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# RELATIONSHIPS BETWEEN SPECTRAL VEGETATION INDICES (SVIs) AND GROWTH STAGES IN A TABLE GRAPE VINEYARD

**Zhulieta ARNAUDOVA, Boyan STALEV**

Agricultural University - Plovdiv, 12 Mendeleev Blvd, Plovdiv, Bulgaria

Corresponding author email: julieta_arnaudova@abv.bg

***Abstract***

*Table grape is a crop with a high nutritional value and frequent control is a guarantee of high quality and yields. The application instruments and methods for remote monitoring in obtaining information on the status of the vineyard will allow farmers to respond adequately to changes in plant development and grape quality. The aim of this study is to use non-destructive methods, such as satellite monitoring in the prediction of phenological changes that occur in the vine crop. The object of the study is a commercial table grape vineyard Vitis vinifera cv Velika in the land of village Granit, Stara Zagora district, Bulgaria in the period 2021-2023. NDVI was calculated using data from Sentinel 2 satellite in the main growth stages. The physiological state of the vines and the growth behaviour in the crop were monitored. An analysis was made of the relationship between the dynamics of the growth and NDVI to predict the yields.*

***Key words**: NDVI, remote sensing, vineyards, vegetation indices.*

## INTRODUCTION

Climate change poses a significant challenge to the global grape industry as it has the potential to disrupt vineyard growth. The profitability and growth of the wine industry in different regions can be affected by climate change, as the development of plantations is highly dependent on weather conditions in the short-term and climate conditions in the long-term (Sun et al., 2023).

Environmental conditions play a crucial role in determining not only yield but also the potential quality of grapes. Furthermore, profitability for growers in certain regions may be stimulated by optimizing yields and reducing production costs, while in other regions it may be stimulated by producing higher quality grapes. The factors that influence profitability include market access and growing conditions. This information is based on a study by Dr. Qun Sun published in 2023.

The growth conditions of vines during critical phenological stages can significantly affect the quality and quantity of grapes. Field observations of vine growth stages are insufficient to capture the spatial variability of vine conditions. Predicting grape yield using traditional methods requires many grape samples. Satellite imagery analysis is used more and more in many domains, from micro - to macro scale (Herbei et al., 2021) and remote sensing data can provide detailed spatial and temporal information on vine development, which is useful for vineyard management (Liang et al., 2017; Sabbatini et al., 2016).

The size and distribution of the sample are determined by the rows and spacing between the vines, which means that spatial variability must be considered. Yield estimation systems are based on sampling: (a) the number of grapevines per hectare; (b) the number of grape berries per vine, with most of them; and (c) the weight of the grape (Clingeleffer, 2016; Wolpert et al., 1992; Tarara et al., 2013). Manufacturers must determine whether, when, and how many fruits to remove during thinning. Therefore, daily observation for optimal vineyard management through ground measurements is unlikely to be representative of field conditions and is expensive to install and maintain, especially for large and distributed production systems.

Remote sensing data has significant advantages over other monitoring techniques as it provides a timely, synoptic, and up-to-date overview of actual crop growing conditions over large areas at several stages during the growing season.

Strong relationships have been found to exist between satellite-based vegetation indices, such as NDVI, and vine development in vineyards (Cunha et al., 2010; Johnson et al., 2003; Hall et al., 2002).

Remotely sensed data can be used to infer vine shape and size (Hall et al., 2001), predict phenols and grape colour (Lamb et al., 2004), and differentiate cultivars in vineyards (Brady et al., 2000; Arkun et al., 2001). Different approaches exist for using vegetation indices and their relationships with analytical measurements. These can be classified into two main categories: using empirical relationships between vegetation indices or by inverting a physical radiative transfer mode (Ganguly et al., 2012; Dong et al., 2016; Huang et al., 2015).
The aim of this study is to use non-destructive methods, such as satellite monitoring for establishing a relationship between analytical measurement and vegetation indices in the prediction of phenological changes that occur in the vine crop.

