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Applicability and efficiency of remote sensing of agricultural areas

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Abstract

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The tendencies in the development of digital equipment and the use of artificial intellect have lead to the introduction of a large number of broad-range innovative products. The problem is in the specific interpretation of the results and accumulation of knowledge on the use of the obtained data. The goals are opening opportunities for sustainable management of the production processes, choice of suitable technology solutions, taking into account the climatic changes, the uncertain phytopathological environment, and preservation of the soils as an invaluable resource. The aims of this investigation were: 1) Following the dynamics of the Normalized Difference Vegetation Index during the phenological development of common winter wheat under the conditions of Dobrudzha region; 2) Generating comparative data to be used during the developmental stages and for outlining tendencies in future observations; 3) Checking the possibilities to use UAV for precise agriculture and the applicability of NIR camera for early detection of stress.

The study was carried out at the trial field of Dobrudzha Agricultural Institute – General Toshevo municipality (43.657963, 28.023110). The phenological development and the formation of productivity during harvest year 2020 – 2021 was evaluated. The possibility to generate a tendency in the change of the curves of the main vegetation indices, of NDVI most of all, was confirmed. The dynamics of NDVI during the phenological development of wheat was followed, and a maximum of 0.5 was registered during the heading stage. Opportunities for evaluation of abiotic and biotic type of stress were identified – late spring frosts and occurrence of yellow rust. The change curves of generated vegetation indices during the vegetative growth of wheat were compared. Similarity in the trends was found between NDVI, EVI 2, MGVRI and SAVI, as well as of VARI, based on the visible light. The comparison between the values of NDVI at fly-over with a UAV and the data from satellite observations revealed similarities. The former are more suitable for the purposes of precise agriculture because they provide a more detailed picture.

Keywords: Normalized Difference Vegetation Index (NDVI); Unmanned Aerial Vehicle (UAV); common wheat; spectral vegetation indices

Introduction

Harmonizing the agro ecological, biological and technological elements with the aim of increasing the yields, the qualitative parameters and their stability is at the basis of the precise agriculture concept. The focus is on limiting the unfavourable effect on the environment, preserving soil fertility and production of safe foods. These are the priorities of the new agricultural policy of the European Union. A certain number of questions arise concerning the practical elements in the production of the respective crops, aiming simultaneously at higher efficiency.

A serious challenge are the climatic changes and their effect. Possibilities are being searched for at three levels: breeding, application of innovative products in response to stress, introduction of new technologies, including artificial intellect and digital methods. The interdisciplinary approaches are an important factor for ensuring competitiveness and development of modern, efficient production. A number of simulation researches show that the mechanic transfer of the tools for precise agriculture is uncertain. The risks are determined by the specific conditions of the environment, their combination, the soil characteristics of the region, the peculiarities of the landscape. An accompanying problem is the large number of images needed to process and their integration into databases. Traditionally, the agronomy evaluation requires multiple field observations, which are often accompanied by organizational problems under unpredictable environments. Precise agriculture is undergoing significant development with the introduction of a number of cost-effective tools (Matese et al., 2015). The rapid technological growth of unmanned aerial vehicles encourages their use for multiple 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), opening up also new perspectives (Sun et al., 2018).

The hyperspectral data are rapidly becoming a suitable practical solution for following the development of the food crops. Worldwide, the tendencies toward improvement and application are multidirectional: phenotyping (Barker et al., 2016; Holman et al., 20169; Jin et al., 2020); phenological development (Deery et al., 2016); resistance to abiotic stress (Singh et al., 2016); distribution of diseases and pests (Van der Wal et al., 2013; Ashourlo, 2014; Wahabzada, 2015); realization of qualitative parameters (Golzarian et al., 2011); specificity of nutrition (Jiang et al., 2019); preservation of soil fertility (Devkota et al., 2020); preservation of bio diversity (Guo et al., 2018); efficiency of mechanization (Torres-Sanchez et al., 2013); introduction of new technologies (Rao & Deepak, 2018).

The aims of this study were: 1) Following the dynamics of the Normalized Difference Vegetation Index during the phenological development of common winter wheat under the conditions of Dobrudzha region; 2) Generating comparative data to be used during the developmental stages and for outlining tendencies in future observations; 3) Checking the possibilities to use UAV for precise agriculture and the applicability of a NIR camera for early detection of stress.

