A Novel Approach for Rapid Detection of Forest Degradation and Diseases Through Anomaly Analysis of Sentinel-2 Spectral Data

Sofiia Drozd[1,2], Nataliia Kussul[1,3] and Hanna Yailymova[1]
[1]*Department of Mathematical Modelling and Data Analysis, National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute" 37, Prospect Beresteiskyi, 03056 Kyiv, Ukraine*
[2]*Department of Electrical Engineering, Mechanical Engineering and Engineering Management, Anhalt University of Applied Sciences, Bernburger Str. 57, 06366 Koethen, Germany*
[3]*Department of Geographical Sciences, University of Maryland, College Park, MD 20742, USA*
sofi.drozd.13@gmail.com, kussul@umd.edu, anna.yailymova@gmail.com

Keywords: Satellite Data, Anomaly Detection, Sentinel-2, Forest Degradation.

Abstract: Forest degradation is an ongoing global issue, with significant environmental impacts that necessitate efficient monitoring and management. This paper presents a simple yet effective method for detecting forest degradation using freely available Sentinel-2 satellite data and an anomaly detection approach. The aim of this study was to develop an accessible and reliable technique that could match the performance of more complex algorithms while using minimal computational resources. The research focused on spectral bands with 10-20 m resolution and vegetation indices (NDVI, NDMI, GCI, PSSRa) to analyze forest damage in the Harz region. The method involved identifying anomalies in the spectral data relative to randomly selected reference points from healthy forest areas, which were verified with high-resolution imagery from Google Earth Pro. The results demonstrated that specific Sentinel-2 bands, particularly B3 and B5, were the most informative for detecting damaged forests, while vegetation indices were less effective. By analyzing anomalies in these bands, we successfully tracked forest degradation from 2020 to 2024, revealing a significant increase in damage between 2020 and 2021, with a total of 68.1 thousand hectares of forest lost by 2024. The theoretical relevance of this study lies in the development of a cost-effective and straightforward method for forest monitoring, while the practical relevance is evident in its potential for large-scale forest management and conservation. This method provides an efficient tool for monitoring forest health with minimal data requirements and computational effort, offering a promising solution for forest managers and conservationists worldwide.

1 INTRODUCTION

Healthy forests maintain ecosystem balance, purify the air, and provide economically important resources for people. However, forests constantly face numerous threats, such as diseases, pests, illegal logging, and climate change, which jeopardize their existence. The forested area of the Harz Nature Park in Germany, for example, has decreased by over 47% from 2001 to 2023, largely due to global warming and poor forest management practices, according to Global Forest Watch estimates [1]. Therefore, it is crucial to regularly monitor forest health to identify issues promptly and take necessary actions for their preservation.

Traditional forest monitoring methods, including visual inspections, are limited and labor-intensive, often failing to detect problems in a timely manner, especially in remote or hard-to-reach forest areas. Forest rangers may miss signs of tree diseases or illegal logging, making it difficult to respond quickly to threats.

In contrast to traditional methods, Earth observation satellites are an effective tool for monitoring forests over large areas [2]. They allow for real-time collection of detailed information on vegetation health, soil moisture, surface temperature, and other parameters. Satellite data is successfully applied for monitoring the consequences of natural disasters [3, 4] and human-induced impacts [5], detecting damage in agricultural fields [6], etc. Satellite imagery can quickly identify changes in forest cover, assess tree health [4], detect illegal logging [7, 5], pest activities [8, 9], and identify other violations. Additionally, satellite imagery enables long-term analysis of forest dynamics [4, 10], helping to predict future issues and take timely measures.

Various methods are used to detect forest damage through satellites, including monitoring vegetation indices such [11, 12], time series analysis [13, 4, 10], and machine learning algorithms [14, 15], including convolutional neural networks or transformers [7, 16, 17]. While these methods are effective in detecting changes in forests, they often require large amounts of data and computational resources, and may need significant processing time.