## MATERIALS AND METHODS

This study focuses on the open field situated in the South-Central region of Bulgaria, specifically in the village of Granit, municipality of Bratya Daskalovi, Stara Zagora district (Figure 1).

Figure 1. Location of study area
(Google Earth 17.06.2022)
L42°14'51.69"N B25° 9'6.36"E

### Experimental design and treatments

NDVI was obtained from Copernicus Land Monitoring Servies as a daily update of Normalised Difference Vegetation Index provided at pan-European level and in near real time. The data were available at 10 m x 10 m spatial resolution from Sentinel-2 HR multispectral satellite imagery (according to Data viewer - Copernicus Land Monitoring Service).

The Normalized Difference Vegetation Index (NDVI) is an effective index for quantifying green vegetation. It is a measure of the state of vegetation health based on how plants reflect light at certain wavelengths. The value range of the NDVI is -1 to 1. Negative values of NDVI (values approaching -1) correspond to water. Values close to zero (-0.1 to 0.1) generally correspond to barren areas of rock, sand, or snow. Low, positive values represent shrub and grassland (approximately 0.2 to 0.4), while high values indicate good health and growth of the vegetation (values approaching 1).
The formula of the NDVI is:

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

where:
- NIR is near-infrared light;
- RED is red light.

For Sentinel-2, the index looks like this:

$$NDVI = \frac{B8 - B4}{B8 + B4}$$

where:
- B8 = 842 nm;
- B4 = 665 nm.

In the event of the plant becoming dehydrated, diseased, afflicted by a disease etc., the spongy layer will deteriorate, resulting in a change in the plant's ability to reflect rather than absorb near-infrared light.
Using the NDVI data in the study regions, the changes in vegetation cover present in the area and the trend in occurrence of agricultural drought can be studied (Sruthi et al., 2015).
The images and sample raster values from NDVI imagery were processed by QGIS 3.10.
Time series imageries were downloaded for the main stages of the vine plant in the experimental field and in situ data collection for 2021-2023. The growth stages are calculated in the Days Of the Year (DOY). The correlations between the studied variables were obtained by regression analysis in Excel Microsoft 365 and were valid within the time range studied.
*In situ* data collection was conducted between 2021 and 2023 in a 30-hectare vineyard. Observations were made on a 1-hectare experimental plot. Phenology and growth of 40 vines, arranged in 4 replicates of 10 vines in two rows, were monitored within the target field.

The planting distance is 2.80 m between the rows and 1.20 m between the vines in each row and stem Gyuyo formation. Pruning involved leaving two fruit canes and two spurs. The climate data for temperature and precipitation has been recorded by the Meteobot climate station in the plantation. The vineyard is cultivated under irrigation.

In situ measurements were carried out during six main stages of grape development: budding, appearance of first leaf, flowering, veraison, technological maturity, and leaf fall. The plants on which the growth dynamics were monitored were not pruned to account for the maximum length of the shoots. Linear growth was recorded until the shoots reached their maximum height. Measurements began when the shoots were 15-20 cm long and were taken every 10-15 days.

The growth dynamics of the shoots have been traced and a correlation has been established between the values of NDVI and the length of the shoots, based on the DOY.

## RESULTS AND DISCUSSIONS

The object of the study is a typical table grape variety Velika, created in 1997 in the IASS "Obraztsov chiflik", Rousse. The main distribution area is in Bulgaria, Italy, Macedonia, Morocco. It belongs to the early ripening grape varieties with ripening period from 15 to 20 August. It is suitable for growing in warm regions with a lack of late spring and early autumn frosts. The development of the vines from forced dormancy to vegetation occurs when the average daily temperature is 10°C In the frame of the experiment, this temperature occurred in late March and early April in all three years. The selected cultivar and vineyard are in a transitional-continental zone, where we have periods of irregular precipitation and large temperature amplitude. The experimental years had a growing season length of 208-215 days (Table 1.)

