ASPECTS REGARDING THE USE OF REMOTE SENSING IN AGRICULTURE, OLTENIA AREA

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Abstract:
Remote sensing is an efficient and modern tool for identifying agricultural crops and their evolution over a year or a longer period. The paper presents the use of European software, in this case LEOWORKS 4.0, which is free and can be used especially in scientific research and education, but also Snap software. With its help, various supervised or unsupervised reports or classifications can be made.

In agriculture in general, various phenomena can occur, from drought to torrential rains, and these can be highlighted with the help of satellite remote sensing recordings. A case study is presented in the OLTENIA area, with the help of the LEOWORKS 4.0 software and the Snap software of the European Space Agency, with the help of supervised and unsupervised classification and many aspects that can lead to a better organization in the field of agriculture and in the study of agricultural crops, of agricultural works.

The use of remote sensing, combined with the use of drones and photogrammetry (lidar, terrestrial laser scanning) and GNSS and geographic information systems solves any problem in terms of monitoring and identifying agricultural crops and their evolution over a year or a longer period.

Key words: *Remote Sensing in agriculture, LEOWORKS 4.0 software, supervised and unsupervised classification.*

INTRODUCERE

Contemporary agriculture faces major challenges generated by climate change, soil degradation, extreme phenomena affecting crop yields, and the need to increase efficiency through precision agriculture. In this context, remote sensing becomes an indispensable tool, having the capacity to provide objective, spatially distributed, and repeatable information regarding vegetation status and biophysical processes at the level of agricultural areas (Drusch et al., 2012). The use of optical and radar sensors integrated into satellite platforms such as Sentinel-2 and Sentinel-1 offers an efficient way of continuously monitoring crops, supporting agricultural management and sustainable land-use policies (ESA, 2023).

Olt County represents an ideal setting for the implementation of these technologies, as it is characterized by significant pedological diversity, fertile soils, and a high vulnerability to drought. The lack of precipitation during the summer season, associated with high temperatures and excessive evapotranspiration, affects crop productivity every year. Therefore, traditional field observation methods, although useful, cannot provide the complete picture necessary for rapid and well-informed decision-making

Table 1. Agro-climatic characteristics of Olt County

Indicator	Value	Importance
Annual precipitation	480–550 mm	determines NDMI, humidity
Average temperature	11.5–12.5°C	influences evapotranspiration
Soil types	chernozem, alluvium	affect spectral reflectance
Drought frequency	high	decreases NDVI in summer

Remote sensing, unlike these methods, can cover the entire county in a few seconds, providing high-frequency and high-accuracy data, indispensable for multi-temporal and multi-annual analyses (Lillesand et al., 2015).

Satellite data are complemented by UAV flights, which allow obtaining centimeter-resolution images, usable in validating vegetation indices and calibrating supervised classifications. GNSS measurements, integrated into ROMPOS systems, provide precise field references, necessary for establishing control points and geometric alignment of satellite products. As Nguyen et al. (2020) emphasize, the combination of satellite sensors and airborne sensors generates a complete information infrastructure, capable of meeting the most demanding requirements of modern agriculture.

The processing of data obtained through these technologies is carried out through advanced software platforms, developed in scientific environments, such as ESA SNAP and LEOWorks 4.0. These tools allow atmospheric corrections, advanced filtering, generation of spectral indices, thematic classifications and statistical analyses, contributing to the accuracy and credibility of the results (Forkuor et al., 2014). The integration of the results into GIS platforms such as QGIS or ArcGIS Pro ensures the possibility of cartographic representation, the production of area statistics and the facilitation of the decision-making process.

MATERIAL AND METHOD

The analysis of agricultural processes in Olt County through remote sensing required the use of an integrated set of satellite, aerial and terrestrial data, as well as the application of a rigorous methodological flow, based on established scientific procedures. In this study, multispectral information from the Sentinel-2 mission and radar data from the Sentinel-1 mission constituted the main set of observations, being complemented by high-precision GNSS measurements and UAV images used to calibrate and validate the results. The satellite data, characterized by high spatial and temporal resolution, allowed the continuous analysis of agricultural areas, monitoring the evolution of vegetation in different phenological stages and detecting subtle changes in crop structure, modulated by the pedoclimatic conditions specific to the Olt region (Drusch et al., 2012; ESA, 2023).

Sentinel-2 images were selected for three representative periods of the agricultural season: spring, when crops are in an early stage of development; summer, when vegetation reaches a maximum biomass; and autumn, when senescence processes become visible.