In our study, we aim to develop a simple and rapid algorithm for accurately detecting forest damage and diseases with minimal data, time, and resource consumption, while maintaining high accuracy compared to deep learning methods. By using free Sentinel-2 satellite imagery, we will create an efficient tool for forest monitoring that allows for rapid responses to changes, even with limited resources and large areas.

2 DATA AND MATERIALS

2.1 Study Area

For our study, we selected the protected areas of the Harz Natural Park (Fig. 1), located in central Germany at the border of Thuringia and Saxony-Anhalt. Selected area covers 2,756 km², most of which is covered by forest. However, due to adverse weather conditions, including droughts, storms, and pest activity, the Harz forest has suffered significant damage in recent years [1].

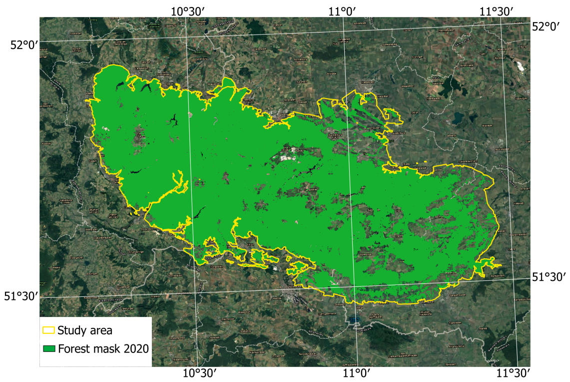

Figure 1: Study area.

To delineate the area of interest, we utilized vector data of Germany's protected areas provided by Protected Planet [18].

To distinguish forested areas from other land cover types, we employed the 2020 forest map with a spatial resolution of 10 meters, created based on Sentinel-2 imagery with support from the Joint Research Centre and the European Commission [19].

Consequently, 2020 was selected as the starting point for our study, focusing on identifying areas that have experienced deforestation or contain weakened and diseased forests since that time.

2.2 Satellite Data Used

To detect forest damage and diseases (unnatural vegetation decline), we used free Sentinel-2 satellite harmonized data, available with an update frequency of approximately five days from 2017 to the present.

The Sentinel-2 satellite has 13 spectral bands, including four bands at 10 meter resolution, six bands at 20 meter resolution, and three bands at 60 meter resolution. For our study, we will focus only on the bands with spatial resolutions of 10 and 20 m because bands with lower resolutions, such as those at 60 m, would not provide the level of detail necessary for our analysis of forest damage and disturbances.

For each year from 2020 to 2024, we selected a time series of images from the months of late spring and early summer (May–June), as trees are actively vegetating during this period. We masked clouds using Sentinel-2 Cloud Probability data with a cloudiness threshold of 20%. A composite was constructed from the cloud-free images, assigning each pixel the median reflectance value.

Additionally, as an extra source for validating the obtained results, we used open high-resolution imagery available for viewing in Google Earth Pro.

3 METHODOLOGY

To detect forest damage and diseases, we propose an anomaly detection method that identifies unusual or unexpected patterns in satellite imagery, deviating from typical forest conditions.

To assess the effectiveness of the proposed approach, we will analyze both individual Sentinel-2 spectral bands (Table 1) and their combinations — commonly used vegetation indices for forest monitoring [20] (Table 2). Specifically, the study will evaluate indices such as Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Normalized Difference Moisture Index (NDMI), Green Chlorophyll Index (GCI) and Plant Senescence Stress Reflectance Index (PSSRa), along with spectral bands with spatial resolutions of up to 20 m, which can provide insights into vegetation changes.

Table 1: Sentinel-2 spectral bands used.

Band	Spacial Resolution (m)	Wavelength (nm)	Description
B2	10	490	Blue
B3	10	560	Green
B4	10	665	Red
B5	20	705	Red Edge 1
B6	20	740	Red Edge 2
B7	20	783	Red Edge 3
B8	10	842	NIR
B8a	20	865	Narrow NIR
B11	20	1610	SWIR1
B12	20	2190	SWIR2

Table 2: Vegetation indices used.

