Leveraging satellite data to support decision-making on forest disturbances in "Skole Beskids" National Nature Park

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Abstract

The forests of the Ukrainian Carpathians, particularly within the “Skole Beskids” National Nature Park, are under increasing pressure from climate change and human activities. These disturbances, which range from climate-induced droughts and pest outbreaks to illegal logging, undermine forest health, reduce carbon sequestration, and disrupt vital ecosystem functions. Effective, data-driven decision-making is essential to respond to these complex challenges and ensure sustainable forest management. This study uses satellite remote sensing to monitor and analyse forest disturbances in the Skole Beskids between 2023 and 2024. A time series of Sentinel-2 multispectral imagery was processed to detect changes in forest cover. This was enhanced using elevation data from the ASTER Global Digital Elevation Model to account for topographic variation. Machine learning techniques, including Random Forest classifiers, were employed to ensure the accurate and scalable classification of land cover changes. Preliminary results suggest that approximately 1.83 hectares of forest cover have been lost, with the most affected areas being those near zones of commercial logging and within structurally sensitive forest compartments, including those adjacent to military forest districts. Sentinel-2 data enabled effective medium-resolution mapping, while AI-enhanced analysis improved the reliability of classifications and minimised the risk of overfitting. This research provides timely and actionable insights, demonstrating the value of satellite-based monitoring as a decision-support tool for forest governance. It contributes to the development of an operational framework for forest monitoring based on remote sensing in the Ukrainian Carpathians, supporting national efforts to establish a Ukrainian National Forest Monitoring System. Future work will explore integrating additional environmental datasets, such as meteorological records and field-based observations, to enhance the accuracy and applicability of forest disturbance detection further.

Keywords

information technology, forest disturbances, remote sensing, satellite imagery, Ukrainian Carpathians

1. Introduction

The forests in the Carpathian are under the permanent influence of climate change and human activity. While the former develops slowly, its impact on the forests is significant, including droughts, insect invasions, and other effects. On the other hand, human activity such as clear-cutting has a rapid impact for a short period but can amplify the effects of climate change over time.

Illegal logging is an enormous problem in the Carpathian region of Ukraine and is leading to huge damage to forests and neighboring ecosystems due to erosion and disturbed water flows, and poor management. Now in Ukrainian forestry, the main approach to forest resources estimation is forest

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management planning, which has some faults, which make the possible to have illegal logging. One of the ways to estimate forest resources the forest disturbances is the usage of satellite data. The usage of satellite imagery might be a financially feasible approach for authorities to implement a monitoring system and to improve the accuracy of forest disturbance identification in the Forest Inventory Map [1].

The overall goal of this study is to develop a methodology based on satellite image interpretation to monitor forest losses in the region of Skole Beskids in the Ukrainian Carpathians. The most useful approach to estimate land cover changes is to use satellite data for different periods. The change detection analysis depends on the input data and the methods, which were used for the analysis. This deeply affects the qualitative and quantitative outcomes of the analysis, even if it deals with the same time frame and region. The results of forest loss detection can also be used in forest protection, where forest loss events could be investigated individually and support forest decision-making.

2. Materials and methods

The expected study area is located in the region of Skole Beskids in the Ukrainian Carpathians in the southern part of Lviv Oblast. It covers 57.966 ha. The attitude of the study area is between 600 m and 1’260 m a.s.l. The climate is temperate continental in the lower parts, cold and wet in the upper ones. The core area of Skole Beskids is the Skole Beskids National Park, which has not only traditional nature park zones but has subcompartment, which is managed by different authorities. On the territory of the national park, there is a military-owned forest district, where there is a very intensive management influence on the forests. From this point of view, this compact area is interesting not only from the ecosystem aspect but from the natural and anthropogenic processes, which make changes in the forest ecosystems. These changes can be estimated using the temporary remote sensing data.

The usage of satellite data provides the best basis for the analysis of forest disturbances due to the imagery, which is available in different resolutions and dates. The investigation used Sentinel-2 Surface Reflectance data (Level-2A), which are freely available through the Google Earth Engine and provided by the European Space Agency’s Copernicus Program. These images, available from 28 March 2017 to the present, fully cover the entire study period. Sentinel-2 imagery includes 12 primary spectral bands with spatial resolutions ranging from 10 to 60 meters, as well as 11 additional “synthetic” bands used for various purposes, such as cloud and snow masking. In addition, three bitmask layers-introduced in February 2024, are available for identifying opaque clouds, cirrus clouds, and snow/ice. In this study, synthetic bands were primarily used to mask clouds and their shadows.

