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BEYOND NDVI: A HYBRID CNN AND PIXEL-BASED ANALYSIS APPROACH FOR MULTIANNUAL ASSESSMENT OF SURFACE DYNAMICS AND VEGETATION HEALTH FROM RGB IMAGES IN THE BANAT REGION

B.D. SIMION[1,2], Loredana COPĂCEAN[1], Luminiţa COJOCARIU[1,3]

[1]University of Life Sciences „King Mihai I" from Timisoara, 119, Calea Aradului, 300645, Timisoara, Romania
[2]Politehnica University of Timisoara, 2, Piata Victoriei, 300006, Timisoara, Romania
[3]Agricultural Research and Development Station Lovrin, 307250, 200, Principala, Lovrin, Romania
Corresponding author: luminita_cojocariu@usvt.ro

Abstract. *Currently, agriculture faces major challenges related to the efficient utilization of natural resources, the optimization of crop productivity, and the maintenance of sustainable practices under increasingly unpredictable climatic conditions. Traditional monitoring techniques are often limited in spatial and temporal coverage, making it difficult to achieve timely and accurate assessments of land surface conditions. This study proposes the creation of an intelligent system for monitoring land surface coverage, encompassing agricultural crops, grasslands, and various land types, utilizing open-source satellite data and integrating machine learning models. The research is applied in the Banat region of Romania, a representative area for lowland agricultural ecosystems. The system acquires 20 meter resolution RGB imagery from the Copernicus browser, which is then processed to compute vegetation indices such as ExGR (Excess Green minus Red Index). These indices are essential indicators for evaluating vegetation health, density, and soil moisture. The processed data are subsequently analyzed using supervised and unsupervised learning algorithms to automatically classify land cover types with a high degree of accuracy. The results demonstrate that the proposed system effectively identifies and monitors diverse land surfaces, supporting improved agricultural management and precision farming strategies. This research highlights the potential of combining remote sensing, open-source satellite imagery, and artificial intelligence to create scalable, cost-efficient tools for sustainable agricultural and environmental monitoring.*

Keywords: *Banat, Neural Network, open-source, RGB.*

INTRODUCTION

The Normalized Difference Vegetation Index (NDVI) is the most widely adopted and standard remote sensing index for monitoring the health, growth, and biomass of vegetation across various environments (GANDHI ET AL., 2015; BOORI ET AL., 2020; BENTO ET AL., 2020). Its pervasive use in fields such as agriculture, forestry, ecology, and land management, for tasks including crop yield estimation, land cover classification, and ecosystem monitoring, stems from its simplicity, broad applicability, and the ease with which it can be calculated (HU ET AL., 2009; HATFIELD ET AL., 2019; SOUBRY ET AL., 2021).

Despite its utility, NDVI has several significant and well-documented limitations that can affect the accuracy and reliability of monitoring efforts (HUANG ET AL., 2020; LI ET AL., 2021). These limitations underscore the need for awareness and the development of alternative methodologies:

• Dependence on Multispectral Sensors: Calculating NDVI strictly requires sensors capable of capturing both red and NIR bands. Variability in sensor quality, calibration, and spectral response across different instruments introduces inconsistencies, which complicates the continuity and comparability of data, especially across different platforms or time periods (HUANG ET AL., 2020; LI ET AL., 2021; ROSSI ET AL., 2019).

• Atmospheric Interference: NDVI values are inherently sensitive to atmospheric conditions like clouds, haze, and water vapor. These factors distort the measured surface reflectance, which in turn reduces the reliability of the data and represents a major source of uncertainty, particularly in satellite-based products (HUANG ET AL., 2020; LI ET AL., 2021).

• Saturation at High Biomass: Perhaps the most critical limitation is that NDVI tends to saturate in dense vegetation or high biomass conditions. Once a certain density, such as a high leaf area index (LAI), is reached, the index loses its sensitivity and no longer accurately registers further increases in biomass. This saturation limits its effectiveness for monitoring mature crops, dense forests, or high-density grasslands (HUANG ET AL., 2020; LI ET AL., 2021).

