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VEGETATION MAPPING BY SATELLITE, DRONE IMAGERY, MACHINE LEARNING AND DEEP LEARNING

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Abstract

High-resolution multispectral images from satellites and unmanned aerial vehicles (UAVs) offer intricate insights into vegetation cover, structure, and composition. Machine learning (ML) and deep learning (DL) algorithms play a pivotal role in analyzing extensive observational data for vegetation mapping across vast distances. These algorithms possess the capability to automatically derive features from images and accurately classify diverse plant species. The integration of satellite and UAV imagery with ML and DL techniques enables the generation of intricate vegetation maps across different spatial and temporal dimensions. These maps serve as valuable resources for diverse applications, including urban planning, biodiversity preservation, agricultural and forestry management, and climate change studies. The article introduces tools aimed at comprehending and overseeing Earth's ecosystems by leveraging satellite imagery for vegetation mapping, alongside machine learning and deep learning methodologies.

Key words: satellite imagery, vegetation index, drone imagery, machine learning, deep learning, GIS

Introduction. The incorporation of deep learning techniques with satellite imagery in environmental monitoring and management has introduced a groundbreaking approach to vegetation cover mapping. This approach, which harnesses

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the advantages of both satellite technology and artificial intelligence analytics, holds significant importance across various domains such as agriculture, urban planning, and environmental preservation [1,2]. The availability of high-resolution satellite imagery now enables meticulous observation of Earth's vegetation cover. Satellites like Landsat, Sentinel, and MODIS offer multispectral images essential for evaluating the status and distribution of vegetation cover. The utilization of machine learning and deep learning, particularly in the realm of computer vision, has revolutionized the processing and analysis of this data [3, 4]. Through the training of artificial intelligence models on extensive datasets, distinct plant species can be identified. Consequently, these models can effectively categorize new satellite images, providing comprehensive and precise maps of vegetation cover. Satellites and multispectral cameras serve as instruments in remote sensing endeavors. They capture the absorption and reflection of sunlight by objects on Earth's surface [5]. Satellites offer insights into the Earth's surface dynamics and alterations over time. On the other hand, multispectral cameras focus on particular land areas, acquiring data to monitor changes in these regions over time. The data gathered through both methods typically aid in the classification and mapping of vegetation cover [6, 7].

Machine learning operates by inputting labelled images containing the desired feature alongside images lacking that feature into a computer algorithm. By utilizing drones to map regions showcasing various features of interest, these can be correlated with corresponding satellite images. Machine learning techniques are regarded as viable options for classifying remote sensing information. Yet, achieving independence from user input remains somewhat inadequate. Thus, the advent of deep learning architecture presents a fresh perspective. Despite appearing novel, deep learning frameworks have roots in history. Broadly, the structure of deep learning networks resembles that of machine learning networks. However, the key distinction lies in feature extraction, which in machine learning is user-determined, thereby constraining feature perception [8–10]. Combining SAVI with other remote sensing indices that directly relate to soil properties or using it alongside techniques for analyzing NDVI time series can enhance the understanding of soil moisture dynamics.

Materials and methods. Vegetation cover is a dynamic biological system composed of interconnected species, and identifying these species at different growth stages and within ecosystems relies on various factors. In remote sensing applications, the NDVI-based method has been recognized as an appropriate index for assessing vegetation cover [11].

