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A FRAMEWORK FOR INNOVATION IN EARTH OBSERVATION APPLICATIONS FOR AGRICULTURE

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Abstract: *Agriculture is a top priority both for Romania and the European Union. Agriculture can largely benefit from the Earth Observation data freely available from the Sentinel 2 satellites within the context of the Copernicus program. The validation and correlation of satellite measurements with the in-situ measured data are extremely important for the correct exploitation of the remote sensing data. One way to foster satellite and in-situ data is to use Artificial Intelligence models and tools for extracting useful information for farmers and landowners. In this article, we identify the current needs in the agricultural domain as well as various aspects where innovation can occur in the data processing chain. We focus on convolutional neural networks as this type of deep learning model is perfectly suited for the analysis of images.*

Keywords: *Earth Observation, Artificial Intelligence, Normalized Difference Vegetation Index, Hyperspectral Imaging*

1. Introduction

The world population will increase from 7.5 to 9.7 billion by 2050, resulting in high agricultural products demand and pressure on natural resources. Although in many countries, agriculture is still the major activity around the world, a decrease in total production and employment in agriculture is observed. Agricultural investments and technological innovations are considered by experts the solution to boost productivity [22]. 6.8 million hectares out of 14.7 million hectares of agricultural capacity in Romania are not or are under-exploited. Consequently, Romania can perform an important role in the strategic autonomy and food security, as well as the sustainability of Europe. Romania's agricultural capacity is being under-exploited because of the usage of obsolete technology and various natural phenomena such as soil fragmentation, erosion, and desertification. Over the past thirty years, precision agriculture has evolved from using satellite imaging for regional decision-making to using low-altitude remotely sensed data

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for field-scale site-specific treatment. Researchers implemented a recurrent neural network on a low-power device for in situ observations. This embedded system works autonomously for 180 days [50]. SMART agriculture requires the integration of such sensors into the field to measure crop health, and soil condition and connect them to the cloud for further access, and communication between device units [41]. In [44] researchers propose a cyber-physical system for precision agriculture that can help farmers to improve agricultural productivity. In the paper [43] authors exemplify the sensors and their purposes in agriculture and show the results of a few devices that are applied in the potato field. Brasov County is considered to be the Potato County of Romania. At the heart of Potato County, the National Institute of Research and Development for Potato and Sugar Beet (NIRDPSB), Brasov plays an important role in the preservation of the potato heritage at the national level [10], [9]. NIRDPSB has more than 60 years of experience in the field. It promotes strategic, fundamental, and applicative research in the potato and sugar beet crop domain. Its research directions are the following: maintaining and improving the genetic heritage in potatoes, sugar beet, and medical plants; creating new potato varieties; improving potato seed quality and biotechnology promoting (in vitro crops, micro- and mini-tubercles); development of integrated and differentiated technologies for potato and sugar beet cultivation with low energy, low prices and environmentally friendly; development of methods for forecasting and warning of major diseases and pests; physical, chemical and biochemical testing of plant material; testing, analysing and fight against major diseases affecting potato crops. NIRDPSB has rich experience in potato cultivation and exploitation, being the only National Institute in Romania dealing with potato research.

In the past decades, there has been a major increase in scientific interest in using remote sensing technologies and many sensors and platforms have been designed for Earth Observation (EO). Massive amounts of remote sensing data, particularly acquired by satellites, are now accessible for research studies. Nowadays, more than a thousand operational satellites are orbiting the planet, many of which are used for remote sensing. For agriculture, remote sensing offers invaluable support for precise agricultural operations at the scale of farmers' fields, but also in the strategic planning and management of agricultural production at regional and national levels [25]. Artificial Intelligence (AI)-based systems and applications have a significant potential for precision agriculture. The Copernicus EU Programme provides free access to accurate Earth Observation data from Sentinel satellites, which can be used for research and AI-based applications aimed at the sustainable development of agriculture in Europe [7].