Table 2. Sentinel-2 bands

Band	Wavelength	Usage
B02	490 nm	EVI, water detection
B03	560 nm	GNDVI
B04	665 nm	NDVI
B08	842 nm	NDVI, NDMI
B11	1610 nm	NDMI
B12	2190 nm	soil-vegetable classification

Each Sentinel-2 scene (level L1C and L2A) was pre-processed using the Sen2Cor module of the ESA SNAP platform, which performs atmospheric correction, aerosol thickness estimation, cloud pixel masking and Scene Classification Layer (SCL)

generation. All images were reprojected into the national Stereo 70 coordinate system (EPSG:3844), to ensure compatibility with cadastral data and local agricultural works (Roy et al., 2019).
Sentinel-1, through its SAR capability to operate in adverse weather conditions, allowed for soil moisture estimation and characterization of agricultural surface roughness, being a valuable complement to optical images. SAR data processing included geometric correction (Range-Doppler Terrain Correction), application of the Lee filter and subsequently Refined Lee to reduce speckle, as well as conversion of backscatter coefficients into sigma-naught units, for a more faithful interpretation of radar interactions with vegetation (Lu & Weng, 2007).
For the geometric calibration of the images and validation of the results, ground control points (GCPs) recorded with GNSS equipment in the RTK system using the ROMPOS service were used, which allowed to achieve a precision of the order of centimeters. These GCPs were used to compare the position of the spectral response of the rasters with the real position in the field, reducing geometric errors and improper alignments that can affect subsequent analyses.
UAV flights, performed with RGB and multispectral sensors with resolutions of 2–5 cm, were the ideal support for calibrating the vegetation indices and for verifying the supervised classifications. UAVs allowed the detection of fine details, such as weeding, differences in plant density or areas affected by diseases, details that cannot be captured by satellite at 10-meter resolution. These data were processed in specialized software, generating high-quality orthophotos that served as a reference in comparisons with satellite results (Nguyen et al., 2020).
Spectral methods played a central role in the analysis process. The NDVI, NDMI, SAVI and EVI indices were calculated using mathematical expressions established in the specialized literature, each having a particular applicability. NDVI, based on reflectance in the red and near-infrared bands, revealed the vigor of vegetation and allowed the monitoring of phenological cycles. NDMI, built on the NIR and SWIR1 bands, was essential in detecting water stress, a critical aspect in the Olt area, characterized by severe drought periods (Gao, 1996). SAVI, developed for regions with low vegetation density, compensated for the influence of soil and improved the interpretation of cultivated lands in the early stages (Huete, 1988). The EVI index, sensitive to dense vegetation, was used especially for maize and sunflower crops during their maximum development period.
Thematic classifications were another defining element of the methodology. Unsupervised classification, performed by the K-Means algorithm, allowed the automatic separation of pixels according to spectral similarities, resulting in distinct categories of surfaces: dense vegetation, sparse vegetation, exposed soil, wetlands and mixed areas. This type of classification was useful in identifying general patterns, but for a precise agricultural interpretation it was necessary to use supervised classifications. Through the Maximum Likelihood method and the Random Forest algorithm, using training sets collected from the field, thematic maps with a high degree of accuracy were obtained, capable of differentiating the main types of crops in the county. The accuracy assessment was carried out through the confusion matrix and the calculation of the global accuracy, according to the recommendations of Olofsson et al. (2014), ensuring the scientific validity of the results.
The integration of all products — satellite rasters, indices, classifications, thematic maps, diagrams and statistical analyses — was carried out in GIS environments, using QGIS 3.34. The platform allowed for complex spatial analyses, zonal statistics for agricultural areas, the generation of thematic maps with standardized cartography and the organization of workflows in a coherent system. Last but not least, through multi-annual

representations and comparison of scenes from different years, information was obtained on the seasonal dynamics and evolution of crops over time, facilitating a complex assessment of the county's agricultural potential.

RESULTS AND DISCUSSION

The results of multispectral and radar analyses on agricultural areas in Olt County provide a detailed picture of the evolution of vegetation during the vegetative period, the distribution of water stress and spatial variations of crops. The integrated interpretation of vegetation indices, thematic classifications and statistical analyses reveals a close correlation between local climatic conditions, pedological structure and agricultural land management. In particular, the dynamics of the NDVI and NDMI indices confirm the vulnerability of the region to water scarcity and emphasize the essential role of multi-temporal monitoring in identifying agricultural stress phenomena, a phenomenon also observed in other specialized studies (Gogoi & Kumar, 2021; Nguyen et al., 2020).