The methodological approach of using the remote sensing data is based on the assumption that different forest disturbance agents leave different spectral, spatial, and temporal footprints on the satellite images in different periods before and after the change [2]. The main forest disturbance agents are storm damage, insect calamities, drought damage, and timber logging [3]. In this research, we are going to detect the state of the damages without detailing the forest disturbance agent, because it needs to have a lot of additional data, and it could be done in the continuation of the investigations.

The strength of the deep learning-based methods is to learn from the different spectro-temporal behavior patterns in the time series. The methodology in this study is based on the analysis of time-series Sentinel-2 multispectral imagery during 2023-2024, which provides high spatial and temporal resolution, using the Google Earth Engine platform [4, 5]. Time series analysis tools used in forest remote sensing today mostly analyze the temporal development of the spectral signal of either a single pixel or an object/segment. However, a lot of contextual spatial information is lost with such an approach. Artificial Intelligence, such as deep learning with neural networks, has become a dominant technology for image classification and land use monitoring, and can include additional context information, like information about the agent of forest disturbance from the enterprise. Combined remote sensing and AI approaches in forestry still offer significant innovation potential for forest mapping, forest monitoring, and risk prediction systems [6]. In the previous investigation there was used one of the possible algorithms Random Forest for analyzing the land cover in the Prykarpattya region, Ukraine [7, 8, 9].

3. Results

Performed forest cover change analysis in Google Earth Engine using a custom JavaScript implementation within the territory of the "Skole Beskids" National Nature Park (Figure 1–Figure 2). The core dataset comprised median Sentinel-2 Surface Reflectance images acquired across different seasons during the 2023-2024 period. A Random Forest classification algorithm was trained on a balanced dataset containing 700 forest and 700 non-forest reference points.

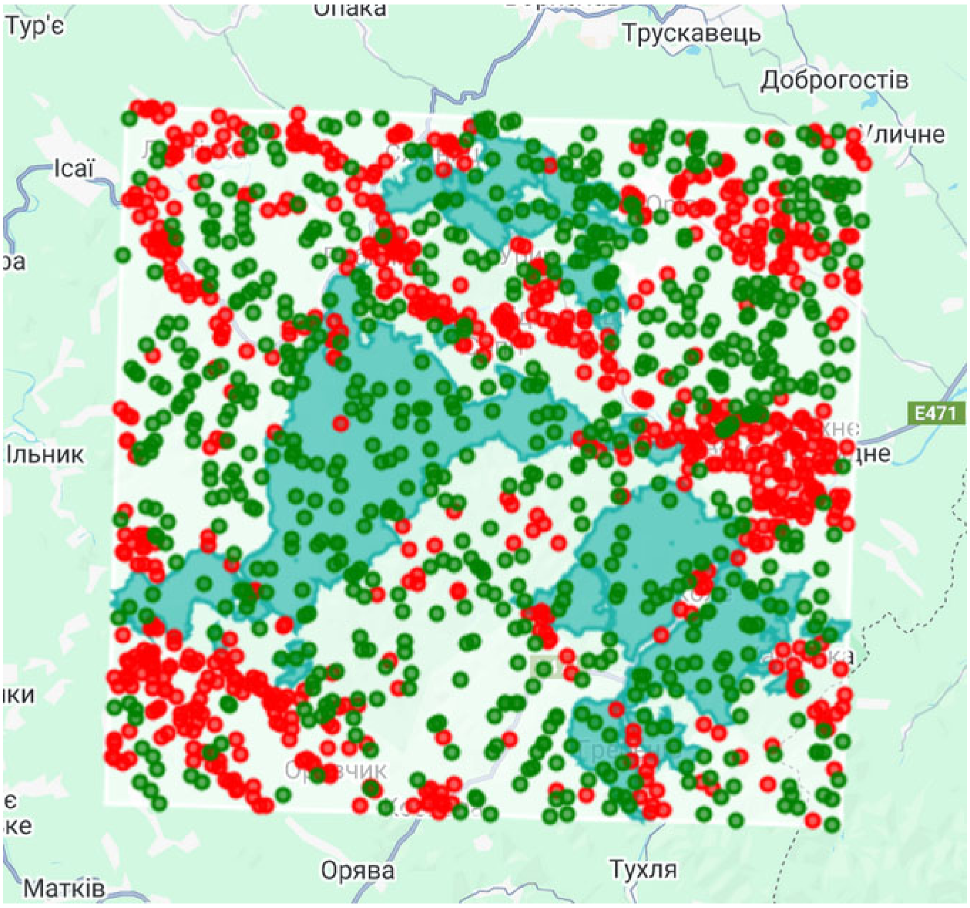

Figure 1: Training points for the classification.

