INTEGRATED UAV TECHNOLOGIES USED IN THE ANALYSIS OF THE CONDITION OF CROPS IN VINEYARDS AND ORCHARDS
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TEHNOLOGII INTEGRATE UAV UTILIZATE ÎN ANALIZA STĂRII CULTURILOR DIN VII ȘI LIVEZI

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ABSTRACT

The use of UAV (Unmanned Aerial Vehicle) technology or drones in the monitoring of vineyards and orchards offers multiple benefits, improving the monitoring, management, and productivity of crops. The main goal of this study was to implement a cost-effective integrated UAV technology that includes the necessary hardware and software elements for analyzing the health and growth of agricultural crops in general, with a particular focus on vineyards and orchards. Based on the analysis, agronomists, experts in the field, or ordinary farmers can implement appropriate management measures, such as adjusting the irrigation process, applying fertilizers or phytosanitary treatments, and potentially using shading for the crops. Continuous crop monitoring allows for the evaluation of the effectiveness of the implemented measures and the adjustment of the crop management strategy. Another important objective was the use of high-precision sensors that can be easily attached to a commercial civil drone. The developed system should have a compact size and low energy consumption and even allow for IoT connectivity. To collect and record data from these sensors, a program written in Python is used, containing specific blocks for data acquisition from each sensor to facilitate the monitoring of environmental factors or energy consumption. Experimental tests conducted in the orchard space at the Faculty of Biotechnical Systems Engineering of the National University of Science and Technology Politehnica in Bucharest, Romania, led to the creation of maps showing the health status of the crops based on vegetation indices. The tests demonstrated that UAVs could rapidly cover large areas and collect detailed data without requiring extensive human resources or costly equipment. The results of the analysis of the drone's flight performance underscore the considerable potential of UAV technologies in revolutionizing precision agriculture, particularly in orchards, providing farmers with powerful tools to improve the sustainability and productivity of their crops.

REZUMAT

Utilizarea tehnologiei UAV (Vehicul aerian fără pilot) sau dronelor în supravegherea viilor și livezilor oferă multiple beneficii, îmbunătățind monitorizarea, gestionarea și productivitatea culturilor. Scopul principal al acestui studiu a constat în implementarea unei tehnologii UAV integrate cu cost redus care să conțină elementele hardware și software necesare analizei stării de sănătate şi creștere a culturilor agricole in general, cu particularizare in zona de vii si livezi. Pe baza analizei, agronomii, experții în domeniu sau fermierii obișnuiți implementează măsuri de management adecvate, cum ar fi ajustarea procesului de irigare, aplicarea fertilizatorilor sau tratamente fitosanitare, eventual acoperirea cu umbrare a culturilor. Monitorizarea continuă a culturilor permite evaluarea eficiența măsurilor implementate și ajustarea strategiei de gestionare a culturilor. Un alt obiectiv important a fost utilizarea de senzori cu precizie ridicata ce pot fi atașați cu ușurința unei drone civile comerciale. Sistemul realizat se impune să aibă un gabarit și un consum de energie redus, și chiar sa permită o conectivitate IoT. Pentru a colecta si înregistra datele de la acești senzori, se folosește un program scris in limbajul Python conținând blocuri specifice pentru achiziția datelor fiecărui senzor, pentru a facilita procesul de monitorizare a factorilor de mediu sau consumul energetic. Testele experimentale realizate in spațiul livezii din Facultatea de Ingineria Sistemelor Biotehnice a Universității Naționale de Știință și Tehnologie Politehnica București, România, au condus la crearea hărților care arata starea sănătății culturii pe baza indicilor de vegetație. Testele au arătat că UAV-urile pot acoperi rapid suprafețe mari și pot colecta date detaliate fără a necesita resurse umane extinse sau echipamente costisitoare. Rezultatele analizei comparative a performantelor de zbor ale dronei in cele doua misiuni executate (zbor liber și cu încărcare) *subliniază potențialul considerabil al tehnologiilor UAV în revoluționarea agriculturii de precizie, în special în podgorii și livezi, oferind fermierilor instrumente puternice pentru a îmbunătăți sustenabilitatea și productivitatea culturilor lor.*

INTRODUCTION

Enforcing intelligent applications in agricultural activities is an imperative and pressing concern worldwide (*Abo-Habaga et al., 2024*).