In this context, RGB imagery, acquired from drones, aerial cameras, or high-resolution satellite sensors (SIMON ET AL., 2020; SIMON ET AL., 2021), has emerged as a promising substitute. RGB images are abundant, inexpensive, and easier to collect compared to multispectral or hyperspectral data. Although RGB sensors lack the NIR band traditionally used in vegetation indices, advances in computer vision and deep learning have enabled the extraction of complex features from standard colour channels. These developments open new possibilities for assessing vegetation dynamics and detecting subtle spatial and temporal patterns in agricultural and natural landscapes.

The present study aims to develop a hybrid approach that combines convolutional neural network (CNN)-based feature extraction with pixel-level vegetation analysis to estimate vegetation health indicators from RGB imagery without relying on NIR data. The proposed pipeline integrates traditional colour-based indices—such as Excess Green Index (ExG)—with high-level features derived from a CNN trained to capture spatial and textural information. By applying this methodology to multiannual RGB datasets from the Banat region of Romania, the study evaluates temporal changes in surface and vegetation conditions over several growing seasons. The main contributions of this work include (1) demonstrating the potential of RGB-only data for large-scale vegetation monitoring, (2) introducing a hybrid analytical framework that bridges traditional pixel-based and AI-driven methods, and (3) providing a regional case study highlighting the applicability of this approach in agricultural and environmental assessment contexts.

MATERIALS AND METHODS

Study Area

The study area for this research is the Banat region of Romania, situated in the western part of the country. This region is geographically and agronomically representative of lowland agricultural systems across Central and Eastern Europe (RUSU, 2007).

The Banat features a temperate continental climate characterized by moderate precipitation and distinct seasonal variations (ŞMULEAC ET AL., 2020). Topographically, it is dominated by fertile plains, which support intensive agricultural activities. The primary agricultural production (BORDEAN ET AL., 2013; AGAPIE ET AL., 2020) in this area includes key European crops such as wheat, maize, sunflower, and rapeseed.

The long-term monitoring capabilities enabled by the dataset, in conjunction with the region's diverse and typical agricultural landscape, make the Banat an ideal and relevant testbed for assessing multiannual changes in surface dynamics and vegetation health (COSTEA ET AL., 2012).

Dataset Description

The dataset used in this research consists of RGB imagery derived from Sentinel-2 satellite data, accessed via the Copernicus Browser. Only the visible spectral bands (red, green, and blue) were utilized in order to assess vegetation dynamics without relying on near-infrared (NIR) information. The temporal coverage spans 2019 - 2025, enabling a seven-year multiannual analysis of surface and vegetation changes across different agricultural and semi-natural environments. The images were downloaded as Level-2A products, which already include atmospheric and radiometric corrections provided by the Copernicus processing chain. Therefore, no additional manual preprocessing was performed. To ensure spatial and temporal consistency, all images were selected based on minimal cloud coverage and comparable acquisition periods within the vegetation growing season (around 1st of May).

Pixel Based Analysis

The first analytical stream focuses on extracting vegetation information directly from the Red (R), Green (G), and Blue (B) bands of the pre-processed RGB images. A suite of colour-based vegetation indices (C-VIs) is computed for every pixel to provide quantitative metrics related to greenness and photosynthetic vigour, serving as surrogates for the standard Normalized Difference Vegetation Index (NDVI) which is unavailable in pure RGB data. The C-VIs include the Excess Green Index (ExG), Excess Red Index (ExR), Visible Atmospherically Resistant Index (VARI), Green Leaf Index (GLI) (MARCIAL-PABLO ET AL., 2018; MEYER ET AL., 2008).

To ensure comparability across the multiannual time series and the different sensors, all computed indices undergo normalization. This involves scaling index values to a common range ([-1, 1]) using min-max normalization, which minimizes radiometric and sensor-specific inconsistencies inherent in the heterogeneous dataset. Subsequently, the spatial and temporal dynamics of vegetation are summarized using comprehensive statistical metrics.

