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MONITORING OF A VINEYARD BY FLYING OVER WITH A UAV

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Abstract

With the help of constant visual control and spectral during the period 2021-2022, the development of a vineyard was followed, and the dynamics of climatic factors were followed. Monitoring of climatic parameters (air temperature, soil temperature, atmospheric humidity, leaf humidity, sunshine, wind direction, evapotranspiration, rainfall) was carried out throughout the growing season of the vineyard. As a result of the observations and reports, some conclusions were drawn related to the effectiveness of drone monitoring. The BNDVI indices, which range from 0 to 1, were measured, and soil and leaf moisture parameters were recorded throughout the growing season. During the drone survey, the dynamics of the vegetation index of the vine was tracked in the established field experiment. The results of the two-year research on yield and quality of grapes fully correspond and are linked to the influence of climatic factors during the growing season and the dynamics and course of phenophases. A difference was reported between the two years, both in terms of climate and grape and wine quality. Considering the non-uniform site and sloping terrain of the vineyard, it was concluded that remote monitoring data is an excellent tool for control, tracking and forecasting, but when considering a specific local site, professional visual inspection and the application of additional analyzes and performance of measures related to cultivation technology.

Key words: *grapes, monitoring, drone, vegetation index, yield, quality.*

INTRODUCTION

Drones are still considered a new tool in agriculture, but their proven utility for assessing plant health in the field and their potential for return on investment make them an attractive addition to the precision toolkit. Interest in the use of drones has grown significantly in recent years, Macrina et al. (2020). Their application in areas such as photography, construction, monitoring are only part of the possibilities of use. Unmanned aerial vehicles (UAVs) can perform planned missions without human intervention, reports Azar et al. (2021). Automated drone survey aims to optimize the detection capabilities and the extraction of object shapes and thus increase the autonomy of surveyed fields (Orengo et al., 2021). This high-tech technology allows farmers to collect, store, combine and analyze the data layers performing precise management of fertilization and irrigation An algorithm was developed to detect the position and number of plants in vineyards using RGB drone images with a plant detection accuracy of 87%, reports Bruscolini et al. (2021) This monitoring tool enables winegrowers to keep their vines under control and improve plant health with targeted actions such as irrigation scheduling or specific treatment with plant protection agents and foliar fertilizers.

Chung et al. (2020) systematize the state-of-the-art approaches for drone application optimization, including construction, agriculture, transportation, security, disaster management, etc. They also present developed mathematical models, methods for solving problems. Drones are highly resource-constrained devices and therefore it is not possible to deploy heavy security algorithms on board, explains Hassija et al. (2021). A surface moisture mapping index (SMMI) model based on a modified normalized difference water index and a topographic wetness index is proposed by a team of scientists, reported Tang et al. (2020). The model combines the emission properties of reflectance from moisture-bearing surfaces of an agricultural field and the slope gradient and micro-topographic positions in the field.

In precision viticulture, the characterization of spatial variability in the field is a crucial step for efficient use of natural resources by reducing environmental impact commented Pagliai et al. (2022). Technologies such as unmanned aerial vehicles (UAVs), mobile laser scanners (MLS), multispectral sensors, mobile applications (MA) and structure-of-motion (SfM) techniques enable the characterization of this variability with little effort. The authors report UAV flight testing, MLS scanning over the vineyard and MA acquisition over 48 georeferenced vines. The obtained results give them reason to state that the analysed instruments are able to correctly distinguish zones with different characteristics.

Since 2010, farmers have been using remote sensing data from unmanned aerial vehicles that have high spatiotemporal resolution to determine the condition of their crops and how their fields are changing, Di Gennaro et al. (2023). According to the authors, imaging sensors such as multispectral and RGB cameras are the most widely used tool in vineyards to characterize vegetative crown development and detect the presence of missing vines along rows. A combination of photogrammetric techniques and spatial analysis tools underpins a methodology for identifying missing vines that works with 92.72% accuracy.

NDVI is widely used to estimate leaf chlorophyll content and photosynthetic activity of plants using aerial images obtained from unmanned aerial vehicles (UAVs) or from satellites (Matese et al., 2015; Campos et al., 2021; 2023).

