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Observation of the vegetation processes of agricultural crops using small unmanned aerial vehicles in Dobrudja region

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Abstract

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The presented study aims to evaluate the effectiveness of small unmanned aerial vehicles used to assess vegetation processes and predict yield. The UAV (Unmanned Aerial Vehicle) is equipped with a 20 MP camera with RGB spectrum and another 12 MP camera with NIR spectrum mounted on it. The flights were conducted in different light conditions throughout the crops growing season in the economic year of 2020/21. Classical yield estimation methods, which consist of manual field sampling of a limited number of plants, are time consuming and are often insufficient in gaining representative yield data. The information obtaining methods have been observed and tested. The application of innovative phenotypological technologies such as UAV, high resolution cameras, and visual computational algorithms allowed for the estimation method testing. The method proved to be time-saving and able to provide accurate estimation data, in comparison to the manual methods.

Keywords: UAV (unmanned aeral vehicle); yield estimation; precision farming

Introduction

The monitoring of vegetation, maturity period and field health condition is extremely important for the production quality. Traditionally, the yield prediction data is collected manually and is randomly assessed by visual or destructive methods, which may involve problems such as low efficiency in terms of time and/or location, as well as representativeness of the sample (Pothen et al., 2016). Yield evaluation by visual inspection including counting of classes and plants and estimating the size is subjective. This leads to errors related to noncorrespondences between the results obtained by different observers due to their different levels of experience. (Roscher et al., 2014). The agroclimatic conditions of the field, the plowed soil, and the mud often cause difficulties in measurement. This is especially true in summer due to the extremely high temperatures, or in winter due to the snow and the cold. In respect to this, technology advances is the key to the future development of agriculture.

Precision agriculture is experiencing significant growth due to the availability of improved and cost-effective tools such as unmanned aerial vehicles (Matese et al., 2015). The rapid technological advances of unmanned aerial vehicles encourage a variety of applications, (Gago et al., 2015; Pôças et al., 2015; Bellvert et al., 2016; Di Gennaro et al., 2016; Poblete-Echeverría et al., 2017; Romboli et al., 2017; Santesteban et al., 2017; Matese et al., 2018) which open new perspectives to traditional remote sensing (Sun et al., 2018).

Spectral vegetation indices are widely used for monitoring and analysis of plant structure changes and plant health status. They are also used to depict phenological changes, as well as to assess the green biomass and yield potential. Some of the most well-known indices are: Enhanced Vegetation Index (EVI), Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI), etc. (Asrar et al., 1984).

Cameras having the ability to detect reflections in the NIR spectrum, close to the visible red light limit are widely used. These define the specific vegetation indices, obtained by the measured reflection values. (Scotford et al., 2005).

The study aims to determine the possibilities of using small unmanned aerial vehicles for the precision agriculture needs.

Material and Methods

Conducting the experiment

The survey was conducted during the agricultural season of 2020-2021. The investigated areas (43.657963, 28.023110) represented an experimental field sown with wheat in the municipality of General-Toshevo, Dobrich District, Bulgaria.

A preliminary flight planning was accomplished, as to optimally make use of the UAV characteristic features, described by the manufacturer. For the most optimal result reporting, a flight altitude of 100 m above the ground was chosen. Due to the specifications of the UAV, its flight time was planned to be less than the theoretical flight time.

The UAV used was the DJI Mavic 2 Pro [dji.com (2021)]. It is equipped with a 20 MP 1” CMOS sensor Hasseblad L1D-20 and is designed for 31 min maximum flight time with a maximum drone speed of up to 72 km/h (at a constant speed of 25 km/h, close to sea level, no wind.) The weight of the Mavic 2 Pro is 907 g.

In addition to the UAV built-in camera, a second one was installed on the MAPIR Survey3W Camera (mapir (2021).]

Fig. 1. Photo of DJI Mavic 2 Pro equipped camera MAPIR Survey 3W_RGN

– Red + Green + NIR (RGN, NDVI) with Sony Exmor R IMX117 sensor – 12 MegaPixel (4000 x 3000 px). This model Red + Green + NIR (RGN, NDVI) detects infrared radiation with a wavelength of 850 nm, as well as red reflection at 660 nm and green reflection at 550 nm (Figure 1).