Photogrammetric analysis of crop conditions in vineyards and orchards is a modern and advanced method for monitoring and evaluating the health and development of agricultural crops using aerial images captured by drones or other aerial platforms. This technique provides a precise and efficient way to obtain detailed information about crop conditions over large areas without the need for on-site inspections. Drones equipped with high-resolution cameras capture images of vineyards and orchards from various angles and at different altitudes to detect plant health issues. The captured images are processed and geometrically corrected to create accurate orthophotos—geographically accurate two-dimensional maps that provide an exact representation of the terrain. The orthorectification process is necessary to eliminate distortions caused by terrain topography and camera angles. Using photogrammetry techniques, three-dimensional (3D) models of the terrain, vines, or trees can be created, allowing for detailed assessment of plant height, vegetation density, and structure. These 3D models are useful for volumetric analysis and for monitoring changes over time (*Ipate et al., 2015; Remondino et al., 2011; Sassu et al., 2021; Xue & Su, 2017*).

Based on the captured multispectral images, vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), are calculated, providing information about plant health and vigor. The values of these indices allow for the identification of areas experiencing plant stress, such as those affected by drought, diseases, or nutritional deficiencies. The generated maps and obtained data are analyzed to detect specific crop issues, such as areas affected by pests, diseases, water shortages, or other stress factors. This information can be used to make informed decisions regarding irrigation, fertilizer application, or phytosanitary treatments. Photogrammetric analysis enables periodic real-time monitoring of crops, providing up-to-date data and allowing for quick interventions when problems are detected (*Toscano et al., 2024; Fascista A., 2022; Cavalaris C., 2023; Vidican et al., 2023; Velez et al., 2023)*.

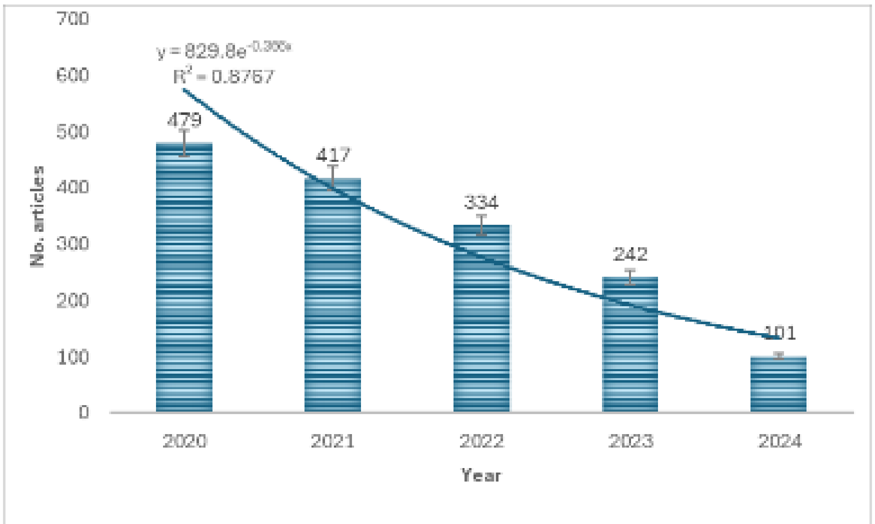

Fig. 1 – The evolution of the number of scientific articles in the last 5 years on the topic of using drones for monitoring vineyards and orchards

The present study began with an in-depth search on the most comprehensive scientific database platform, Google Scholar, using a combination of the defined key terms "UAV drone monitoring orchard and vineyards" (*Singh et al., 2022*). In just 0.11 seconds, 4,140 papers were detected, of which 563 are review articles. The graph in Figure 1 shows the number of articles published over the years 2020-2024. A clear downward trend in the number of published articles is observed, from 479 in 2020 to 101 in 2024. This decrease is described by an exponential curve, indicating a rapid decline in the early years, followed by a slower decrease in the subsequent years.

This trend may suggest a decrease in interest or resources allocated to this specific field, or a shift in focus to another area of research. However, without additional information, definitive conclusions about the reasons for this decline cannot be drawn.