Table 1. Phenological development of the Velika cultivar (Granit)

| Year | Budding | First leaf | Flowering | Veraison | Maturity | Fall leaf | Vegetation period |
|---|---|---|---|---|---|---|---|
| 2021 | 10.04 | 28.04 | 8.06 | 30.07 | 15.09 | 4.11 | 208 |
| 2022 | 28.03 | 10.04 | 31.05 | 20.08 | 19.09 | 28.10 | 215 |
| 2023 | 26.03. | 5.04 | 14.06 | 28.08 | 16.09 | 26.10 | 215 |

The Meteobot station's meteorological model data is used to determine the vineyard's stages. The results indicate a direct correlation between the availability of minimum temperatures required for phenological growth and the development of the winter buds and dormant buds in the vine during the experimental years.

In 2022, a climatic anomaly was observed in terms of vine phenology. The data from soil and atmosphere temperature sensors showed that growth stage development was primarily temperature dependent. However, in 2022, less precipitation was recorded in the spring, leading to budding as early as 10 April. The lack of rainfall caused the vines to stop developing, resulting in a delay in the following phenophases (Figures 2 and 3).

The application of satellite imagery in the early stages of grapevine development and the values of the vegetation index (NDVI) from the beginning of active vegetation (130 DOY) would provide practical information to grape producers for conducting measures that reactivate growth processes and transition to subsequent phenophases. The growth of shoots in viticulture indicates the physiological state of the vineyard and its readiness to produce high-quality grape raw material.

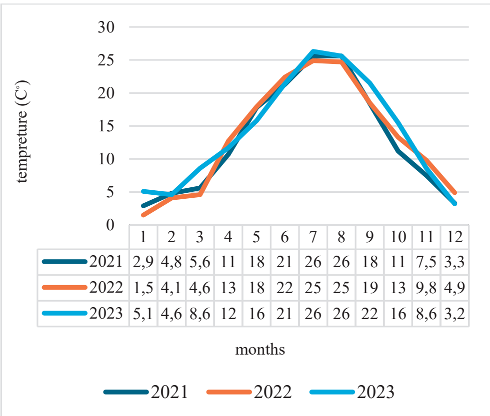
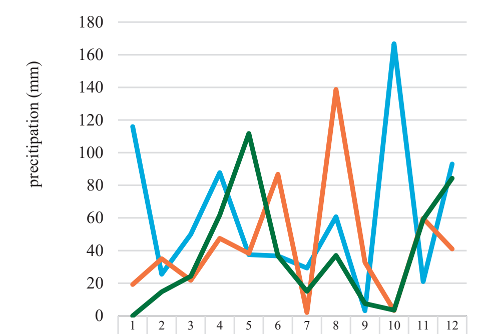



Figure 2. Climate characteristics for the experimental period




| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2021 | 116 | 25,5 | 50 | 87,8 | 37,5 | 36,8 | 29,3 | 60,8 | 3,10 | 167 | 21 | 93 |
| 2022 | 19,2 | 35,0 | 21,7 | 47,5 | 38,2 | 86,7 | 2,00 | 138, | 32,7 | 3,25 | 59,7 | 41,0 |
| 2023 | 0,00 | 14,7 | 24,2 | 61,7 | 111, | 36,7 | 15,0 | 37,0 | 7,50 | 3,50 | 59,0 | 84,2 |

months

Figure 3. Precipitation for the experimental period

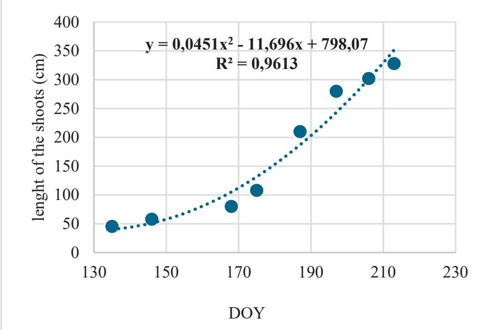
The results of our three-year experiment show that the formation of leaf mass on the shoot depends on environmental factors and the care provided by the producer. The growth in the first measurement dates indicates lower activity, which is due to temperature fluctuations and cold soil.