Material and Methods

The survey was carried out within the boundaries of the trial field of Dobrudzha Agricultural Institute, Petleshkovo village, General Toshevo municipality (43.657963, 28.023110). The phenological development and the formation of the productivity of common winter wheat during harvest year 2020 – 2021 was evaluated.

North-east Bulgaria, where Dobrudzha Agricultural Institute is situated, is characterized by soil and climatic conditions favourable for the development of cereals (Figure 1). The altitude is 235 m. The low temperatures without snow cover during the winter months are critical. The absolute minimum temperature for this region is – 29.4°C, and the absolute maximum +41.1°C. Due to the frequent flows of cooling ground-level air currents coming from the sea, the spring here is late with 10-15 days. The summer is cool, and the autumn is long, with gradual cooling of the weather. There are two distinct periods of drought, in March – April and July – August. The mean annual sum of rainfalls is 510 mm. The leached chernozem soils are predominant in the region. Due to the heavy composition of the soil, the values of the hydrological indices are comparatively high.

The conditions of harvest year 2020-2021 were comparatively favourable for the development of wheat. Sowing was carried out within the dates suitable for this region. During the autumn-winter period, the temperatures remained high, favouring tillering. Under field conditions, damages

Fig. 1. Location of the experiment

from late frosts were registered at the end of February. The main reason for their occurrence was the preceding period of de-hardening with high temperature amplitudes. At midday, the daily temperatures exceeded 12°C, while the night and morning ones dropped as low as -10°C. Direct freezing was not observed. The damages were limited to various degrees of frost nip on the leaves. In comparison to the mean long-term data, the vegetative growth took longer than usual and the main reason for this were the lower temperatures in April and at the beginning of May. Abundant leaf mass was formed, and the plants grew higher. The persistent low temperatures during the reproductive period in combination with high atmospheric humidity caused the fast wide spreading of yellow rust. The susceptible cultivars were rapidly defoliated, becoming a main limiting factor of yield.

UAV Platform and Sensors

UAV-DJI Mavic 2 Pro (https://www.dji.com/en/mavic-2), equipped with 20 MP 1″ CMOS sensor Hasseblad L1D-20 (Figure 2) was used. It is capable of 31 min maximum flight time at maximum speed of up to 72 km/h (at constant speed 25 km/h, close to the sea level, no wind). The weight of Mavic 2 Pro is 907 g. The maximum climbing speed is 4 m/s (mode P).

Additionally, a second MAPIR Survey3W Camera – Red+Green+NIR (RGN, NDVI) with sensor Sony Exmor R IMX117 – 12 MegaPixel (4000 x 3000 px) was installed, which reads close to infrared 850 nm, red 660 nm and green 550 nm light.

Test fly-overs were undertaken during November-December of 2020 at different altitudes to determine the pixel size of the pictures from the two cameras. The proper setting of coordinates and the maximal scanning zone per flight at different altitudes was tested (Figure 3). The multispectral investigation carried out at altitude 100 m above the terrain, with 80% overlapping from both directions, gave resolutions of 2.34 cm/pixel (Hasseblad L1D-20) and 3.75 cm/pixel (MAPIR Survey3W). The flights were performed from 17.11.2020 to 30.06.2021.

Fig. 2. UAV Platform

Fig. 3. Flight Plan

Table 1 presents the main meteorological factors, which affected the flights. The total number of days, in which flights were performed, were 22, with 43 fly-overs above the zone of observation. The total number of photos exceeded 30 500. These photos provide raw footage for a series of maps based on the reflected light. The quality check after the initial processing gave mean values of 18737 (MAPIR Survey3W) and 70430 (Hasseblad L1D-20) key points of imaging. The relative difference between the initial parameters of the camera and the optimized parameters was 0.374 – 0.401%, which was significantly below the recommended variation of 5%. Pix4Dmapper (Pix4d, 2022) calculated 6072.13 – 39009 overlaps of calibrated image. The total number of overlaps was within the range 5+ for almost the entire area above the field.

Multispectral vegetation indices

The tested near infrared light based indices (NIR) are presented in Table 2, and those from the RGB (Red, Green and Blue) camera, which is standard equipment of the UAV, are given in Table 3.

Results and Discussion

The footage from the field platform allowed generating orthomosaic and the corresponding sparse Digital Surface Model (DSM) before densification. On the basis of the footage, the respective vegetation indices were generated. Reflection indices based on multispectral images from MAPIR Survey3W are given in Figure 4 a-e.