The works cited in references *Zhang et al., (2021); Lopez-Granados et al., (2020)* provide a comprehensive review of the existing literature concerning crop management in vineyards and orchards using aerial drones, highlighting the significant potential of UAV technology; these reviews emphasize various applications of UAVs in managerial decision-making processes, focusing particularly on the diversity of data processing techniques and the accuracy of monitoring capabilities. In the studies referenced as *Zhou et al., (2021); Bilotta & Bernardo, (2021); Kasimati et al., (2023)*, there is a detailed discussion on the critical importance of utilizing drones for crop forecasting and selective harvesting, as well as for pest control and the efficiency of irrigation systems; these studies underscore the transformative impact of drone technology on agricultural practices. Moreover, in the paper referenced as *Modica et al., (2020)*, it is anticipated that an increasingly substantial source of information will be provided by unmanned aerial vehicle (UAV) platforms, which are predominantly equipped with multispectral optical cameras, to map, monitor, and analyze the temporal and spatial variations in crops through specialized maps of spectral vegetation indices. The discussion further mentions the necessity for solid knowledge in geographic information systems (GIS) and computer image processing, which are essential for field data collection and the creation of vegetation health maps; the capture of aerial images and video files for plant health analysis, along with their integration into GIS programs, facilitates the early detection of fruit tree health issues, thereby enabling the rapid implementation of measures to optimize crop yields.

Currently, the development of drones and their equipment with the most advanced sensors is clearly essential for monitoring and data collection. In the case of applying treatments through spraying in orchards, such as those for fruit trees, olive trees, or citrus, the role of aerial drones remains one of the most controversial aspects, deeply connected to economic, technical, and environmental fields. In the study done by *Campos et al., (2019)*, a major objective was to determine possible correlations between experimental data from remote sensing and the actual characteristics of the upper parts of trees or plants, including branches and leaves. This correlation is necessary for the development of a variable-rate application technology for treatments, based on the health status maps previously developed (*Ioja et al., 2024; Ghazal et al., 2024*).

Special attention is given in some works to the use of artificial intelligence in the processing and understanding of images captured by UAVs during the monitoring and evaluation of production in fruit orchards or vineyards (*Lopez-Garcia et al., 2022; Popescu et al., 2023*). The complex characteristics of UAV trajectories and flights in these areas are easily managed through the implementation of neural network systems. The structure of the applications, databases, software, and the performances obtained are systematically analyzed to recommend the most effective solutions to end-users. The complex applications analyzed, such as crop and tree identification and classification, disease and pest detection, production evaluation, and growth condition assessment, lead to significant improvements in efficiency and accuracy in orchard management, providing essential information for optimizing interventions and maximizing agricultural yield (*Poblete et al. 2017; Zhou et al., 2021*).

Convolutional neural networks (CNNs) are used in the monitoring of orchards and vineyards to analyze aerial or ground images captured by drones, satellites, or fixed cameras (*Zhang et al., 2021; Popescu et al., 2023; Osco t al., 2020; Chen et al., 2019*). These networks are capable of identifying and classifying various critical aspects of crops, such as plant health, the presence of pests, development stages, and even water stress.

- **Monitoring Plant Health:** CNNs can detect early signs of diseases or nutritional deficiencies by analyzing variations in the color and texture of leaves and fruits (*Khattak et al., 2021*). This enables rapid intervention to prevent the spread of problems.
- **Pest Identification:** By analyzing images in detail, convolutional networks can recognize the presence of pests and affected areas, aiding in the application of precise and effective treatments (*Liu & Wang, 2020*).
- **Yield Estimation:** CNNs can be used to count fruits or assess their size and distribution in real-time (*Vasconez et al., 2020; Miranda et al., 2023*), providing more accurate estimates of the expected harvest.
- **Development Stage Detection:** Convolutional networks can analyze images to determine the growth stages of plants, allowing for better planning of harvesting and other agricultural activities.

The main goal of this paper is to develop an innovative agricultural crop monitoring system based on an aerial drone, which can have various applications and contribute to more efficient resource use. By implementing better-informed and more tailored agricultural practices to the specific conditions of each plantation, the system also aims to significantly reduce the negative environmental impact. From this proposed goal, several key research objectives emerge, as follows: the ***Aerial Photogrammetry*** section briefly describes the approaches to image processing for providing detailed and useful information. By formalizing the task as a sequential labeling problem, the ***Image Processing*** section designs an image classifier for identifying plant diseases using the K-means algorithm. The ***Convolutional Neural Networks*** section reports significant improvements in understanding the use of the method primarily for image recognition and classification. Considerations regarding real-time object detection are presented in this paper in the ***Fruit Recognition in an Orchard with YOLOv4*** section. An analysis of the drone battery's energy efficiency in various scenarios is addressed in the ***Flight Performance Analysis*** section. These objectives aim to develop efficient and scalable systems capable of integrating artificial intelligence technologies to provide precise information for optimizing agricultural processes.