Various machine learning techniques have been applied in smart agriculture, like Random Forest for crop prediction [20], Decision Tree [45] and k-Nearest Neighbors [54] for plants' leaf disease detection. Nowadays, deep learning models are widely used due to their high performance in classification and prediction. Convolutional neural networks (CNNs) [58] are usually preferred due to their higher effectiveness compared to other machine learning models [37]. Another reason is that they are perfectly suited to work with image input data.

2. Methodology

The area where our current and future studies are being conducted is in Romania's central part, Brasov County. Satellite images for this study were freely downloaded from the Copernicus Open Access Hub in the Brasov region. Figure 1 is an RGB colour composite with 10 *m* resolution that was captured by Sentinel-2A satellite and processed in SNAP ESA software. It shows the location of the Research, Development, and Innovation (RDI) Institute of the Transilvania University of Brasov, emphasizing in its surrounding area the various experimental crops (marked in red, blue, and green) for potato and sugar beet, belonging to NIRDPSB.

The scientific challenges and needs in Artificial Intelligence and Agriculture were identified through discussions with representatives from the National Institute of Research and Development for Potato and Sugar Beet Brasov, Romania, and the Research-Development Institute for Grasslands Brasov, as well as other institutes, companies, and farming associations In the context of AI on remote sensing/EO Data for Agriculture, we identified the following challenges: cartography of agricultural crops, crop identification (differentiation), vegetation status monitoring, health status monitoring (early detection of the presence of pests), yield prediction/production capacity monitoring and evolution of technological quality of the agricultural crops, computation of vegetation indices and their biological and agronomic significance and map generation

Fig. 1. *Sentinel 2A satellite view of the NIRDPSB experimental fields (2022).*

for the identification of specific plant stress (e.g., need of water and fertilizers), change detection based on vegetation indices or other pixel or local features for the early detection of plant stress, efficient processing strategies - e.g., interest detection on free low-resolution data followed by the acquisition of more precise data, compression, simplification, including focal estimates, etc. The data that we consider include mainly satellite data and in-situ measurements. For the satellite data, we consider using the Sentinel-1 images (SAR), Sentinel-2 images (multispectral data), PRISMA images (hyperspectral data), and Pleiades high-resolution images, as well as data from future Copernicus missions. Regarding the in-situ measurements, two types of data are considered: i) vegetation indices (NDVI), chlorophyll content, water content, etc., and ii) hyperspectral images. For all data and measurements, we consider both the representation as time series and data cubes.

3. Innovation in EO for Agriculture

3.1. The in-situ level

Various in-situ measurements are regularly performed every year in order to monitor several experimental crops of the NIRDPSB. For soil, the following in-situ measurements are performed (indicating in parentheses the equipment that is used): humidity (TDR300), temperature, electrical conductivity (VERIS), compaction (FieldScout SC900), and profile-based humidity and temperature dynamics. Regarding the crops, the following in-situ measurements are performed: crop reflectance (CropScan), chlorophyll concentration (SPAD502), NDVI (NDVI Meter), phenology data, and climate data from various meteo stations [41], [43]. All the measurements are georeferenced using GPS in order to integrate all data in GIS and produce various maps, including vegetation indices maps. The most used and unanimously accepted vegetation indices are computed and used for monitoring (e.g. NDVI and Leaf Area Index (LAI)). The vegetation indices maps are interpreted and used as they are, but very often they are used to perform correlations with the vegetation indices maps computed based on multispectral satellite images. Various other vegetation indices exist: Atmospherically Resistant Vegetation Index (ARVI) [33]; Green Difference Vegetation Index (GDVI) [51], [34]; Green Vegetation Index (GVI) [34]; Optimized Soil Adjusted Vegetation Index (OSAVI) [46]; Simple Ratio (SR) [6]; Soil Adjusted Vegetation Index (SAVI) [28]; Transformed Difference Vegetation Index (TDVI) [4]; Visible Atmospherically Resistant Index (VARI) [21]; Modified Chlorophyll Absorption Ratio Index Improved (MCARI2) [26]; Normalized Difference Water Index (NDWI) [19]; Normalized Difference Nitrogen Index (NDNI) [49], [17]; Normalized Difference Infrared Index (NDII) [27], [31]; Cellulose Absorption Index (CAI) [15], [14]; etc.