The NDVI values calculated for the period April–October indicate a typical evolution of southern regions characterized by moderate to severe drought. In spring, NDVI records medium to high values due to moderate precipitation in March and April, which favors germination and early plant development. In June, NDVI reaches its annual maximum, approximately 0.75–0.80, reflecting the maximum accumulation of biomass. The significantly reduced values recorded in July and August are associated with prolonged periods of high temperatures and poor precipitation, which affect the ability of plants to maintain the photosynthetic rhythm. The steep decrease in NDVI during this period reflects the reduction of green areas and possible crop degradation, an aspect also confirmed by UAV analyses carried out during the same period.

For the spatial representation of NDVI, a thematic map was generated (Fig. 1) that highlights the contrast between irrigated areas, which show high values, and non-irrigated areas, where the values are visibly lower.

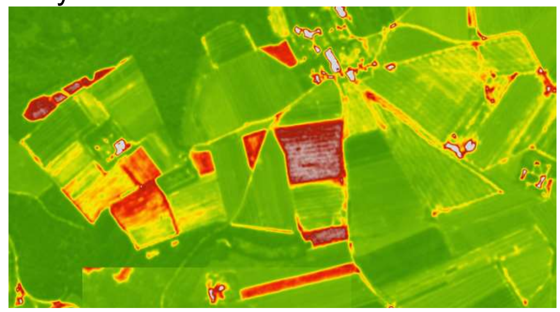

Figure 1. NDVI map of Oltcounty

This difference overlaps with the previously described pedological patterns, with alluvial soils typically maintaining higher NDVI values, while reddish-brown and sandy soils are more vulnerable to rapid moisture decreases. In this sense, NDVI confirms climatic and pedological observations, in agreement with the model described by Lillesand et al. (2015), according to which crop reflectance is strongly influenced by soil texture and water availability.

Table 3. NDVI by crop type – average values June 2024 (Sentinel-2)

Crop	NDVI minimum	NDVI average	NDVI maximum	Agronomic interpretation
Maize	0.62	0.78	0.86	Dense vegetation, peak season
Sunflower	0.55	0.71	0.80	Normal development, high dependence on precipitation
Wheat	0.45	0.63	0.70	Entry into the final phase (July)
Natural grasslands	0.32	0.49	0.60	High variability, many areas affected by drought
Free arable land	0.05	0.12	0.20	Reflects land preparation, exposed soil

NDMI analysis, derived from the NIR–SWIR1 spectral combination, provides a complementary picture of crop moisture, being a sensitive indicator of water stress. The NDMI map for August (Fig. 2) highlights areas affected by severe drought. Low values (<0.1) accurately delineate areas with weakened crops, bare soil or regressing vegetation. Areas with high NDMI are concentrated near active irrigation systems, indicating the importance of hydrotechnical infrastructure in maintaining crop vigor in a predominantly arid climate.

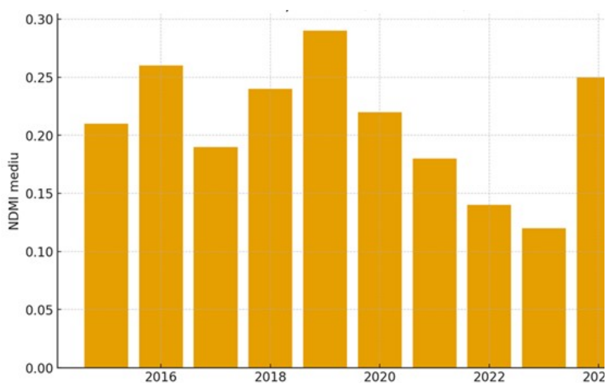

Figure 2. Evolution of NDMI in Olt County

According to Gao (1996), the combination of NIR and SWIR makes NDMI particularly relevant in the context of water scarcity, an aspect perfectly illustrated in Olt County. For further analysis, a multi-annual comparison was made between NDVI for the years 2019, 2021 and 2023 (Table 4), demonstrating how climate variations influence crop evolution.

