SATELLITE IMAGERY USAGE IN AGRICULTURE. CASE STUDY
/
UTILIZAREA IMAGINILOR SATELITARE ÎN AGRICULTURĂ. STUDIU DE CAZ

Anca Daniela MOICEANU[1], Georgiana MOICEANU[2], Gigel PARASCHIV*[2], Mario CRISTEA*[3]
[1] Aider Association / Romania;
[2] National University of Science and Technology "POLITEHNICA" Bucharest / Romania;
[3] National Institute for Research-Development of Machines and Installations Designed for Agriculture and Food Industry - INMA Bucharest/ Romania;
Tel: +0745371861; E-mail: gigel.paraschiv@upb.ro and mario.cristea@yahoo.com
DOI: https://doi.org/10.35633/inmateh-72-68

Keywords: *agriculture, satellite images, NDVI index, crops.*

ABSTRACT
All sizes of farms can benefit from satellite imagery, not only big producers. When paired with artificial intelligence (AI) and deep machine learning techniques, satellite photography becomes an effective tool for monitoring agricultural conditions and anticipating issues in the field. As a result, using satellite photos to guide crop farming choices can help determine when to apply nutrients and irrigation. This paper focuses on monitoring through satellite sensors with an emphasis on the facilities offered by the European Copernicus Program through Sentinel-2 satellites the crops from a farm from Calarasi County, Borcea commune.

REZUMAT
Toate dimensiunile fermelor pot beneficia de imagini prin satelit, nu numai marii producători. Atunci când este asociată cu inteligența artificială (AI) și tehnicile profunde de învățare automată, fotografia prin satelit devine un instrument eficient pentru monitorizarea condițiilor agricole și anticiparea problemelor din domeniu. Ca rezultat, utilizarea fotografiilor din satelit pentru a ghida alegerile agricole poate ajuta la determinarea momentului în care să se aplice substanțele nutritive și irigarea. Această lucrare se concentrează pe monitorizarea prin senzori satelitari, cu accent pe facilitățile oferite de Programul european Copernicus prin sateliții Sentinel-2, a culturilor de la o fermă din județul Călărași, comuna Borcea.

INTRODUCTION
To produce more, produce better, not to pollute, not to make people sick, to remain profitable are the challenges that today's farmers must address. According to reports, agriculture is the largest consumer of water resources, accounting for 70% of the world freshwater; human consumption has tripled in the last 50 years, and resource exploitation occurs at a rate 30% higher than nature can regenerate. In this perspective, the challenges of producing more with a smaller environmental impact are evident.

Environmental conditions such as climate, topography, soil type, and latitude determine the agricultural potential of a region, but technological and social factors determine how and whether this potential is realized. Large volumes of data from multiple sources need to be transformed into information for quick and accurate decision-making, and for knowledge-based action. Remote data collection, complex analyses of historical and real-time data, and the need for accurate predictions are all essential for a sustainable future for people, farms, and the environment.

Precision agriculture, agriculture 4.0, and digital agriculture have emerged out of the necessity to bring control to a sector dependent on numerous factors. Agriculture 4.0 emerged with the technologies of the Fourth Industrial Revolution, also known as Industry 4.0, in 2011, characterized by the use of technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), Big Data (BD), Cloud Computing, or other smart systems and devices for crop and farm management (*European Agricultural Machinery Association, 2016; European Agricultural Machinery, 2017; European Commission, 2017; European Parliamentary Research Service (EPRS), 2016; Zhang et al., 2020; Vladut et al., 2020*).

Agriculture 4.0, analogous to Industry 4.0, refers to integrated networks of internal and external operations. This means that digital information exists for all sectors and processes of the farm; electronic communication with external partners, suppliers, or end consumers is also established; and the transmission, processing, and analysis of data are (largely) automated (*Kovács et al., 2018; Khanal et al., 2020; Ukaegbu et. al., 2021*).

Sensors are key facilitators behind the IoT concept, thanks to technological advances that have reduced their size and made them smarter and more cost-effective. Spatial and temporal variabilities that significantly impact agricultural production can be controlled mainly through two approaches: (1) a mapping-based approach or (2) a sensor-based approach (*Araújo et al., 2021, Dainelli et al, 2023*).

In the agricultural context, Cloud Computing has gained popularity in recent years by providing (1) a cost-effective storage solution for data (text, images, video, etc.) that has significantly reduced the cost of data storage for companies; (2) intelligent computing systems to transform raw data into knowledge and further into quantitative analysis-based decisions; (3) a secure platform that allows the development of various forms of IoT. Despite numerous benefits, it comes with limitations related to data privacy and network latency (resolved through edge and fog computing) (*Sott et al., 2021*).

Big Data can play a key role in transforming data into added value for stakeholders in the agricultural chain because it can efficiently aggregate, process, and visualize large and complex datasets. Using large volumes from multiple sources, both in real-time and historical, with the ability to process, predict, and monitor, significant changes are expected in farm management and agricultural operations (*Araújo et al., 2021*).