MATERIAL AND METHODS

I. Aerial Photogrammetry

Photogrammetry is a well-developed technology that combines photography and precise measurements to provide detailed and useful information about the surrounding world. The final products of photogrammetry include digital 3D models of the terrain, topographic maps, orthophotos (geometrically corrected aerial images), and various precise measurements of dimensions, volumes, and distances (*Srinivas et al., 2012; Zhang et al., 2023*). The photogrammetry process includes:

- Capturing images from different angles to ensure complete coverage of the object or terrain being studied;
- Orientation and calibration using Ground Control Points (GCPs) and algorithms to align and calibrate the images, correcting any distortions;
- 3D reconstruction of the object or terrain using photogrammetry software by analyzing the perspective differences in the captured images.

When creating an orthophoto mosaic (Figure 2) from multiple aerial or satellite images, each image must be geometrically corrected and then stitched together with other images to cover the entire area of interest (*Gharibi & Habib A., 2018; Rosell & Sanz, 2012; Altunbasak et al., 2003*). Seamlines define the locations where these images are joined.

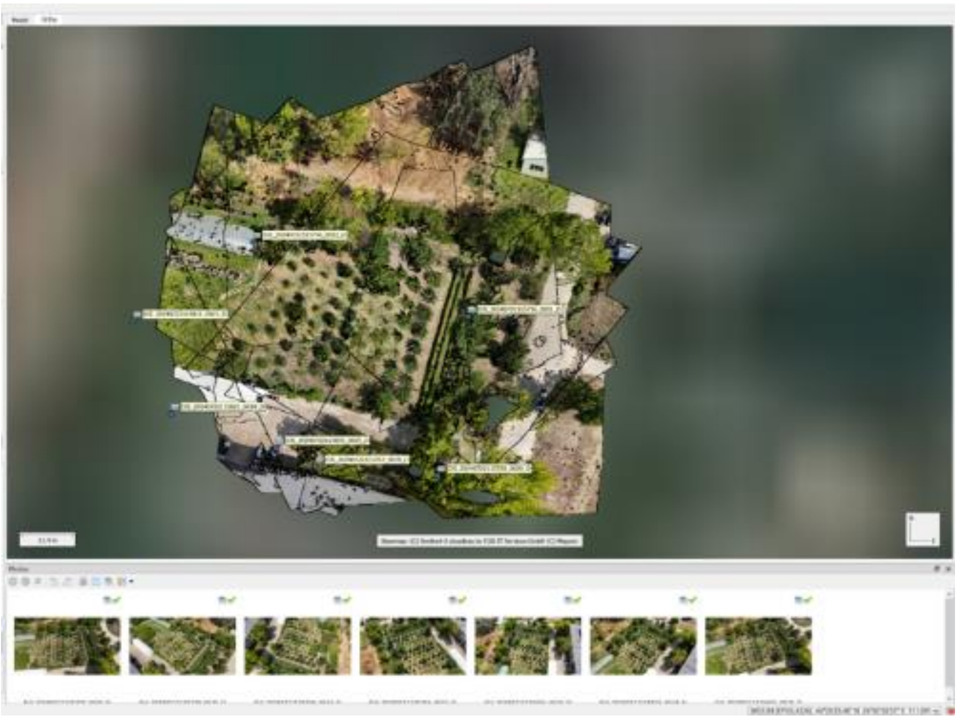

Fig. 2 – Orthomosaic with Image Identification and Seamlines (Screenshot from Agisoft Program)

Radial correction is an important process in photogrammetry and image processing, aimed at eliminating radial distortions introduced by the camera's optical system. These distortions often occur at the edges of the image, where straight lines may appear curved. The radial correction process involves modeling and compensating for these distortions to restore the correct geometry of the image.

Classification of Radial Distortions:

- Barrel Distortion: Straight lines at the edges of the image appear to curve outward, giving the image a "barrel" shape. This type of distortion is common in wide-angle lenses.
- Pincushion Distortion: Straight lines at the edges of the image appear to curve inward, toward the center, creating a "pincushion" effect.