In Figure. 1 and Figure. 2 are taken following designations: white – envelope; dark green – boundaries of "Skole Beskids" National Nature Park; green dots – forest; red dots – non-forest.

To ensure accurate classification, a cloud and shadow masking algorithm has been implemented based on the following criteria:

- (I) only images with less than 50% cloud cover were considered;
- (II) cloud and shadow masking was performed using the Scene Classification Layer (SCL), which identifies classes such as
  - Cloud Shadows (3),
  - Medium Probability Clouds (8),
  - High Probability Clouds (9)
  - Cirrus (10)

. Images exceeding 50% cloud cover were omitted entirely. In addition, all pixels classified under the cloud- and shadow-related SCL categories mentioned above were masked and excluded from the classification process.

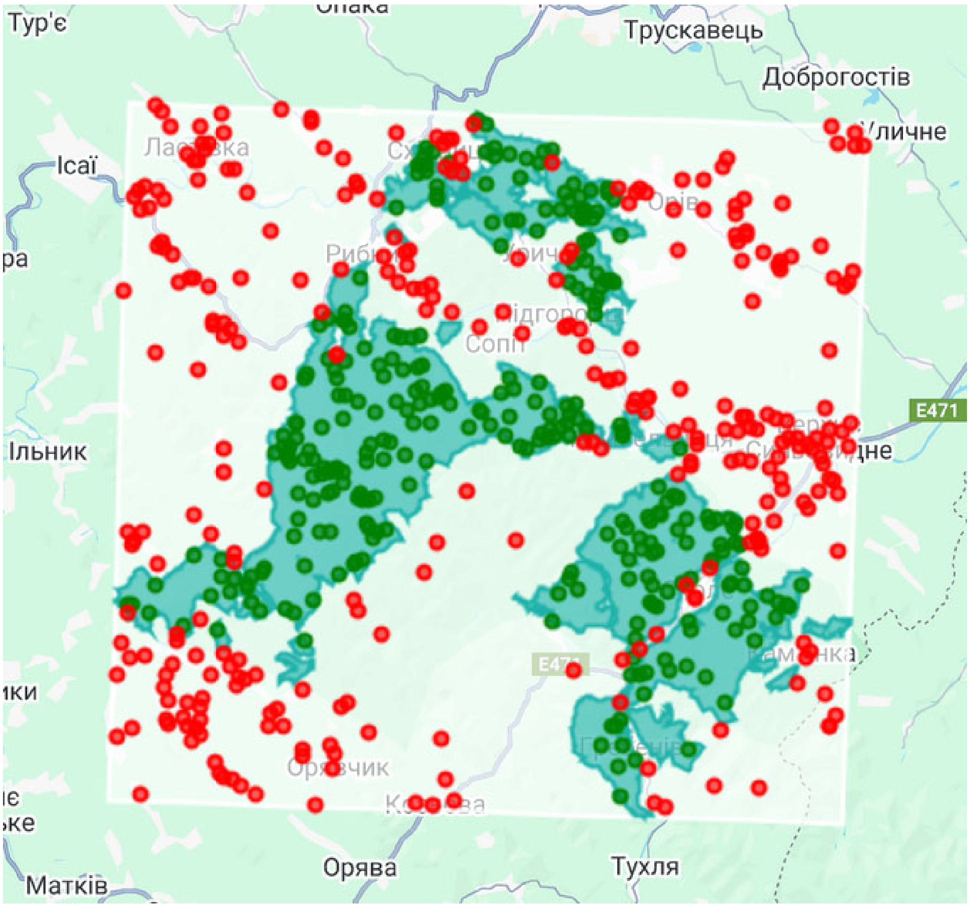

Figure 2: Checking points for the classification.

Year-round image interpretation was deemed unsuitable for this study due to seasonal variability in forest appearance. Given the seasonal variability in forest appearance, particularly between broadleaved and coniferous species, median composite images were generated for each season – winter, spring, summer, and autumn – to improve detection accuracy. This seasonal approach improves the detection and interpretation of forest cover changes (Figure. 3–Figure. 4).