The Soil-Adjusted Vegetation Index (SAVI) helps to minimize the impact of soil brightness on plant reflectance, which is especially important when working in areas where a significant portion of the surface is exposed soil and allows us to assess the condition of vegetation and its dependence on soil conditions also in Barda region (Fig. 4). Similarly, scientific research considered relevant for soil

scientists was also carried out in other economically important regions of Azerbaijan [12]. The Normalized Difference Vegetation Index (NDVI), which utilizes artificial intelligence, is employed for monitoring vegetation cover and assessing its health [13]. In arid regions, SAVI is particularly useful because it helps to reduce the impact of bright soils on the assessment of vegetative health and density. SAVI can detect lower percentages of vegetation cover compared to NDVI, making it more effective for monitoring areas with limited plant growth. Initially, satellite imagery of the targeted area is acquired. The imagery is sourced from the Landsat 8 satellite. Subsequently, the area is delineated within specified boundaries for analysis [14, 15]. Following this, the model of the area is constructed using the NDVI formula. If we explain it technically, green-leaved plants absorb sunlight and use it as an energy source during photosynthesis. Therefore, living plants appear brighter in near-infrared (NIR) cameras. The chlorophyll contained in plant leaves strongly absorbs visible light (VIS) (0.4–0.7 μm) for use in photosynthesis. The special cellular structure of the leaves strongly reflects near infrared light (0.7–1.1 μm). As a result, the more leaves the plant has, the more the wavelengths of light are affected. NDVI is calculated as follows: $\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{RED})/(\mathrm{NIR} + \mathrm{RED})$.

Deep learning techniques have been employed in the study, with ArcGIS Pro software serving as the primary tool for implementing these techniques. The image classification process entails inputting data, processing it, and generating land cover maps, particularly vegetation maps, while also evaluating the effectiveness of the applied methods. Image classification is executed using the "Classify Pixels with Deep Learning" tool within ArcGIS Pro. Leveraging ArcGIS Pro tools ensures accurate and precise handling of the data being processed. For the research, Landsat 8 satellite imagery obtained from Earth Explorer was used, and pixel-based classification was performed using deep learning methods with the tools available in ArcGIS Pro. Additionally, a machine learning method has been applied to generate the NDVI map (Fig. 1).

As shown in Fig. 1, water bodies are depicted in blue, residential areas and buildings in orange, barren lands in brown, forests and grasslands in green, areas with sparse vegetation in light green, and areas with dense vegetation in red [16, 17]. Application of deep learning method – Land cover classification of Absheron peninsula is shown in Fig. 2.

NDVI technology allows for:

- the assessment of vegetation density and quality in all soil areas, as well as their individual sections;
- the calculation of productivity and the assessment of the health and growth of plants;
- discussion of soil productivity.