The mathematical model for radial correction is based on modeling radial distortions using polynomials or various mathematical functions. The most common model for correcting radial distortion is based on a higher-order polynomial that describes how a pixel shifts depending on its distance from the optical center (*Altunbasak et al., 2003*).

a) Coordinates before correction*:* Let's assume we have the coordinates of a point in the image, (x,y), which are the pixel coordinates before correction. Radial distortion affects these pixels based on their radial distance from the optical center of the image.

b) Radial distance (1)**:** The radial distance r is the distance from the center of the image (assuming the distortion is symmetric relative to the optical center) to the point (x,y):

$$r = \sqrt{x^2 + y^2} \quad (1)$$

c) Radial distortion model. Radial distortion can be modeled with a polynomial of the 2nd (2) or 3rd (3) order. The basic formula to calculate the new position of the corrected point is:

$$x_{cor} = x \cdot (1 + k_1 \cdot r^2 + k_2 \cdot r^4 + k_3 \cdot r^6 + \cdots) \quad (2)$$

$$y_{cor} = y \cdot (1 + k_1 \cdot r^2 + k_2 \cdot r^4 + k_3 \cdot r^6 + \cdots) \quad (3)$$

where the coefficients k_1, k_2, k_3, etc., are the radial distortion coefficients, which are determined practically through camera calibration.

d) Camera calibration. The camera calibration process involves photographing a known pattern (such as a grid of points or a checkerboard) and adjusting the coefficients so that the model in the image matches the real model. Camera calibration can be performed using specific algorithms, such as Zhang's method, which is commonly used in computer vision (*Zhang Y.J., 2023*).

e) Applying the correction. After the coefficients are determined, the above formula is used to recalculate the positions of each pixel in the corrected image. Essentially, the formula is applied to every pixel in the image to obtain a new position that corrects the effect of radial distortion.

f) Interpolation. In the correction process, since points may be shifted to positions that do not exactly coincide with a pixel, interpolation of color values is necessary. Common interpolation methods include bilinear interpolation or cubic interpolation to ensure a smooth transition and a corrected image without visible artifacts.

Fig. 3 – Point cloud construction with identification of used images (screenshot from Agisoft program)

For practical implementation examples, in programming languages like MATLAB or Python, there are functions and libraries (such as OpenCV) that can automatically apply these corrections once the distortion coefficients are known.

The Digital Surface Model (DSM) represents the actual surface of the Earth, including all objects that cover it. It is constructed based on the point cloud through interpolation or triangulation to create a continuous surface. A point cloud from the Digital Surface Model (DSM) represents a collection of points in three-dimensional coordinates (X, Y, Z) that describe the terrain surface and all objects on it, such as buildings, vegetation, and other structures (Figure 3). The DSM is different from a Digital Terrain Model (DTM), which represents only the terrain surface without any objects above it. In addition to spatial coordinates, each point can also have other attributes, such as the intensity of reflected light (in the case of LIDAR), color (in the case of RGB photogrammetry), or other spectral data (*Beumier & Idrissa, 2016*).

II. Hardware components

The DJI Mini 4 Pro is a commercial drone from the DJI series, and it is one of the smallest and lightest, weighing just 249 grams (Figure 4 a). It is easy to transport and can be used in many countries without requiring registration or a license. Equipped with a high-performance 1-inch sensor camera, it is capable of capturing high-resolution images and superior quality 4K HDR video. An advanced 3-axis gimbal technology (Figure 4 b) ensures electronic stabilization of the video camera, allowing for continuous and stable image capture. With a flight time of up to 34 minutes, due to the intelligent battery that includes safety features such as overcharge and overheating protection, the drone also has advanced obstacle avoidance systems for safe navigation, significantly reducing the risk of accidents. For precise positioning and accurate tracking of planned trajectories, the drone uses GPS (Global Positioning System) and GLONASS technology. Various automated and intelligent flight modes, such as QuickShots, ActiveTrack, and Point of Interest, make it easy to capture impressive images and videos. Intelligent features allow the drone to automatically return to the takeoff point in case of a weak signal, low battery, or at the user's command. The drone benefits from the OcuSync system, which provides stable and clear video transmission over long distances, up to 10 km, allowing for more precise control and a safer flying experience. Data encryption for the DJI Mini 4 Pro against interception involves the use of technologies and protocols that protect data transmitted between the drone and the controller (pilot) or between the drone and data storage servers. This includes encryption of video streams, telemetry, control data, and other sensitive information that might be transmitted or stored. The encryption protocol used by DJI is based on AES (Advanced Encryption Standard), a strong and widely used cryptographic standard.

a **b**

Fig. 4 – DJI Mini 4 Pro with payload (a) and gimbal (b)

