell Lake Erie experiment station located in Portland, New York (latitude, longitude) in 2020. The 33-year old vineyard located at an area of 7.03 acres. The plot was planted in 1989 with Concord variety of wine grapes (*Vitis vinifera* L.). The climate in the area is colder than New York city with an average annual rainfall of 42 inches, temperature varies 20F to 78F.

Figure 3 Map of experimental field extracted from Google Satellite

3.3 Sentinel-2 Data Acquisition and Processing

The multispectral images of the experimental field recorded by Sentinel-2 were downloaded through the Copernicus Open Access Hub (www.scihub.copernicus.eu) website. Cloud-free photographs from this web database were picked based on how close they were to the dates of the experiment and how well they covered the experimental area. These images were then exported to QGIS software (version 3.22.8) where the vector files were rasterized to obtain NDVI and EVI raster images of the experimental plot. Google Satellite was used to obtain clear images of the experimental vineyard. To create NDVI raster pictures with a 10 m pixel resolution, the spectral bands B4 (650-680 nm) and B8 (785-900 nm), which correspond to the red and near infrared regions, respectively, were extracted. Furthermore, to create EVI raster pictures also with 10m spatial resolution, the spectral bands B2 (458-523 nm), B4 (650-680 nm), and B8 (785-900 nm) corresponding respectively to blue, red, and near infrared regions, were extracted using QGIS.

NDVI was computed using the formula:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

Where,

NIR stands for the spectral reflectance measurements acquired in the near-infrared region (band 8) and

Red refers to the spectral reflectance measurements obtained in the red (visible) region (band 4)

Similarly, EVI was calculated using the formula:

$$EVI = G\ x\ \frac{(NIR - Red)}{(NIR + C1\ x\ Red - C2\ x\ Blue + L)}$$

Where,

G is the gain factor (value = 2.5),

NIR is the surface reflectance in the near infrared region (band 8),

Red is the surface reflectance in the visible red region (band 4),

Blue is the surface reflectance in the visible blue region (band 2),

L is the adjustment for canopy background which addresses the non-linear, differential NIR and red radiant transfer through a canopy (value =1),

C1 and C2 are the coefficients for atmospheric resistance, which uses values from the blue band to correct for aerosol influences in the red band (C1 = 6 and C2 = 7.5).

3.4 Statistical Analysis

The yield data from the experimental field was exported to QGIS where the yields from individual vines were converted into yield per NDVI pixel by using the GroupStats plugin. Similarly, the NDVI and EVI per pixel were extracted from the satellite data by using the zonal statistic function of QGIS. The NDVI and EVI data were combined with the yield data by using the spatial join function within the MMQGIS plugin. The total yield and average yield per pixel was obtained. The pixel-wise data of NDVI, EVI, and total yield were exported with Microsoft Excel where the yield values (kg per pixel of 10 m x 10 m area) were converted into metric tons per hectare. Then, the spatial correlation between yield and each VI was quantified using the Pearson's correlation coefficient (R). Scatter plots were prepared and coefficient of determination (R^2) was calculated for each data pair. Analysis of Variance(ANOVA) was done to test if the calculated correlation coefficient was statistically significant. The relationships were compared, results were presented in the form of graphs and charts, and interpretation was done.

4 RESULTS AND DISCUSSION

The experiment was conducted to study the efficiency of different vegetation indices to predict the yield of grape vineyards in Portland, New York condition. Sentinel-2 satellite imagery-derived NDVI and EVI values were compared with ground-measured yield of grapes using Pearson's correlation analysis. The results obtained are presented in the form of graphs and are discussed below:

4.1 Sentinel-2 NDVI and EVI

Figures 4 and 5 show the 10 m resolution maps of NDVI and EVI, respectively over the experimental field on September 23, 2020. 225 different pixels with varying degrees of reflectance, each representing 10 m x 10 m area of the vineyard were obtained.

From the maps, it was observed that NDVI and EVI have different distributions with variable spatial patterns of the vegetation conditions within the field. The values of NDVI ranged from 0.6 to 0.9 whereas those of EVI ranged 0.6-1, which clearly demonstrates a high degree of similarity between the NDVI and EVI values. The NDVI and EVI maps also portray within field spatial variation in vine development over the experimental field. The pixels with darker shades show areas with greener, healthier plants whereas lighter shades represent areas with lighter green or more yellow plants. The range of NDVI values for very healthy plants is 0.66-1 (Kraetzig, 2020). The range obtained in this study i.e. 0.6-1 indicates that all the plants in the experimental field are healthy.

