Precision viticulture using multiple sensors and aerial robotics (VITISENSE) for better financial outcomes and disease management practices

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ABSTRACT

The deployment of Unmanned Aerial Systems (UASs) are the newest and most versatile tools for input optimization in several agricultural sectors, including viticulture. This drone technology is characterized by high precision, flexibility and low operational costs. To monitor an area of 31.4 hectares with grapevines, we deployed a UAV equipped with high-resolution hyperspectral camera RedEdge-M 5.5, to capture more than 3400 aerial images and provide a comprehensive overview of the vineyards. The flight plans were always registered on the Drone Aware – GR (DAGR) online system and the flights were performed according to National Aviation regulations and regulations of the International Civil Aviation Organization. The imagery obtained from drone facilitated the creation of detailed maps and 3D models of vineyards topography, aiding in site characterization and vineyard design. Furthermore, the associated software system was able to provide data for the determination of vegetation indices NDVI, SAVI, OSAVI, RDVI, EVI, PRI, MCARI, TCARI, ARI2, CRI2, WBI, enabling growers to detect early signs of stress, disease, or nutrient deficiencies. The ability to acquire data at different stages of the growing season facilitates informed decision-making, optimizing resource allocation and maximizing yield. The utilization of drones for capturing images of vine crops facilitated the management of spatial and temporal variability in the field. As technology continues to evolve, the integration of drones and advanced analytics holds promise for further optimizing grape production, sustainability, and profitability in the wine industry.

Keywords: Financial outcomes, precision viticulture, sensors, robotics, vegetation index, plant disease

1. INTRODUCTION

Precision agriculture utilizes multiple technologies to manage the spatial and temporal variability associated with agricultural production, to improve crop performance, economic benefits, and environmental quality. In viticulture, such techniques are used to improve the efficient use of inputs (e.g., fertilizers and chemicals), yield forecasting and selective harvesting of grape quality. Remote and proximal sensors become reliable instruments to disentangle vineyards' overall status, essential to describe vineyards' spatial variability at high resolution and give recommendations to improve management efficiency. Aircraft remote sensing campaigns can be planned with greater flexibility, but they are difficult and expensive. Satellite image acquisition of large areas saves a considerable time but has a low and inadequate resolution for precision viticulture (PV). Among all the remote sensing technologies for spatial and temporal heterogeneity detection, unmanned aerial systems (UASs) are the newest tools and likely the most useful in terms of high accuracy, flexibility, and low operational costs. UASs are often combined with imaging sensors, which allow the acquisition of images at higher spatial resolutions than those offered by satellites. Post-processing techniques combined with machine learning tools evolved to the point that the visual indications contained in an image can be extracted and transformed into useful information for farm management [1]. Generally speaking, PV technologies aim to decrease costs in crop management by enhancing yield and quality of production. The profit margin can be increased with the the application of precision farming methods. Vineyard output can be effectively characterized, monitored, and protected by the plant design and variations in the surface area and volume occupied by foliage. By establishing a site-specific crop management system, farmers may