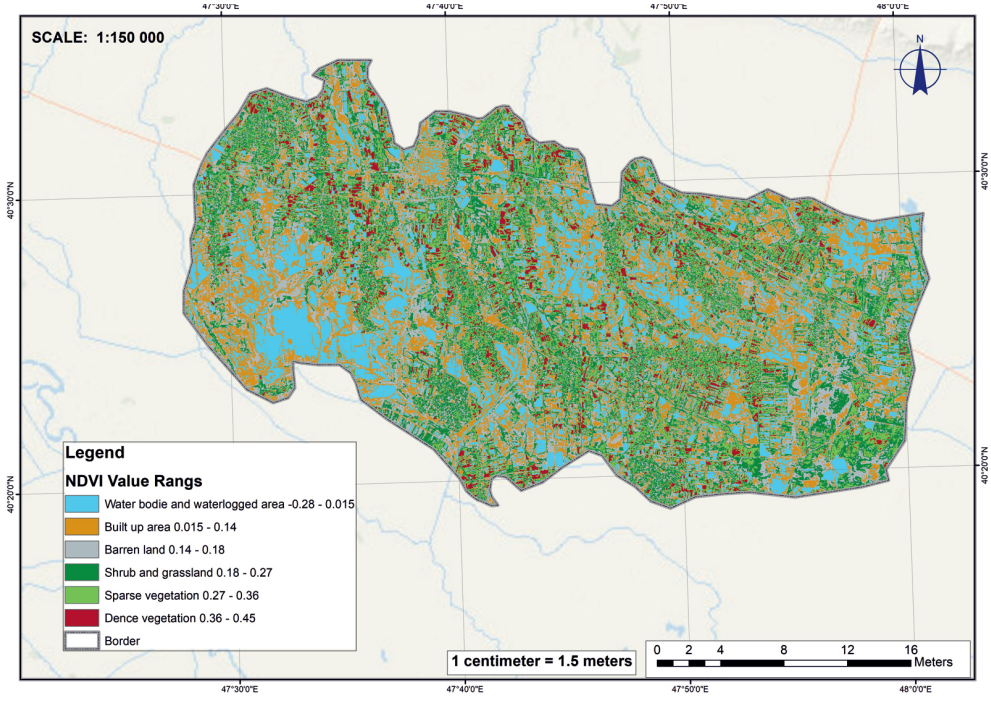


Fig. 1. NDVI map of Ujar region (source: by authors, 2024)

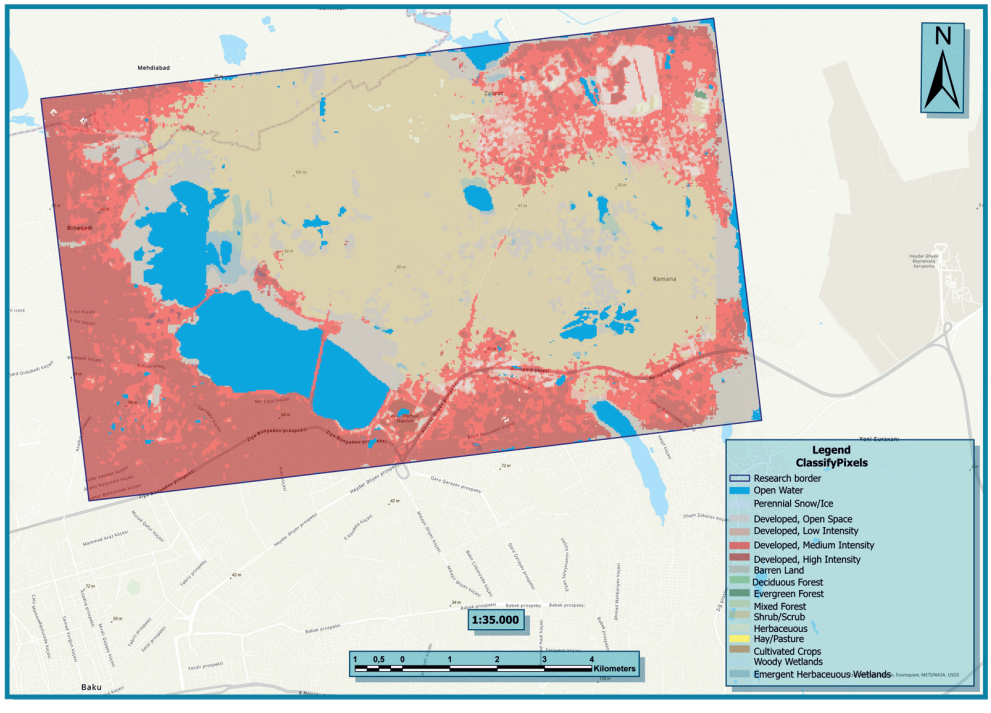


Fig. 2. Application of deep learning method – Land cover classification (Absheron peninsula)