Decision Support Systems (DSS) do not have a universally accepted definition, but according to *European Parliamentary Research Service (EPRS), (2016)*, it can be defined as a human-computer system that uses data from various sources, aiming to provide farmers with a list of advice to support their decision-making process under different circumstances. One of the most representative features of ADSS is that it does not give direct instructions or commands to farmers, as the farmer is in the position to make the final decision (*Zhai et al., 2020*).

Remote sensing, in general, is considered a technique to collect data remotely through instruments that are not in physical contact with the objects being investigated/researched/tracked/monitored. Of the entire electromagnetic spectrum, only a narrow range of wavelengths is used in remote sensing. These include energy measurements from the visible spectrum, reflected infrared, thermal infrared and microwave regions. The platforms used for these measurements are satellites, (UAVs) drones, unnamed ground vehicles (UGVs), tractors or other devices with manually operated sensors. Measurements made with sensors on tractors or handheld devices are called proximity sensors.

Satellite remote sensing today has extensive applications in various fields of activity, including agriculture. A large number of past constraints in the use of remote sensing methods for precision farming were overcome with the launch of Sentinel-2 A+B. The Sentinel-2 constellation, with an improved spatial, spectral and temporal lens, was specifically designed to address problems in the farming community, both farmers and researchers (*Segarra et al., 2020*).

The use of time series of satellite images in many applications leads to multitemporal analyses that depend on comparing the results between these images. In this respect, it is necessary to convert the digital pixel values into physical units, i.e. radiance, thus allowing an objective comparison of images and the correct determination of the nature and magnitude of changes during the analyzed period. This includes applications that rely on the use of vegetation indices. For analyses and interpretations of satellite images, as well as for establishing the degree of accuracy of the information obtained from them, additional data are needed that constitute "ground truth" (*Vorovencii, 2015*).

Among the many applications of remote sensing in agriculture, vegetation indicators (IV) are important tools to analyze the health of vegetation, because it allows to observe whether the growth is homogeneous or if the crop is subjected to some stressor. In addition, artificial intelligence models combined with remote sensing data and vegetation indices are used for harvest prediction or other applications related to crop nutrition, water stress, weed, insect or plant disease infestation, and soil properties such as organic matter content, nutrients, pH, and salinity (*Radočaj et al., 2023, Araújo et al., 2021*).

Plants interact with sunlight differently, which is called a spectral signature. Incident solar radiation can follow three paths: it can be transmitted, reflected or absorbed. The electromagnetic radiation reflected by plants contains information about their biophysical composition and physiological state, and can be measured using satellite sensors, such as those placed in ESA Sentinel-2 (*Segarra et al., 2020*).

Initially, the notion of vegetation index (VI) arose from the need to identify and delimit vegetation on multispectral images; this approach is based on the characteristics of spectral responses of vegetation in relation to other bodies on the Earth's surface (*Thieme et al., 2020*). VI are a subset of the category of spectral indices (IS) and represent one of the most widely used approaches for analyzing satellite data in the optical domain, for various applications.

VI is based solely on the interpretation of spectral responses of objects interacting with incident solar radiation. The most useful spectral ranges for vegetation surveillance by remote sensing are between 600 – 700 nm and 750 – 1350 nm. Vegetation indices are a very efficient means of monitoring and evaluating drought phenomena at image scale due to the possibilities of precise discrimination of vegetation, as well as correlations with biophysical parameters that determine the state of vegetation and turgidity such as plant height, foliar index, biomass, etc.

The Normalized Difference Vegetation Index (NDVI) is a non-linear transformation of visible (RED) and near-infrared (NIR) bands being defined as the difference between these two bands, divided by their sum (*Belgiu et al., 2018, Guzinski & Nieto, 2019, Muhammad, 2019*): NDVI = (NIR-RED)/(NIR+RED). NDVI is a "unit of measurement" of vegetation development and density and is associated with bio-physical parameters such as: biomass (tons/ha), foliar area index (LAI), very often used in crop growth models, percentage of vegetation cover of land, photosynthetic activity of vegetation. In general, NDVI values are between -1.0 and 1.0, with negative values indicating clouds or water and positive values close to 0 indicating soil not covered by vegetation, high positive NDVI values indicate sparse vegetation (0.1-0.5) to dense vegetation (>0.6).

Indirectly, NDVI is used to estimate the effects of precipitation over a certain period, to estimate the vegetation status of different crops and to estimate the quality of the environment as a habitat for different animals, pests and diseases.

Related to research done considering wheat fields it must be said that Vannoppen et al. concluded that a negative correlation was observed between high temperatures in June for spring wheat and also for winter wheat, which states as a negative impact on the yield (*Vannoppen et al, 2020*). Also, previous studies proved that using dynamic monitoring of NDVI to asses wheat trials were of help and can be further used in forecasting yields (*Duan et al, 2017; Goodwin et al, 2018)*.

Further use of NDVI as a prediction model for wheat experimental trials, is the topics studied by researchers which stated that it could help but it is more valuable if other agronomic traits are added. Thus, the results showed that the prediction accuracy was higher by 50% and lower by 10% in the root mean square error for wheat experimental trials in Spain (*Garcia-Romero et al, 2023)*.

Also, Miller et al. studied six small grain and two corn fields using NDVI, which proved that using NDVI they were able to map the soil and weather conditions in order to predict the plant's variable rate (*Miller et al, 2024*).

