MONITORING DEFORESTATION IN THE ADMINISTRATIVE TERRITORY OF CURĂȚELE COMMUNE USING SENTINEL SATELLITE DATA AND GIS PROCESSING AND INTERPRETATION ALGORITHMS

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Abstract: *Considering the ongoing deforestation around the Apuseni Mountains, particularly in the Curățele commune of Bihor county, a comparative study between the years 2017-2022 was deemed necessary. Using GIS processing and interpretation algorithms, a multi-temporal analysis of satellite data sets enabled the visualization of deforestation on a large scale, aiding in monitoring its negative effects. To understand the area's topography, a digital elevation model was analyzed and correlated with the remote sensing data to assess the impact of deforestation on land characteristics, such as water drainage patterns, increased erosion risk, and loss of local flora and fauna. Moreover, by identifying yearly changes in the forest landscape, proactive measures can be taken to prevent further environmental damage or degradation.*

Keywords: *deforestation; remote sensing; GIS; data extraction*

1. Introduction

Forests represent a vital component for humans, playing a significant role in maintaining natural balance and biodiversity, by offering host for an impressive variety of animal species, plants and trees, providing essential habitats for wildlife. Through their root systems, trees, actively contribute to preventing soil erosion and stabilizing sloped terrains, thereby safeguarding land structure and mitigating natural disasters. Moreover, forests are vital in combating floods, landslides, droughts and the soil desertification, climate change as absorbing significant amounts of carbon from the atmosphere, contributing to reducing the greenhouse effect and slowing down the global warming [1]. Therefore, these are an essential element in climate change mitigation strategies.

From a socio-economic perspective, forests represent a valuable resource serving as the primary source of raw material for the timber industry, providing the necessary material for construction, furniture, and various wood products. Additionally, during colder seasons, wood harvested from forests is used as bioenergy for heating homes, thereby reducing dependence on fossil fuels. At the same time, forests offer employment opportunities, generating jobs in the timber industry, in forest management and conservation, as well as in forest tourism [2]. Thus, they contribute to the well-being, sustainability, protection, and conservation of natural heritage for future generations.

Degradation, deforestation, and wildfires occurring in forested regions represent major sources of carbon dioxide emissions into the atmosphere, directly contributing to the phenomenon of global warming by amplifying the greenhouse effect. Technological advancements have introduced new methods and tools for detecting and monitoring deforestation using remote sensing data. Sensors mounted on satellites are utilized in accordance with active and passive remote sensing principles to collect satellite data, and these sources of information, through processing and interpretation, can highlight changes occurring in the forest landscape. Due to the difficulty of the terrain, which often represent an impediment in direct analysis of tree cutting, satellite imagery and photogrammetric data overcome this challenge, allowing the analysis over a large area in a non-destructive and non-invasive way providing data in a relatively short timeframe and at lower costs [4].

Deforestation is studied through the satellite data because it has become one of the most serious environmental issues humanity faces today, making deforestation a broad topic that requires heightened attention, as logging activities completely destroy the forest cover [3]. The scale of this phenomenon is global, with the extent of deforestation increasing from year to year, facilitated by unrealized and outdated legislative plans that remain unimplemented. Satellite data analysis not only allow the identification of areas where deforestation has occurred but can also provide insights into the causes of this phenomenon, such as human activity through legal or illegal logging, expansion of agricultural fields, or rural and urban area development, all of which lead to the loss of forested territory [1]. Rational management of natural resources is a necessary aspect; therefore, to address this key factor, political strategies and plans to combat deforestation must be developed, with the primary goal of conserving forest resources.

However, deforestation analysis through remote sensing data still has certain aspects that leave spaces for improvement. Distinguishing between legal and illegal deforestation is quite challenging based on satellite imagery. The accuracy of vegetation classification faces some challenges, with dependence on weather conditions and cloud cover at the time of satellite image acquisition, spatial and radiometric resolution, temporal resolution (revisit period), being just some of the aspects that require finding solutions.