Table 4. Annual average NDVI (2015–2024)

An	NDVI mediu	Observații agronomice
2015	0.56	relatively wet year
2016	0.58	very good conditions
2017	0.61	excellent vegetative development
2018	0.52	high water stress
2019	0.59	good recovery
2020	0.63	multiannual maximum
2021	0.57	moderate variability
2022	0.49	extreme drought
2023	0.54	partial recovery
2024	0.56	values close to normal

In years with above-average rainfall (2019), NDVI recorded a constant evolution and high values throughout the summer. In contrast, 2023, characterized by prolonged drought, showed a sharp decrease in NDVI, especially in the south of the county, where soils are more permeable and water retention capacity is reduced. This type of multi-temporal analysis is essential for risk assessment and anticipation of production losses, being widely used in recent studies on agricultural monitoring (Roy et al., 2019).

Thematic classifications represent another important component of data interpretation. Unsupervised classification using the K-Means algorithm allowed the generation of a thematic map that successfully separates the major land cover categories: dense vegetation, moderate vegetation, sparse vegetation, exposed soil, wetlands and transition areas. This model, shown in Fig. 3, provides an unconditional, objective representation of spectral similarities. However, supervised classification, using the Random Forest algorithm, has demonstrated superior performance in identifying dominant crops such as maize, sunflower and wheat, presenting an overall accuracy of approximately 90% and good separation between classes (Olofsson et al., 2014). The results obtained are comparable to those reported in the international literature, which confirms the robustness of the applied methodology.

The added value of multi-temporal analysis becomes evident in the NDVI difference figures (Fig. 4), where seasonal variations are clearly represented by a chromatic scheme that distinguishes areas with increasing, stagnating or decreasing biomass. Such maps are particularly useful for farmers, as they allow early identification of problem areas, facilitating rapid and efficient interventions in the field.

Validation of satellite results using UAV imagery confirmed the distribution of water stress areas, as well as the accuracy of supervised classifications. UAVs revealed minor deviations, especially in areas with sparse or mixed vegetation, but these differences do not exceed two pixels equivalent to Sentinel-2 resolution, confirming the methodological performance. In general, the agreement between satellite and UAV data aligns with the conclusions reported by Nguyen et al. (2020), regarding the complementarity between aerial and space observations.

Based on all analyses, it can be concluded that the state of vegetation in Olt County is strongly influenced by climatic factors, especially the distribution of precipitation and high temperatures in the summer season.

The results also confirm that the combined use of Sentinel-1 and Sentinel-2 data, together with UAV and GNSS technologies, allows for a complex and rigorous characterization of agricultural areas, providing a valuable tool for sustainable planning and management of agricultural resources.

CONCLUSIONS

The integration of remote sensing technologies with geographic information systems has demonstrated remarkable potential in the monitoring and analysis of agricultural areas in Olt County, a region where climatic factors, soil structure and seasonal variations directly influence the evolution of crops.

The multi-temporal analysis carried out on the basis of Sentinel-2 satellite images, complemented by Sentinel-1 radar information, allowed highlighting the state of vegetation at different times of the agricultural season and the systematic identification of areas vulnerable to water stress, confirming the specific climatic characteristics of southern Romania.

The calculated vegetation indices, in particular NDVI and NDMI, have demonstrated their usefulness in distinguishing phenological stages, crop vigor level and spatial variability of humidity, providing a detailed picture of the biological processes that characterize cultivated areas.

Supervised and unsupervised classifications contributed to the delimitation of land use types and the identification of the main crops in the county, and the results obtained showed a high degree of accuracy, supported by validations with UAV images and GNSS measurements. This concordance between multiple data sources confirms the robustness of the applied methodology, as well as the capacity of modern spectral and spatial analysis tools to provide information with operational relevance for agricultural practice. Moreover, the use of GIS platforms facilitated the coherent integration of satellite and aerial products, leading to the creation of detailed thematic maps and the possibility of performing complex spatial and statistical analyses. The results obtained demonstrate that the vegetation dynamics in Olt County is mainly influenced by the precipitation regime and the intensity of water stress, and periods of prolonged drought lead to significant decreases in spectral indices, reflecting the decrease in biomass and the vulnerability of crops. Thus, the systematic implementation of remote sensing technologies in agriculture can contribute significantly to the optimization of agricultural work, to the anticipation of problems affecting productivity and to the substantiation of decisions regarding water resource management, fertilization and technological interventions.

Overall, the study confirms that the combined use of satellite, UAV and GNSS data, together with GIS analysis, represents an indispensable tool for precision agriculture, supporting the sustainable development of the agricultural sector and improving its competitiveness at regional level. By rigorously applying the proposed methodology, local authorities, farmers and researchers can benefit from a solid analytical platform, capable of providing relevant and updated information for the assessment of crop status, risk management and strategic planning of agricultural activities in Olt County.

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