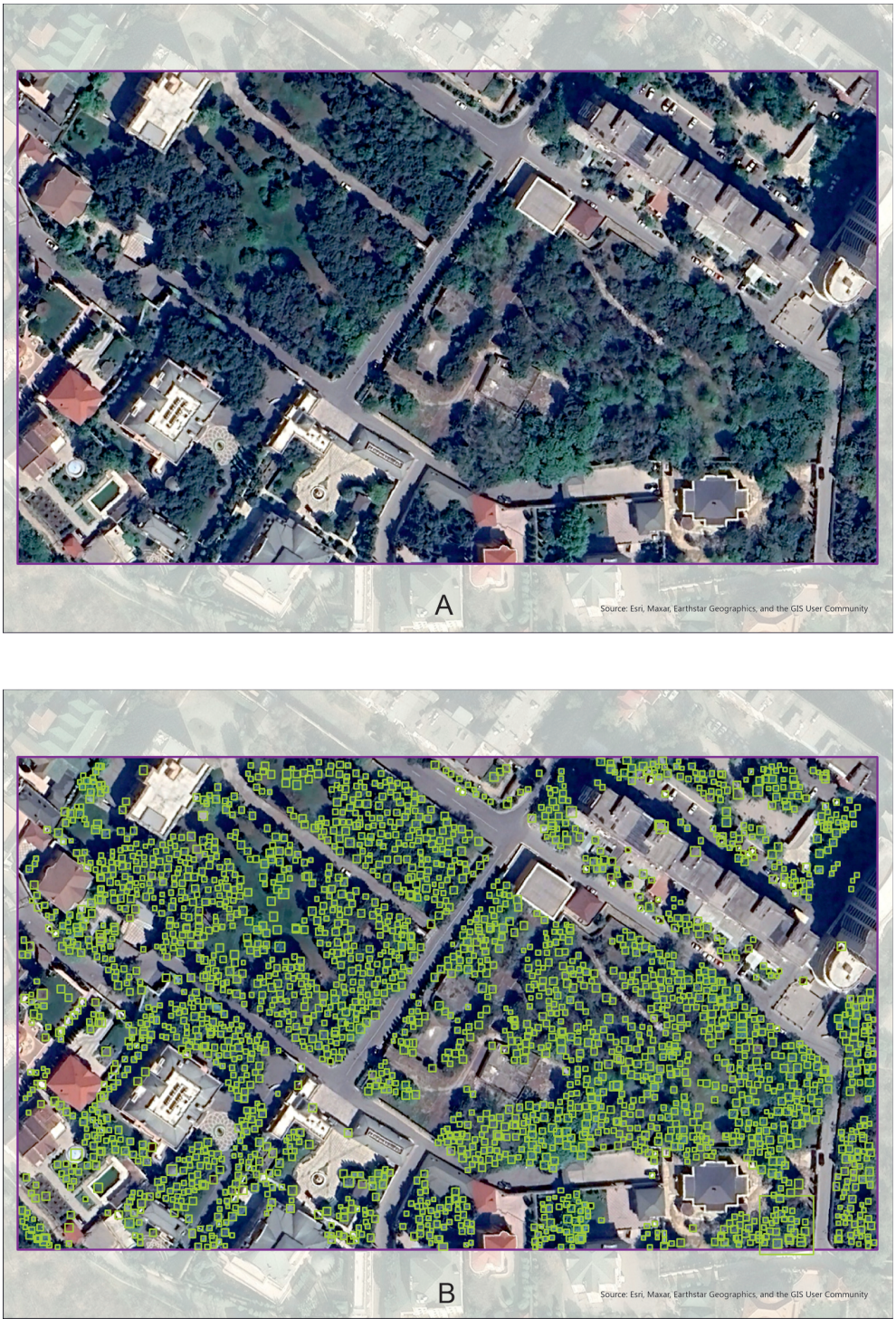


Fig. 3. A. Application of deep learning method – Land cover classification (Absheron peninsula); B. Research area and image processed with the deep learning method