The primary classification algorithm used in this study was Random Forest [10, 11], which was applied to distinguish between forest and non-forest land cover using a training dataset of 1,400 points. The Random Forest classifier utilized 50 decision trees to distinguish between forest and non-forest classes based on the training dataset.

The classification resulted in thematic maps representing two classes: forest cover (shown in green) and non-forest cover (shown in yellow). These maps were generated for each season in both 2023 and 2024. As an example, Figure.5–Figure. 6 shows the classification results for the spring seasons of 2023 and 2024.

Accuracy assessment was performed using a validation dataset of 600 points – 300 labelled as forest and 300 as non-forest classes. The evaluation process [12], including the generation of a confusion matrix (Table 1) and the calculation of the overall accuracy and the Kappa coefficient, was carried out within the classification script.

The confusion matrix revealed a high classification accuracy for forest areas, with 296 out of 300 forest validation points correctly identified. However, non-forest classification was less accurate, with 93 points misclassified as forest, likely due to the presence of scattered trees in urban or agricultural landscapes resembling forest cover in satellite imagery. This misclassification can be attributed to the presence of scattered trees in urban or agricultural areas, which can resemble forest cover in satellite imagery. The overall classification accuracy was 83.8% and the Kappa coefficient of 67.6%. While these

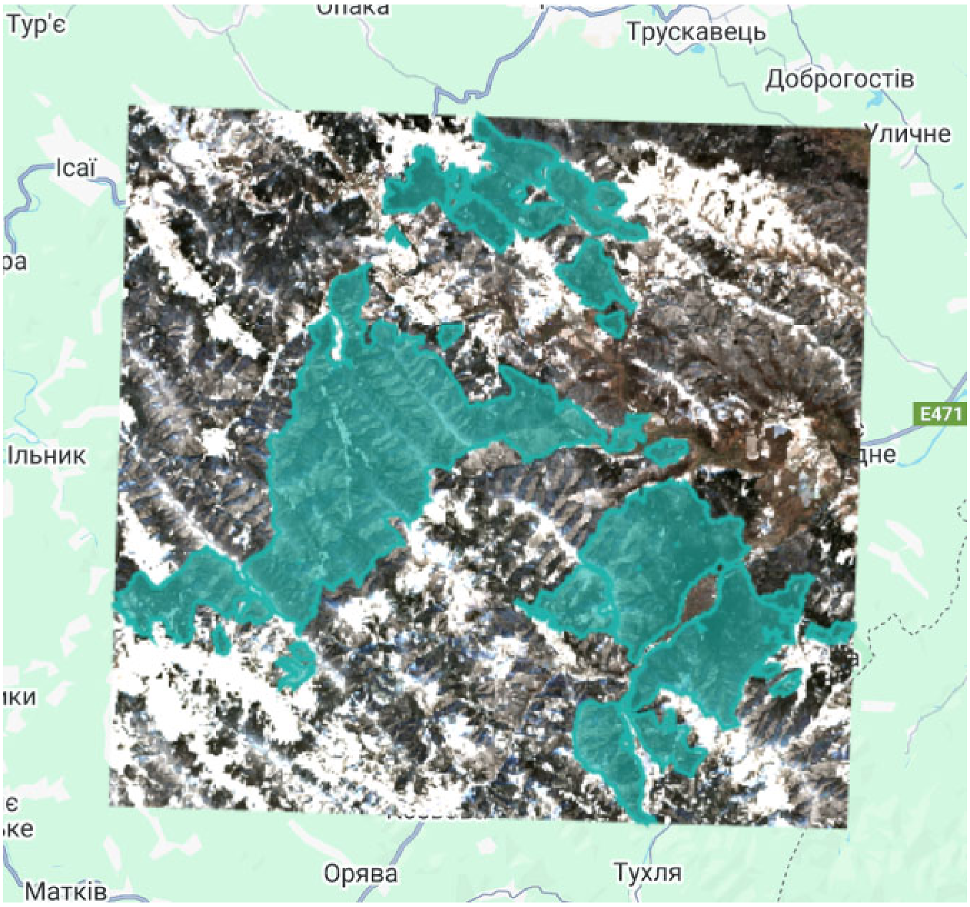

Figure 3: The winter season 2023 median images for classification.

Table 1
The Confusion Matrix of the Classification

Class	Forest	Non-forest	Total
Forest	296	4	300
Non-forest	93	207	300
Total	389	211	600

results are acceptable, they are not highly precise and suggest the need for improvements. Enhancing the accuracy would require expanding the training and validation datasets and incorporating ground-truth data verified through field observations.