The crop reflectance spectral data can be acquired using the CropScan technology. We show in Figure 2 the spectral reflectance curves obtained using CropScan for two sugar beet crops - one healthy and one stressed expressed in percentages as a function of wavelength in nm. The CropScan offers the reflectance values for wavelengths comprised between 460 nm and 1500 nm. For the stressed sugar beet crop, the spectral curves indicate that the vegetation status of the plant is not the desired one, the plant lacks water, nutrients, or both. This was confirmed by the in-situ measurements (NDVI, NI, SR, and chlorophyll content).

Ground-level referencing plays an important role in the validation of EO data. In Spring 2017 we developed the metal colour chart for in-situ usage, which is presented in Figure 3. The colour chart is composed of eight squares, each of them of 0.5 × 0.5 m size, painted in the following colours: white, red, green, blue, black, magenta, yellow, and cyan. The resulting total size of the colour chart is 1 × 2 m.

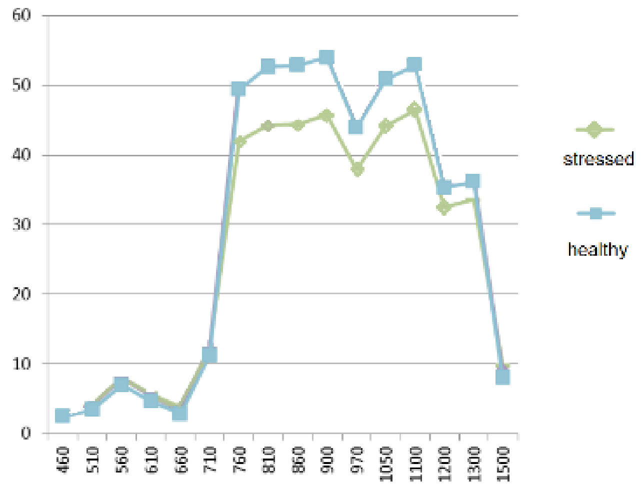

Fig. 2. *Spectral reflectance curves for two different sugar beet crops.*

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Fig. 3. *Spectral reflectance curves for two different sugar beet crops (used from* [29]*).*

We performed various in-situ spectral measurements on the colour chart, using a portable spectrometer. The raw measured values represent the radiance expressed in $counts/\mu W$, at 1 ms integration time. The measurements are depicted in Figure 4 for the eight patches of the colour chart, as well as the radiance of the sunlight. The reflectance curves for the eight patches of the colour chart were computed by normalizing the radiance values with respect to the radiance of the illuminant (sunlight on a sunny day, which should correspond to a CIE D65 standard illuminant).

The referencing is very important for the validation of multi or hyperspectral image acquisition. The in-situ colour chart and multispectral measurements will be further used to validate the acquisition with a portable Specim IQ hyperspectral camera or to perform colour correction of the acquired aerial views acquired with the hexa-spectral camera. Further on, all the data (in-situ measurements, multispectral measurements, and images) will be correlated to the measurements (e.g., of vegetation indices) performed on Sentinel-2 multispectral images.

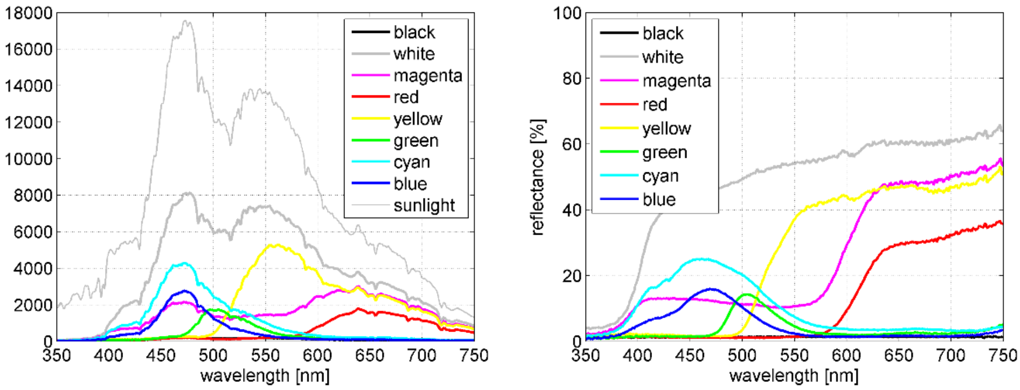


Fig. 4. *The radiance (a) and the reflectance (b) curves of the colour patches and the incident sunlight*