Considering all these factors and the continuous technological advancement, this paper utilized satellite technology on a farm in Calarasi county, Borcea commune, to determine the NDVI index, presenting the evolution of three types of crops: wheat, corn, and sunflower. The research question asked is: “What is the potential of satellite imagery in agriculture for monitoring and analyzing crop conditions, specifically focusing on the NDVI index for wheat, corn, and sunflower crops?”

MATERIALS AND METHODS

To fulfil the objective of the work, a farm from Calarasi County, Borcea commune, was chosen. Alissa Farm SA operates in the combined cultivation of oilseeds and cereals industry. Alissa Farm S.A brings together the operations of three farms: Concordia Agro, Agricom Borcea, located in Balta Ialomiţei Island (Balta Borcea), and Tudor 92, located on the terrace. The three farms were spread over a geographical area, relatively extensive, (30 km from east to west) with differences in both climate and soil properties. The most striking differences appear between terrace and island soils, therefore the technologies applied also differ with implications on economic performance. Alissa Farm manages a total area of 13,630 ha (arable, permanent, and temporary area).

The studied farm is located in an area with special importance for Romanian agriculture, being the main agricultural region in the country that includes approx. 40% of the total arable areas in Romania. Out of the total area it administers, only an area of 701.4 ha was analyzed. According to satellite measures, the selected area has an area of 690.06 ha, the analyzed plots being established with Google Earth. To accurately determine the size and to have a high degree of accuracy of satellite images, a Trimble J5 GPS was used (Figure 1). For easy highlighting of plots and easy processing and interpretation of results, a system of notations highlighted in Figure 1b has been established.

a. b.

Fig. 1 - Plot determination using Google Earth, a. surface determination, b. plot monitoring

The measurements provided by the satellite were in the form of vector images with an area of 100 km^2, one for each of the 13 wavelengths, covering the light spectrum. The Sentinel products used are made available free of charge to ESA users through the Copernicus Open Access Hub environment. The platform was queried for products using the filter engines: Interrogated period 01.09.2019- 30.10.2020, Mission Sentinel – 2, the S2A* is a S2B, products S2MSISA, cloud cover [0 to 4].

The search generated 97 UTM (Universal Transverse Mercator) 35TNK products that were downloaded. Regarding the use of satellite images in the analysis, the OGOR application was used to monitor the evolution of NDVI in the analyzed area. The OGOR application works according to the following protocol:

- calculates the footprint of each product on all bands;
- generates and records FMASK rasters at UMT level from L1C products, thus classifying clouds, shadows, snow, water and pixels of clear terrain with better accuracy than that available in L2A products;
- generates and records NDVI, NDWI, and EVI rasters at UTM (Universal Transverse Mercator) level from L2A products.

Establishing in advance the coordinates of the terrain, raster images for red and green wavelength were used, by applying the formula of NDVI (B8-B4/B8+B4) and a map of vegetation was built at the date of observation. The first image downloaded was on 15.02.2020, and the following with a frequency of 5 days until dates 30.10.2020. In total, 65 images were analyzed from February to October 2020, 25 of which were removed due to cloud cover, and 40 were used for this work.

Table 1

Renaming of analyzed plots

Den. no.	Farm plot name	Rename for analysis
1	B52	A
3	B99	B
4	BI00	C
5	B95	D
6	B96A	E
7	B96B	F
8	B102	G
9	B102A	H
10	B103A	I
1	B52	A

RESULTS

Regarding the area measured, for each plot, the deviation was calculated to ensure the accuracy of the measurements and to be able to accurately specify the results of the analysis. Thus, in the table below you can find the data on the areas of each plot of land.

Table 2

Measured surface

Plot	GPS RTK (ha)	Google Earth (ha)	Difference (GPS- GE ha)
A	83,09	81,00	+ 2,09
B	97,42	97,90	-0,48
C	96,85	97,40	-0,55
D	25,01	25,17	-0,16
E	46,27	46,89	-0,62
F	55,96	56,58	-0,62
G	122,55	123,98	-1,43
H	6,6	6,59	+0,01
I	7,8	7,78	+0,02
TOTAL	146	146,77	-0,77

Regarding the NDVI analysis on the terrain, the main results are highlighted in Figure 2.