With the increase in the average daily temperature, the growth rate accelerates and reaches 4-5 cm per day. The observation indicates that most of the new vegetative growth is formed within 160-180 days from the beginning of vegetation (200-220 DOY) (Figure 4).

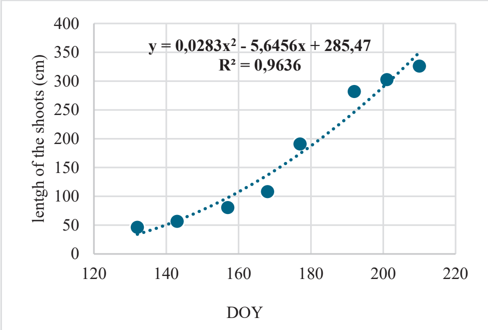
The obtained dependencies between the length of the shoots in the active vegetation period have a high degree of multiple correlation. During the first two years of the study period, the growth is described with a second-degree polynomial curve and equation due to the delayed growth. However, for the year 2023, the relationship is linear. The multiple correlation coefficient $R^2$ is 0.96-0.98 for the three years**.**

The relationship between NDVI values during the active vegetation period and the occurrence of the four main stages in the vineyard was investigated.

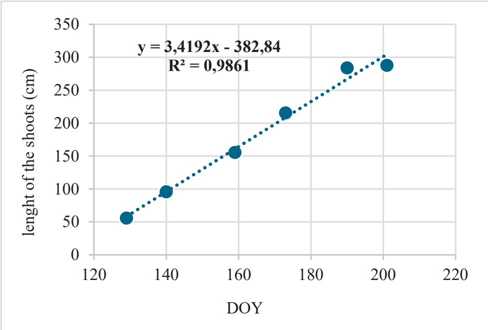
The relationships found showed very high and high correlation coefficients throughout the active period. For 2021 $R^2 = 0.98$, $R^2 = 0.78$ for 2022. The lowest value of the coefficient is recorded in 2023, which is characterized by the lowest shoot growth and high temperatures (Figure 5).




a) 2021




b) 2022



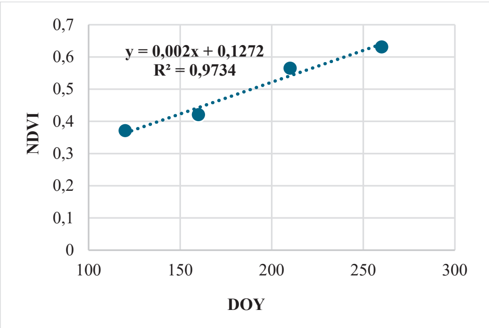

c) 2023

Figure 4. Shoot growth dynamics over the three experimental years

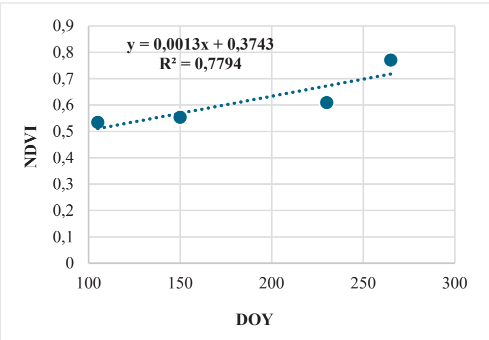
To reduce the duration of analytical in situ measurements, a correlation was discovered between shoot growth and reported NDVI values. This enables in situ observations to be limited to the main vegetation stages, with the remaining data interpreted by predicting vegetation index and shoot length data.