UAVs have surveillance advantages that are characterized by high flexibility in flight planning, low operating costs, and high spatial ground resolution of captured images at different heights and with different resolutions. One of the disadvantages is that they are difficult to apply in the presence of clouds. NDVI can only refer to the crown of the vine (its leaf mass), and when NDVI is reported with satellite images it represents an average value between the NDVI for the vine and the inter-row distances covered by weeds or soil in each pixel (Khaliq et al., 2019).

These visualization inaccuracies are the basis for the results being indicative and indicative of trends. UAV monitoring is necessary to specify the terrain with its strong and weak points, but not to predict the condition of the vines, as well as the expected yield from them. Remote surveys have been done in perennials for NDVI and the evaluation of leaf vegetative mass of the vine (Rey-Caram`es et al., 2015; Caruso et al., 2017) yield and fruit quality (Lamb et al., 2004; Matese et al., 2021).

Despite the widespread use of NDVI in precision viticulture, there are no studies aimed at distinguishing the specific impact of leaf area and leaf chlorophyll concentration on the resulting NDVI vegetation index. Such information can be crucial when there is a water or nutrient deficit (Caruso et al., 2023)

Data from drone coverage of perennial crops is an addition that can give guidance on the overall condition of the plot, take into account problems related to waterlogging or drying of the soil surface (overall or locally), unfavorable soil conditions in local areas, as well as areas with lack of/or nutritional macro or micro elements from a given cultivated area.

The purpose of the study is to study the terrain with remote monitoring to study the advantages and disadvantages of the vineyard, considering the non-uniform plot and sloping terrain.

MATERIALS AND METHODS

During the period 2021-2022, monitoring of the permanent plantations was carried out by flying over with unmanned aerial vehicles (UAVs). Satellite imagery is for the entire vegetation and UAV imagery is in the "seed pouring" phase.

In the monitored vineyard, climate indicators (air temperature, soil temperature, atmospheric humidity, leaf humidity, sunshine, wind direction, evapotranspiration, rainfall) were monitored throughout the growing season, as well as two-year irrigations with drone to track the dynamics of the vine vegetation index. As a result of the observations and reports, some conclusions were drawn related to the effectiveness of drone monitoring. The BNDVI indices, which range from 0 to 1, were measured, as were the limits of soil and leaf moisture throughout the growing season.

In the vineyard there are marked vines of the Syrah variety, to which normalization of the bunches and defoliation in the area around the bunches have been applied. The observed vines of each variant have a load of 28 winter eyes.

There are 30 pieces of each variant formed. vines: lime 1. Control - without green prunings; var. 2. Bunch rationing - 15 bunches left per vine in the "pea" phase; var. 3. Norming and

defoliation - 15 bunches per vine are left in the "pea" phase and defoliation in the area of bunches in the "shattering" phase.
The yield by variants was reported and the mass values of one bunch were averaged by variants. The results of the experiment were processed by means of one-factor analysis of variance. Comparative evaluation was performed using the Duncan Test to assess differences at the 0.05 level of statistical significance.
Of the technological indicators for grapes, the following were measured:
- grape sugars, % - Dujardin hydrometer;
- titratable acids (TC), g/l - titration with 0.1n NaOH under bromothymol blue indicator.

RESULTS AND DISCUSSIONS

The study was conducted in the region of Stara Zagora, Bulgaria with geographical coordinates are 42°33′ North latitude and 25°53′ East GMT (GPS).
The region refers to the European-continental climatic region, Transitional-continental subregion, which includes the region of Eastern Central Bulgaria covering the Thracian lowland.
The region is characterized by a continental warm temperate climate with an average annual rainfall of 565.1 mm and an average annual temperature of 15.1°C.

Figure 1. The top image area "a" shows the area surveyed by the UAV, and area "b" shows the monitored area where the vineyard is located

The years of the survey are characterized as very warm. Vegetation in 2021 starts in the middle of March in 2021, and in 2022 at the end of March (Figure 1). The months of July and August coincide with the "pea" phase and the beginning of the ripening of the grapes, which reach their final size and begin to ripen. The need for rainfall and optimum temperature during this period are crucial for the quality and quantity of the yield obtained. During this period, the average daily temperature averaged over ten days reaches almost 30^0C. The temperature of the soil also increases, which makes it difficult for the root system to function when there is a lack of soil moisture. The amounts of precipitation during this period of the growing season are minimal. These temperature conditions combined with the minimum amounts of precipitation in July, August and September and the low atmospheric humidity make it difficult for the physiological processes in plants to proceed normally, as a result of which partial leaf fall is observed. The loss of part of the leaf mass delayed the technological maturity of the grapes.
In 2022, the vegetation started during the last ten days of March (Figure 1) and the values of the average day-night temperature in the following months were 3-4°C lower than the previous year, which also affected the soil temperature. The air temperature and the

amount of precipitation is more favorable in 2022 (Figures 2-4).