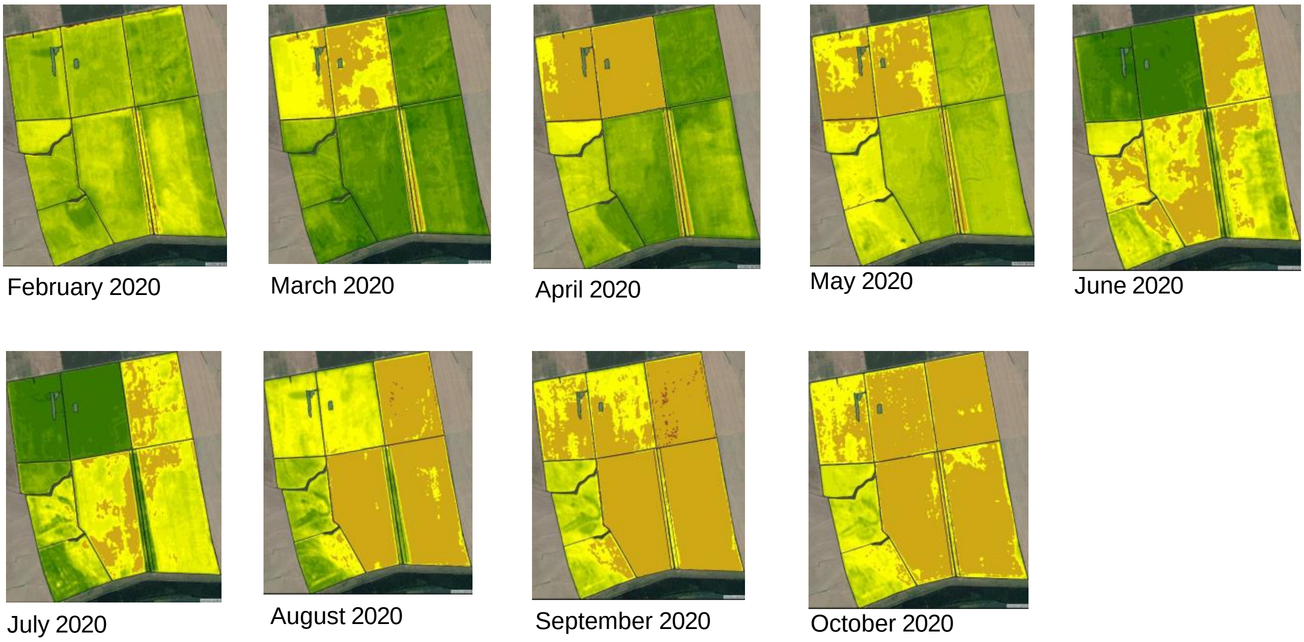

Fig. 2 - NDVI maps obtained during the analyzed period

At the same time, to compare the satellite results with those in the field, three types of crops were chosen (wheat, corn and sunflower) which were analyzed in terms of evolution using the NDVI index. The satellite images obtained in the case of wheat cultivation are shown in Figure 3.

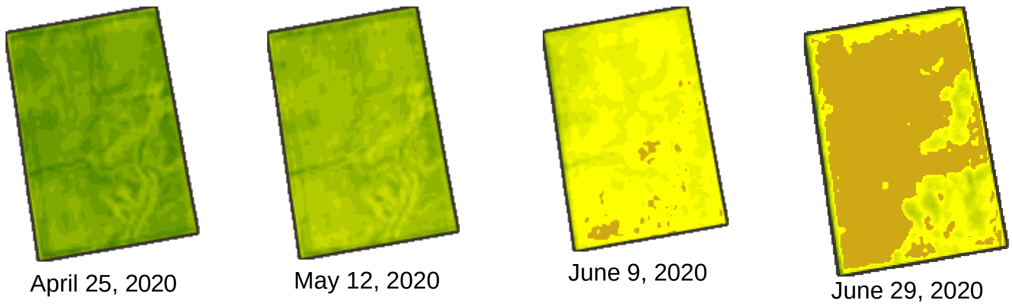

Fig. 3 - Evolution of NDVI for wheat on plot C (B100)

These images show the evolution during February and June, which, in terms of data obtained, can be seen in Figure 4 for wheat crop.

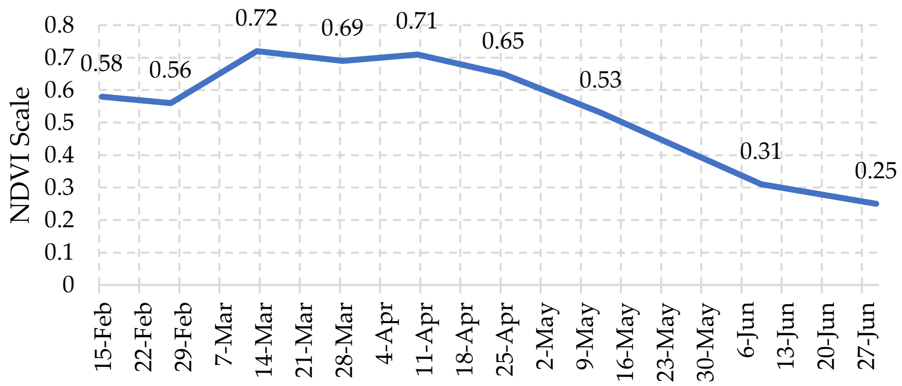

Fig.4 - Wheat crop evolution of NDVI from February to July 2020

Similarly, in Figure 5, the evolution from May to September is presented for corn crop.