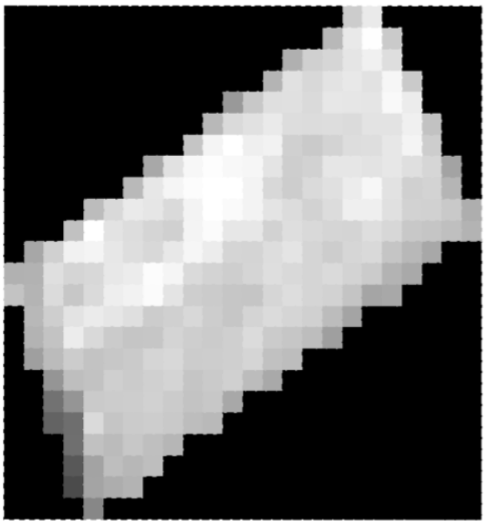

Figure 4 Normalized Difference Vegetation Index (NDVI) map computed from Sentinel-2 satellite imagery

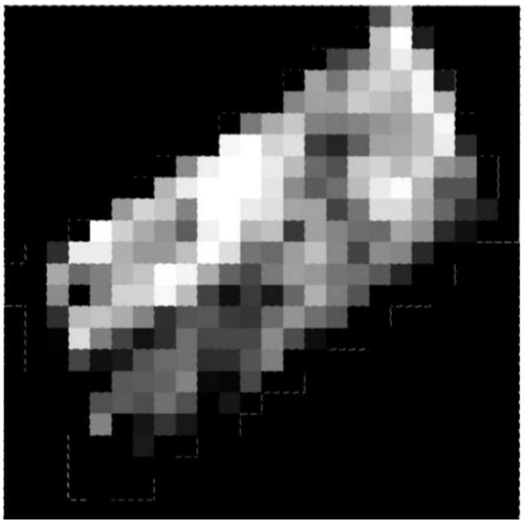

Figure 5 Enhanced Vegetation Index (EVI) map computed from Sentinel-2 satellite imagery

Furthermore, it can be clearly seen that the EVI map (Figure 5) has superior image quality with more distinct pixels as compared to the NDVI map (Figure 4). This distinction indicates the superiority of EVI in identifying spatial variability in vineyards over NDVI. The difference between the images is because of reduction of background noise and atmospheric impacts in case of EVI, which is supported by the study of Somvanshi and Kumari (2020) as well.

4.2 Grape Yields

The overall yield of grapes was found to be 7.2 mt ha^{-1}. The yield of grapes across the 225 pixel blocks ranged from a minimum 3.1 mt ha^{-1} to maximum 11.7 mt ha^{-1} with a standard deviation of 1.8 mt ha^{-1}.

4.3 Relationship Between VIs and Yield

The NDVI and EVI images were used to compute spatial correlations with yield data collected for the experimental vineyard in September, 2020. The correlation coefficients are shown in Figure 6 and 7. The R curves for NDVI and EVI have similar trends with negative slope and the value of correlation coefficient equaling -0.188 and -0.23 in case of NDVI and EVI, respectively with yield of grapes; the coefficient of determination (R^2) being 0.036 and 0.053, respectively (Appendix 1 & 4). The analysis of variance demonstrated that the Pearson's correlation coefficients were statistically significant at 5% level of significance (Appendix 2, 3, 5, & 6). This indicates that there is no relationship of NDVI or EVI with yield of grapes in the case of this study.