Determining the Optimal Flight Altitude

Test flights were made (during the months of April to June 2021), at different heights, to determine the correspondence between the photo pixel size and the area of the terrain in centimeters. The results are shown in Table 1.

It is obvious from the results that even at an altitude of 100 m (which is the maximum altitude of the UAV used) the resolution of 4.09 cm/px is accurate enough to take into account the smallest changes in biomass. The resolution for satellite observations is 3-10 m per pixel.

Table 1. Pixel size according to height

Sensor MAPIR Survey 3W_ RGN_3.4_4000X3000 -12MP	Sensor Hasseblad L1D-20c_10.3_5472X3648 -20 MP
Height 20 m – 0.77 sm/px	Height 20 m – 0.47 sm/px
Height 30 m – 1.21 sm/px	Height 30 m – 0.51 sm/px
Height 40 m – 1.56 sm/px	Height 40 m – 0.94 sm/px
Height 60 m – 2.48 sm/px	Height 60 m – 1.41 sm/px
Height 75 m – 3.08 sm/px	Height 75 m – 1.44 sm/px
Height 90 m – 4.06 sm/px	Height 90 m – 1.79 sm/px
Height 100 m – 4.09 sm/px	Height 100 m – 2.34 sm/px

Testing The Maximum Observable Plot Size

Based on the manufacturer’s specifications, the maximum flight time is 31 min. [dji.com (2021)] Based on a relevant reference, it has been established that it is possible to use the maximum flight altitude of the UAV of 100 m. A series of flights were conducted to determine the largest area that can be observed in a single flight. The theoretical flight time does not correspond to the actual flight situation due to variables such as wind, humidity and air temperature.

During the flights, it was found that after the UAV battery dropped to 25%, there was a warning signal for low charge, and after the charge fell below 15%, the UAV went into a controlled landing mode, at the coordinates of its current location.

It was found that the optimal flight time in scan mode is about 19 min.

The size of the scanned area depends on the horizontal speed of the UAV for the specific model. For the conducted experiments (Table 2), it varies from 8 to 10 m/s. The size of the field that can be flown depends on the photos overlap which can be chosen to be 70, 80 or 90%.

Table 2. Comparison of flight data

Date	Height, m	Overlap, %	Zone, m	Area, ha	Battery on landing, %	Distance, m
22.5.2021	100	70	829x639	52.9	30	7018
30.5.2021	100	70	997x724	72.2	13	8441
5.6.2021	100	80	547x494	27	44	7005
25.6.2021	100	80	695x562	39	24	7297
9.7.2021	100	70	745x665	125	10	7749
			842x705		18	8370
			842x692		27	8302

An overlap of 80% and a flight area size of 547x494 m was proved to be optimal for flying in almost all weather conditions – this flight was performed 14 times during the area scanning.

Three consecutive flights on 09th July 2021 and the simultaneous image processing obtained date about a field with an area of 1,125 km^2.

Flight Planning

The flight dates were planned according to the agricultural crops vegetation. Two kinds of software were used for planning the flights – Pix4Dcapture (Figure 2).

Figure 2 is the flight plan using Pix4Dcapture on the satellite image and only on the map. The flight plans thus created were slightly adjusted after the first flights and then used for almost all subsequent flights over this field. The final flight plans, created for the specific field, can be used even in the next agricultural year.