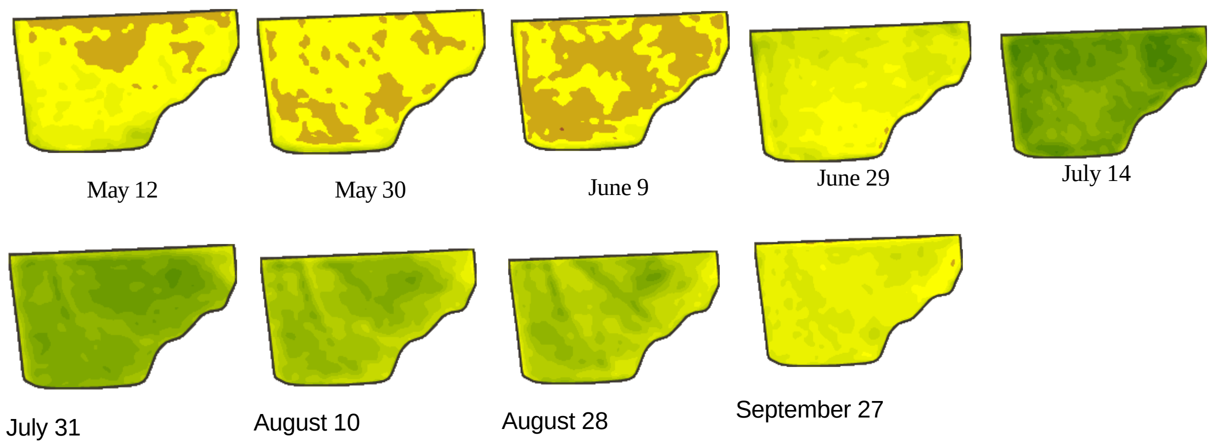

Fig. 5. NDVI evolution for corn crop. Plot D (B95).

In Figure 6, the NDVI evolution for corn crop is presented.

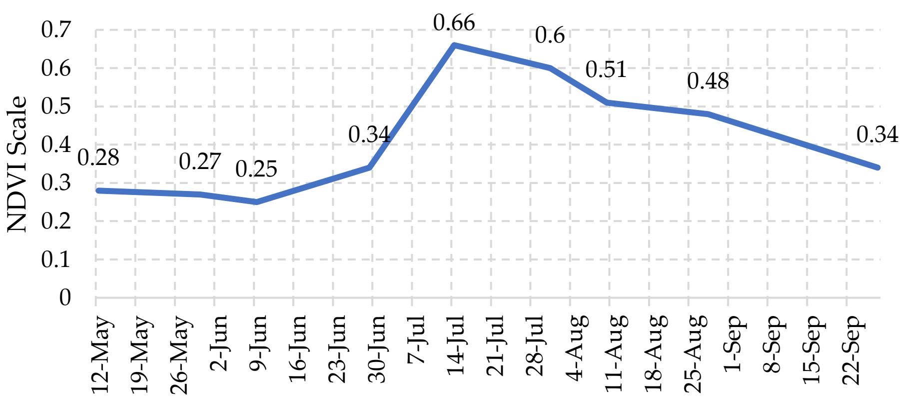

Fig. 6 - NDVI evolution of corn crop during May - September 2020

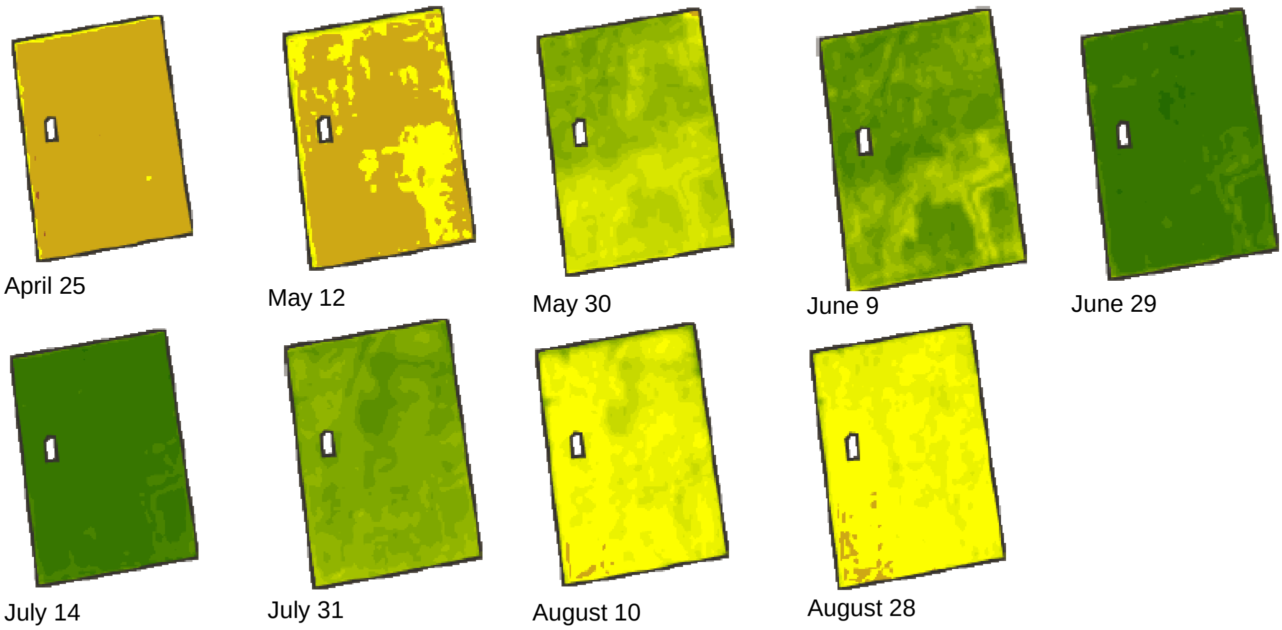

Fig. 7 - Evolution of the NDVI for sunflower cultivation on plot B (B99)