Table 1. Meteorological specificity during the flights

	10.2.2021	23.2.2021	5.3.2021	19.3.2021	2.4.2021	9.4.2021	16.4.2021	23.4.2021	30.4.2021	7.5.2021	14.5.2021	22.5.2021	25.5.2021	30.5.2021	5.6.2021	14.6.2021	25.6.2021	30.6.2021
Wind speed m/s	7.2	2.4	5.7	4.0	5.8	3.6	6.8	4.9	1.0	6.70	6.2	1.0	5.1	4.7	3.4	1.0	4.1	5.0
Wind direction	W	NW	W	W	SW	N	W	NW	SE	S	S	SE	N	W	N	W	NW	S
Humidity, %	69	71	45	78	54	57	54	76	71	54	73	53	45	46	45	60	62	89
Solar radiation, w/m^2	116.7	123.4	93.7	202.2	134.5	105.5	127.8	165.2	190.3	215.7	203.3	286	224	262.1	170.9	163.4	140.9	130.2

Table 2. Near infrared light based indices

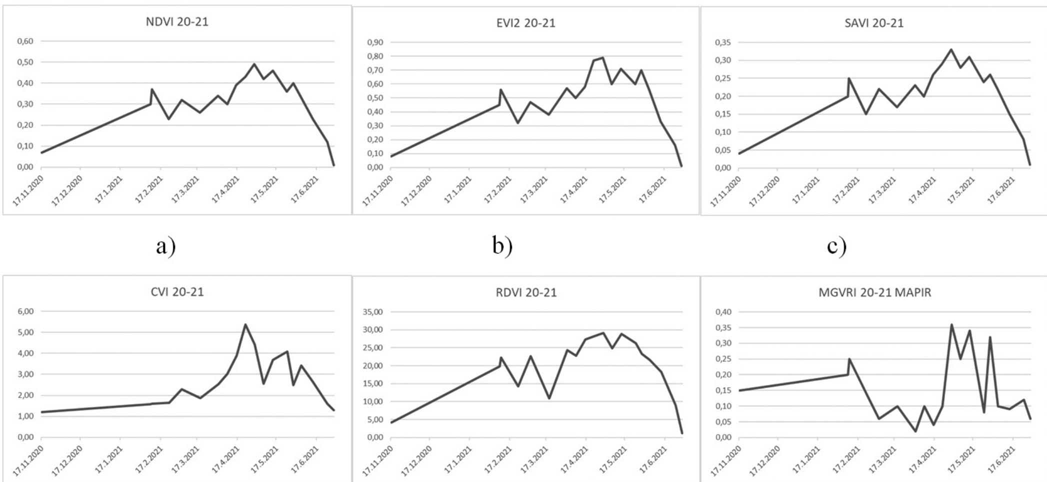
Index*	Formulation	Reference
NDVI	(nir-red)/(nir+red)	Rouse et al., 1974)
SAVI	(nir-red)/((nir+red)*(1+1/2))	Huete, 1988
EVI2	2.5*((nir-red)/(nir+2.4*red+1))	Jiang et al., 2008; Stevens, 2009
CVI	(nir*red)/(green^2)	Vincini et al., 2008
RDVI	(nir-red)/(nir+red)^0.5	Rougean et al., 1995

*NDVI – Normalized Difference Vegetation Index; SAVI – Soil Adjusted Vegetation Index; EVI2 – Enhanced Vegetation Index 2; CVI – Chlorophyll Vegetation Index; RDVI – Renormalized Difference Vegetation Index.

Table 3. Visible light based indices

Index*	Formulation	Reference
MGVRI	(green^2-red^2)/(green^2+red^2)	Bendig et al., 2015
RGVBI	(green-(blue*red))/(green^2+(blue*red))	Bendig et al., 2015
GLI	(2*green-red-blue)/(2*green+red+blue)	Louhaichi et al., 2001
VARI	(green-red)/(green+red+blue)	Gitelson et al., 2002

* MGVRI – Modified Green Red Vegetation Index; RGVBI – Red-Green-Blue Vegetation Index; GLI – Green Leaf Index; VARI – Visible Atmospherically Resistant Index.



a) b) c)

d) e) f)

Fig. 4. Indices over dates based on NIR: a) NDVI; b) EVI; c) SAVI; d) CVI; e) RDVI; f) MGVRI

The index most commonly used in practice for monitoring of seasonal and/or annual variations of the field crops is NDVI. The variation over developmental stages is obtained through temporal series of values related to the condition of the crops (Zhu et al., 2021). The dynamics of its change provides data on the phenological development, the physiological status, the level of available nutrients and allows identifying types of biotic and abiotic stress, but is dependent on the conditions of the environment (Xie et al, 2015; Vannoppen et al., 2020). Its values vary from -1 to +1. Essentially, the healthy plants give bright reflection in the near infrared range of the electromagnetic spectrum, and dim reflection in the visible red range.