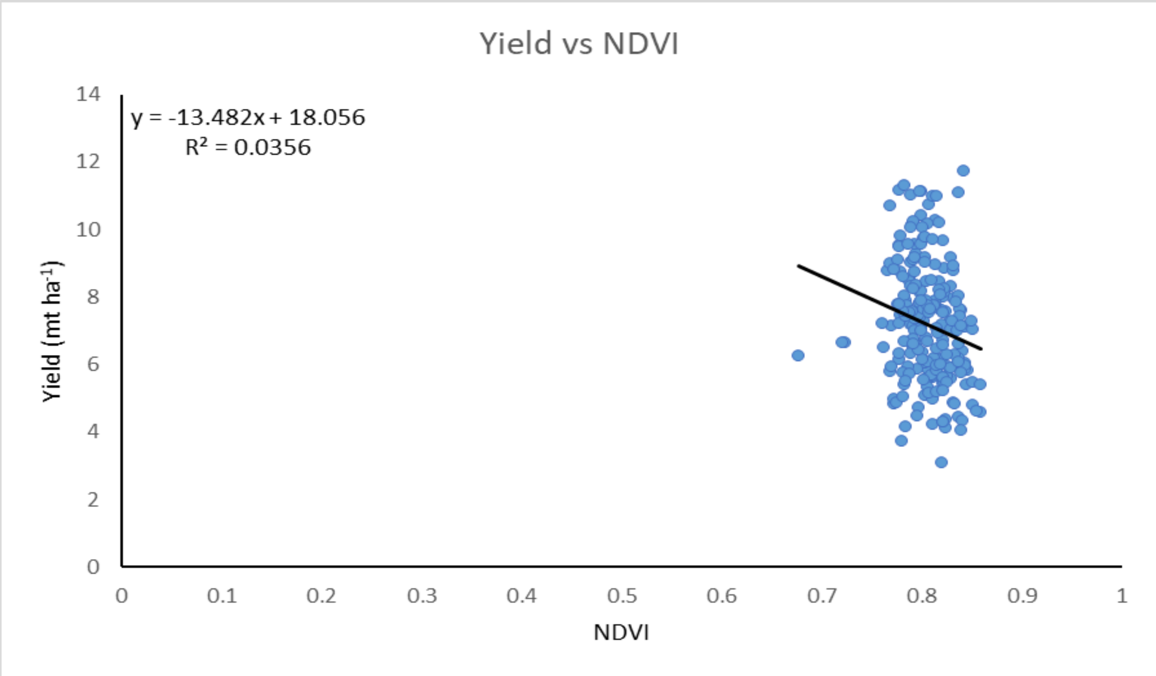

Figure 6. Scatter plots between Normalized Difference Vegetation Index (NDVI) values from satellite map (x-axis) and yield (mt ha^{-1}) (y-axis) with regression model and data pair correlation coefficient.