3.2. The ground level

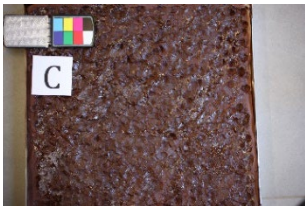
At the ground level, we considered soil surface roughness, which is an important parameter of the soil. Soil roughness represents the soil surface irregularities as a direct consequence of soil texture, aggregate size, rock fragments, vegetation cover, and land management [55]. Soil roughness plays an important role in water surface storage, infiltration, overland flow, floods, and ultimately sediment detachment and erosion [3], [23]. One of the widely used measurements for roughness is defined by [2]: the soil roughness is computed as the natural logarithm of the standard deviation (STD) of multiple height measurements after eliminating the possible bias (like slope and oriented roughness, or the 10% of upper and lower extreme values). However, according to [13], the STD of height measurements after eliminating the slope effects is sufficient for the measurement of random roughness. We considered this technique in our study. Methods for soil roughness measurement can be divided into two broad categories: contact and non-contact. Contact methods are the roller chain method [48] and the pinboard method [2]. They are also referred to as reference methods. Non-contact methods are Terrestrial Laser Scanning (TLS) [5], stereophotogrammetry [1], and Xtion Pro [39]. A study and comparison of all these methods are presented [55]. As in-lab preparatory experiments for the future in-situ measurement campaign foreseen for spring 2023, we created several artificial surfaces and performed several soil roughness measurements. In the chain method, the chain is one meter long and the soil roughness is estimated by computing the index in eq. (1) [48]:

$$Cr = \left(1 - \frac{L_2}{L_1}\right) \times 100 \qquad (1)$$

where, L_1, - is a distance over a surface that indicates the size of the chain (1 m) and, L_2, - is the Euclidean distance measured by a ruler over the sample surface (m).

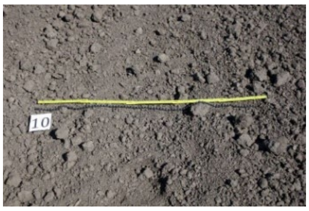
We validated the pinboard setup by performing several in-lab measurements (Figure 5 (a), (b) and (c)). For the in-situ measurement campaign, we took 12 different measurements in a field with chain and pinboard. Figure 5 (d) shows the usage of a chain method while Figure 5 (e) shows the usage of a pinboard. Figure 5 (f) is the close-range format of the pinboard setup to record the height of the pins and it was taken with a Canon 5D Mark II digital camera with 1 m distance from the pinboard and 30 cm height from the ground. These parameters were kept as standard in all measurements. With the value of the height of the recorded pins, we computed the STD. Figure 5 (g) indicates the locations of the 12 measurements in the field, for more details, see [43]. Furthermore, we conducted in-lab experiments with laser on multiple surfaces such as Figure 5 (h) and (i). We used this data to train CNN networks namely, VGG-11 and ResNet-18 to estimate soil roughness [30].

(a) In-lab usage of pinboard on Sample B



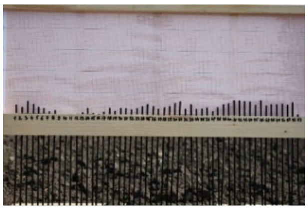
(b) Sample C

(c) Sample D

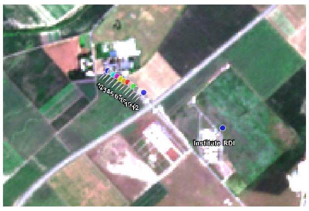


(d) Chain measurement on soil in-situ

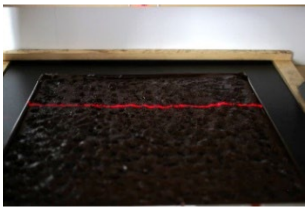
(e) In-situ usage of pinboard



(f) In-situ usage of pinboard (close view)