Vegetation index	Formula	Application
NDVI	$\frac{B8-B4}{B8+B4}$	Vegetation health, density, and photosynthetic activity.
NDMI	$\frac{B8-B11}{B8+B11}$	Monitoring vegetation and soil moisture, drought assessment.
GCI	$\frac{B9}{B3}-1$	Chlorophyll content estimation.
PSSRa	$\frac{B7}{B4}$	Detection of vegetation stress and senescence.

First, we select several areas with damaged forests, identified using freely available high-resolution imagery from Google Earth Pro dated 26.06.2023.

We randomly select n points for healthy forest and n points for damaged forest across different areas. Then, using Sentinel-2 image for the corresponding date, we calculate the average values within the spectra of the studied bands and vegetation indices separately for pixels of healthy and damaged forest (1, 2). Based on the values obtained, we calculate the relative difference between the average values of healthy and damaged forest pixels in different spectra (3) and thus identify the most sensitive spectra as the bands/indices with the highest relative difference.

$$Mean_h = \frac{1}{n}\sum_{i=1}^{n} V_h(x_i, y_i) \quad (1)$$

$$Mean_d = \frac{1}{n}\sum_{i=1}^{n} V_d(x_i, y_i) \quad (2)$$

$$RelDiff = \frac{Mean_h - Mean_d}{Mean_h} \quad (3)$$

where $V_h(x_i, y_i)$ and $V_d(x_i, y_i)$ are the pixel values for healthy and damaged forest at positions (x_i, y_i).

In addition, we visually assess which spectral bands or indices are the most informative for detecting forest damage.

Once these indicators are identified, we apply the following approach:

1) **Defining reference areas**.
   Randomly select n points of healthy forest to calculate the reference spectral characteristics, against which anomalies will be detected.
2) **Sampling and averaging spectral values**.
   We extract pixel values from selected points and calculating the average value of these pixels for each band or index.
3) **Detecting anomalous areas**.
   We use (4), where anomalies are defined as pixels with values differing from the average healthy forest by more than a threshold coefficient (k), which we set as 10%, in the studied spectrum (band or index).

$$Anomaly_i = \begin{cases} 1, & \text{if } |V_{p_i} - \overline{V_{h_i}}| > k \cdot \overline{V_{h_i}} \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

   where V_p is the value of the pixel in the studied spectrum i, $\overline{V_\mathrm{h}}$ is the average value of the healthy forest pixels, k is the threshold coefficient, set to 10%.
4) **Combining detected anomalies across different spectra**.
   To reduce false-positive results, we combine anomalies from the bands/indices that are most sensitive to forest damage. Thus, areas with anomalous values in all spectra simultaneously are classified as damaged or diseased forest (5):

$$Forest_{damage} = \prod Anomaly_i \quad (5)$$

4 RESULTS

4.1 Determining the Most Informative Spectral Data of Sentinel-2 for Detecting Forest Damage

Figure 2 presents an image of a selected area of interest from June 2023 in ultra-high resolution from Google Earth Pro (Fig. 2a) and in high resolution from Sentinel-2 (Fig. 2b). This area was chosen to visually illustrate the appearance of damaged forest patches in different spectral ranges of Sentinel-2.

Figure 3 displays this area in various spectral bands of Sentinel-2, while Figure 5 shows its representation through vegetation index spectra.

From Figure 5, it is evident that damaged areas are most clearly distinguishable in spectral bands B2, B3, B4 (10 m) and B5, B11, B12 (20 m). Other bands do not provide such effective visual identification of damaged forests.

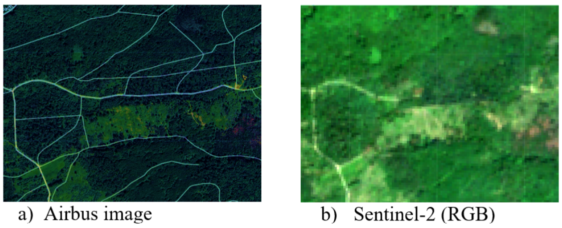

Figure 2: Sample area with damaged forest, coordinates: 51°48’41.68” N, 10°51’06.94” E.