CNN – feature extraction

The second stream employs a Convolutional Neural Network (CNN) for extracting high-level, abstract semantic features that are not explicitly captured by simple band arithmetic. The developed CNN architecture is a custom model that employs a series of convolutional layer, a flattened layer and 2 fully connected layers, making it structurally analogous to the ResNet18 framework, selected for its balance of representational power and computational efficiency (Figure 1).

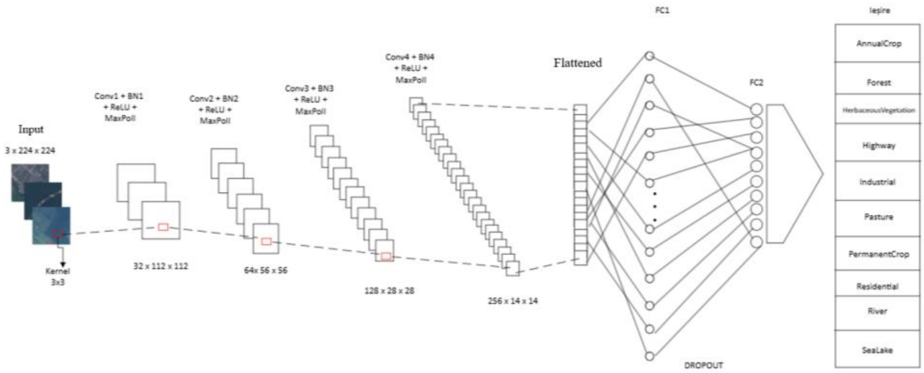

Figure 1. CNN model architecture

The convolutional neural network (CNN) component of the proposed framework was designed to extract high-level spatial and textural features from RGB imagery, providing a deep representation of vegetation structure and surface characteristics. A custom CNN architecture was developed in PyTorch, inspired by residual learning concepts from ResNet models, but implemented and trained entirely from scratch. Unlike conventional transfer learning approaches, no pretrained weights were used, ensuring that the network learned features specifically relevant to satellite and aerial imagery of vegetation surfaces.

The model, referred to as SatelliteCNN, consists of four convolutional blocks with increasing feature depth (32, 64, 128, and 256 filters), each followed by batch normalization, ReLU activation, and max pooling. This hierarchical design enables progressive abstraction from low-level colour and edge information to high-level spatial textures characteristic of vegetation canopies. The convolutional feature maps are flattened and passed through two fully connected layers (1024 and N output units, where N is the number of land-cover classes in the EuroSAT-RGB dataset), with dropout regularization (rate = 0.5) applied to mitigate overfitting. The network was optimized using the Adam algorithm (learning rate = 0.001) and a cross-entropy loss function. A learning rate scheduler was employed to adaptively reduce the learning rate when validation performance plateaued.

Training was performed on the EuroSAT-RGB dataset, a large-scale benchmark derived from Sentinel-2 imagery, which was split into 80% training and 20% test data (HELBER ET AL., 2018). Data augmentation techniques, including random rotations, horizontal and vertical flips, and color jittering, were applied to enhance generalization. The model achieved its best validation accuracy after 50 epochs, with weights saved for feature extraction.

After training, deep features were extracted from the final convolutional layer prior to the fully connected layers, capturing spatial-spectral patterns representative of vegetation and surface variability.

RESULTS AND DISCUSSION

The hybrid analytical method that combined convolutional neural network (CNN) classification with vegetation colour index computation was applied to monitor the evolution of vegetation vigour on the analysed parcel between 2019 and 2025. The mean Excess Green Index (ExGR), calculated from Sentinel imagery around May 1st (±5 days), provides an annual indicator of canopy development at the beginning of the vegetative season.

As shown in Table 1, ExGR values fluctuated across the study period, ranging from a minimum of –0.082 in 2020 to a maximum of 0.373 in 2023. Overall, a positive trend is observed, indicating improved vegetation greenness and canopy density over time.

Table 1.