(g) In-situ measurement locations



(h) Laser on sample C

(i) Laser on the soil surface

Fig. 5. *Usage of chain and pinboard setups, in-situ measurement locations and in-lab experiments with the laser to estimate soil surface roughness using CNN*

3.3. The satellite image analysis level

Human vision is limited to a very small part of the electromagnetic spectrum, called the visible spectrum. Multispectral and hyperspectral cameras are capable of acquiring data both in the visible and outside the visible spectrum, very often the infrared spectrum. The spectral data can be very useful for many applications: object detection [57], issues detection in farming (nutrient deficiencies, diseases, etc.) [38], forensic medicine [16], biomedicine [8], food safety and quality control [24], etc. Due to the multi-dimensional nature of the spectral data, the visualization of a colour display with only 3 colour channels is a challenge. Various methods have been proposed for the visualization of remote sensing data.

The band selection approach is to select three spectral bands and map them into R, G, and B colour channels [52]. More complex band selection methods have been proposed [53]. Transform-based visualization is done by converting the spectral data cube to a feature space that is suitable for dimension reduction [12]. The most widely adopted one is principal component analysis (PCA) which proposes a display strategy based on the first three principal components of the spectral data and mapping them into R, G, and B colour channels, which capture the most significant variation in the data. Other types of approaches include image fusion based on a weighted sum of spectral bands [32]; multiresolution-based techniques based on a decomposition of the data on base images to generate multi-resolution pyramidal representations [56]; or wavelet-based techniques [35], [36]. Another example of an AI-based approach is described in [42] where authors proposed an ANN model to visualize the hyperspectral data, the study inspired by [11].

In Figure 6 we show a snapshot of our own MATLAB GUI used for the visualization, segmentation, and analysis of both LANDSAT and Sentinel-2 images. The GUI implements various analysis tasks: choice of spectral bands for band selection-based image visualization, pixel spectral signature display for the selected pixel of interest, image segmentation based on pixel spectral signature through k-means classification with the possibility of choosing the number of classes, etc. We are currently extending the interface to be able to work with Sentinel-2 images as well by developing new visualization techniques using AI models [42] as well as developing new datasets for training the CNN models.

For future work, we focused on Sentinel-2 Level-2 images which is atmospherically corrected, Surface Reflectance products [59] and a time series of images was downloaded for free from the ESA Open Access Hub. The satellite images were imported into the SNAP ESA software application [60] and resampled at 10 m spatial resolution. The next step was setting the area of interest to the following coordinates: North latitude bound = 45.679°, West latitude bound = 25.513°, South latitude bound =45.662°, East latitude bound = 25.57°. The band selection for rendering the colour RGB composites of the Sentinel-2A images was 4,3,2.