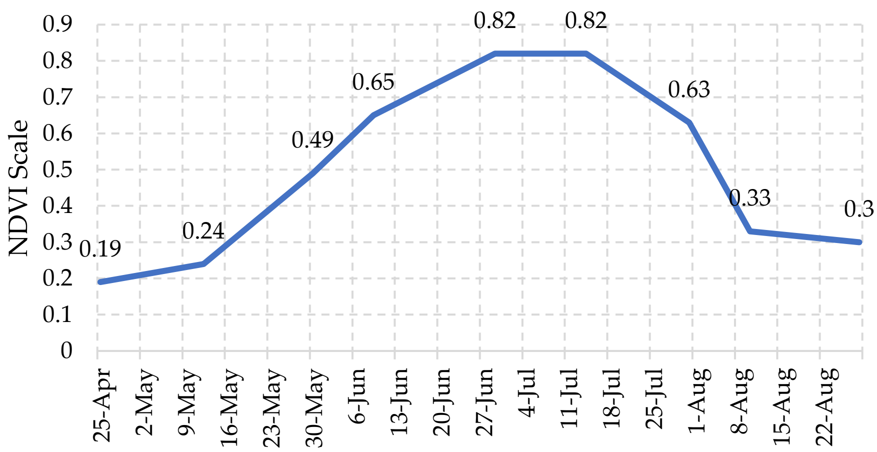

Fig. 8 - NDVI evolution for sunflower from April to August 2020

Figures 7 and 8 present the satellite images and the NDVI index for the sunflower crop.

DISCUSSION

On February 15, 2020, at the time of the first image consultation, vegetation was found on all soils selected for analysis (A – J) with an average NDVI of 0.47 on the entire analyzed area. Following the dynamics of the images over time, in March it can be observed an increase in NDVI values on plots C, G, J, and maps indicating an increase in chlorophyll content, while on the rest of the analyzed plots NDVI values were decreasing.

Going to the real land it was found that plots C, G, J were occupied by wheat crops. Thus, it was found that out of the total analyzed area, which is 690.06 ha, the area cultivated with wheat was 368.15 ha, meaning a percentage of 38.86%. The April 2020 analysis shows a decrease in NDVI values on all analyzed plots. The area under wheat (C, G, J) continued to show the highest NDVI values (mean 0.62). On the rest of the surface the indices were declining, with an average of 0.29 (A, B, H, I, D, E, F).

From the images obtained in May 2020, it can be seen that vegetation was decreasing throughout the analyzed area (A-J) with NDVI values of 0.34. In June, monitoring shows an increasing trend of NDVI on plots A, B, H, and I, reaching an average of 0.70 on June 29, 2020. On the rest of the analyzed areas, the trend is downward, more pronounced on the area occupied by wheat (C, G, J) where NDVI decreased to 0.30.

In July, the growth trend on A, B, H, I is maintained, and NDVI maps show a maximum reached on July 14, 2020 when the index values were 0.82. Going to the real land, on July 31, 2020 it was found that on plots A, B, H, I was the sunflower crop in bloom. Therefore, it follows that out of the total analyzed area (690.06 ha), 28.00% was occupied by sunflowers, meaning 193.27 ha.

Also, on the same date, it was found that wheat parcels were harvested (C, G, J), which is also visible on the NDVI map, which shows index values of 0.21. From the questions addressed to the farmer, it was found that the production on the analyzed plots was 1.5 t/ha. During the same visit, plots D, E, F were inspected and found to be cultivated with maize. The NDVI analysis shows that the maximum values for this crop were reached on July 31, 2020, with average values on plots D, E, F of 0.54. It follows that out of the total analyzed area of 690.06 ha, 18.64% was occupied by maize crops, i.e. 128.64 ha.

The analysis of August 2020 shows a decreasing trend for both sunflower (A, B, H, I) and maize (D, E, F) with average values of 0.45 for sunflower and 0.50 for corn. In September, plots A, B, H, I (sunflower) showed an average NDVI value of 0.25. From the questions addressed to the farmer, it was found out that on August 28, 2020 the sunflower was harvested, which is correctly indicated by NDVI maps. The average yield on the analyzed plots was 2.64 t/ha. NDVI indices for maize are down throughout September, averaging 0.43.

During the last field visit on October 03, 2020, it was found that corn plots (D, E, F) were not harvested, but NDVI maps showed values of 0.34. From subsequent questions addressed to the farmer, it was found out that corn was harvested on November 05, 2020 with an average yield of 2.5 t/ha.

The hardship of the year 2020 could be seen through the analysis. The 2020 production was 45% lower for corn than 2019, 41% lower for wheat production and 54% lower for sunflower. The decline was also presented in the data gathered at a national level, the drought affected the plots and could be seen throughout the maps obtained in the research.