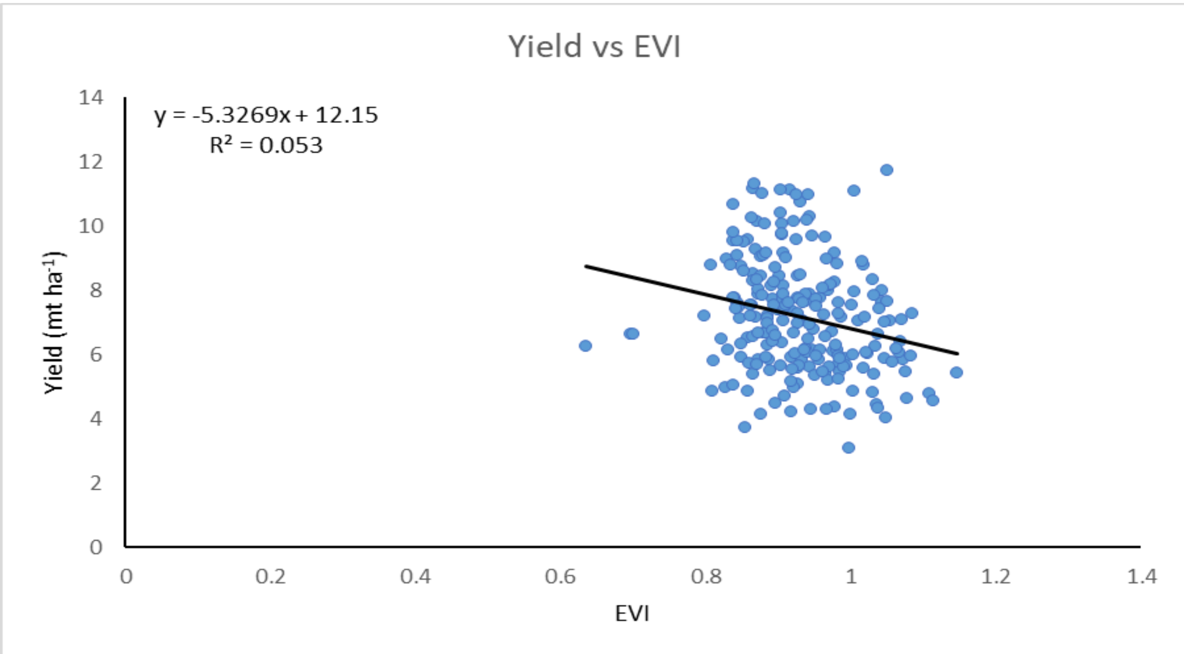

Figure 7. Scatter plots between Enhanced Vegetation Index (EVI) values from satellite map (x-axis) and yield (mt ha^{-1}) (y-axis) with regression model and data pair correlation coefficient.

The findings of this study are opposed to the results of many previous studies which have demonstrated strong positive correlation between NDVI and yield of grapes (Ballesteros et al., 2020; Sun et al., 2017). The low correlation between the satellite-based vegetation indices and grape yields could be attributed to a number of factors like season, soil effect, canopy growth, and management practices. In the study by Cunha et al. (2010), the correlation between NDVI and wine grape yield was shown to be considerably negative, which was explained by the fact that grapevines with high canopies and excessive vegetation growth might cast shade and result in low bud fruitfulness. Similarly, the correlation between NDVI and grape yield was observed to have low and negative values in the study conducted by Ballesteros et al. (2020) as well. In that case, the conflicting results were attributed to the soil effect, which is known to be a major limitation of using satellite-based remote sensing techniques in crops with inter-row spaces, such as vineyards (Ballesteros et al., 2015). In the study conducted by Khaliq et al. (2019) as well, the NDVI maps derived from the Sentinel-2 satellite imagery were not in accordance with the in-field assessment of crop vigor. In the same way, the NDVI and EVI in this study have no relationship with grape yields with very low, negative value of correlation coefficients, indicating that the relationship between satellite-based vegetation indices and wine grape yield has varying performance under different environmental conditions and management strategies. In addition, several studies have shown changes in the correlation coefficients between VIs and yields in different points of time during the growing season of grapes. As this study has used the satellite data of only one day, that day could have lied outside the optimal correlation window, thereby, resulting in low, negative correlation. Sun et al. (2017) found that the highest correlation of both NDVI and LAI with yields came from 1-day intervals. Similarly, Esquerdo et al. (2011) found that a full-season averaging window was optimal for estimating soybean yields in Brazil using NDVI. In examining the link between remotely sensed indices and agricultural production in Brazil, Anderson et al. (2016) also discovered that in some areas, adding additional time-averaging (moving upwards in the plots) aids in enhancing correlations of VIs with yields. Arab et al. (2021) evaluated the correlations between yield and indices (NDVI, LAI, and NDWI) in all months and found that the associations between grape yield and the studied indices were very low during the flowering and harvest periods but relatively high during maximum canopy expansion. Since the correlation between the VIs and yield in this experiment was studied during the harvest period i.e. September, the association could have been low because of the seasonality of vegetation indices.

To sum up the results, the relationship between NDVI and EVI with yield is non-existent and statistically significant, therefore, suggesting that satellite imagery based vegetation indices have very low effectiveness in predicting the yield of wine grapes and therefore, these indices cannot be directly used to reliably describe vineyard variability.

5 CONCLUSION

The present findings concluded that the correlation of NDVI and EVI with yield of grapes was -0.188 and -0.23, respectively. These low values of correlation coefficients indicate that decametric satellite (i.e. Sentinel-2) remote sensing based vegetation indices do not effectively predict the yield of grape vineyards. The VIs show variable relationships with yields, depending on season, soil and canopy management strategies. Therefore, there is a need to consider satellite data of multiple time frames to identify optimal correlation window for reliable yield mapping. Further study needs to be done to identify best remote sensing platform and best vegetation index for reliable yield estimation of wine grapes.

6 LIMITATIONS AND RECOMMENDATIONS

The research was carried out for a single season in a single location, with limited resources. Therefore, it's possible that the results might not apply to wider locations. Since grapes are grown in a variety of different agro-ecologies and environmental conditions, the study's findings might be difficult to generalize and hence might not accurately reflect the situation on a national or international scale. Moreover, as the NDVI and EVI values were calculated from satellite data of a single day, the findings of this study might not have represented the optimal correlation between the VIs and grape yield. Therefore, additional multi-location and multi-year trials with multiple time-series data are required to further validate the findings of this study.