RESULTS

The experimental location was an arable area situated within the campus of the Faculty of Biotechnical Systems Engineering at the University Politehnica of Bucharest (at the coordinates of the takeoff/landing point 44.440218° N and 26.045350° E) at an altitude of 78 m, as shown in Figure 5 a and b. The topography of the site is relatively homogeneous and flat. The orchard, containing various fruit tree species, generally apples, pears, plums, nectarines, peaches, apricots, and rows of grapevines, was monitored through the execution of two flight missions. The experiments conducted in this study were carried out with maximum safety concerning other aircraft, infrastructure, and individuals, in accordance with the regulations of the Romanian Civil Aeronautical Authority (AACR). The flight missions were conducted within the pilot's visual range at a maximum altitude of 80 meters above ground level to avoid collisions. The flight missions were planned in compliance with all current regulations (as per flight request No. 10139 - 202473091447 approved by the Ministry of National Defense).

The processing of the captured aerial images (focused on a point of interest (POI) configured at the center of the monitored area) from the selected points along the route (Figure 5c) and the analysis of vegetation indices were carried out using the Agisoft Metashape Professional software. To analyze the drone's performance in terms of energy consumption, maneuverability, and flight autonomy, two missions were conducted: one free flight and one flight with a payload, both following the same planned route. Along the route, 7 waypoints were configured/designed at an altitude of 78 meters above the ground, from which images of the monitored area, including the fruit orchard and rows of grapevines, were captured. Additionally, a point of interest was configured at a distance of 1 meter above the ground, located in the center of the monitored area.

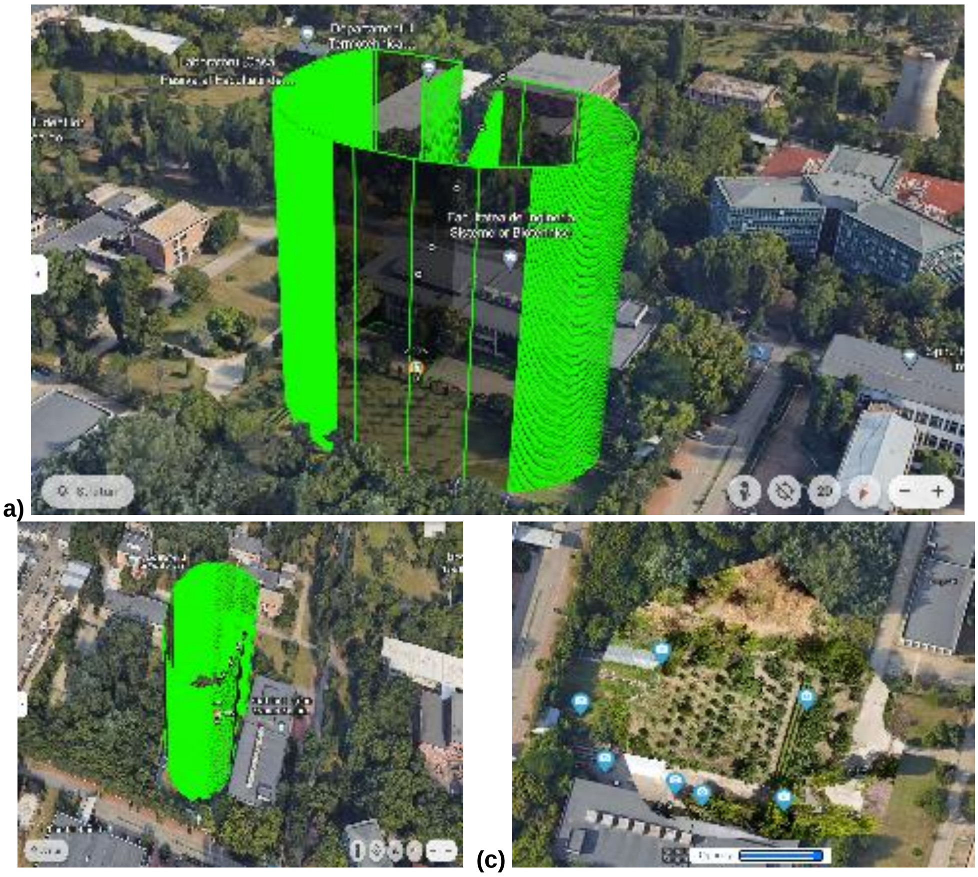

Fig. 5 – Experiment location - University Politehnica of Bucharest campus: (a) Flight mission 1, Google Earth screenshot; (b) Flight mission 2; (c) Image capture locations in the monitored area

Photogrammetric Analysis

In the method proposed by the study (*Alganci et al., 2018*), the processing of the digital surface model (DSM) involves several steps, starting with image capture and ending with model analysis. Figure 6 shows one of the aerial photographs taken by the drone with a high-definition camera at point 5 of the route, located at coordinates Lon 26.065390 and Lat 44.440345, to create a digital surface model.