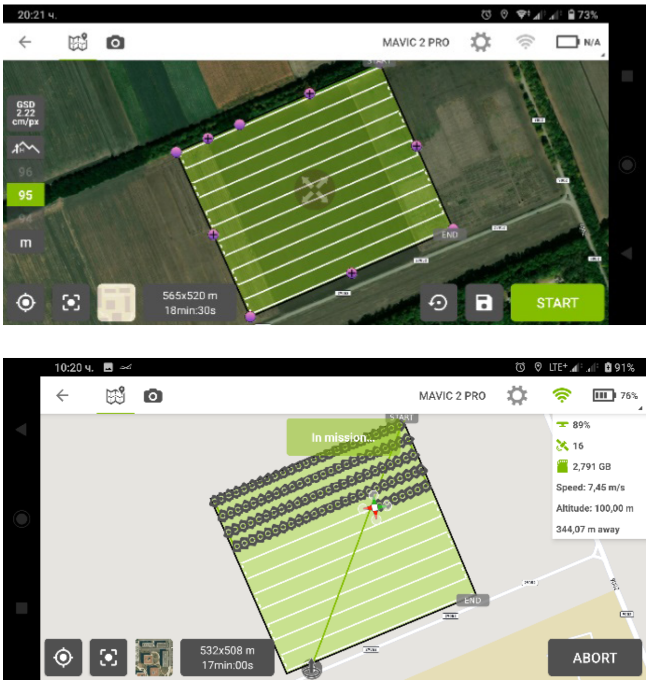

Fig. 2. Flight plan with Pix4Dcapture on the satellite image and only on the map

Errors Related to the Height and Position Geocoordinates

The main reported flight errors were related to the GPS module errors in coordinate reading. The height error is when processing (Figure 3), where the flight path is clearly distinguishable at different heights, and the real one is shown in Figure 4.

Figure 4 shows another type of error. These are the red dots which there are not specified by GPS coordinates and

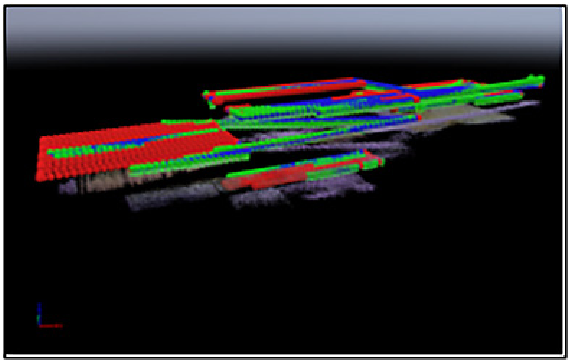

Fig. 3. MAPIR Survey 3W

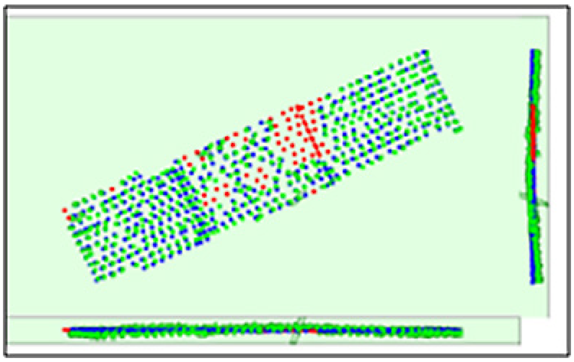

Fig. 4. Raw images

as a result, they cannot be positioned by the processing software. Consequently, they are excluded from the calculations and there remain empty spots in the generated vegetation indices.

Meteorological Conditions Effect on data Collection

A leading factor in conducting flights is the preliminary check of the weather forecast. The main problem are the wind gusts which deflect the UAV or do not allow it to continue on its route. During the experiment 3 out of 53 flights did not reach the designated shooting area and 7 did not complete the entire mission.

Taking photos after rain or when there is dew on the plants significantly changes the reflective characteristics. This means incorrect data on the plants condition.

Very low or very high temperatures are also an obstacle because they are beyond the operating temperature range. The low temperatures, in combination with the high humidity, causes icing on the UAV propellers. Furthermore, very low temperatures, below 0°C, can cause a sharp drop in the battery charge. At very high temperatures, there is intense heating of the battery and the motors. Very high temperatures can also ignite the battery.

During the experiments, there was no problem with the high temperatures and when the temperatures were very low, the plants were at rest and taking pictures was not necessary.

Problems related to Birds of Prey

In all the experimental flights, there were two cases of birds of prey being interested in the UAV. In the first case, a falcon dived towards the UAV, but did not collide with it.