The downloaded images from the NDVI time series cover only the four main phases from April to mid-September. The measured shoot lengths are for a period of active growth from

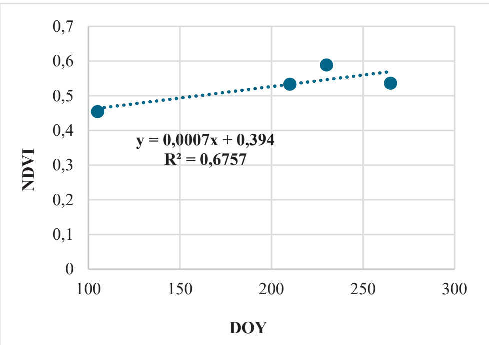
May to July, over an average of 15 days, based on the occurrence of the phenophases. The equations that relate NDVI and DOY to vegetation stages have a wider validity than the measured shoot lengths. They can be used to predict results and derive a mathematical model for the relationship between NDVI values and shoot length.




a) 2021




b) 2022



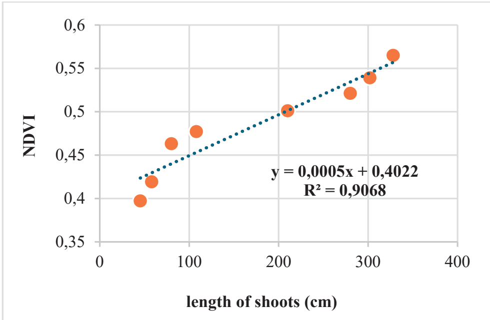

c) 2023

Figure 5. Relationship between NDVI values and active vegetation stages

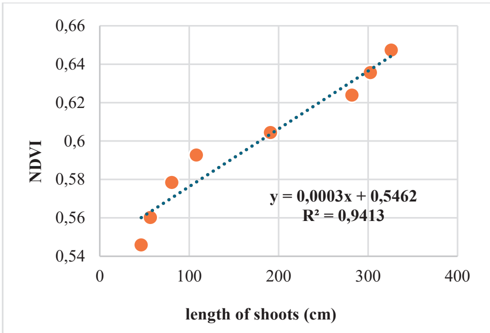
The resulting models have a high degree of multiple correlation and are a reliable indicator for relating satellite data to in situ measurements.

The growth processes are demonstrated based on the satellite images and NDVI values.

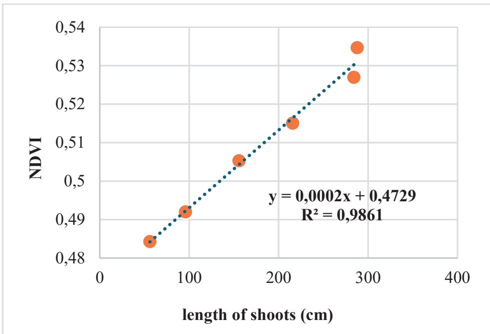
Figure 6 presents the mathematical models for the three experimental years.




a) 2021




b) 2022




c) 2023

Figure 6. Mathematical model of dependence between NDVI value and length of the shoots

## CONCLUSIONS

The study presents information on the phenological and growth processes of the vine during its annual development cycle.

The prediction of growth dynamics and NDVI values will enable the optimization of pruning timing in vineyards.
The use of digital tools, such as satellite images, enables us to apply appropriate agronomic practices to restore the growth and vigour potential of the vine crop in the event of a delay in the phenological phases and the formation of vegetative mass.

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## REFERENCES

Arkun, S., Dunk, I.J., Ranson, S.M. (2001). Hyperspectral remote sening for vineyard management. In *Proceedings of the 1st National Conference on Geospatial Information & Agriculture*, Sydney, Australia, 586–599.

Brady, J., Wiley, S. (2000). Tading AIMS amongst the vines. Aust. Grapegrow. *Winemak. 441*, 73–75.

Clingeleffer, P. (2016). Crop Development, Crop Estimation and Crop Control to Secure Quality and Production of MajorWine Grape Varieties: A National Approach. http://research.wineaustralia.com/wp-content/uploads/2012/09/CSH-96-1.pdf.

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.