Fig. 6 – The image captured at point 5 of the planned route

The camera is equipped with a 1/1.3-inch CMOS sensor and supports up to 4x digital zoom, allowing for the capture of distant details without significantly compromising image quality. It can capture photos at a resolution of up to 48 megapixels, ensuring extremely detailed images; real-time video transmission is supported at 1080p over distances of up to 10 km. The geographic coordinates of the points along the flight path where the camera was programmed to capture images are provided in Table 1.

Table 1

Geographic coordinates of the waypoints along the flight path

Waypoints	Longitude (E)	Latitude (N)
Waypoint1	26.045899	44.440040
Waypoint2	26.046240	44.440021
Waypoint3	26.046326	44.440355
Waypoint4	26.045724	44.440513
Waypoint5	26.045390	44.440345
Waypoint6	26.045493	44.440151
Waypoint7	26.045788	44.440079

The Red-Blue Normalized Difference Vegetation Index (NDVI-RB), sometimes also referred to as the Visible Color Difference Index in the context of the red and blue bands, is determined using the following relationship (*Qiao et al., 2022*):

$$\mathrm{VNDVI}_{RB} = \left(\frac{R-B}{R+B}\right) \qquad (4)$$

This value represents a ratio that captures the characteristics of vegetation, contrasting the reflectance of the red (R) and blue (B) bands to highlight areas where red light is absorbed (indicating photosynthetic activity) and blue light is reflected. The image in Figure 7 was processed using the unstandardized formula of the vegetation index, displayed in an NDVI (Normalized Difference Vegetation Index) palette.

Applying a specific NDVI color palette to this index means that the image is colored in a way that highlights areas with high vegetation health (green) and areas with low vegetation health or non-vegetative areas (in brown, yellow, or light tones). The NDVI color palette ranges from -1 to 1, with higher values (closer to 1) indicating dense and healthy vegetation, and lower values (closer to -1) indicating bare soil, water, or deteriorated vegetation. Green areas indicate regions where the absorption of the red band is high relative to the blue band, signifying healthy plant material. Brown and lighter colors represent vegetation health ranging from moderate to low or areas with sparse vegetation. In the context of the applied formula, this suggests areas where the difference between red and blue reflectance is less pronounced, indicating potentially stressed vegetation or bare soil.

Fig. 7 - Normalized Difference Red-Blue Vegetation Index (NDVI-RB).

The Normalized Difference Index of Visible Colors (VNDVIBR - Visible Normalized Difference Vegetation Index - Blue Red) presented in Figure 8 is less common compared to the classic NDVI, but it can be used to evaluate vegetation based on reflectance in the blue (B) and red (R) bands, especially in situations where near-infrared (NIR) band data is not available.

It is calculated using the following formula (*Qiao et al., 2022*):