2. Area of interest (AOI)

Curățele is a commune located in Bihor County, is composed of villages Curățele, which is also the commune's administrative center, Cresuia, Beiușele, Nimăiești, and Pociovelіștea. Situated in the historical region of Crișana, it extends over an area of 9090 hectares according to geometric data extracted from Eterra, and it is part of the North-West development region of Romania.

The predominant relief forms are represented by plains and hills, Curățele is located at the meeting point of the Criș plain with the Pădurea Craiului mountains, Vlădeasa mountains, and Bihor mountains. The hydrography of the area is composed of several valleys: Nimăiești, Corbu, Mizieș, and Iadului. In terms of altitude, the highest peaks are Dealul Mare at 957 meters, Măgura Beiușele at 1004 meters, and Piatra Tisei at 1057 meters. The main access route found near the deforested areas is county road DJ 108J (the primary road for timber exploitation), along which an entire network of forest roads has been established. Additionally, in the southern part of the analyzed forest area, access roads consist of dirt roads coming from the localities of Cresuia, Beiușele, and Meziad.

In Figure 1.1, it can be observed that 55-60% of the commune is covered by forest, and in the satellite images from the years 2017 and 2022, the phenomenon of deforestation is identifiable through a simple visual inspection. The fact that deforestation is visible in satellite imagery suggests that it has a significant extent. In the case study, the focus is on extracting the surface area of deforested zones.

Figure 2.1 Area of interest - RGB Composite year 2022

3. Materials and methods

Materials and working methods can be divided into three parts, according to the input data, as follows:

- The processing, analysis, and extraction of deforested surfaces from satellite data;
- The processing and analysis of the digital elevation model (DEM);
- Correlation of satellite data with topographic data.