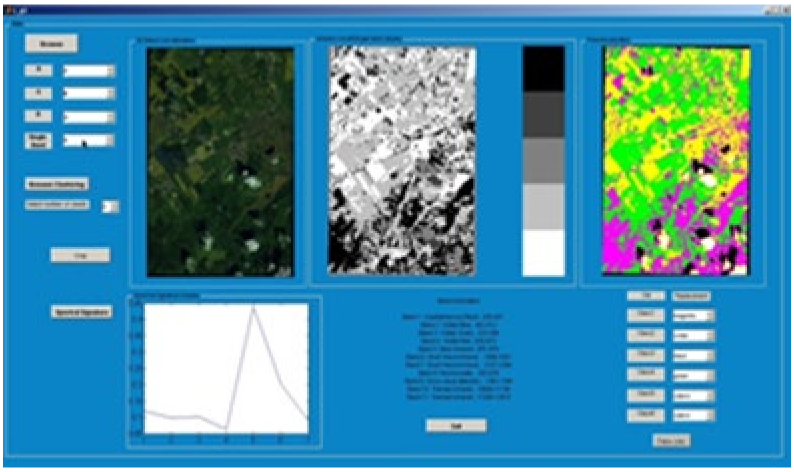
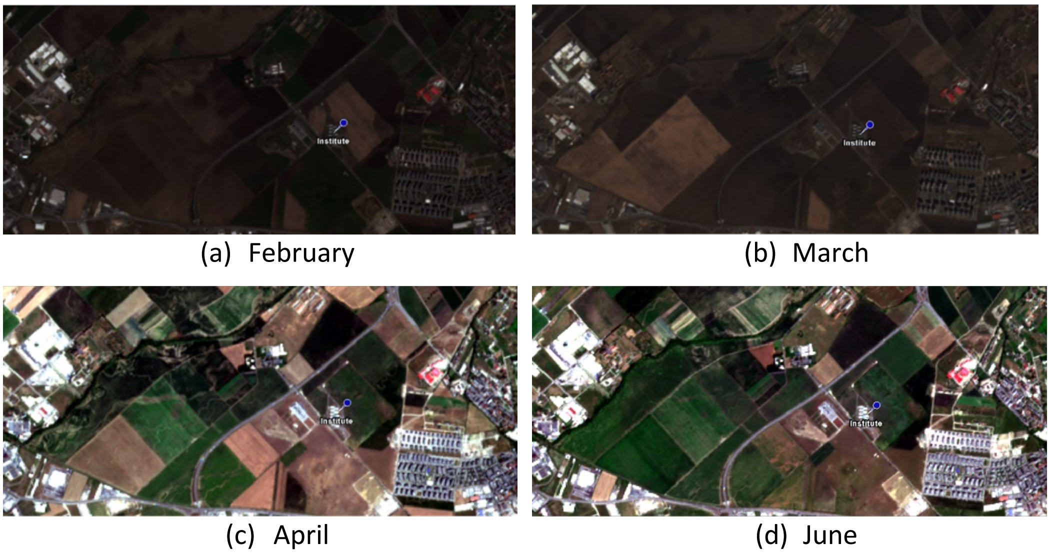


Fig. 6. *A snapshot of the MATLAB GUI used for LANDSAT image visualization, segmentation, and analysis.*

A subset of four images from 2022 is depicted in Figure 7. The following dates correspond to the time series: 19th February, 14th March, 13th April, and 29th June respectively.



(a) February (b) March

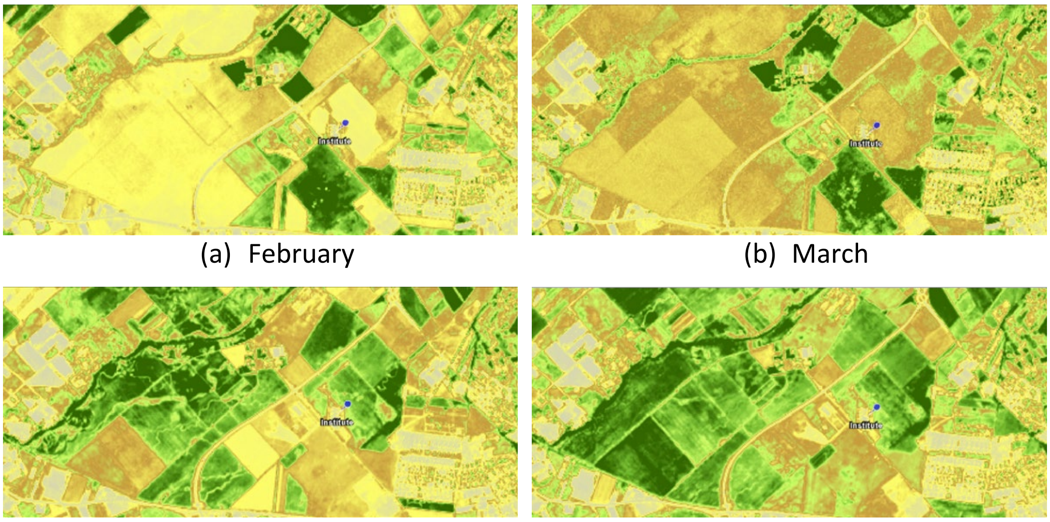
(c) April (d) June

Fig. 7. *Colour RGB composites of the Sentinel 2A images acquired for 4 consecutive months in 2022 over the area of interest.*

Based on the remote sensing multi-spectral images, a series of vegetation indices can be computed for the analysis of vegetation status and health. Normalized Difference Vegetation Index (NDVI) is the most widely used vegetation index [47]. NDVI is computed as indicated in eq. 2 based on the red and near-infrared spectral bands. The differentiated reflection between red (RED) and near-infrared (NIR) bands allows the monitoring of the green vegetation's density and intensity using solar radiation's spectral reflectivity [18].