CONCLUSIONS

Developments in precision agriculture and smart farming are meant to take farm performance to another level. One of the tools used by the new type of agriculture is remote sensing. Remote monitoring offers multiple advantages to farmers through the data it provides, replacing energy-intensive, time-consuming, and perhaps even less accurate methods of collecting field data. In this context, this paper focuses on monitoring through satellite sensors with emphasis on the facilities offered by the European Copernicus Program through Sentinel-2 satellites.

The multispectral satellite images provided by Sentinel-2 dedicated to agriculture have a spatial resolution of 10-20 m/pixel and a temporal resolution of 10 days, but the constellations (Sentinel 2A and 2B generate images every 5 days. Spectral resolution allows the determination of the physiological properties of plants, which can then be calculated and transformed into vegetation indices.

The Normalized Difference Vegetation Index (NDVI) is an index used to determine the development of vegetation in the field and is possible due to chlorophyll present in leaves that absorbs solar radiation in the red band and reflects in the NIR (near-infrared) band.

Calculating the difference between the two bands, the value of the NDVI index can be obtained, which is strongly correlated with the health of the crop.

This study demonstrated the application of satellite-derived NDVI indices to effectively monitor and analyze crop conditions over a growing season in Calarasi County, using Sentinel-2 satellite imagery.

The findings underscore the value of this approach in precision agriculture by providing timely data that can influence farming decisions.

- Wheat Harvest Timing: The NDVI analysis enabled the identification of the peak vegetative growth of wheat and the subsequent decline, indicative of the nearing harvest period. Specifically, the NDVI values for wheat plots showed a marked decrease in early July, suggesting the beginning of the harvesting activities. This temporal correlation provides a non-invasive method to monitor crop maturity and optimize harvest timings.
- Sunflower and Maize Analysis: The study also tracked the growth patterns of sunflowers and maize, with NDVI peaks reflecting key growth stages. For sunflowers, the highest NDVI readings in mid-July corresponded with full bloom, observed directly during field visits. Maize showed a gradual increase in NDVI values until late July, aligning with the critical growth phases leading up to grain filling.

- Agricultural Insights: The data revealed that the year 2020 posed significant challenges, with lower than average yields reported for maize, reflecting broader regional impacts of adverse weather conditions. This highlights the NDVI's utility in capturing the effects of environmental stressors on crop health and productivity.
- Recommendations for Future Applications: The research supports the integration of NDVI monitoring into regular agricultural practices, providing a reliable, cost-effective tool for managing crop health and optimizing resource allocation. Future studies could expand on this by incorporating additional variables such as soil moisture levels and plant phenological data to enhance the predictive accuracy of crop yield and health assessments.
- Limitations: The study's scope was initially limited due to the availability and accessibility of detailed agricultural data, such as specific hybrids used, moisture levels, and phytosanitary measures. These parameters are indeed crucial for a comprehensive agricultural assessment but often require ground-level data collection or detailed records that may not be readily accessible or available in public databases.

REFERENCES

Araújo, S. O., Peres, R. S., Barata, J., Lidon, F., & Ramalho, J. (2021) Characterizing the Agriculture 4.0 Landscape—Emerging Trends, Challenges and Opportunities. *Agronomy,* 11(4), 667. https://doi.org/10.3390/agronomy11040667

Belgiu, M., & Csillik, O. (2018) Sentinel-2 cropland mapping using pixel-based and object-based time-weighted dynamic time warping analysis. *Remote Sensing of Environment*, 204, 509–523. https://doi.org/10.1016/j.rse.2017.10.005

Dainelli, R.; Saracco, F. (2023) Bibliometric and Social Network Analysis on the Use of Satellite Imagery in Agriculture: An Entropy-Based Approach. *Agronomy*, 13, 576. https://doi.org/10.3390/agronomy13020576

Duan, T., Chapman, S. C., Guo, Y., Zheng, B. (2017). Dynamic monitoring of NDVI in wheat agronomy and breeding trials using an unmanned aerial vehicle. *F Crop Res*. 210, 71–80. doi: 10.1016/j.fcr.2017.05.025

European Agricultural Machinery Association. (2016). CEMA - European Agricultural Machinery - NEW! Drones + Smart Machines: what are the benefits in farming? https://www.cema-agri.org (accessed on 25 June 2022)

European Agricultural Machinery. (2017). Digital Farming: what does it really mean? https://www.Cema-Agri.Org/ . https://www.cema-agri.org (accessed on 15 November 2022)

European Commission. (2017). Digital Transformation Monitor Industry 4.0 in agriculture: Focus on IoT aspects. https://ati.ec.europa.eu/. (accessed on 25 August 2022)

European Parliamentary Research Service (EPRS). (2016). Precision agriculture and the future of farming in Europe. https://www.europarl.europa.eu (accessed on 13 May 2023)

Gracia-Romero A, Rufo R, Gómez-Candón D, Soriano JM, Bellvert J, Yannam VRR, Gulino D., Lopes MS (2023) Improving in-season wheat yield prediction using remote sensing and additional agronomic traits as predictors. *Front. Plant Sci.* 14:1063983. doi: 10.3389/fpls.2023.1063983