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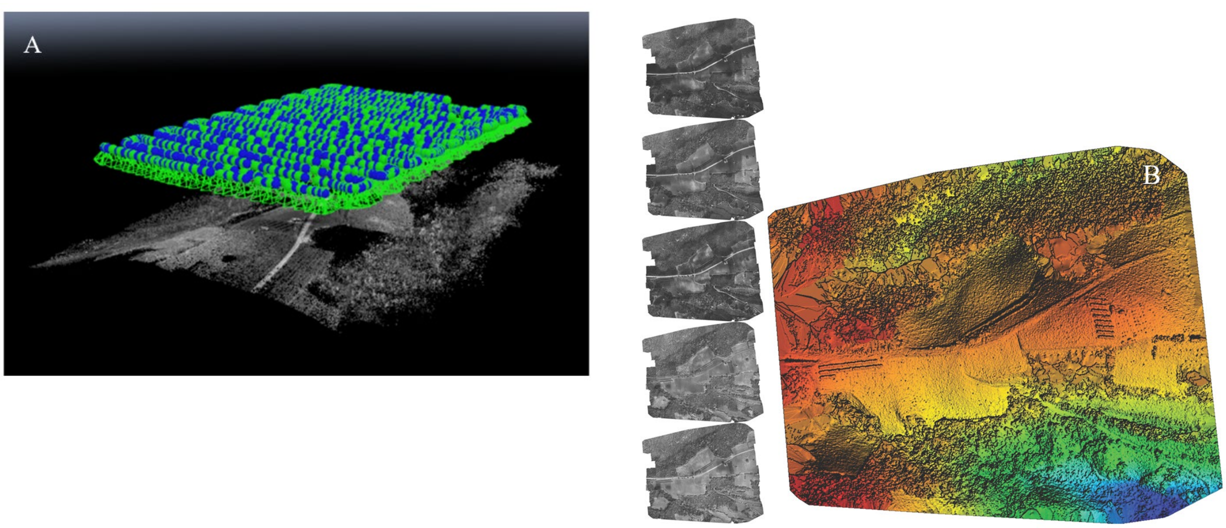
detect the vegetative development of the crop, diagnose deficiencies, and optimize canopy treatments with the use of accurate knowledge about the area and volume filled by the rows. In a related study, Giovos et al. [2] compiled the existing vegetation indices used in viticulture, which were calculated from images obtained from remote sensing platforms such as satellites, airplanes, and UAVs. The results showed that the most used vegetation index is the NDVI, which is typically applied for monitoring and assessing the water stress of vineyards and delineating management zones. Furthermore, there are multiple grapevine diseases responsible for yield quality and quantity decrease and economic losses to the wine industry worldwide. Di Gennaro et al. [3] suggest a methodology to investigate the relationships between high-resolution multispectral images (0.05 m/pixel) acquired using a UAS, and grapevine leaf stripe disease (GLSD) foliar symptoms monitored by ground surveys. This approach showed high correlation between NDVI index and GLSD symptoms, and discrimination between symptomatic and asymptomatic plants. Albetis et al. [4] presented the potential of spectral bands, vegetation index, and biophysical parameters to detect grapevines affected by the bacterial agent Candidatus Phytoplasma vitis and transmitted by the insect Scaphoideus titanus (Ball). As a result of innovations in UAS technology, lower purchase costs, and an increasing use of such systems, UASs are a key tool for decision support in the customary use by winegrowers. This approach can optimize and limit the inputs and diminish potential environmental damage caused by an inappropriate application of products, as well as reduce the management cost. Additionally, these technologies strive to ensure traceability and environmental sustainability by minimizing the use of chemical inputs and water. Consequently, the application of PA positively increases profits and limits input costs [1].

2. METHODOLOGY

On March 31, 2023, an unmaned aerial system equipped with an integrated GPS receiver and navigation system was used for the flight campaign on a vineyard near Naoussa, Greece, by the Surveying and Geoinformatics company Exorixi SA. A DT-5Bands imaging device, which is built around the industry-leading MicaSense RedEdgeTM sensor, was used to capture multispectral UAV photos. This sensor consists of five independent high accuracy sensors. The flora response was recorded at five spectrum bands (SB): blue, green, red, red-edge, and near infrared (NIR). With a UAV flying at 5 m/s, the flight height was set at 100 m. Using these particular parameters allowed for the best possible photogrammetric processing, with an 85% forward and a 70% side overlap. Pix4D software (https://pix4d.com/) was used to manage and process the UAV images (Fig. 1). Pixel values were converted to surface reflectance in each spectral band, thanks to the calibrated ground panel used before and after the flight (to check stability of the illumination).