Following the classification and accuracy verification [13, 14, 11], forest cover between 2023 and 2024 within the "Skole Beskids" National Nature Park were assessed by comparing seasonal maps to identify areas where forest transitioned to non-forest cover. This was achieved by comparing the classified maps from both years and identifying areas where forest cover in 2023 changed to non-forest cover in 2024. The results of this change detection are shown in Figure.7

Change detection results indicated that the majority of forest loss during the analyzed period occurred outside the boundaries of the "Skole Beskids" National Nature Park. Within the park itself, a zonal statistics analysis estimated forest loss at 1.83 hectares, out of a total detected change area of 8.176 square kilometers within the broader envelope. Further investigation with park personnel attributed these changes primarily to biotic factors, including spruce dieback and windthrow events during the study period.

The results of the zonal statistical analysis were exported as CSV file to Google Drive to facilitate further analysis and support ongoing seasonal monitoring. Additionally, a dedicated web platform was

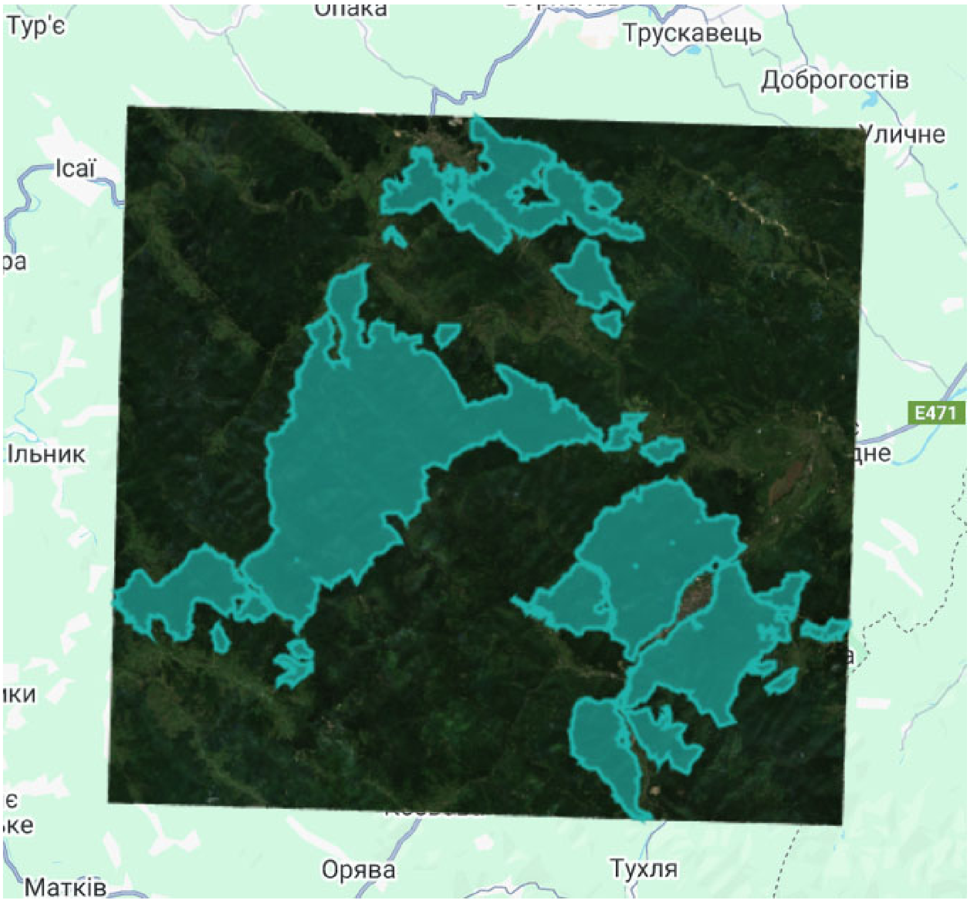

Figure 4: The summer season 2023 median images for classification.

developed to display near-real-time forest cover changes. This webpage displays near-real-time forest cover changes and notifies park staff when disturbances are detected: https://eurizon.nltu.edu.ua/.

The output of the Google Earth Engine script – specifically, the generated CSV file – feeds directly into the website, where changes are mapped and labelled by forest management unit (compartment and sub-compartment) according to the park's forest inventory database (Figure.8).