Goodwin, A. W., Lindsey, L. E., Harrison, S. K., Paul, P. A. (2018). Estimating wheat yield with normalized difference vegetation index and fractional green canopy cover. *Crop Forage Turf Man* 4 (1), 1–6. doi: 10.2134/cftm2018.04.0026

Guzinski, R., & Nieto, H. (2019). Evaluating the feasibility of using Sentinel-2 and Sentinel-3 satellites for high-resolution evapotranspiration estimations. *Remote Sensing of Environment*, 221, 157–172. https://doi.org/10.1016/j.rse.2018.11.019

Khanal, S., KC, K., Fulton, J. P., Shearer, S., & Ozkan, E. (2020), Remote Sensing in Agriculture—Accomplishments, Limitations, and Opportunities. *Remote Sensing,* 12(22), 3783. https://doi.org/10.3390/rs12223783

Kovács, I., & Husti, I. (2018), The role of digitalization in the agricultural 4.0 – how to connect the industry 4.0 to agriculture? *Hungarian Agricultural Engineering*, 33, 38–42. https://doi.org/10.17676/hae.2018.33.38

Miller O., Mondal P., Sarupria M., (2024). Sensor-based measurements of NDVI in small grain and corn fields by tractor, drone, and satellite platforms, *Crop and Environment*, 3(1), 33-42, ISSN 2773-126X,https://doi.org/10.1016/j.crope.2023.11.001

Muhammad U.H., Muhammad S. (2019), GIS & remote sensing for precision agriculture. https://Www.Technologytimes.Pk/.https://www.technologytimes.pk/2019/03/28/gis-remote-sensing-agriculture/

Radočaj, D.; Plaščak, I.; Jurišić, M. (2023), Global Navigation Satellite Systems as State-of-the-Art Solutions in Precision Agriculture: A Review of Studies Indexed in the Web of Science. *Agriculture,* 13, 1417. https://doi.org/10.3390/agriculture13071417

Segarra, J., Buchaillot, M. L., Araus, J. L., & Kefauver, S. C. (2020). Remote Sensing for Precision Agriculture: Sentinel-2 Improved Features and Applications. *Agronomy,* 10(5), 641. https://doi.org/10.3390/agronomy10050641

Sott, M. K., Nascimento, L. D. S., Foguesatto, C. R., Furstenau, L. B., Faccin, K., Zawislak, P. A., Mellado, B., Kong, J. D., Bragazzi, N. L.. (2021) Agriculture 4.0 and Smart Sensors. The Scientific Evolution of Digital Agriculture: Challenges and Opportunities. *Preprints,* Published. https://doi.org/10.20944/preprints202105.0758.v1.

Thieme, A., Yadav, S., Oddo, P. C., Fitz, J. M., McCartney, S., King, L., Keppler, J., McCarty, G. W., Hively, W. D. (2020). Using NASA Earth observations and Google Earth Engine to map winter cover crop conservation performance in the Chesapeake Bay watershed. Remote Sensing of Environment, 248, 111943. https://doi.org/10.1016/j.rse.2020.111943

Ukaegbu, U.F.; Tartibu, L.K.; Okwu, M.O.; Olayode, I.O. (2021) Development of a Light-Weight Unmanned Aerial Vehicle for Precision Agriculture. *Sensors*, 21, 4417; https://doi.org/10.3390/s21134417

Vannoppen, A.; Gobin, A.; Kotova, L.; Top, S.; De Cruz, L.; Vīksna, A.; Aniskevich, S.; Bobylev, L.; Buntemeyer, L.; Caluwaerts, S.; De Troch R., Gnatuik N., Hamdi R., Remedio R.A, Sakalli A, Van de Vyer H., Schaeybroeck B., Termonia P.,(2020) Wheat Yield Estimation from NDVI and Regional Climate Models in Latvia. *Remote Sens*., 12, 2206. https://doi.org/10.3390/rs12142206

Vladut V., Caba I.L, Constantin A-M, Voicu Gh., Maican E., Vilcu C. Lefter B. (2020), Principles of integration the agri-drones in agricultural production environments. New concepts towards Agriculture-5.0, *Annals of the University of Craiova-Agriculture, Montanology, Cadastre Series*, Vol. 51/2, DOI: 10.52846/AAMC.2021.02.70;

Vorovencii, I., (2015). Teledetecţie satelitară. Editura Matrix Rom Bucureşti. ISBN 978-606-25-0142-6. 600 pag.

Zhai, Z., Martínez, J. F., Beltran, V., Martínez, N. L. (2020). Decision support systems for agriculture 4.0: Survey and challenges. *Computers and Electronics in Agriculture,* 170, 105256. https://doi.org/10.1016/j.compag.2020.105256

Zhang, J.; Wang, C.; Yang, C.; Jiang, Z.; Zhou, G.; Wang, B.; Shi, Y.; Zhang, D.; You, L.; Xie, J. (2020). Evaluation of a UAV-Mounted Consumer Grade Camera with Different Spectral Modifications and Two Handheld Spectral Sensors for Rapeseed Growth Monitoring: Performance and Influencing Factors. *Precis. Agric.*, 21, 1092–1120; https://doi.org/10.1007/s11119-020-09710-w