In the second case, a pair of hawks circled over the UAV during a mission, but did not attack.

It is desirable to choose a UAV with bright colors that are not found in nature, so as birds of prey not to show interest in it. The bright colour would also help in case of an emergency landing in the monitored field for the easier detection of the UAV.

Spoofing Attack

UAV hacking is possible in theory, but the flights are performed over extensive agricultural areas and the maximum remoteness of DJI Mavic 2 Pro flight radius by specification is 5 km. Its communication system consists of a duplex transmitter operating at a frequency of 2400 – 2483 GHz, a WiFi control module with 2.4 GHz frequency for controlling and monitoring the UAV flight parameters. The WiFi module provides video data transmission through a channel with a frequency of 5.725 – 5.850 GHz, ensuring real-time images for the ground control operators. In addition, the size of the area that is possible to be flown over is relatively small, which ensures the mandatory visual control of the UAV at all times. The theoretically established maximum length (distance traveled) is not more than 7 km.

Results and Discussion

Figure 5 shows the change of the NDVI index for an observed field sown with wheat, for the whole vegetation period. The minimum and maximum values of the index are shown. Figure 6 shows for the same field NDVI index but by OneSoil [Free apps for precision farming (2021)].

There are differences between the two charts, but there are also general trends of peaks and lows of the NDVI index. Although there are differences in the absolute values, the overall change curve is similar.

The cloudiness effect on the results is shown in Table 3. The data are from two consecutive fields, on the same route, at intervals of 30 minutes but after a change in the cloudiness conditions. The NDVI, SAVI, EVI2 and CVI indices are obtained as a result of a near-infrared

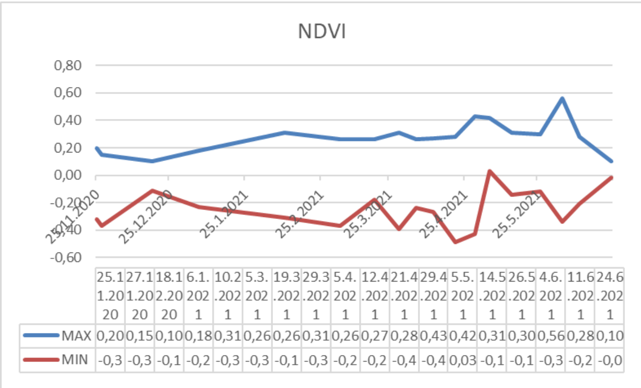

Fig. 5. The change in the NDVI index reported with UAVs

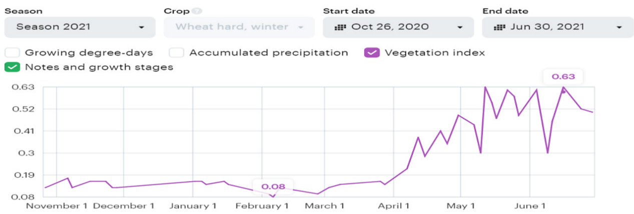

Fig. 6. Change of the NDVI index by OneSoil

Table 3. Influence of cloud cover on results

Index	Cloudy	In the sun
NDVI	0.49	0.45
SAVI	0.33	0.30
EVI2	0.79	0.75
CVI	4.41	4.18
MGVRI	0.36	0.39

light processing and they report a minimal decrease. The MGVRI index is on the RGB spectrum and increases in value.

Observations have shown that the change in reflection in the NIR spectrum occurs long before the change in the RGB spectrum. Figure 7 shows the appearance and growth of a spot with disturbed vegetation – surrounded by an oval. The spot appeared in the photo of field 2 on 30 May 2021 and by 05 June 2021 it had grown significantly. In the photo of the field, which was taken on 05 June 2021, there is still no visual damage to the wheat (Figure 8).