REFERENCES

Acevedo-Opazo, C., Tisseyre, B., Ojeda, H., Ortega-Farias, S., & Guillaume, S. (2008). Is it possible to assess the spatial variability of vine water status? *Journal International des Sciences de la Vigne et du Vin*, 42(4), 203–2019. https://doi.org/10.20870/oeno-one.2008.42.4.811.

Anastasiou, E., Balafoutis, A., Darra, N., Psiroukis, V., Biniari, A., Xanthopoulos, G., & Fountas, S. (2018). Satellite and Proximal Sensing to Estimate the Yield and Quality of Table Grapes. *Agriculture*, 8(7), 94. https://doi.org/10.3390/agriculture8070094

Anderson, M. C., Zolin, C. A., Sentelhas, P. C., Hain, C. R., Semmens, K., Tugrul Yilmaz, M., Gao, F., Otkin, J. A., & Tetrault, R. (2016). The Evaporative Stress Index as an indicator of agricultural drought in Brazil: An assessment based on crop yield impacts. *Remote Sens. Environ*, 174, 82–99.

Aquino, A., Millan, B., Diago, M. P., & Tardaguila, J. (2018). Automated early yield prediction in vineyards from on-the-go image acquisition. *Computers and Electronics in Agriculture*, 144, 26–36. https://doi. org/10.1016/j.compag.2017.11.026.

Arab, S. T., Noguchi, R., Matsushita, S., & Ahamed, T. (2021). Prediction of grape yields from time-series vegetation indices using satellite remote sensing and a machine-learning approach. *Remote Sensing Applications: Society and Environment*, *22*, 100485. https://doi.org/10.1016/j.rsase.2021.100485

Arnó, J., Martínez Casasnovas, J. A., Ribes Dasi, M., & Rosell, J. R. (2009). Review. Precision viticulture. Research topics, challenges and opportunities in site-specific vineyard management. *Spanish Journal of Agricultural Research*, *7*(4), 779. https://doi.org/10.5424/sjar/2009074-1092

Ballesteros, R., Intrigliolo, D. S., Ortega, J. F., Ramírez-Cuesta, J. M., Buesa, I., & Moreno, M. A. (2020). Vineyard yield estimation by combining remote sensing, computer vision and artificial neural network techniques. *Precision Agriculture*, *21*(6), 1242–1262. https://doi.org/10.1007/s11119-020-09717-3

Ballesteros, R., Ortega, J. F., Hernández, D., & Moreno, M. (2015). Characterization of vitis vinifera l. Canopy using unmanned aerial vehicle-based remote sensing and photogrammetry techniques. American Journal of Enology and Viticulture, 66(2), 120–129. https://doi.org/10.5344/ajev.2014.14070

Blackmore, S. (1999). Developing the principles of precision farming. *Proceedings of AgroTech 99 Conference*, January 1999, Barretos Institute of Technology, Brazil.

Bramley, R. G. V., & Hamilton, R. P. (2005). Understanding variability in winegrape production systems 2. Within vineyard variation in quality over several vintages. *Australian Journal Of Grape And Wine Research*, 11(1), 33–42. https://doi.org/10.1111/j.1755-0238.2004.tb00006.x.

Chavez, R. O., Clevers, J. G. P. W., Decuyper, M., De Bruin, S., & Herold, M. (2016). 50 years of water extraction in the Pampa del Tamarugal basin: Can Prosopis tamarugo trees survive in the hyper-arid Atacama Desert (Northern Chile)? *J Arid Environ*, 124, 292–303.

Cunha, M., Marçal, A. R. S., & Silva, L. (2010). Very early prediction of wine yield based on satellite data from Vegetation. *Int. J. Remote Sens*, 31, 3125–3142.