NDVI allows qualitative evaluation of the canopy; it is a signal for the occurrence of changes (Alvaro et al., 2007; Cabrera-Bosquet et al., 2011) but does not provide diagnosis of a specific status. Freezing, drought, outbreak of pathogens and pests are only a part of the variability of factors, which determine the expression of the genetic potential. The values of the index are a good opportunity to undertake further observations and make a wider assessment. Within this experiment, NDVI gradually decreased from the first footage (value 0.07) to the first half of February (0.37) (Figure 4a). This index is directly dependent on the specific conditions of the period – warm winter months with higher mean daily temperatures, intensive tillering of wheat, and subsequent sharp cold weather with negative temperatures. In practice, the plants did not fall into full dormancy. The high temperature amplitudes and the long period with frosts, which lasted until mid-day, were the reason for the damages on the leaf mass observed to different degrees (Figure 5). When flying over the field platform immediately after the occurrence of

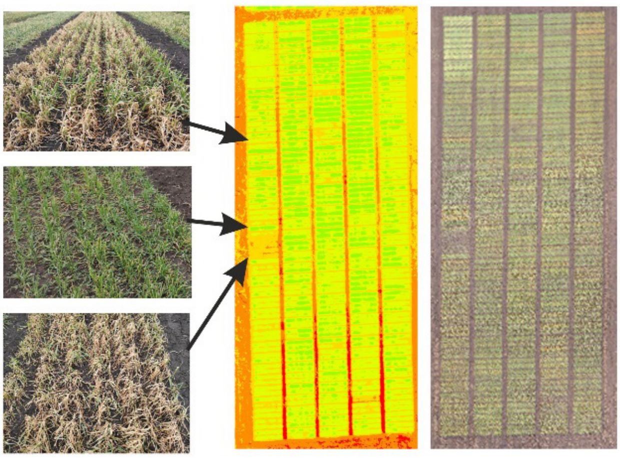


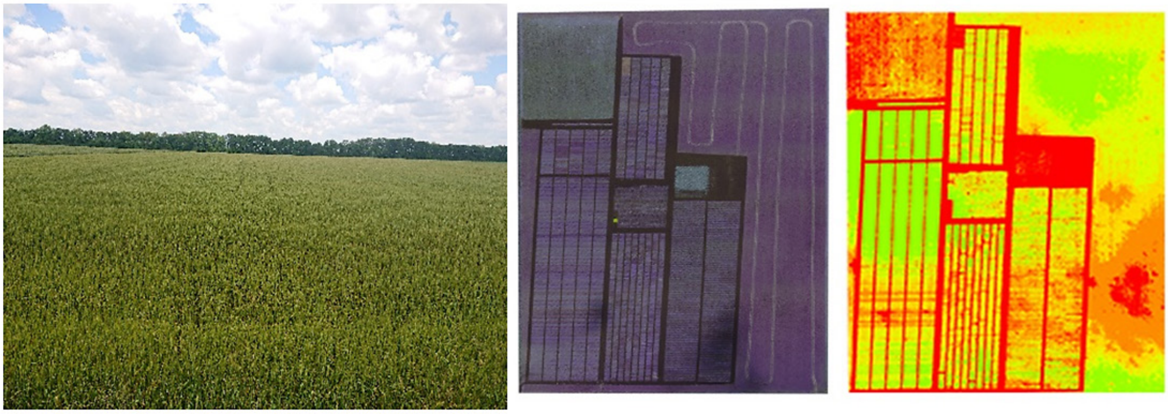
Fig. 5. NDVI and pictures of the experimental field after late frosts in February of 2021

the stress conditions, the index was significantly lower – 0.22, and the maximum threshold value to the mass booting stage was as high as 0.33. The highest NDVI was registered at the end of the booting-heading stage (0.5), and then started decreasing. This result is directly related to the health status of wheat. The long-lasting low temperatures during the reproductive period favoured the fast outbreak of yellow rust (*Puccinia striiformis*) – a pathogen, which is becoming economically important in the recent years.