This system is accessible to park staff and provides valuable information to support operational decision-making and forest management. The use of Google Earth Engine enabled automated satellite image classification, accurate detection of forest loss, spatial quantification of changes and performance assessment of the classification approach. The main advantage of this methodology lies in its near-real-time monitoring capability, rapid web publication of results and an alert system that supports timely forest management interventions.

4. Discussion and Conclusion

This study highlights the value of leveraging satellite remote sensing data, specifically Sentinel-2 imagery, in combination with machine learning techniques to support data-driven decision-making regarding forest disturbances in the "Skole Beskids" National Nature Park. The analysis revealed a total forest cover loss of approximately 1.83 hectares during the 2023–2024 monitoring period, demonstrating the feasibility and effectiveness of the proposed approach for timely forest disturbance detection.

The integration of medium-resolution Sentinel-2 imagery with artificial intelligence-driven classification significantly improved the accuracy of disturbance mapping and land cover differentiation. Notably, areas of significant forest loss were identified near commercial logging zones and military forest districts, indicating clear anthropogenic impacts on forest integrity. These results are consistent

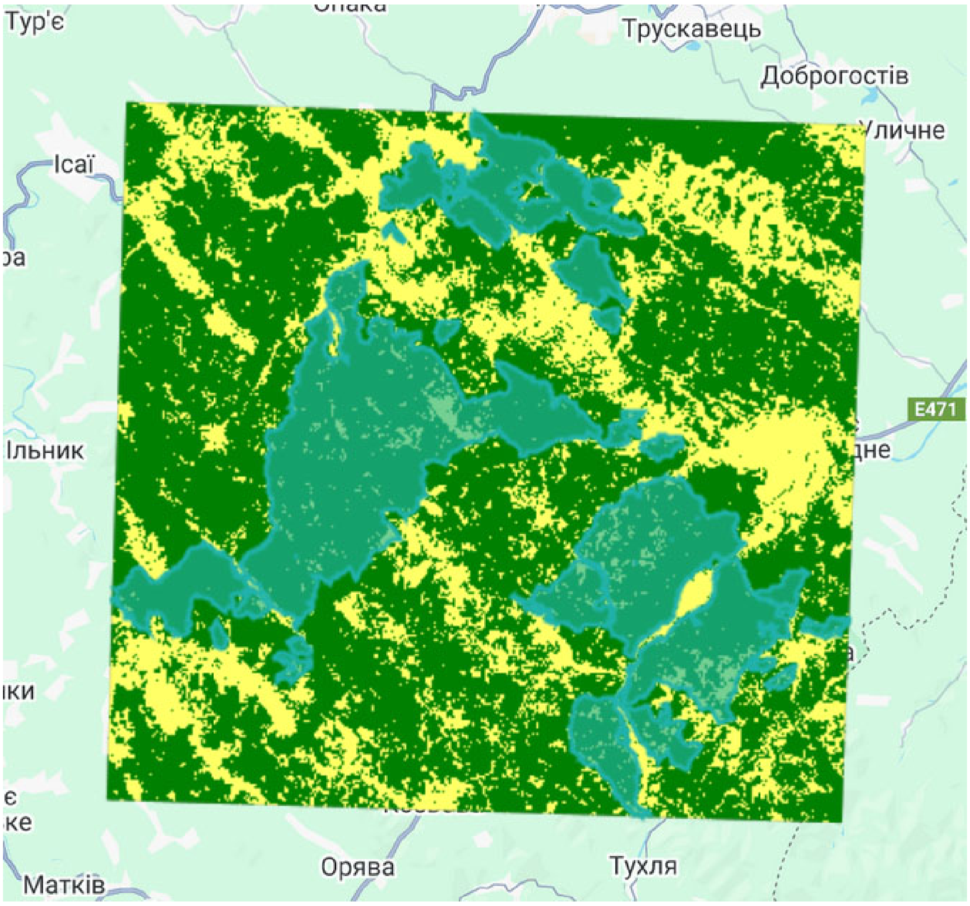

Figure 5: Classified spring 2023 median images.

with earlier studies emphasizing the compounding effects of human activities and climate change on Carpathian forest ecosystems [1].

The presented methodology offers a scalable, cost-efficient alternative to traditional forest monitoring systems, which often rely on inconsistent field observations and delayed reporting. By providing consistent and repeatable data across spatial and temporal scales, satellite-based monitoring enables more informed and proactive forest management responses, including early detection of illegal logging and evaluation of forest health dynamics [3].