Di Gennaro, S., Dainelli, R., Palliotti, A., Toscano, P., & Matese, A. (2019). Sentinel-2 Validation for Spatial Variability Assessment in Overhead Trellis System Viticulture Versus UAV and Agronomic Data. *Remote Sensing*, *11*(21), 2573. https://doi.org/10.3390/rs11212573

Dorigo, W. A., Zurita-Milla, R., de Wit, A. J. W., Brazile, J., Singh, R., & Schaepman, M. E. (2007). A review on reflective remote sensing and data assimilation techniques for enhanced agroecosystem modeling. *International Journal of Applied Earth Observation and Geoinformation*, 9(2), 165–193. https://doi.org/10.1016/j.jag.2006.05.003

Dutrieux, L. P., Verbesselt, J., Kooistra, L., & Herold, M. (2015). Monitoring forest cover loss using multiple data streams, a case study of a tropical dry forest in Bolivia. *ISPRS J Photogramm Remote Sens*, 107, 112–125.

Esquerdo, J. C. D. M., Zullo Júnior, J., & Antunes, J. F. G. (2011). Use of NDVI/AVHRR time-series profiles for soybean crop monitoring in Brazil. *Int. J. Remote Sens*, 32, 3711–3727.

Giovos, R., Tassopoulos, D., Kalivas, D., Lougkos, N., & Priovolou, A. (2021). Remote Sensing Vegetation Indices in Viticulture: A Critical Review. *Agriculture*, 11, 457. https://doi.org/10.3390/agriculture11050457

Hall, A. & Wilson, M. A. (2013). Object-based analysis of grapevine canopy relationships with winegrape composition and yield in two contrasting vineyards using multitemporal high spatial resolution optical remote sensing. *Int. J. Remote Sens*., 34, 1772–1797.

Hall, A., Lamb, D. W., Holzapfel, B., & Louis, J. (2002). Optical remote sensing applications in viticulture - a review. Australian Journal of Grape and Wine Research, 8(1), 36-47. https://doi.org/10.1111/j.1755- 0238.2002.tb00209.x

He, M., Kimball, J. S., Maneta, M. P., Maxwell, B. D., Moreno, A., Beguería, S., & Wu, X. (2018). Regional crop gross primary productivity and yield estimation using fused landsat-MODIS data. *Remote Sens*. 10, 372

Herrero-Huerta, M., González-Aguilera, D., Rodriguez-Gonzalvez, P., & Hernández-López, D. (2015). Vineyard yield estimation by automatic 3D bunch modeling in feld conditions. Computers and Electronics in Agriculture, 110, 17–26. https://doi.org/10.1016/j.compag.2014.10.003

Huang, S., Tang, L., Hupy, J. P., Wang, Y., & Shao, G. (2020). A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. *Journal of Forestry Research*, *32*(1), 1–6. https://doi.org/10.1007/s11676-020-01155-1

Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X., & Ferreira, L.G.. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sens. Environ.*, 83 (1-2), 195–213.

Jaafar, H. H., & Ahmad, F. A. (2015). Crop yield prediction from remotely sensed vegetation indices and primary productivity in arid and semi-arid lands. *International Journal of Remote Sensing*, 36(18), 4570–4589. https://doi.org/10.1080/01431161.2015.1084434.

Khaliq, A., Comba, L., Biglia, A., Ricauda Aimonino, D., Chiaberge, M., & Gay, P. (2019). Comparison of Satellite and UAV-Based Multispectral Imagery for Vineyard Variability Assessment. *Remote Sensing*, *11*(4), 436. https://doi.org/10.3390/rs11040436

Kraetzig, N. M. (2020). 5 Things To Know About NDVI (Normalized Difference Vegetation Index). *Retrieved from https://up42.com/blog/tech/5-things-to-know-about-ndvi*

Latrou, G., Mourelatos, S., Gewehr, S., Kalaitzopoulou, S., Latrou, M., & Zartaloudis, Z. (2017). Using multispectral imaging to improve berry harvest for wine making grapes. *Ciência Téc. Vitiv.*, 32(1) 33-41.