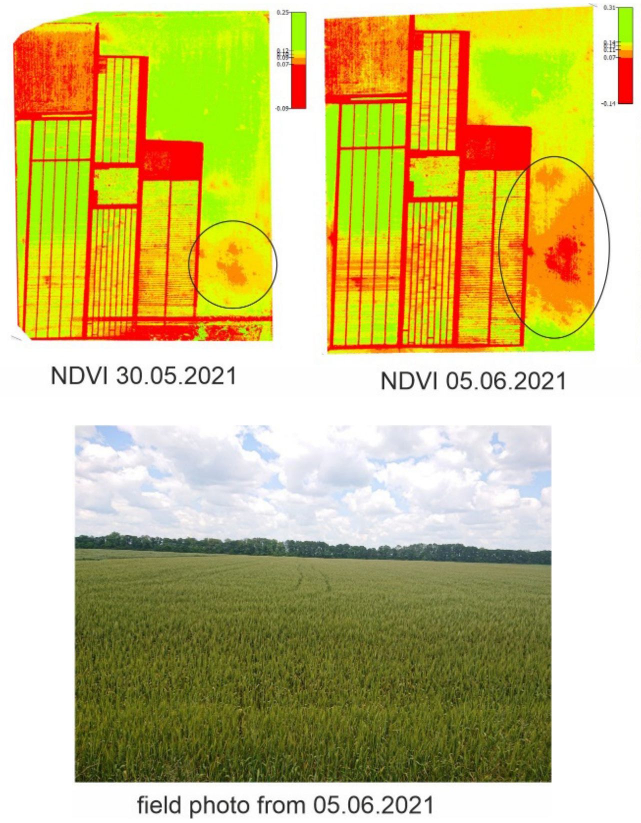

Fig. 7. Appearance of a spot with disturbed vegetation and a photo of the affected area

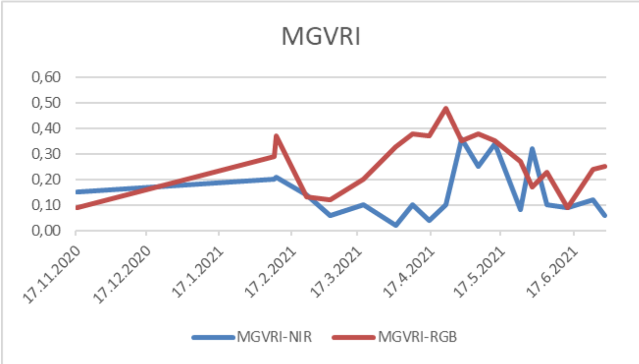

Fig. 8. Vegetation indices MGVRI of field 2 of the NIR and RGB camer

Comparison of the Vegetation Results Based on RGB and NIR Camera

When comparing the change in the MGVRI index obtained from the two independent cameras MAPIR Survey 3W_RGN and the camera of DJI Mavic 2 Pro with sensor Hasseblad L1D-20 we can trace clear peaks and lows. This makes it possible to use the factory-equipped UAV camera to monitor the trends in the development of the agricultural crops.

Conclusions

The study made on the territory of Dobrudja, aiming to monitor the vegetation process in the agricultural crops development, using small UAVs, leads to the following conclusions:

Despite the climatic features of the area, it is possible to use an unmanned aerial vehicle of the class DJI Mavic 2 Pro.

The size of the areas that can be observed with such a UAV is about 250 to 300 acres when using one battery and up to 900 acres with the use of 3 batteries with the above-specified type of UAV.

The obtained results correspond to the tendencies of change in the vegetation processes according to the satellites data. Compared to the satellite images, the size of the pixels used for storing the information from the fields is much smaller which makes the observation much more accurate.

The flights at low altitude of 100 m allows for observing the terrains in cloudy weather, which is an obstacle for satellite observations. This makes it possible to observe agricultural crops during long periods of dense cloud cover.

The cloud passages and the sharp illumination change have little effect on the results obtained, without influencing the trend of change in the vegetation index.

The conclusions of the present study will be used for planning and monitoring of agricultural crops in the economic year 2021-22.

References

Asrar, G., Fuchs, M., Kanemasu, E. T. & Hatfield, J. L. (1984). Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat. *Agronomy Journal, 76,* 300– 306.