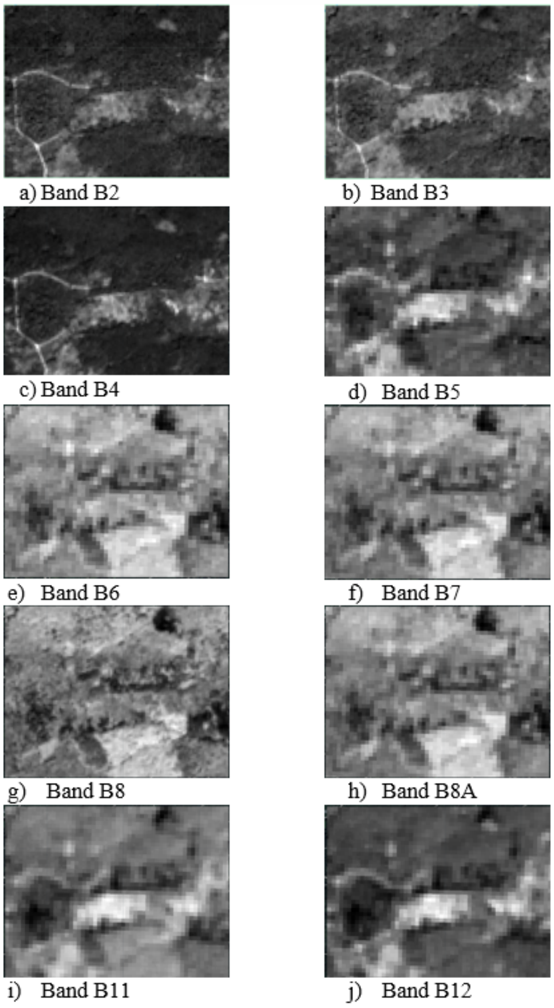

Figure 3: Sample area in the spectrum of the Sentinel 2 bands.

The bar chart in Figure 4 presents a numerical comparison of the mean values of the bands for healthy and damaged forest areas, while the line graph represents the relative difference between these values. Notably, for all bands, the pixel values of damaged forests exceed those of healthy forests. The largest discrepancies are observed in bands B3 (-40%) and B5 (-49.7%), making them the most informative spectral bands for detecting forest damage using Sentinel-2 data.

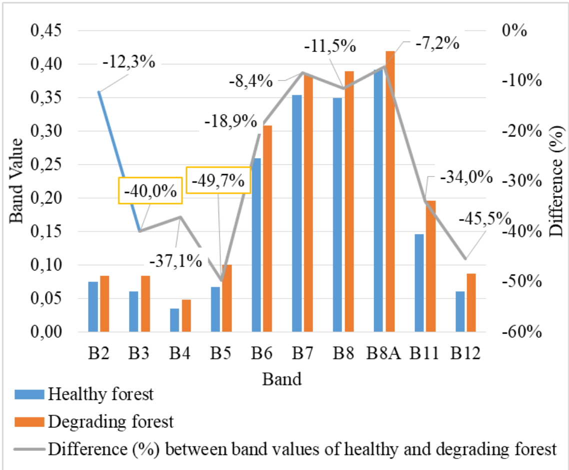

Figure 4: Histogram of average pixel values of Sentinel-2 bands for healthy and damaged forest.