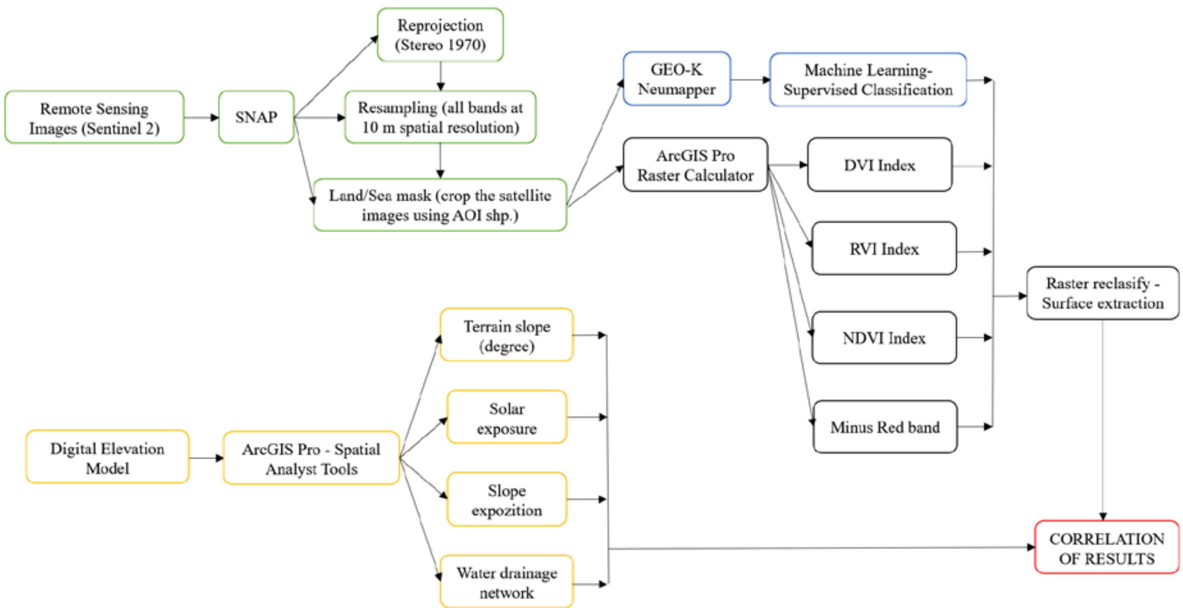

Figure 3.1 Workflow

The workflow begins with the identification of remote sensing data, a step in which the data must meet certain quality requirements so that the deforestation phenomenon can be distinguished within them. The data resolution must be sufficiently good, and cloud cover, brightness, and the time of day when the satellite images were captured should be optimal. Satellite images were downloaded from the Copernicus Data Workspace platform, following search configurations that selected datasets corresponding to the dates of 31.07.2017 and 25.07.2022. Therefore, the analyzed area was studied with a 5 years difference from the first dataset, during approximately the same period of the year, to have approximately the same vegetative stage of the forest. The downloaded satellite data files are very large in spatial dimension. The size of a satellite image with L2A pre-processing level is 110x110 km, representing 12100 km2. Considering that the area of Curățele covers only 9090 hectares or 90.9 km2, it was deemed appropriate to crop the satellite image according to the outline of the commune. To obtain the outline of the administrative unit Curățele, the Eterra platform was utilized. The outline has the extension *.dxf, which is not compatible with all software used in the remote sensing data processing. Therefore, the extension *.dxf file was converted into a vector file *.shp type using the Global Mapper program.

The raw data downloaded from the Copernicus platform is provided in the WGS84 projection system, so it is necessary to convert them into the national Stereographic 1970 projection system using Reprojection command. Additionally, a resizing of the spatial resolution of the satellite data was performed after the B2-Blue band using Resampling command, so that all 12 bands have a resolution of 10x10 meters. After extracting the bands using the Subset command, they are clipped using the Land/Sea Mask command so that the satellite images have the geometry of the Curățele administrative unit. Finally, the data is exported from the SNAP program in *.geotiff/.bigtiff format, which is compatible with the ArcGIS Pro program.

ArcGIS Pro is the central software for the present study, within which the majority of data processing and analysis is conducted. Due to its functions and capabilities in analyzing surfaces and satellite data, the program enables the extraction and correlation of information obtained from the analyses applied to the datasets. The focus of the analyses is to bring to light the researched issue, ultimately quantifying the extent of deforestation occurring within the analyzed area during the studied time period.

To eliminate classification errors generated by agricultural lands due to changes in crops and vegetation types during the analyzed period (2017-2022), it was deemed appropriate to remove areas that are not of interest and narrow down the AOI only to the forested area using ArcGIS Pro. The initial AOI encompassed 9090 hectares; after narrowing down the study area to only include the forested zone, the researched area was reduced to approximately 5200 hectares.

Figure 3.2. Narrowing the AOI only to the forested area - 2017 RGB Composite

To extract quantitative information regarding deforested areas, a series of remote sensing indices specialized were utilized:

a. Difference Vegetation Index (DVI) involves subtracting the near-infrared band from the red band. Using the Raster Calculator function within the ArcGIS Pro program, the DVI index was calculated for the two years under analysis.

General formula for calculating the DVI index:

$$DVI = NIR - RED \tag{3.1.}$$

b. Ratio Vegetation Index (RVI) represents a division between the near-infrared band and the red band. Vegetation generally exhibits a noticeable response in the red and near-infrared regions of the electromagnetic spectrum. It shows low reflectance in the red band because red radiation is absorbed by plants, while in the near-infrared region, vegetation exhibits high reflectance, making it easier to discriminate.

General formula for calculating the RVI index:

$$RVI = \frac{NIR}{NIR} \tag{3.2.}$$

To validate the DVI and RVI indices, a third index is necessary, which should be compared with the results of the two indices and with the color images corresponding to the analyzed years.

c. Normalized Difference Vegetation Index (NDVI), represents a ratio between the NIR and RED bands. Vegetation in the near-infrared region exhibits strong reflection, while in the red region, it shows strong radiation absorption. Both cases favor vegetation identification in satellite images. Vegetation in the red region of the spectrum emits only a small amount of solar radiation received by the sensor; however, in the near-infrared region, vegetation exhibits a higher spectral response, resulting in a lighter color. In both cases, soils devoid of vegetation show the maximum reflectance.