Furthermore, the development of this remote sensing framework contributes to the broader efforts of establishing a Ukrainian National Forest Monitoring System, in line with international best practices. Incorporating auxiliary datasets – such as meteorological records, LiDAR data, and in-situ ground truth observations – could further enhance classification accuracy and disturbance detection capabilities.

Future research should focus on optimizing classification algorithms, integrating additional remote sensing sources (e.g., radar, hyperspectral data), and analyzing the underlying drivers of forest disturbance, including socio-economic and environmental variables. Validation of the forest disturbance maps with field-based assessments remains crucial to evaluate their effectiveness in capturing various disturbance types [14].

This study underscores the potential of satellite remote sensing, supported by machine learning, as a robust tool for forest disturbance assessment and supporting forest decision-making. The generated insights not only enhance scientific understanding but also provide actionable information for forest managers, policymakers and other stakeholders, contributing to the long-term conservation of biodiversity and ecosystem services in the Skole Beskids region.

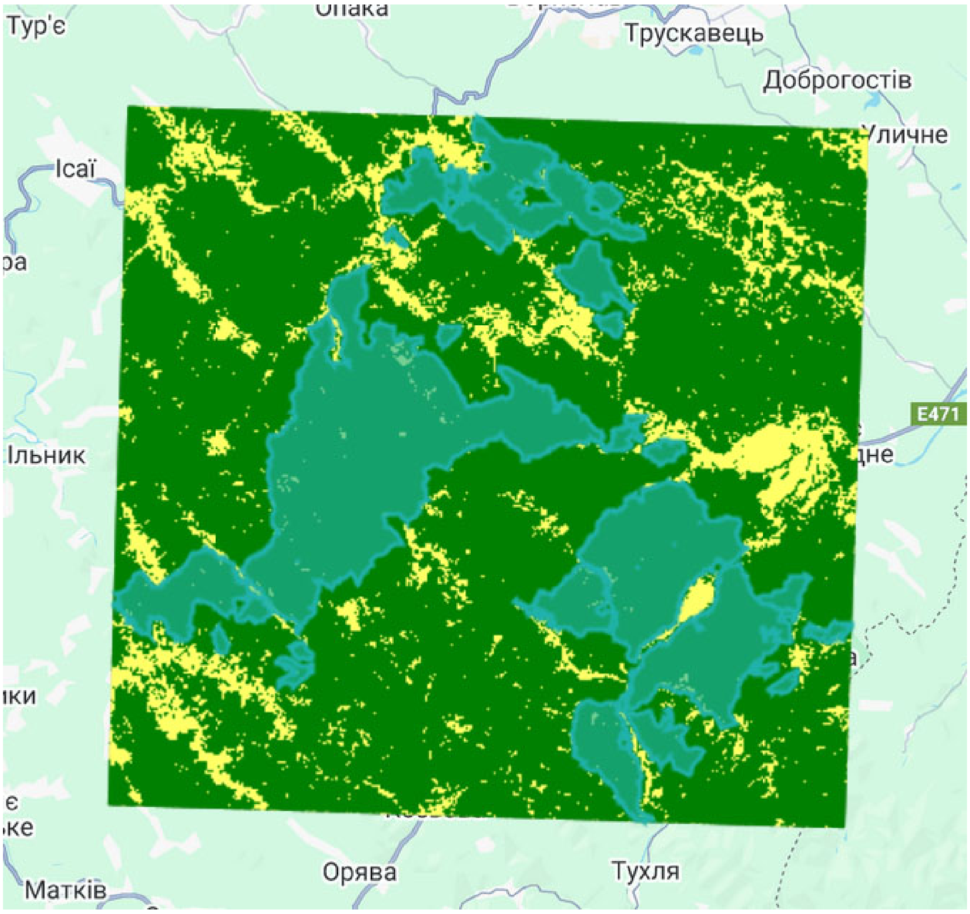

Figure 6: Classified spring 2024 median images.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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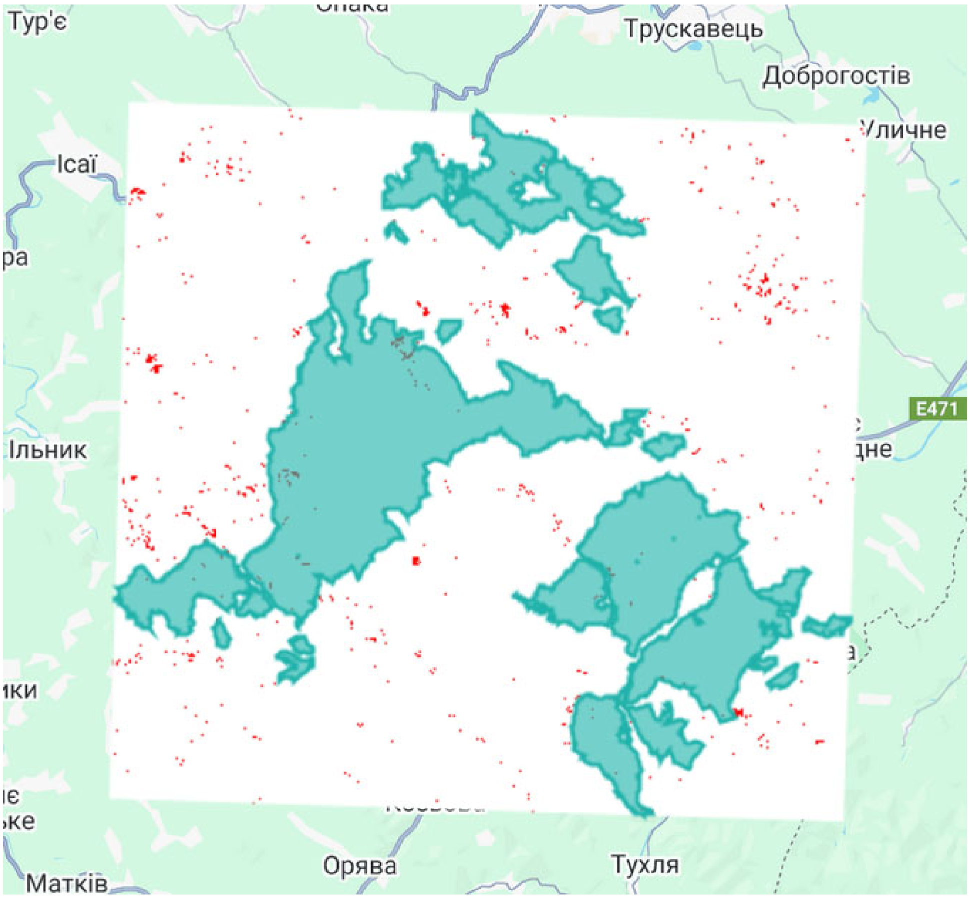

Figure 7: Change detection analysis between forest cover and non-forest cover maps from 2023 to 2024 (red – forest loses; white – no changes).

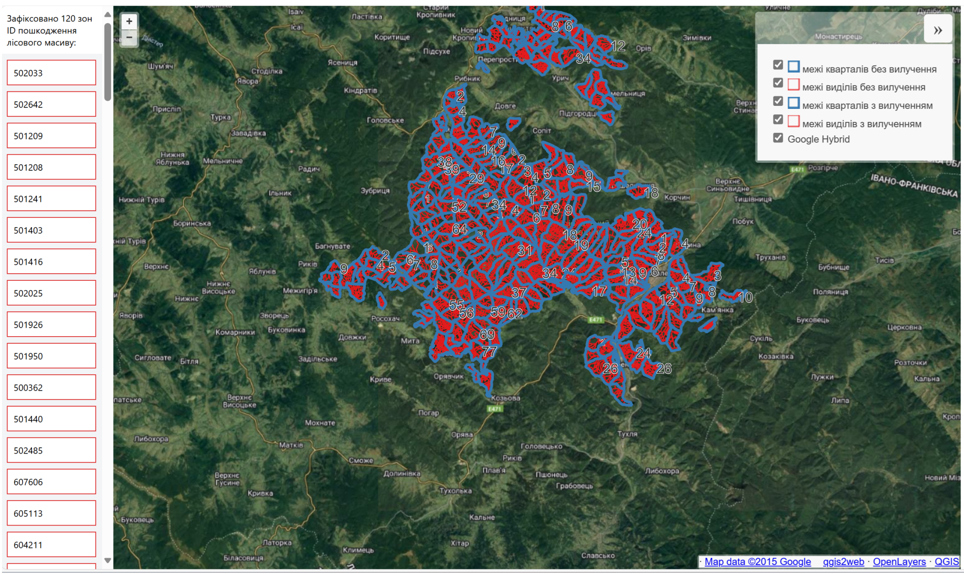

Figure 8: The view of the webpage about detected forest losses in the "Skole Beskids" National Nature Park.

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