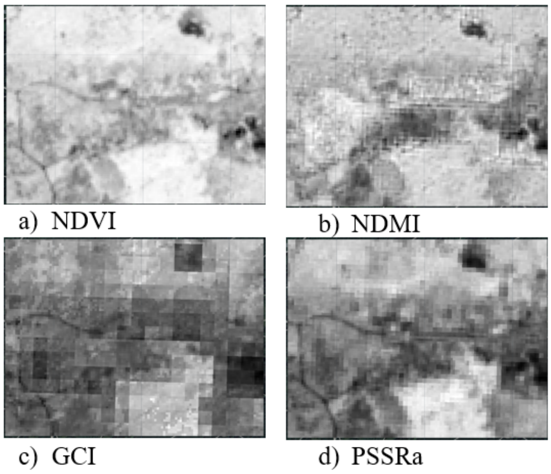

Figure 5: Sample area in the spectrum of the Sentinel 2 vegetation indices.

Regarding vegetation indices, visual analysis of the images (Fig. 5) indicates that they are not sufficiently effective for clearly distinguishing between pixels of healthy and damaged forests. However, numerical analysis reveals that the vegetation index values for damaged forests are significantly lower than those for healthy forests, particularly for GCI (-47%) and PSSRa (-21.4%) (Fig. 6). Nevertheless, due to the low visual separability of damaged forest areas from healthy ones using vegetation indices, we decided to focus solely on spectral bands B3 and B5.

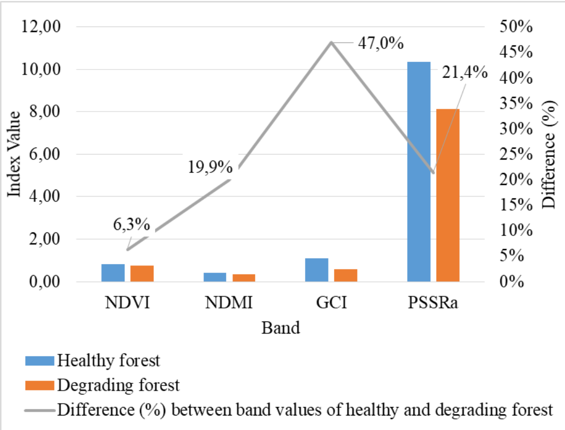

Figure 6: Histogram of average pixel values of Sentinel-2 vegetation indices for healthy and damaged forest.

Thus, for further analysis and detection of damaged forests, we will utilize the intersection of anomalies identified in bands B3 and B5.

4.2 Identifying Damaged Forest Areas Through Anomaly Detection

Figure 7 shows an example of detecting damaged forest areas using the proposed approach based on anomaly analysis in spectral channels B3 and B5. As shown in the figure, the combination of anomalies detected in these channels allows for clear differentiation between healthy and damaged forest areas, almost without missing any damaged areas and minimizing the number of false positives.

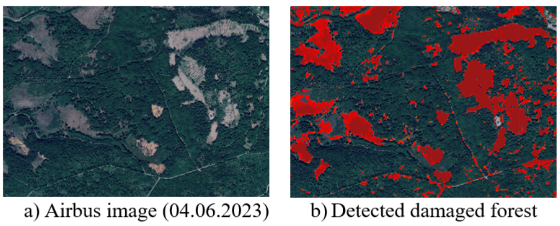

Figure 7: Example of detecting damaged forests. Coordinates: 51°34’59.36” N, 10°59’47.50” E.

By applying this method, we evaluated the dynamics of forest damage from 2020 to 2024 (Fig. 8) and calculated the areas of degraded land.

As seen in Figure 9, the area of damaged forest sharply increased between 2020 and 2021 (from 25.13 to 49.41 thousand hectares) and continues to grow each year, although the rate of increase is slowing. The highest concentration of degraded forest is observed in the central and western parts of the Harz, in the regions of Thuringia and Lower Saxony, while to the east, in Saxony-Anhalt, the extent of the damage is smaller. As of 2024, the total area of degraded forest in the Harz amounts to 68.1 thousand hectares.