General formula for calculating the NDVI index:

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{3.3.}$$

For a more comprehensive analysis of the investigated phenomenon, the minus function will be applied between the Red band of 2017 and the Red band of 2022 to highlight the areas where changes have occurred during the analyzed period.

Formula:

$$MINUS\ RED = RED\ 2017 - RED\ 2022 \tag{3.4.}$$

The minus function has a triple utility, as it can represent:

- areas showing changes present in 2022 but not in 2017;
- areas that remained the same during the analyzed period;
- areas showing changes to elements present in 2017 but that have disappeared from the image taken in 2022.

The supervised classification was performed in the Neumapper GEO-K program, which specializes in extracting elements of interest from satellite images using machine learning. The first step involved importing RGB composites, adjusting the color of RGB images using the histogram, creating a neural network, defining input and output parameters (4 input parameters: red, green, and blue bands, and the background of the cropped image recognized by the program as black; 2 output parameters: land class and forest class), collecting training samples for the neural network, training it, obtaining the result, and exporting it.

Using the digital elevation model downloaded from Global Mapper, with a resolution of one meter per elevation, the topography analysis of the studied area was conducted in ArcGIS Pro. The analysis of surfaces involved utilizing tools within the Spatial Analyst Tools , resulting in raster images and thematic maps depicting: slope inclination (degree), slope exposition, solar exposure or slope orientation relative to the sun (solar radiation), and water drainage network.

4. Results and discussions

As observed in the Materials and Methods section, the research study comprises several elements, which has generated a multitude of outcomes. In the following part, only an amount of the results obtained from the analyses applied to satellite images will be presented, while the analysis of the terrain topography will be correlated with an area showing considerable deforestation.

The minus function applied to the red band reveals the changes that occurred within the studied landscape over the course of the five years.