Li, L., Zhang, Q., & Huang, D. (2014). A review of imaging techniques for plant phenotyping. Sensors, 14, 20078–20111. https://doi.org/10.3390/s141120078

Matese, A., Toscano, P., Di Gennaro, S., Genesio, L., Vaccari, F., Primicerio, J., Belli, C., Zaldei, A., Bianconi, R., & Gioli, B. (2015). Intercomparison of UAV, Aircraft and

Satellite Remote Sensing Platforms for Precision Viticulture. *Remote Sensing*, *7*(3), 2971–2990. https://doi.org/10.3390/rs70302971

Mathews, A. J., & Jensen, J. L. (2012). An airborne LiDAR-based methodology for vineyard parcel detection and delineation. *International Journal of Remote Sensing*, 33(16), 5251-5267. https://doi.org/10.1080/01431161.2012.663114

Meyers, J. M., Dokoozlian, N., Ryan, C., Bioni, C., & Vanden Heuvel, J. E. (2020). A New, Satellite NDVI-Based Sampling Protocol for Grape Maturation Monitoring. *Remote Sensing*, *12*(7), 1159. https://doi.org/10.3390/rs12071159

Pádua, L., Marques, P., Adão, T., Guimarães, N., Sousa, A., Peres, E., & Sousa, J. J. (2019). Vineyard variability analysis through UAV-based vigour maps to assess climate change impacts. *Agronomy*, 9(10), 581. https://doi.org/10.3390/agronomy9100581

Panda, S. S., Ames, D. P., & Panigrahi, S. (2010). Application of vegetation indices for agricultural crop yield prediction using neural network techniques. *Remote Sensing*, 2, 673–696. https://doi.org/10.3390/rs2030673.

Pastonchi, L., Di Gennaro, S. F., Toscano, P., & Matese, A. (2020). Comparison between satellite and ground data with UAV-based information to analyze vineyard spatio-temporal variability: This article is published in cooperation with the XIIIth International Terroir Congress November 17-18 2020, Adelaide, Australia. Guests editors: Cassandra Collins and Roberta De Bei. *OENO One*, *54*(4), 919–934. https://doi.org/10.20870/oeno-one.2020.54.4.4028

Pastor-Guzman, J., Atkinson, P., Dash, J., & Rioja-Nieto, R. (2015). Spatiotemporal variation in mangrove chlorophyll concentration using Landsat 8. *Remote Sens*, 7(11), 14530–14558.

Pettorelli, N., Vik, J. O., Mysterud, A., Gaillard, J. M., Tucker, C. J., & Stenseth, N. C. (2005). Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends Ecol Evol*, 20(9), 503–510.

Pôças, I., Paço, T. A., Cunha, M., Andrade, J. A., Silvestre, J., Sousa, A., Santos, F. L., Pereira, L. S., & Allen, R. G. (2014). Satellite-based evapotranspiration of a super-intensive olive orchard: Application of METRIC algorithms. *Biosyst. Eng*, 128, 69–81.

Prasad, A. K., Chai, L., Singh, R. P., & Kafatos, M. (2006). Crop yield estimation model for Iowa using remote sensing and surface parameters. International Journal of Applied Earth Observation and Geoinformation, 8, 26–33. https://doi.org/10.1016/j.jag.2005.06.002

Robinson, N. P., Allred, B. W., Jones, M. O., Moreno, A., Kimball, J. S., Naugle, D. E., Erickson, T. A., & Richardson, A. D. (2017). A dynamic landsat derived normalized difference vegetation index (NDVI) product for the conterminous United States. *Remote Sens*. 9, 863

Rouse, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. Monitoring vegetation systems in the Great Plains with ERTS. In: Fraden SC, Marcanti EP, Becker MA, Eds. 3rd ERTS-1 Symposium. December 10–14, 1973; NASA SP-351, Washington DC, U S A. 309–317. ftp://landsat-legacy. gsfc.nasa.gov/outgoing/documents/LL-36976330531.pdf.

Silvestroni, O., Lanari, V., Lattanzi, T., Palliotti, A., Vanderweide, J., & Sabbatini, P. (2018). Canopy management strategies to control yield and grape composition of Montepulciano grapevines. *Australian Journal of Grape and Wine Research*, 25(1), 30-42. https://dx.doi.org/10.1111/ajgw.12367

Simms, É. L. & Ward, H. Multisensor NDVI-Based Monitoring of the Tundra-Taiga Interface (Mealy Mountains, Labrador, Canada). Remote Sens. 2013, 5, 1066–1090.

Somvanshi, S. S. & Kumari, M. (2020). Comparative analysis of different vegetation indices with respect to atmospheric particulate pollution using sentinel data. *Applied Computing and Geosciences*, 7, 100032. https://doi.org/10.1016/j.acags.2020.100032

Song, J., Smart, R. E., Dambergs, R. G., Sparrow, A. M., Wells, R. B., Wang, H., & Qian, M. C. (2014). Pinot Noir wine composition from different vine vigour zones classified by remote imaging technology. *Food Chemistry*, 153, 52-59.