Figure 4 presents the dynamics of the rest of the generated indices based on near infrared light. The index EVI2 (Jiang et al., 2008; Stevens, 2009 (Figure 4b) is similar to NDVI at dense vegetative mass and minimal topographic effects, leading to similar results in the tendency to change. SAVI (Huete, 1988) (Figure 4c) was developed for assessment of areas with less vegetation in order to eliminate the effect of soil. Since the indices are qualitative evaluation of the canopy, after tillering of wheat, the correlation coefficient in the formula of SAVI made it similar to NDVI. SAVI (Huete, 1988) (Figure 4c) is more sensitive to the content of chlorophyll. It is used from the beginning to the middle of the crops' growth cycle in a wide range of soil types and sowing conditions. In wheat, after formation of normal plant stand, it shows tendencies similar with NDVI. RDVI (Rougean et al., 1995) (Figure 4e) calculates near infrared and red light similar to NDVI and also gives similar tendencies.

MGRVI (Bendig et al., 2015) (Figure 4f) gives good results, being able to efficiently distinguish vegetation from soil. It is influenced by clouds and shadows, which may be associated with more developed plants in comparison to adjacent areas. Due to the flat landscape of the location of the experiment, there were no problems with shadowing. In this survey, the index MGRVI was calculated twice (Figure 4f and 9a) from the two cameras used for observation. Due to their different spectral characteristics, the values did not coincide, but when comparing the change curves, similarities and results close to NDVI were observed

Due to the specificity of its physiological specialization and the difficulty in prognosticating its spreading, the plants rapidly defoliated, especially the early genotypes. At the time of shooting (05.06.2021), no visible changes in the wheat status were noticed, which, however, were clearly visible on the NDVI map as a red zone (Figure 6). After a more detailed agronomic assessment, the beginning of local yellow rust development was registered. NDVI dynamics was directly related to the phenological development of wheat (Figure 7). The highest NDVI values were reported during heading – milk maturity (Sultana et al., 2014; Gizaw et al., 2016; Aranguren et al., 2020), in some instances exceeding 0.8. The surveys were carried out under differ-



a) b) c)

Fig. 6. Pictures in RGB (a), from NIR camera (b) and NDVI (c) of the experimental platform

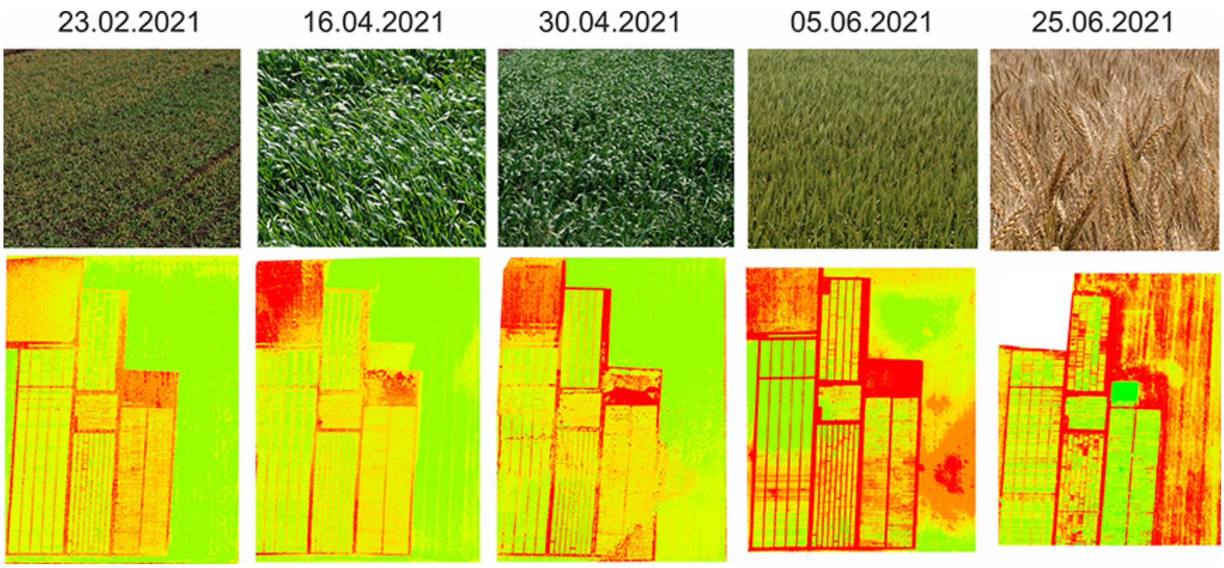


Fig. 7. RGB and NDVI, and picture of the crop over shooting dates

ent conditions and levels of fertilization. The established correlations with yield were significant, but the differences between the correlation coefficients over developmental stages were within a narrow range. Such results show that at each stage of the phenological development, NDVI can be an indicator of the genotype's response to a specific factor of the environment. The observations of our team on the tendencies in the variation of NDVI in the region of South Dobrudzha showed that the index in wheat did not exceed 0.5 (Atanasov, 2021; Mihaylov, 2020; Mihaylov et al. 2021).