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{2}$$

The NDVI values range from −1 to +1. The NDVI usually gives a negative result for the water areas, around 0 for the land area with little to zero vegetation and positive values usually indicate regions of land with developed vegetation. Consequently, NDVI served as a tool for analysing and predicting changes in vegetation status or health, as a direct influence of the environmental conditions. In Figure 8 we show the NDVI pseudo-coloured images computed using ESA SNAP based on the images in Figure 7. The colour palette, 'meris vegetation index' from SNAP software was chosen so that the green colour represents the areas covered with vegetation (where usually the temperature is relatively low) and the yellow-orange colour represents the areas with built-up areas or with precarious vegetation (where the temperatures are relatively higher). The density and health of the vegetation are indicated by the NVDI value computed for each pixel in the satellite images, thus measuring the vegetation's greenness. The index is based on the contrast between the red and near-infrared spectral bands: the red band indicates the absorption of chlorophyll pigments, while the near-infrared band the high reflection of plant materials.



(a) February (b) March

(c) April (d) June

Fig. 8. *NDVI pseudo-coloured images.*

4. Framework

In this section, we describe the framework for our future work from two perspectives: first, the one of the AI4AGRI project, and second, the legal aspects framing the analysis of agricultural fields based on EO data. The AI4AGRI project 2022-2025, financed under grant agreement no. 101079136, aims to create an excellent research centre at Transilvania University of Brasov, Romania, dedicated to AI in EO for the agricultural sector. The project is implemented in a consortium with two top research institutes in France and Italy in AI and EO: Université Toulouse III Paul Sabatier (and the affiliated Université Toulouse II Jean Jaurès) and Università degli Studi di Roma Tor Vergata, respectively. AI4AGRI research centre will operate to train young scientists in the domain of AI and EO data analysis for agriculture, providing various products like vegetation status maps for Romanian farmers based on EO data using AI. The AI4AGRI project aims to develop administrative and management skills for research and innovation by enhancing networking activities between partners through joint research, short-term staff exchanges, expert visits, short-term training, joint summer schools, and workshops, as well as conference attendance, dissemination of research results, and outreach activities.

5. Conclusion

In this paper, we introduced the framework for innovation in Earth Observation applications for agriculture in the context of the AI4AGRI project financed by the European Union. Agriculture is a high priority for the European Union and Romania. The potential of the land in Romania for agriculture is huge and Brasov County is especially known for its large number of potato crops. On the other hand, available remote sensing data about agricultural land that the Copernicus programme offers provide farmers with opportunities for improvement in their production. However, using such datasets is a challenge, and this framework can overcome challenges and potentially lead to innovation. We identified that there are 3 levels of measurement for the conditions of crops: ground level, drone level (low altitude), and satellite level. At the ground level, we explored several in-situ measurements, and we specifically focused on soil roughness estimation, including CNN-based approaches as it represents an important parameter highly correlated to the humidity of the soil. We employed chain and pinboard methods to measure soil roughness while at the drone level, measurements were performed by a drone with a multispectral camera that is attached to it. Finally, at the satellite level, we performed visualization, segmentation, and analysis of the remote sensing images from LANDSAT, Sentinel 2 and PRISMA (Italian Space Agency) hyperspectral images. SNAP software and our own built MATLAB GUI were employed for visualization purposes and analysis. Furthermore, a review of available techniques and challenges in hyperspectral image visualization was addressed. The proposed framework can be improved by continuing further studies and contributions with support from AI4AGRI which aims at creating an excellent research center at Transilvania University of Brasov, Romania, dedicated to AI in EO for the agricultural sector.

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Funded by
the European Union

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