Sozzi, M., Kayad, A., Gobbo, S., Cogato, A., Sartori, L., & Marinello, F. (2021). Economic Comparison of Satellite, Plane and UAV-Acquired NDVI Images for Site-Specific Nitrogen Application: Observations from Italy. *Agronomy*, *11*(11), 2098. https://doi.org/10.3390/agronomy11112098

Spalding, E. P., & Miller, N. D. (2013). Image analysis is driving a renaissance in growth measurement. Current Opinion in Plant Biology, 16, 100–104. https://doi.org/10.1016/j.pbi.2013.01.001

Sun, L., Gao, F., Anderson, M., Kustas, W., Alsina, M., Sanchez, L., Sams, B., McKee, L., Dulaney, W., White, W., Alfieri, J., Prueger, J., Melton, F., & Post, K. (2017). Daily Mapping of 30 m LAI and NDVI for Grape Yield Prediction in California Vineyards. *Remote Sensing*, 9(4), 317. https://doi.org/10.3390/rs9040317

Tian, J., Wang, L., Li, X., Gong, H., Shi, C., Zhong, R., & Liu, X. (2017). Comparison of UAV and WorldView-2 imagery for mapping leaf area index of mangrove forest. *Int J Appl Earth Obs Geoinf*, 61, 22–31.

Tisseyre, B., Ojeda, H., & Taylor, J. (2007). New technologies and methodologies for site-specific viticulture. *J. Int. Sci. Vigne Vin*, 41, 63-76.

Vicente-Serrano, S. M., Camarero, J. J., Olano, J. M., Martín-Hernández, N., Peña-Gallardo, M., Tomás-Burguera, M., Gazol, A., Azorin-Molina, C., Bhuyan, U., & El Kenawy, A. (2016). Diverse relationships between forest growth and the normalized difference vegetation index at a global scale. *Remote Sens Environ*, 187, 14–29.

Xue, J. & Su, B. (2017). Signifcant remote sensing vegetation indices: a review of developments and applications. *J Sensors*, 1353691.

Yang, M. D., Chen, S. C., & Tsai, H. P. (2017). A long-term vegetation recovery estimation for Mt. Jou-Jou using multi-date SPOT 1, 2, and 4 images. *Remote Sens*. 9, 893.

Zhu, X. & Liu, D. (2015). Improving forest aboveground biomass estimation using seasonal Landsat NDVI time-series. *ISPRS J Photogramm Remote Sens,* 102, 222–231

APPENDICES

Appendix 1. Output of linear regression analysis between Normalized Difference Vegetation Index (NDVI) and yield of grapes in Portland, New York in September, 2022.

Regression Statistics	
Multiple R	0.1887
R Square	0.0356
Adjusted R Square	0.0313
Standard Error	1.7297
Observations	225

Appendix 2. Mean squares from ANOVA of regression Normalized Difference Vegetation Index (NDVI) and yield of grapes in Portland, New York in September, 2022.

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	24.6438	24.6438	8.2365	0.0045
Residual	223	667.2178	2.9920		
Total	224	691.8617			

Appendix 3 Interpretation of regression coefficients with p-value for NDVI vs yield

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	18.0555	3.7877	4.7669	0.0000	10.5913	25.5198
NDVI	-13.4820	4.6976	-2.8699	0.0045	-22.7394	-4.2245

Appendix 4. Output of linear regression analysis between Enhanced Vegetation Index (EVI) and yield of grapes in Portland, New York in September, 2022.

Regression Statistics	
Multiple R	0.1887
R Square	0.0356
Adjusted R Square	0.0313
Standard Error	1.7297
Observations	225

Appendix 5. Mean squares from ANOVA of regression Enhanced Vegetation Index (EVI) and yield of grapes in Portland, New York in September, 2022.

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	24.6438	24.6438	8.2365	0.0045
Residual	223	667.2178	2.9920		
Total	224	691.8617			

Appendix 6. Interpretation of regression coefficients with p-value for EVI vs yield

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	18.0555	3.7877	4.7669	0.0000	10.5913	25.5198
NDVI	-13.4820	4.6976	-2.8699	0.0045	-22.7394	-4.2245