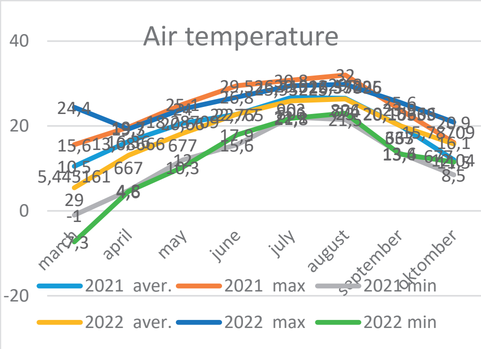


Figure 2. Air temperature (min., max., average)

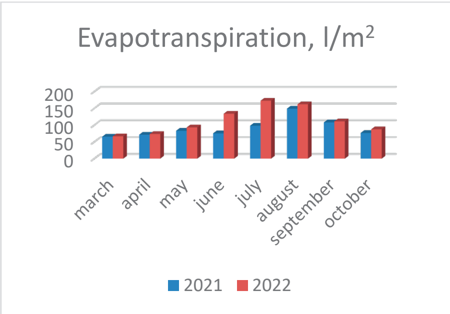


Figure 3. Evapotranspiration, l/m^2

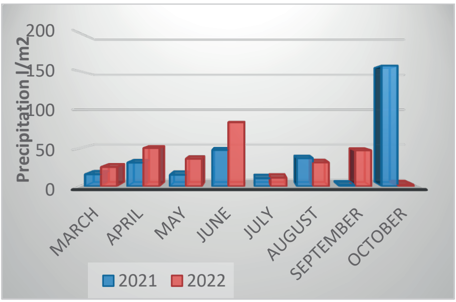
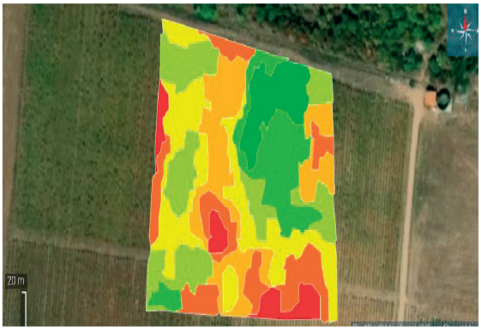


Figure 4. Precipitation, l/m^2

Through remote monitoring, a rapid and non-destructive analysis of the state of the vineyard was carried out. The series of photographic images taken during the two years of the study allow models to be made for yield prediction, water stress management, phenological development, etc. Figure 4 shows the distribution of moisture in the surface soil horizon at a specific moment. The monitoring allows to trace the available moisture in the soil at any moment of the vegetation. In this particular case, the observation shows the moisture in July 2022, the period of active vegetation when the vines need available moisture for their growth and development. From the image it can be seen that a large part of the vineyard is experiencing a water deficit. With a lack of moisture, the assimilation of water and the minerals dissolved in it is difficult.

The uneven distribution of moisture in the monitored massif also leads to differences in the development and productivity of individual plants relative to the area of the field. As a result of the uneven moistening of the soil horizon and the unfavorable vegetation in 2021/2022, uneven ripening of the bunches was observed and differences and fluctuations in the mass of the bunches after reaching technological maturity were found.



a)

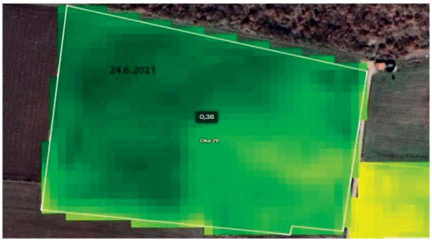
Prescription table

Zone	Average value	Area [ha]	Rate [units/ha]	Amount [units]
	0.25	951.92	0.00	0.00
	0.29	0.25	0.00	0.00
	0.32	0.29	0.00	0.00
	0.35	0.36	0.00	0.00
	0.38	0.32	0.00	0.00
	0.42	0.23	0.00	0.00
	0.47	0.13	0.00	0.00
Total:		1.68		0.00