ExGR mean from 2019 to 2025

Year	ExGR mean lot A	Precipitation 30 days before[1] (mm)	Temperature means 30 days before[2] (°C)
2019	0.078	12.7*	13
2020	-0.082	4.3	10.3
2021	0.261	22.2*	9.3
2022	0.161	32.6*	10.6
2023	0.373	58.6	9.3
2024	0.242	23.4	13.8
2025	0.266	16.8	12.8

[1] - Averages taken from the website: https://meteostat.net, Timișoara weather station.
[2] - Averages taken from the website: https://meteostat.net, Timișoara weather station.

The lowest value in 2020 may be attributed to the low cumulative precipitation (only 4.3 mm in the previous 30 days) and relatively low average temperature (10.3 °C), which likely delayed early-season growth. In contrast, the highest ExGR in 2023 coincides with the highest recorded precipitation (58.6 mm), confirming the sensitivity of vegetation indices to soil moisture availability.

Between 2021 and 2025, ExGR values remained positive and relatively stable (0.16–0.37 range), suggesting consistent vegetation development and possibly improved land management practices. This pattern may reflect both favourable climatic conditions and adaptation of local agricultural strategies, such as optimized grazing timing or canopy conservation practices.

A moderate positive relationship can be visually observed between ExGR and precipitation, supporting the assumption that water availability is a major driver of vegetation greenness. The influence of temperature appears secondary, as the years with higher average temperatures (e.g., 2019 and 2024) do not directly correspond to the highest ExGR values (Figure 2). This indicates that within the studied temperature range (9–14 °C), moisture stress is more limiting than temperature for early spring vegetation development.

The CNN model used for classification achieved an accuracy exceeding 95% on the test dataset, ensuring reliable extraction of vegetated areas at the parcel level (SIMION, 2025). This high precision supports the validity of the observed trends and demonstrates the robustness of the hybrid approach in handling RGB satellite data with minimal manual intervention.

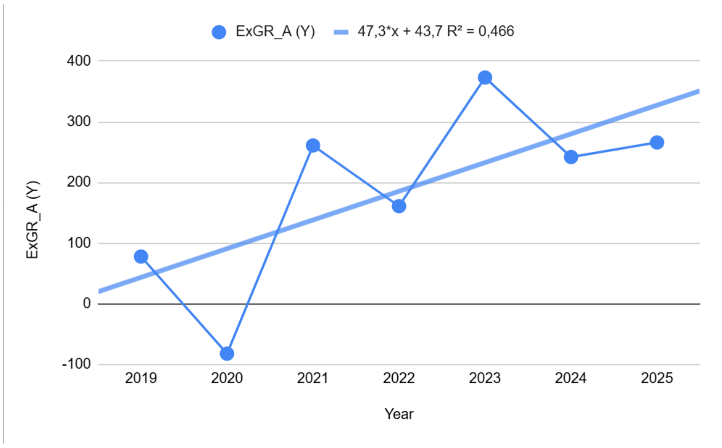

Figure 2. Graph with the evolution trend of ExGR

The integration of CNN-based classification with vegetation indices allows for continuous and automated monitoring of agricultural parcels (Figure 3).

The hybrid method effectively captures both temporal dynamics and climatic influences on vegetation, enabling early detection of stress or productivity changes. As such, this workflow represents a cost-efficient and scalable solution for precision agriculture and supports sustainable management through data-driven decision-making (COSTEA ET AL., 2012; ZLINSZKY ET AL., 2015; COPĂCEAN ET AL., 2019; ZHANG ET AL., 2021; WANG ET AL., 2022).