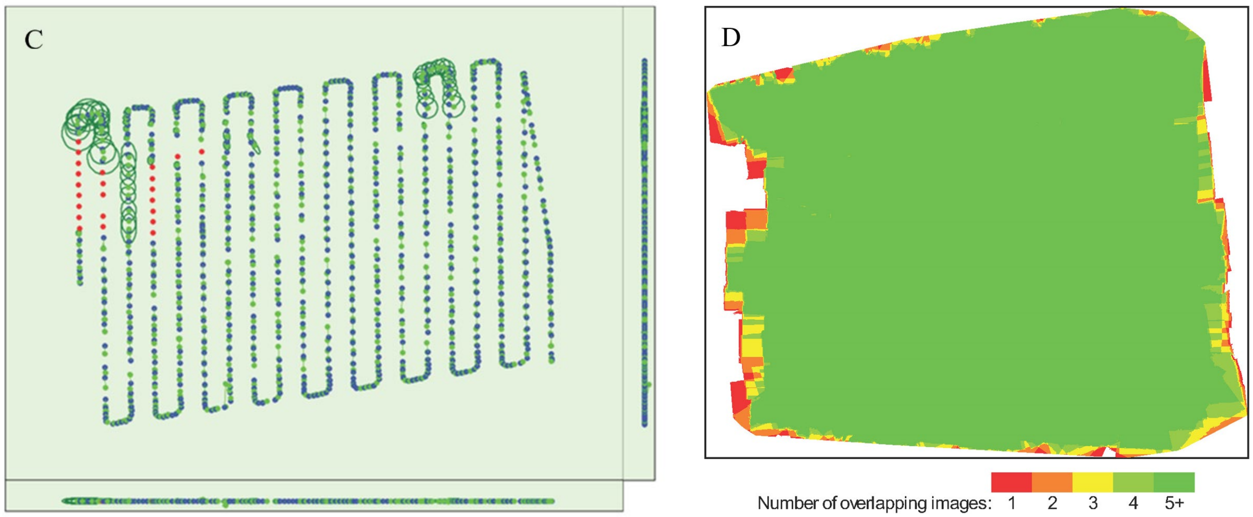


Figure 1. Data acquisition, processing and analysis: A. Final 3D visualization of the vineyard over flight; B. Orthomosaic and corresponding sparce Digital Surface Model (DSM) before densification; C. Computed image/Manual tie points positions; D. Number of overlapping images computed for each pixel of the orthomosaic (red and yellow areas indicate low overlap; green areas indicate an overlap of over 5 images for every pixel).

3. DATA

A set of ten vegetation indices (VI) were calculated from the five spectral bands (SB) of the UAV images. These were chosen because of their potential relevance to discriminate vegetation's greenness, density, and health. Table 1 gives formulas and corresponding references for the vegetation indices selected. The selected VI were used for monitoring and mapping temporal and spatial variations of biomass and plant productivity (NDVI, OSAVI, NDRE). Among them, NDVI (Fig. 2) and its variants BNDVI and GNDVI are used for estimating vigor, chlorophyll content and photosynthesis rates throughout the crop cycle based on how plants reflect specific electromagnetic spectrum ranges.

Table 1. Predefined vegetation indices generated with Pix4Dfields software

Vegetation Indices (VI)	**Formula**
BNDVI (Blue Normalized Difference Vegetation Index)	BNDVI = NIR−B/NIR+B
EVI (Enhanced Vegetation Index)	EVI=2.5*((NIR-R)/(NIR+6*R-6*B+1))
GNDVI (Green Normalized Difference Vegetation Index)	GNDVI = NIR−G/NIR +G
LCI (Leaf Chlorophyll Index)	LCI= (NIR - RE)/(NIR + R)
NDRE (Normalized Difference Red Edge)	NDRE= (NIR-RE)/(NIR+RE)
NDVI (Normalized Difference Vegetation Index)	NDVI=NIR−R/NIR+R
OSAVI (Optimized Soil Adjusted Vegetation Index)	OSAVI = [(NIR-R)/(NIR+R+L)]·(1+L)
RDVI (Renormalized Difference Vegetation Index)	RDVI= (NIR-R) / SQRT(NIR+R)
SIPI2 (Structure Intensive Pigment Index 2)	SIPI2 =(NIR-G/NIR-R)
VARI (Visible Atmospherically Resistant Index)	VARI =(G-R/G+R-B)

Legend: R—Red; G—Green; B—Blue; NIR—Near InfraRed; RE— RedEdge; L is a soil fudge factor that varies from 0 to 1

4. RESULTS

The selected VIs were used for monitoring and mapping variations of biomass and plant productivity. Among them NDVI is the most widely used in precision agriculture and is also suitable to detect disease disorders. In the present study NDVI and its variations provided a detailed status of the vineyard (Fig. 2). Furthermore, NDVI and OSAVI indices were probably reflecting the result of cumulative water deficits in a long-term response