Data viewer – Copernicus Land Monitoring Service

Dong, T., Liu, J., Qian, B., Zhao, T., Jing, Q., Geng, X., Wang, J., Huffman, T., Shang, J. (2016). Estimating winter wheat biomass by assimilating leaf area index derived from fusion of Landsat-8 and MODIS data. *Int. J. Appl. Earth Obs. Geoinf., 49*, 63–74.

Ganguly, S., Nemani, R.R., Zhang, G., Hashimoto, H., Milesi, C., Michaelis, A., Wang, W., Votava, P., Samanta, A., Melton, F., et al. (2012). Generating global Leaf Area Index from Landsat: Algorithm formulation and demonstration. *Remote Sens. Environ., 122*, 185–202.

Hall, A., Lamb, D.W., Holzapfel, B., Louis, J. (2002). Optical remote sensing applications in viticulture—A review. *Aust. J. Grape Wine Res., 8*, 36–47.

Hall, A., Louis, J., Lamb, D. (2001). A method for extracting detailed information from high resolution Multispectral images of vineyards. In *Proceedings of the 6th International Conference on Geocomputation*, Brisbane, Australia, 24–26 September 2001.

Herbei, M.V., Bertici, R., Sala, F. (2021). Geomatic methods for management planning of protected areas. case study: Paniova forest, Timis County, Romania. *Scientific Papers. Series E. Land Reclamation, Earth Observation & Surveying, Environmental Engineering, X*, 301-310, Print ISSN 2285-6064

Huang, J., Tian, L., Liang, S., Ma, H., Becker-Reshef, I., Huang, Y., Su, W., Zhang, X., Zhu, D., Wu, W. (2015). Improving winter wheat yield estimation by assimilation of the leaf area index from Landsat TM and MODIS data into the WOFOST model. *Agric. For. Meteorol., 204,* 106–121.

Johnson, L.F., Roczen, D.E., Youkhana, S.K., Nemani, R.R., Bosch, D.F. (2003). Mapping vineyard leaf area with multispectral satellite imagery. *Comput. Electron. Agric., 38,* 33–44.

Lamb, D., Weedon, M.M., Bramley, R.G.V. (2004). Using remote sensing to predict grape phenolics and colour at harvest in a Cabernet Sauvignon vineyard: Timing observations against vine phenology and optimising image resolution image. *Aust. J. Grape Wine Res., 10,* 46–54.

Sabbatini, P., Dami, I., Howell, G.S. (2016) Predicting Harvest Yield in Juice and Wine Grape Vineyards. Predicting_Harvest_Yield_in_Juice_and_Wine_Grape_Vineyards_(E3186).pdf (msu.edu)

Sruthi, S., M.A. Mohammed Aslam (2015). Agricultural Drought Analysis Using the NDVI and Land Surface Temperature Data; a Case Study of Raichur District. *International Conference on Water Resources, Coastal and Ocean Engineering (ICWRCOE 2015),* Aquatic Procedia, 4, 1258 – 1264.

Sun, L., Gao, F., Anderson, M.C., Kustas, W.P., Alsina, M.M., Sanchez, L., Sams, B., McKee, L., Dulaney, W., White, W.A., et al. (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

Sun, Q., Granco, G., Groves, L., Voong, J., Van Zyl, S. (2023). Viticultural Manipulation and New Technologies to Address Environmental Challenges Caused by Climate Change. *Climate, 11*(4), 83, https://doi.org/10.3390/cli11040083

Tarara, J.M., Chaves, B., Sanchez, L.A., Dokoozlian, N.K. (2013). Analytical determination of the lag phase in grapes by remote measurement of trellis tension. *HortScience, 48*, 453–461.

Wolpert, J.A., Vilas, E.P. (1992). Estimating Vineyard Yields: Introduction to a Simple, Two-Step Method. *Am. J. Enol. Vitic., 43*, 384–388.

http://msue.anr.msu.edu/uploads/resources/pdfs/Predicting_Harvest_Yield_in_Juice_and_Wine_Grape_Vineyards_%28E3186%29.pdf.