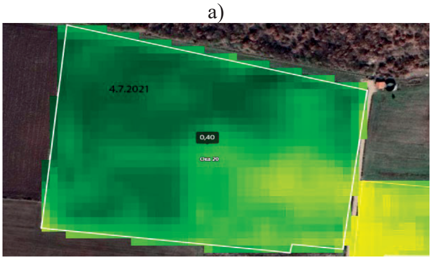
b)

Figure 5. Distribution of moisture in the surface soil layer in July 2022

Plants have been found to capture visible light for the process of photosynthesis. On the other hand, near-infrared (NIR) photons do not have enough energy for photosynthesis, but they carry a lot of heat that is reflected by plants and can be captured by cameras. This reflection mechanism breaks down when the leaf dies. Near infrared sensors take advantage of this property by monitoring the difference between NIR reflectance and visible light reflectance. This calculation is known as the normalized difference vegetation index (NDVI).



a)



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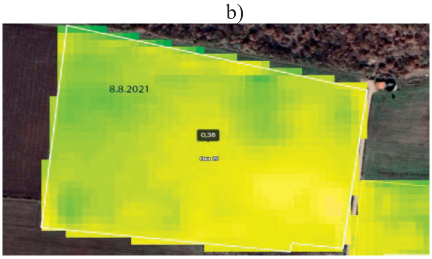

c)

Figure 6. Development of the vegetation index NDVI in 2021

High NDVI means high plant density and low NDVI indicates problem areas in the field. Through NDVI, areas of the field where crops are growing better can be clearly distinguished from those where they are not, allowing zones to be created where the correct amount of fertilizer can be applied to each location in the field.

The NDVI index is related to many plant properties. By tracking changes in the arrays, various changes that affect crop productivity can be identified. Areas with permanent water deficit or waterlogging can be located, the health status of plants can be monitored.

By means of the vegetation index NDVI, the health status of the plants, the phenological development and the biomass of the plants are determined. It is standardized and has values between -1 (absence of any vegetation) and +1 (abundant vegetation). Differences in illumination and the influence of land suitability can be compensated for:

$$NDVI = (NIR - Red) / (NIR + Red)$$

In Figure 6 traces the development of the NDVI index in 2021. The series of photographs show an increase in the index from 0.38 measured in June to 0.40 measured in early July. The rise in values coincides with the period of intense vine growth. While in August, a decrease in the index was already recorded, which is due to the decrease in the photosynthetic activity of the green parts of the vine and an increase in transpiration, which is further stimulated by the lack of moisture for the roots of the vine.

Meivel et al. (2021) are of the opinion that real-time monitoring associated with NIR imaging enables the tracking of plants and soil conditions, as well as the vegetation index responsible for vegetation growth, etc.

In the second year, remote aerial monitoring was carried out using an unmanned aerial system (drone) equipped with a specialized camera allowing the generation of the vegetation index NDVI (measuring the possibilities of absorption and reflection of incoming light by vegetation, its photosynthetic capacity and biomass concentration). The camera's multispectral and solar sensors capture the amount of light that is absorbed and reflected by the vines. The UAVs used have a high spatio-temporal resolution. To carry out accurate surveys and evaluations of vineyards, according to Ferro et al. (2023) it is important to choose the appropriate sensor or platform because the algorithms used in post-processing depend on the type of data collected.

In the second year, during the observations, weeding in the inter-rows was not recorded, while in the first year, when measuring and photographing the vine array, the entire array was observed as a whole.

Each photo taken by the hyperspectral camera is accompanied by a legend and index values are indicated (Figure 7). The NDVI Vegetation Index - can also reveal the presence of weeds, pests, water shortages and other problems, giving the grower the information needed to identify and quantify the problems, and then how best to deal with them.

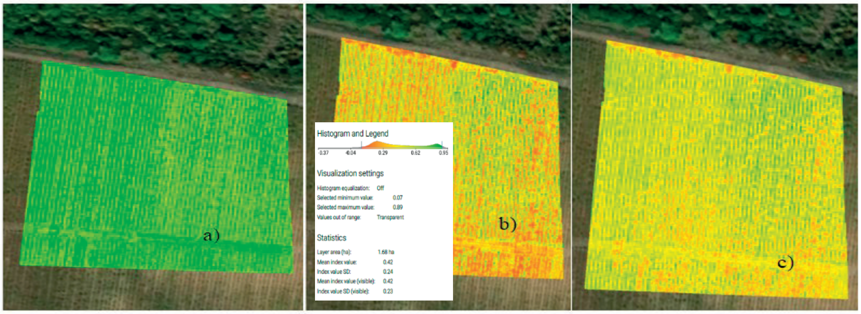

Figure 7. Development of the vegetation index NDVI in 2022.