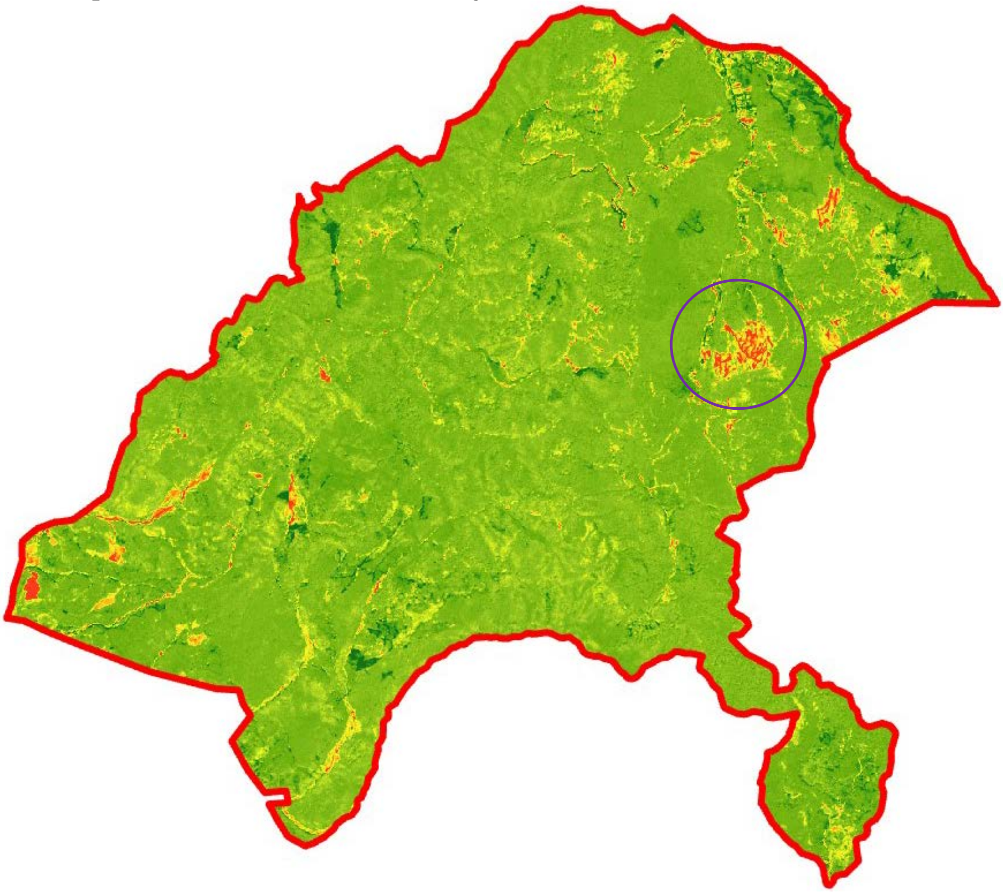

Figure 4.1 Minus function between Red 2017 - Red 2022

The meaning of figure 4.1 is the following:

- the red, orange and yellow color represents the areas that present changes in the 2022 image, such as the visible deforestation in the upper right part;
- the light green color depicts the areas where no changes occurred during the analyzed period;
- the dark green color indicates changes, as elements present in 2017 are no longer visible in 2022. For example, in the upper part, elements highlighted in dark green represented forest roads or vegetation-free soils in 2017, but these were covered by vegetation in the 2022 image.

In Figure 4.2, a faithful result obtained from the calculation of the NDVI index can be observed. This result is validated within the RGB image corresponding to the year 2022, where, through the reclassification of the index into the two interest classes land-black (non-forest) and forest-green, areas without vegetation (deforestation, forest roads, vegetation-free soil) can be observed.

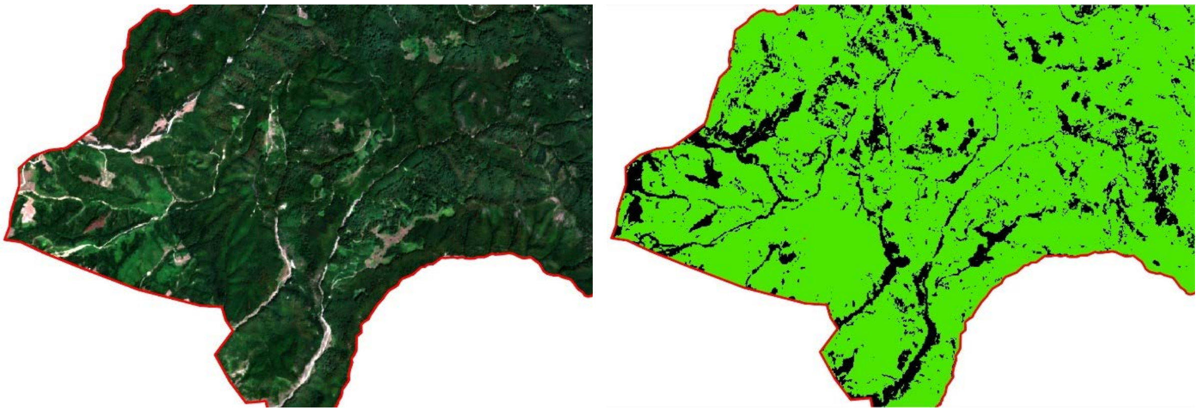

Figure 4.2 The RGB composite and the reclassified NDVI index of 2022

The evolution of surface dynamics can be observed in Figure 4.3, which represents the graph of changes detected by each index.