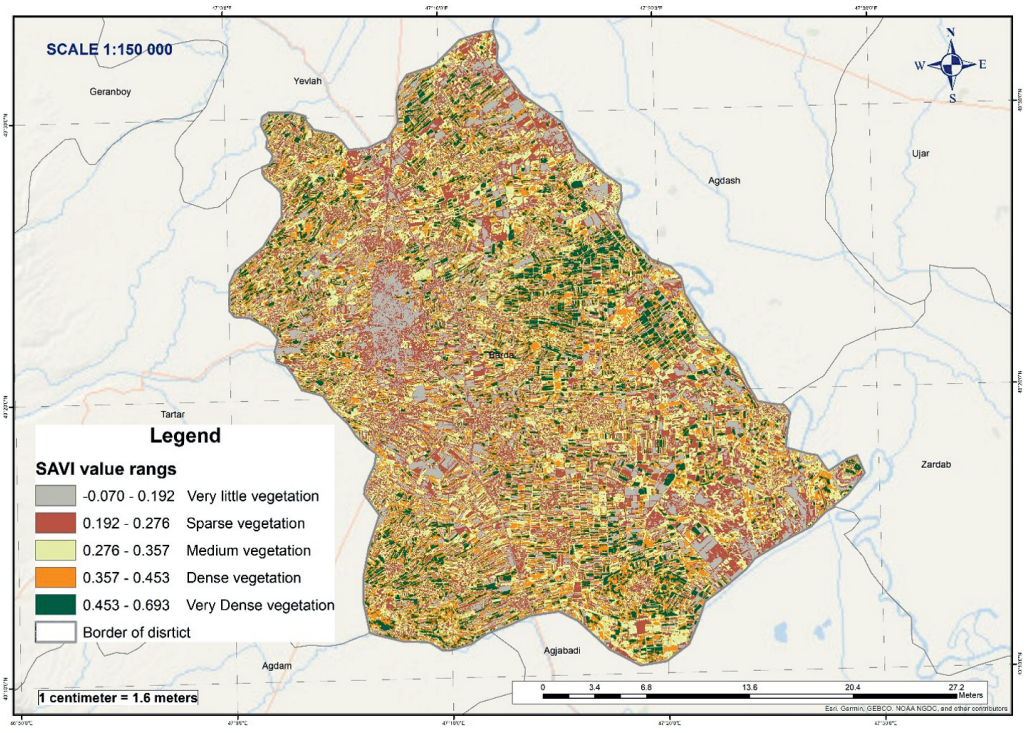


Fig. 4. SAVI map of Barda region (source: by authors in 2024)

Results and discussion. Thanks to NDVI technology, it is possible to learn about the condition of crops and soil in agricultural fields (fields, land, etc.) and to analyze the health of vegetables or plants by analyzing NDVI images. The most significant advantage of this technology is that it allows for the easy analysis of areas that are inaccessible by foot or vehicle, using drones and NDVI technology. It is possible to extract the selected research area from the obtained image using the Extract by Mask tool. Then, by selecting the Classify Pixels Using Deep Learning tool under Spatial Analyst and entering the relevant data, we perform pixel-based classification using the deep learning method. The obtained results have been visualized as follows. The productivity of the area is average (Fig. 3, 4).

Deep learning algorithm is employed to identify trees in high-resolution drone or aerial images. The detection of trees serves various purposes including vegetation control, forestry, and urban planning. High-resolution aerial and drone imagery is particularly effective for tree detection due to its extensive spatial and temporal coverage.

The image was brought into the ArcGIS Pro program for georeferencing before being processed. Using the Georeference tool, the image was aligned with coordinates. After georeferencing the image, the deep learning Tree Detection method was applied to extract trees in the research area. The obtained result

can be visualized as follows: Fig. 3A represents the research area, and Fig. 3B represents the processed image.

Conclusion. The mapping of vegetation cover using images from satellites and drones, along with machine learning and deep learning methods, represents a significant advancement in environmental monitoring and analysis. This comprehensive approach leverages the capabilities of cutting-edge technology to obtain detailed information about the distribution, condition, and dynamics of vegetation across various landscapes.

The integration of machine learning and deep learning methods with satellite and drone imagery has numerous applications in various fields. For example, in agriculture, accurate mapping of vegetation cover can optimize resource allocation, monitor the condition of crops, and support decision-making regarding continuous cultivation practices. In environmental monitoring, these technologies enable the assessment of the quality of habitats, identification of ecosystem disturbances, and monitoring of biodiversity trends.

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