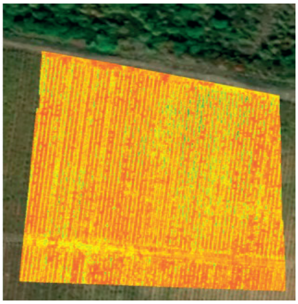

Figure 8. Determination of the Modified Chlorophyll Absorption in Reflectance Index (MCARI)

Figure 9. Determination of the Normalized Difference Water Index (NDWI)

The performance of high-resolution imagery was evaluated by considering the well-known relationship between the Normalized Difference Vegetation Index (NDVI) and crop vigor, reported Khaliq et al. (2019). The advantage of drone monitoring is that other indices can be determined, such as the Green Normalized Difference Vegetation Index (GNDVI) for evaluating photosynthetic activity. This index is more sensitive to crop chlorophyll than NDVI. The more intense the green, the more developed the vegetative mass.

MCARI is an index that responds to leaf chlorophyll concentration and ground reflectance. High index values mean low chlorophyll concentrations. Low chlorophyll indicates nutrient deficient plants, pest infestation.

The Normalized Difference Water Index (NDWI) is another index that measures plant moisture content in near real time. Information on the presence of water stress is an important point in the management of water resources.

The high-tech instrumentation used in precision agriculture enables rapid and non-destructive analysis of a large set of data. In the present study, several surveys were conducted, as a result of which the indices were established. In practice, it is necessary to carry out monitoring during the entire period of crop development. Through the capabilities of autonomous vineyard monitoring techniques, the series of photographic images and videos captured by the drone camera can be used for forecasting, crop yield modeling, disease prediction, stress management. On the basis of the obtained results, preventive measures can be taken and optimal practices can be applied to obtain high yields. According to Di Gennaro et al. (2023) the development of a methodology represents an effective decision support for the proper management of missing vines, which is essential to preserve the productive capacity of the vines and, more importantly, to ensure economic returns to the farmer.

In precision agriculture, the characterization of spatial variability in the field is a step towards optimal use of resources and minimization of negative environmental impacts.

Table 1. Comparative evaluation of indicators for yield, sugars and titratable acids according to the pruning option for Syrah variety

Year	Variants	Yield of 1 vine, g	Mass of 1 bunch, g	Mass of 100 grains, g	Sugars %	Titratable acids, g/l
2021	Control - without green prunings	3074±22[a]	106±5[b]	112±3[b]	189±1[c]	6.45±0.12[a]
	Normalized	2055±22[c]	137±3[a]	117±3[ab]	203±1[b]	5,94±0,07[b]
	Normalized and defoliated	2145±18[b]	143±4[a]	124±4[a]	209±1[a]	5.65±0.10[b]
	Average value	2425±163	129±6	118±2	200±3	6.02±0.13
	P-Value	0.000	0.002	0.094	0.000	0.004
2022	Control - without green prunings	2185±9[a]	104±5	131±5	228±1[a]	7.00±0.04[a]
	Normalized	1650±25[c]	110±4	128±4	226±1[a]	6.72±0.04[b]
	Normalized and defoliated	1785±13[b]	119±5	127±3	219±1[b]	6.88±0.03[a]
	Average value	1873±81	111±3	129±2	225±1	6.87±0.04
	P-Value	0.000	0.140	0.766	0.002	0.006

[a, b, c] - evidence of differences at a statistical significance level of 0.05.

To study the influence of the pruning variant on the productivity of the grapes, as well as the content of sugars and titratable acids, a one-factor analysis of variance was applied for each of the years of study. Comparative evaluation was conducted using the Duncan Test to assess differences at the 0.05 level of statistical significance. Both the average values of each indicator for the corresponding type of pruning, as well as the standard error, giving information about the degree of variation of the characteristic, were calculated.