Bellvert, J., Marsal, J., Girona, J., Gonzalez-Dugo, V., Fereres, E. & Ustin, S. L. (2016). Airborne thermal imagery to detect the seasonal evolution of crop water status in peach, nectarine and saturn peach orchards. *Remote Sens., 8,* 1–17. doi: 10.3390/rs8010039.

Di Gennaro, S. F., Battiston, E., DiMarco, S., Facini, O., Matese, A. & Nocentini, M., (2016). Unmanned aerial vehicle (UAV)-based remote sensing to monitor grapevine leaf stripe disease within esca complex in vineyard. *Phytopathol. Mediterr., 55,* 262-275. doi: 10.14601/Phytopathol_Mediterr-18312.

Gago, J., Douthe, C., Coopman, R. E., Gallego, P. P., Ribas-Carbo, M. & Flexas, J. (2015). UAVs challenge to assess water stress for sustainable agriculture. *Agric. Water Manage., 153,* 9–19. doi: 10.1016/j.agwat.2015.01.020

Matese, A., Toscano, P., Di Gennaro, S. F., Genesio, L., Vaccari, F. P. & Primicerio, J. (2015). Intercomparison of UAV, aircraft and satellite remote sensing platforms for precision viticulture. *Remote Sens., 7,* 2971–2990. doi: 10.3390/rs70302971.

Poblete-Echeverría, C., Olmedo, G. F., Ingram, B. & Bardeen, M. (2017). Detection and segmentation of vine canopy in ultra-high spatial resolution rgb imagery obtained from unmanned aerial vehicle (UAV): a case study in a commercial vineyard. *Remote Sens., 9,* 268. doi: 10.3390/rs9030268.

Pôças, I., Paço, T. A., Paredes, P., Cunha, M. & Pereira, L. S. (2015). Estimation of actual crop coefficients using remotely sensed vegetation indices and soil water balance modelled data. *Remote Sens., 7,* 2373–2400. doi: 10.3390/rs70302373.

Pothen, Z. & Nuske, S. T. (2016) Automated assessment and mapping of grape quality through image based color analysis. *IFAC-PapersOnLine, 49,* 72–78. doi: 10.1016/j.ifacol.2016.10.0111.

Romboli, Y., Di Gennaro, S. F., Mangani, S., Buscioni, G., Matese, A. & Genesio, L. (2017). Vine vigour modulates bunch microclimate and affects the composition of grape and wine flavonoids: an unmanned aerial vehicle approach in a Sangiovese vineyard in Tuscany. *Aust. J. Grape Wine R., 23,* 368–377. doi: 10.1111/ajgw.12293.

Roscher, R., Herzog, K., Kunkel, A., Kicherer, A., Töpfer, R. & Förstner, W. (2014). Automated image analysis framework for high-throughput determination of grapevine berry sizes using conditional random fields. Comput. *Electron. Agric., 100,* 148–158. doi: 10.1016/j.compag.2013.11.008.

Santesteban, L. G., Di Gennaro, S. F., Herrero-Langreo, A., Miranda, C., Royo, J. B. & Matese, A. (2017). High-resolution UAV-based thermal imaging to estimate the instantaneous and seasonal variability of plant water status within a vineyard. *Agric. Water Manage., 183*, 49–59. doi: 10.1016/j.agwat.2016.08.026

Scotford, I. M. & Miller, P. C. H. (2005). Applications of Spectral Reflectance Techniques in Northern European Cereal Production: A Review, Biosystems Engineering, *Volume 90, Issue 3, March 2005, Pages 235-250*. https://doi.org/10.1016/j.biosystemseng.2004.11.010

Sun, W. & Du, Q. (2018). Graph-regularized fast and robust principal component analysis for hyperspectral band selection. *IEEE Trans. Geosci. Remote Sens., 56,* 3185–3195. doi: 10.1109/TGRS.2018.2794443

Free apps for precision farming (2021). https://onesoil.ai/en/.

dji.com(2021).https://www.dji.com/en/mavic-2

mapir(2021).https://www.mapir.camera/collection /survey3/products/survey3w-camera-red green-n.

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