$$\mathrm{VNDVI}_{BR} = \left(\frac{B-R}{B+R}\right) \quad (5)$$

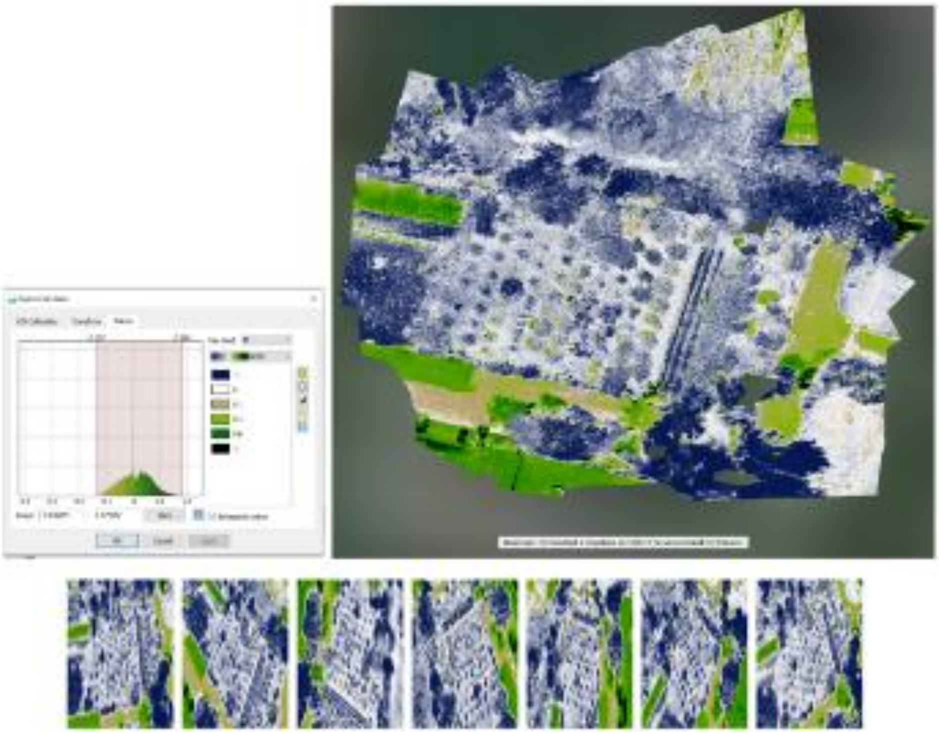

Fig. 8 - Normalized Difference Blue-Red Vegetation Index (NDVI-BR)

Because healthy vegetation usually absorbs red light (used in photosynthesis) and reflects more light in the blue band, this index is somewhat unusual, but it can still provide useful information about the relative health and type of vegetation. In this context, lower values (towards -1) represent healthier and more vigorous vegetation, while values closer to 0 and towards 1 represent areas with less vegetation, stressed or less vigorous vegetation, or even the absence of vegetation.

Fig. 9 - Vineyard monitoring: (left) color image showing the rows of vines; (right) low contrast image where the details exhibit strong negative activation (dark) as well as positive activation (bright)

In Figure 9, a comparison is presented between the color and black-and-white images used to highlight certain characteristics or anomalies in the vegetation, which might be important for monitoring the vineyard's condition. The left frame shows a color image depicting a vineyard with 3 rows of vines. The vegetation is dense and well-defined, with the leaves and stems of the plants clearly visible. In the background, a building and a few trees can be seen, indicating that the vineyard is located in a natural environment, in the garden of the Faculty of Biotechnical Systems Engineering. The right frame shows the same image, but in a black-and-white format with reduced contrast. The image is more difficult to interpret visually, but it seems to depict the same area or a similar area, though the details are much more blurred. The contrast between dark and light areas may indicate the presence of differences in temperature, humidity, or vegetation health that are not evident in the color image.

Fig. 10 – Implementation of artificial intelligence algorithms in image processing for orchard monitoring

Figure 10 shows the implementation of artificial intelligence algorithms to extract specific information from a natural scene. These three images, taken together, suggest a process of vegetation analysis and monitoring, where different image processing techniques are used. In the first frame (left), the image is an ordinary color one, showing the vegetation in natural conditions, with clear details of the trees and surrounding vegetation. The sky is blue, the vegetation is green and healthy, and the background includes trees and possibly other elements of the natural environment. The second frame (middle) presents a slight adjustment in saturation, although the differences from the first image are subtle. This frame is used to highlight certain details of the vegetation or to prepare the image for further analysis. The third frame (right) shows an image with strong contrast, with accentuated dark areas. The vegetation appears much more defined, and fine details of leaves and branches are highlighted. This processing can be used to isolate certain characteristics of the vegetation, such as density or the health status of the plants, and this image might be intended for spectral analysis or to detect anomalies or variations in vegetation composition.

CONCLUSIONS

The application of unmanned aerial vehicle (UAV) technology and artificial intelligence in precision agriculture provides a significant advantage in managing current issues. This combination of technologies facilitates efficient operations and rapid interventions, optimizing resources and thus contributing substantially to increased production and minimized expenses.

The use of applications that implement artificial intelligence algorithms for assessing the health of crops is essential for precise and automated monitoring in agriculture, offering the ability to quickly and efficiently analyze complex images to detect problems or quantify yields. In conclusion, this information is extremely important for optimizing resources in various work scenarios, as well as for planning future operations within the agricultural farm.

The presented study has fully demonstrated its usefulness, contributing to the expansion of knowledge in the field of vineyard and orchard monitoring through a significantly more cost-effective solution compared to those currently available on the open market.

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