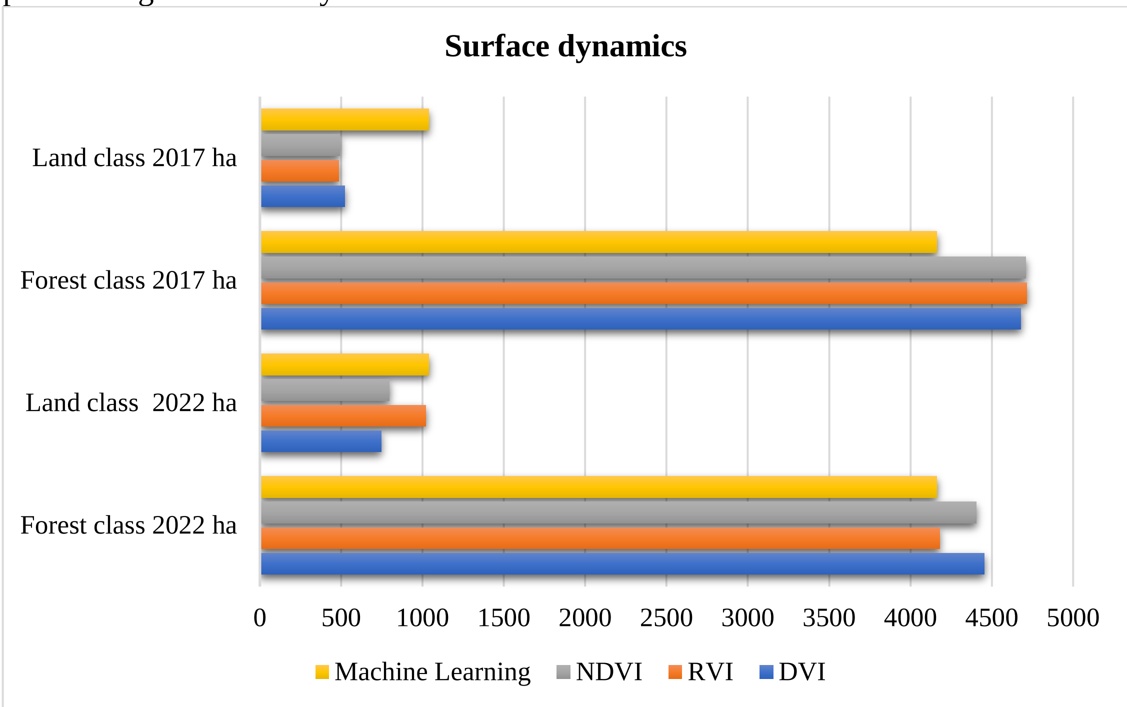

Figure 4.3. Surface dynamics

The remote sensing indices detected a decrease in the forest-covered area, with the DVI index indicating a decrease of 226 hectares, the RVI index indicating a decrease of 537 hectares, and the NDVI index indicating a decrease of 305 hectares. Supervised classification conducted using the GEO-K Neumapper program did not identify significant changes in the analyzed classes. The minus function applied to the RED band determined a decrease of 399 hectares. However, the minus function represents changes between the analyzed images, which can be negative (deforestation) or positive (natural regeneration of deforested areas or afforestation - reintegration into the forest class).

In accordance with the above, it can be observed that a homogeneous result was not obtained among the deforested areas. The following part will highlight a deforested area recognized in most applied analyses, but also after in the field inspection. A visibly deforested area spanning approximately 40 hectares has been identified in the upper North-East part of the AOI. (Figure 4.4).