In the winter months, values under 0.15 are low and imply poor development of the plants; in case of unfavorable combination of meteorological conditions, there is high danger of freezing. Values of 0.15 – 0.20 are typical of crops with low tillering, which are also threatened by risk of damages. Levels of 0.20 – 0.30 indicate normal development of wheat for this stage. With the elongation of the photoperiod and the beginning of active vegetative growth, the values reach 0.5. At a later stage, the high indices may be due to some fault in the production technology, for example secondary weed infestation (Free Apps for Precision Farming, 2021).

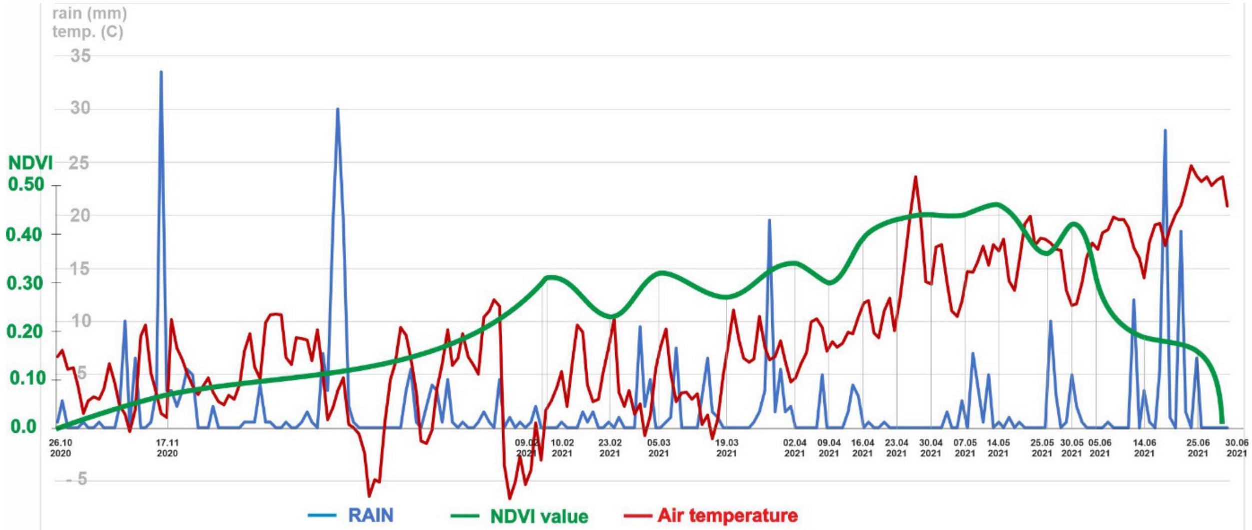


Fig. 8. NDVI against the background of the climatic changes during the observed period, 2020-2021