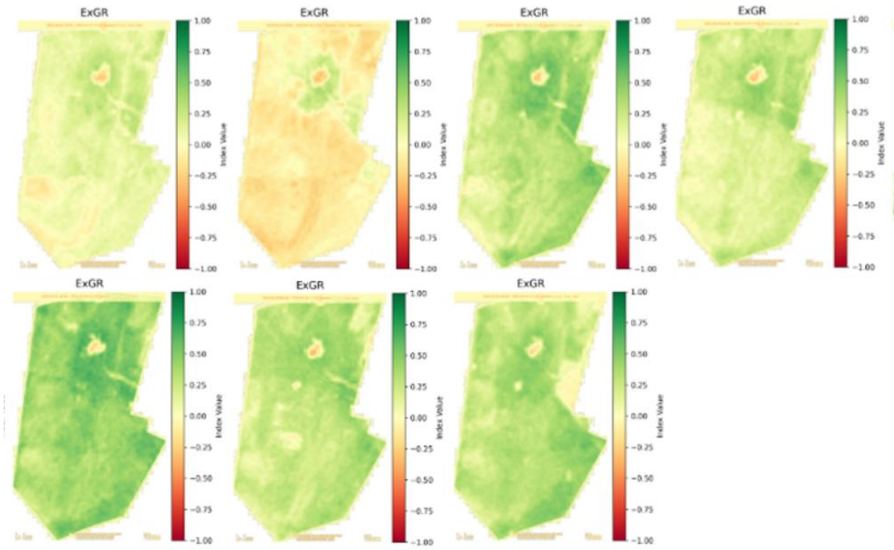

Figure 3. ExGR index from 2019 (left) to 2025(right)

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Nevertheless, some limitations must be acknowledged. The absence of near-infrared (NIR) data constrains the capacity to detect early signs of stress, as many physiological changes in vegetation occur before they are visible in the RGB spectrum. In addition, illumination variability, resulting from atmospheric conditions, time of capture, or sensor angle, introduces potential inconsistencies in reflectance values. While the hybrid method mitigates part of these issues through preprocessing and statistical normalization, further refinement is required to achieve higher accuracy in temporal trend estimation.

Future research should focus on integrating RGB data with complementary information sources such as multispectral imagery and LiDAR data. The inclusion of NIR or red-edge bands would allow for more precise quantification of chlorophyll content and biomass estimation. Moreover, the application of Long Short-Term Memory (LSTM) neural networks could enhance temporal prediction by learning complex patterns in vegetation dynamics, enabling early detection of degradation or recovery trends. Expanding this approach to diverse ecosystems beyond grasslands would further validate its robustness and generalizability.

CONCLUSIONS

This study demonstrates that RGB imagery, even when derived from publicly available satellite sources such as the Copernicus Sentinel program, can provide valuable insights into vegetation health dynamics over time. By focusing on grasslands, which represent relatively stable ecosystems with limited anthropogenic and seasonal variability, the analysis isolates vegetation-related changes and minimizes confounding environmental factors. The results reveal a clear upward trend in greenness from 2019 to 2025, indicating a gradual improvement in vegetation vigour across the study area.

The hybrid analytical approach proposed in this research—combining convolutional neural network (CNN) classification, RGB-based colour index computation, and statistical trend analysis—proved to be both robust and adaptable. The CNN effectively classified vegetation areas and reduced background noise, while the colour-based indices (derived from visible spectral bands) captured subtle temporal changes in vegetation reflectance. This integrated framework enhanced the reliability of RGB-based assessments, bridging the gap between traditional visual analysis and more complex multispectral or hyperspectral monitoring methods.

One of the main advantages of this approach lies in its accessibility and scalability. Unlike multispectral sensors that require dedicated equipment and calibration, RGB imagery from the Sentinel program or other open-access sources can be processed with minimal resources. This makes the method particularly attractive for large-scale or long-term environmental monitoring, supporting sustainable land management where advanced remote sensing tools are not readily available. By demonstrating the feasibility of using RGB imagery for continuous vegetation health assessment, the study contributes to the development of low-cost, data-driven solutions that align with the goals of precision agriculture and environmental sustainability.

This study highlights the potential of combining open-access RGB imagery, deep learning, and statistical analysis as an effective framework for sustainable vegetation monitoring. The methodology bridges the gap between advanced remote sensing technologies and practical, resource-efficient applications, demonstrating how artificial intelligence can support environmental stewardship and long-term ecosystem resilience..

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