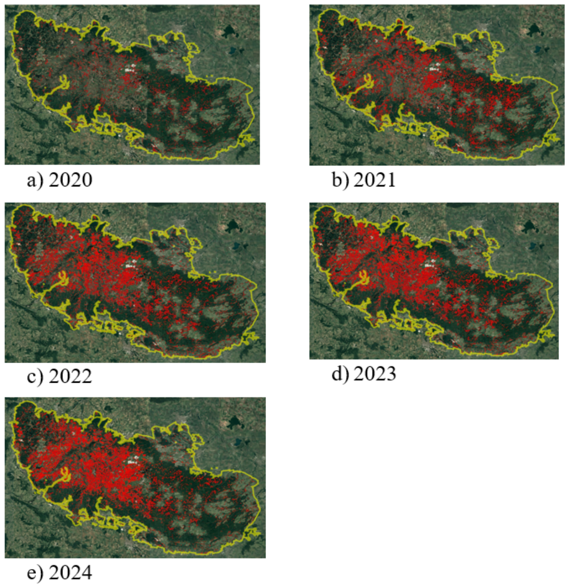

Figure 8: Detected damaged forests on the territory of the Harz, 2020-2024.

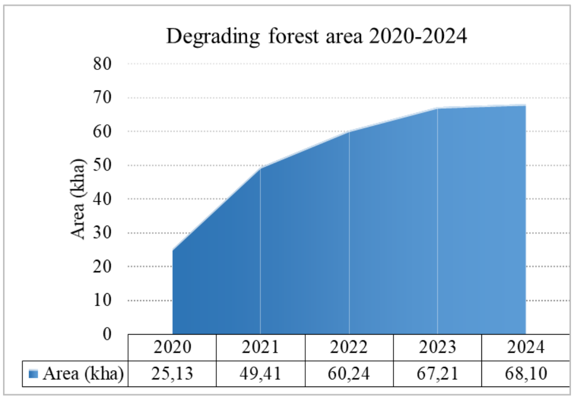

Figure 9: Dynamics of changes in the area of degraded forests in the Harz, 2020-2024.

5 CONCLUSIONS

In this study, we proposed a simple method for detecting degrading forests based on free Sentinel-2 satellite data and an anomaly detection approach, analyzing the forest areas in the Harz region. We examined individual Sentinel-2 channels with spatial resolution of 10-20 m and four vegetation indices—NDVI, NDMI, GCI, and PSSRa—on test plots with damaged forest, using high-resolution imagery from Google Earth Pro

(2023) as auxiliary data for verification. It was found that specific Sentinel-2 spectral channels were more effective for detecting degrading forests than vegetation indices. The most informative Sentinel-2 channels were identified as B3 (green) and B5 (red edge 1), with B4 and B12 also proving to be useful.

By defining anomalous pixel values in the B3 and B5 channels relative to randomly selected reference areas (healthy forests), we successfully detected damaged forest areas with high accuracy and minimal time, data, and computational resource costs. Using the developed method, we were able to track the dynamics of forest loss in the Harz region and calculate the areas of damage. It was determined that the largest losses occurred between 2020 and 2021 (approximately 24.27 thousand hectares of forest were lost), after which the trend gradually slowed down, though it remained negative. By 2024, the total loss of forest in the Harz region amounted to 68.1 thousand hectares.

Thus, this study demonstrates that anomaly detection in Sentinel-2 imagery can serve as an effective, cost-efficient method for monitoring forest degradation, enabling the assessment of forest loss over time and providing valuable information for forest management and conservation efforts. The method can be adapted to other regions, facilitating broader applications in forest health monitoring.

ACKNOWLEDGMENTS

This research was supported by the European Union and Land Sachsen-Anhalt through the ReSeDiUm project: Algorithms and Methods for Land Area Measurement to Estimate Land Areas, as well as the Horizon Europe projects funded by the European Union: SWIFTT (Satellites for Wilderness Inspection and Forest Threat Tracking, 2022–2025, grant agreement No. 101082732) and FUTUREFOR (Copernicus Applications for Next-Generation Forest Monitoring, 2024–2027, grant agreement No. 101180278).

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