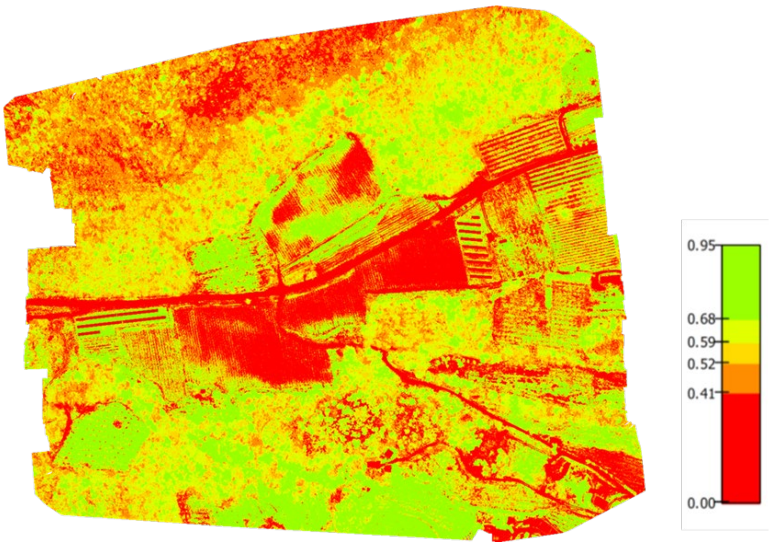


Figure 2. Normalized Difference Vegetation Index map for biomass calculation. Values close to 1: the more intense the green, the more vigorous the vegetation and vegetation cover. Values close to 0: correspond to areas with very little vegetation, early stages of cultivation, bare soil, or non-productive areas.

5. CONCLUSION

Viticulture has shown the greatest technological advances among all agricultural sectors thanks to the higher profit margin from producing high-quality wine. In assessing the productivity of vineyards using remote sensing and satellite monitoring tools, it has been concluded that radar data can be used to assess soil moisture and identify crops at a similar level to optical data. NDVI indicators in combination with a geoinformation system has quicker access to reliable information about crops (or farmland), and timely decisions can be made on when to harvest, when to fertilize, and other current activities. By using NDVI data, it is possible to quickly estimate the physiological condition of crops and monitor vegetation development. NDVI data can be used to forecast productivity. As a result, economic effects and financial planning are improved. Furthermore, precision viticulture with the use of multiple sensors and aerial robotics can provide a high-resolution metric of vegetation health. It is likely to help farmers optimize agricultural production and manage resources more sustainably if they can identify within-field variability in crop conditions on a timely and repeatable basis.

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REFERENCES

[1] Alberto Sassu, Filippo Gambella, Luca Ghiani, Luca Mercenaro, Maria Caria and Antonio Luigi Pazzona, "Advances in unmanned aerial system remote sensing for precision viticulture,". Sensors, 21(3), (1 Feb 2021). https://doi.org/10.3390/s21030956

[2] Rigas Giovos, Dimitrios Tassopoulos, Dionissios Kalivas, Nestor Lougkos and Anastasia Priovolou, "Remote sensing vegetation indices in viticulture: A critical review", Agriculture 2021, 11(5), (18 May 2021). https://doi.org/10.3390/agriculture11050457

[3] Salvatore F. Di Gennaro, Enrico Battiston, Stefano Di Marco, Osvaldo Facini, Alessandro Matese, Marco Nocentini, Alberto Palliotti and Laura Mugnai, "Unmanned Aerial Vehicle (UAV)-based remote sensing to monitor grapevine leaf stripe disease within a vineyard affected by Esca complex" Phytopathol. Mediterr. 55(2), (29 Jul 2016). https://doi.org/10.14601/Phytopathol_Mediterr-18312

[4] Johanna Albetis, Sylvie Duthoit, Fabio Guttler, Anne Jacquin, Michel Goulard, Hervé Poilvé, Jean-Baptiste Féret and Gérard Dedieu, "Detection of Flavescence Dorée grapevine disease using unmanned aerial vehicle (UAV) multispectral imagery". Remote Sens. 9(4), (24 March 2017). https://doi.org/10.3390/rs9040308