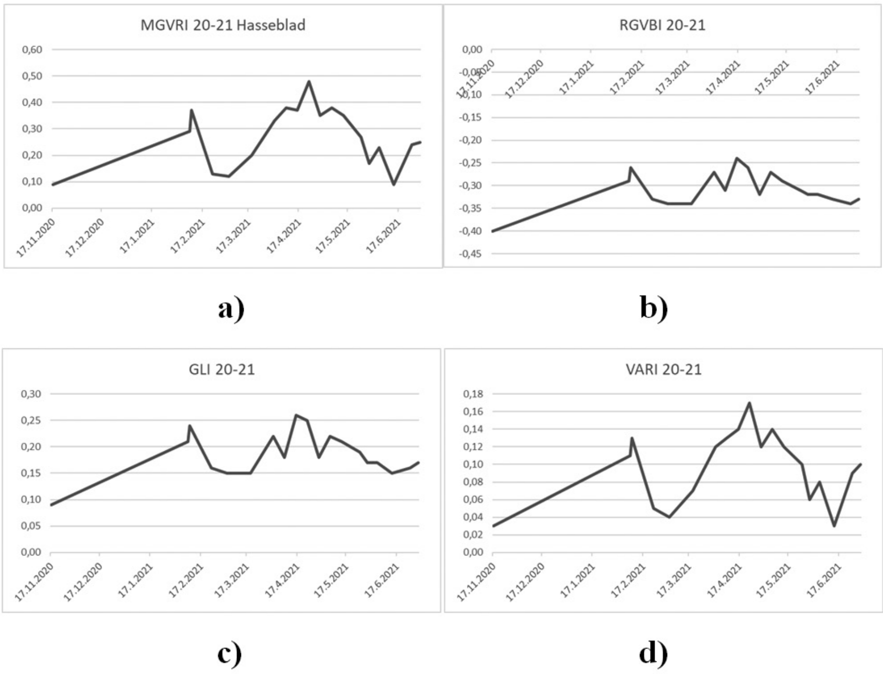


Fig. 9. Indices over dates based on RGB: a) MGVRI; b) MGVBI; c) GLI; d) VARI

Such tendencies can be visualized, following the dynamics of NDVI over shooting dates (Figure 7). During the vegetative growth of the plants, there were no permanent droughts and therefore the temperature was probably the main factor, which affected the variation of the index. With the biomass accumulation, the values increased until the beginning of February. Then the temperatures dropped down sharply causing frost nips on the leaves of a part of the genotypes. In the next survey, the index decreased with 0.1. There was a positive tendency toward increase only after the durable warming in March. The sharp decrease of NDVI during grain filling was again related to stress, this time of biotic nature – the outbreak of yellow rust (Figure 8).

GLI (Louhaichi et al., 2001) (Figure 9c) had the opposite behavior in comparison to MGRVI. This index was efficient for identification of open soil and was not efficient for evaluation of vegetation. VARI (Gitelson et al., 2002) (Figure 9d) was with minimal sensitivity to the atmospheric effects allowing more precise evaluation of vegetation. When the sunlight reaches the atmosphere of the earth, it disperses in all directions due to the gasses and particles in the air. The blue light is more prone to dispersion than all other colors, and has shorter wavelength than the rest of the visual spectrum. This vegetation index registers the presence of blue when calculating spectral data. Due to the specificity of the survey, the height of shooting was 100 m but not thousands of meters as in satellite observation, and the index was not sensitive to the atmospheric effects. The dynamics of change was similar to that of NDVI. Slightly higher values were observed at the end of the vegetative growth of plants. The main reason was the secondary weed infestation following the abundant rainfalls in June and the transition of wheat to physiological maturity.

The results from the obtained reflection indices based on multispectral images from Hasseblad L1D-20 are presented in Figure 9a-d. RGBVI (Bendig et al. (2015) (Figure 9b) behaved in a similar way to excessive green, the quality conceding to the results from MGRVI. RGBVI demonstrated different behavior of the canopy in areas with presence of yellow spots. The obtained values were with a minus sign, making them less convenient for use, although the tendencies to change were similar.

These results, however, are only initial and are to be verified within a trial field at DAI with wheat genotypes of different phenological development, and which can be well differentiated by biological traits and resistance to stress.

The use of UAV for observation is advantageous due to repeatability, low operating cost, low flight altitude, and last but not least – lower dependency on the meteorological conditions. As a part of the precise agriculture concept, the satellite systems allow a wider global monitoring but the low resolution is usually a disadvantage (Barnes, 2018).

Figure 10 shows comparison between the NDVI values from this survey and the results from satellite observation from Free apps for precision farming (2021). The data are from Sentinel 2. The overlapping zones are marked with 1 to 10. The digital levels differed due to the fact that the camera