Given the results in Table 1, it should be considered that in 2021 the type of applied pruning has a statistically significant effect on all the studied indicators, and in 2022 - only on yield from one vine, content of sugars and titratable acids.

In 2021, the highest yields were found in the vines without green pruning (3074 g), and the lowest - in normal pruning. The normalized and defoliated version of pruning has a positive effect on the mass of grapes (143 g) and per hundred grains (124 g), as well as on the content of sugars (209 g/dm^3). The richest in titratable acids are the vines without green prunings (6.45 g/dm^3).

In 2022, it turns out again that the most productive are the vines without green prunings, whose yields reach 2185 g. Significantly less productive are normalized and defoliated (1785 g), and the lowest productive - normalized (1650 g). Grapes from vines without green prunings (228 g/dm^3) and normalized (226 g/dm^3) are the richest in sugars. The highest content of titratable acids was found in grapes without green prunings (7.00 g/dm^3), followed by normalized and defoliated (6.88 g/dm^3) and normalized (6.72 g/dm^3).

Linear regression is a statistical method for constructing a linear relationship between a set of independent variables and dependent variables. Through regression analysis, the nature of the relationship between the studied indicators is presented. The coefficient of determination (R^2 = 0.8927) was calculated when analyzing the relationship between yield and mass of 100 grains. A strong positive correlation dependence was established.

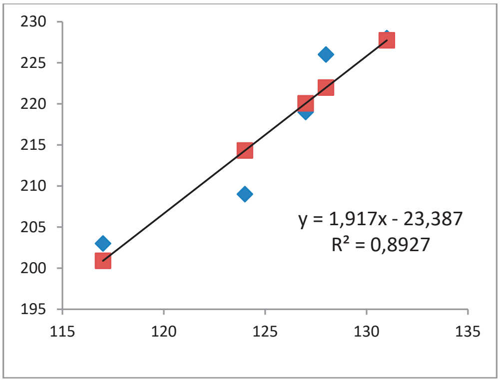

Figure 10. Linear regression model between sugars and 100 grains mass

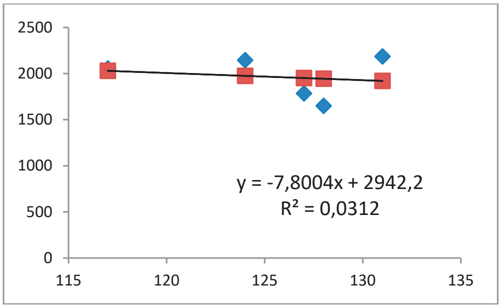

Figure 11. Linear regression model between yield and weight per 100 grains

From the linear model in Figure 11, it can be seen that there is a weak correlation between yield and mass per 100 grains. The calculated coefficient of determination (R^2 = 0.0312). A strong positive correlation was found between the mass of one bunch and sugars, with a coefficient of determination R^2 = 0.895.

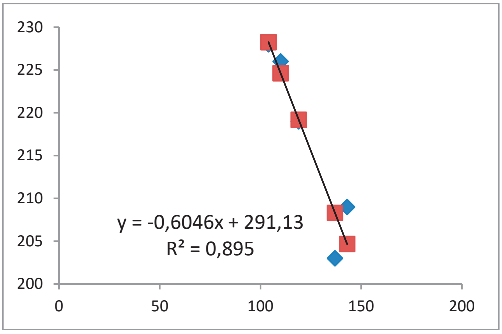

Figure 12. Linear regression model between mass of 1 bunch and sugars

The results showed that the remote monitoring of perennial crops provides indicative data, taking into account the trend of some indicators tracked during the vegetation period. When registering a low vegetation index during the growing season, for example, it is necessary to look for the reasons, to take soil samples, to make an irrigation or any other measure that is necessary to ensure the health status of the vines.

CONCLUSIONS

As a result of the conducted remote monitoring, it can be concluded that the development and growth of the vegetative mass of the vine corresponds to the recorded vegetation index of the vine for the phenophase in which the monitoring was conducted.

The influence of climatic factors greatly affects the development, growth, yield and physiology of the vine. Vegetation indices are a complex assessment of the whole terrain, not just the plant itself, and with UAVs a difference in the captured geometric image is taken into account, which affects the NDVI values.

Linear regression models show a strong positive correlation between the mass of one bunch and sugars, with a coefficient of determination R^2 = 0.895, as well as between the yield and the mass of 100 grains (R^2 = 0.8927).

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