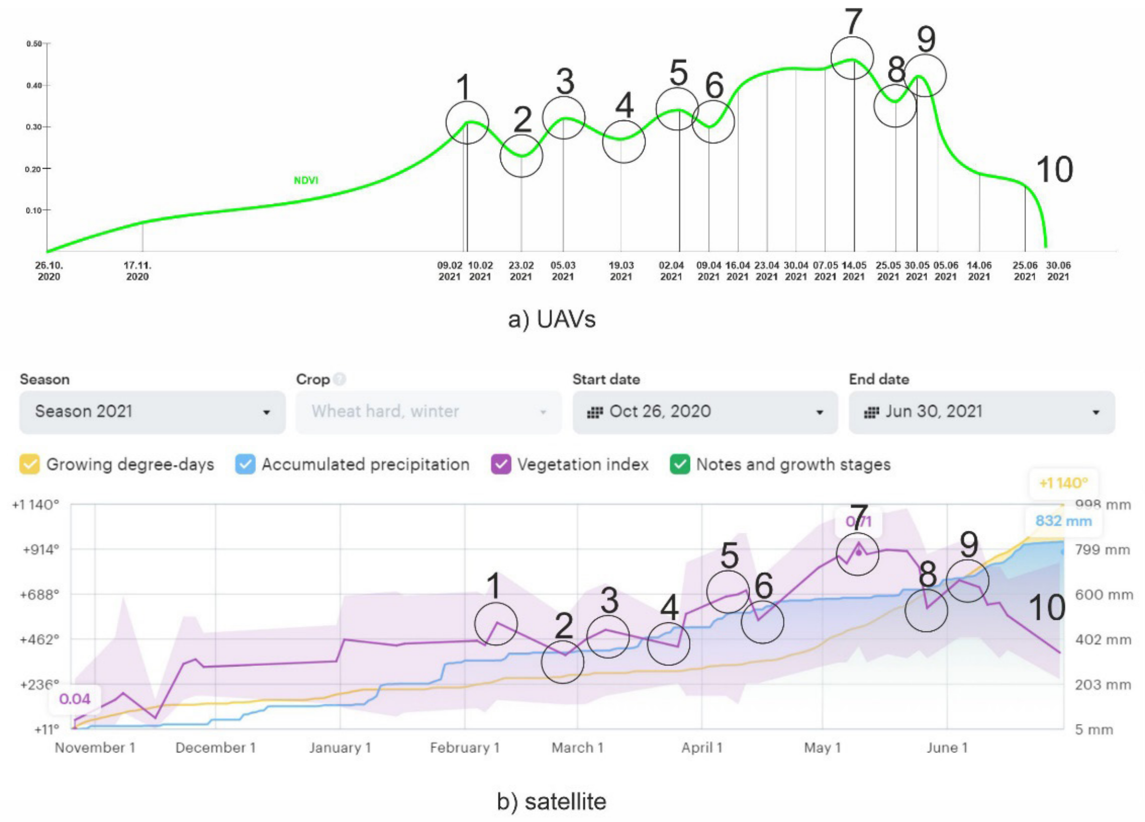


Fig. 10. Comparison of NDVI obtained from observation with UAV, a) and from satellite, b)

used for the observation was with values of red 660 nm and infrared light 850 nm, and of the Sentinel 2 channel B4 red – 665 nm and channel B8 infrared – 842 nm. A similar change dynamics in NDVI was observed, identifying the key moments of wheat development and the occurrence of a certain type of stress: increase of the index until the first decade of February, when wheat was in intensive tillering (1); reaction after late frosts (2); fluctuations during booting stage as a result from high temperature amplitudes (3-6); intensive accumulation of biomass with a maximum reached at heading stage (7); defoliation problems due to occurrence of yellow rust (8-9); beginning of physiological maturity (10). In spite of the established similarities, the satellite data could hardly give a detailed evaluation of the crop and additional observations would be needed. In certain cases the macro images provided by the satellite could be sufficient for solving specific tasks and depended on the set goals (Du et al., 2017; Benincasa et al., 2018; Gavrilovskaya et al., 2021).

Conclusion

The survey was a part of a formulated hypothesis on the possibility to evaluate the condition of the crop by UAV and to validate the results under the conditions of South Dobrudzha region. By a single fly-over with the used model, it was possible to scan from 30 ha, with 80 % overlap, to 50 ha with 70 % overlap. The flight time was about 20 min, at horizontal meandering speed 9-10 m/s. Among the meteorological factors, wind speed was a major limiting factor. The use of an infrared camera was a suitable opportunity for early diagnostics of zones with stress.

The possibility to generate tendencies in the change of the curves of major vegetation indices, especially of NDVI, was confirmed. The dynamics of NDVI was followed during the phenological development of wheat, reaching a maximum of 0.5 at heading stage. Opportunities for evaluation of abiotic and biotic types of stress were identified: late spring frosts and occurrence of yellow rust.

The change curves in generated vegetation indices during the vegetative growth of wheat were compared. Similar trends were found between NDVI, EVI 2, MGVRI and SAVI, as well as VARI, based on visible light.

The comparison between the values of NDVI at fly-over with UAV and the data from the satellite observation revealed a similarity. The former remain more suitable for the purposes of precise agriculture, allowing a more detailed picture.

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