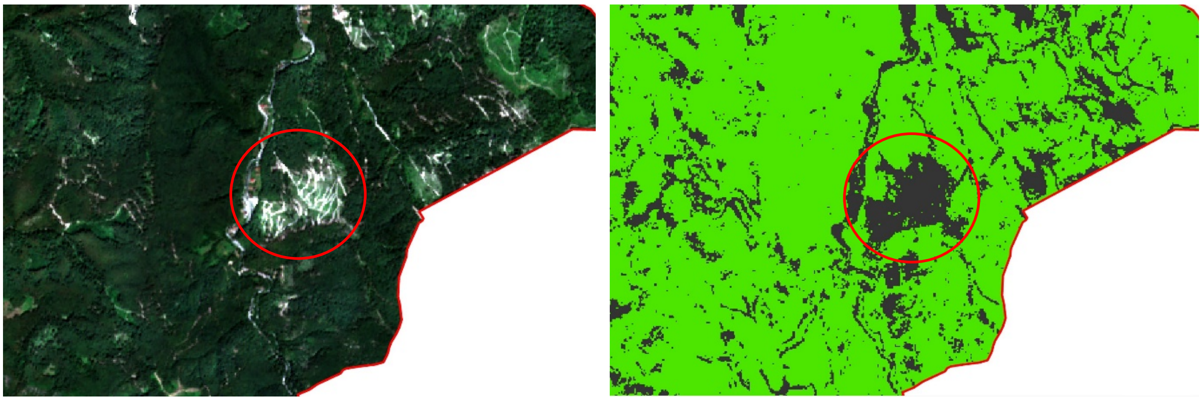

Figure 4.4. The RGB composite and the reclassified RVI index 2022

On 10.07.2023, a field visit was conducted in an area exhibiting visible deforestation both in satellite imagery and in the analyses performed. The purpose of the visit was to confirm the presence of deforestation in the studied area, identify tree species and their dimensions, visualize the main access routes to the deforested area, routes through which the timber was extracted from the forested area, and capture photographs using the DJI Phantom 4 V2 drone to visually depict the extent of the investigated phenomenon.

The main tree species found in the deforested areas is beech. It is among the primary types of trees used as fuel during the cold season for heating homes, as it has significant calorific power. Furthermore, in the field, the circumference of trees near the deforested areas was measured at 1.3 meters above the ground, ranging between 70 and 150 cm. The circumference of the trees helps determine their age, thus allowing for an estimation of the amount of timber harvested. Using data collected from the field, correlated with information found on the National Forest Inventory website, the volume of extracted timber could be determined. For the Transylvania region, the average timber volume per hectare for beech species is approximately 413 cubic meters per hectare, resulting in a volume of 16,520 cubic meters for the 40 hectares.

Figure 4.5. Deforested Area - Image Captured with DJI Phantom 4 v2 Drone

Within the 40 hectares of deforestation, detected in satellite images and validated during the field visit, the terrain slope in that area varies between 15° and 30°, which is why the logging roads are so winding. In terms of slope orientation, the area faces west and northwest, which means that the respective area receives a lower amount of solar energy. Water runoff from the slopes occurs through two discharge areas, with the water collected by Valea Iadului at the base of the slope. The fact that water runoff occurs in a deforested area, without vegetation may favor soil erosion in that perimeter.

5. Conclusions

Monitoring and analyzing deforestation through satellite data is an increasingly relevant topic in specialized research. Satellite images provide a rich source of information, allowing the study of large areas over short periods and at reduced costs, making them extremely valuable across various domains with considerable applicability.

By correlating remote sensing data with ancillary information, a possibility for complex analysis, extraction, and interpretation of results is opened, facilitating the understanding of changes in land use dynamics. The use of GIS processing and interpretation algorithms in deforestation analysis is an essential foundation, as it enables perspectives on natural resource management, biodiversity conservation, expansion of inhabited areas, and legal planning.

Remote sensing indices, machine learning principles, and minus function are essential tools for extracting information from satellite images in quantitative terms. However, in the analysis process, several factors can influence the quality of the obtained results. These factors include data spatial resolution, environmental conditions during satellite image acquisition, time of day of image capture, preprocessing corrections applied to the images, and changes within the analyzed perimeters over time. These factors can positively or negatively impact the satellite information analysis process. For instance, higher spatial resolution can lead to more accurate identification of deforestation details and characteristics. However, weather or atmospheric conditions can affect image clarity, and changes within the analyzed area can introduce uncertainty errors in the interpretation process. It is important to consider these factors and apply processing and analysis methods correctly to obtain precise and relevant results. Additionally, validation and verification of obtained results through comparison with field data or other information sources are necessary. Thus, attention must be paid to and all these factors must be taken into account in the satellite data analysis process to draw feasible conclusions anchored in reality.

Using remote sensing data, we can detect areas affected by deforestation, however, it's crucial to acknowledge that determining the legality of deforestation based on this data is impossible. Monitoring systems based on satellite data can provide valuable information for identifying deforested areas, but interpreting this data in the context of the legality of logging activities (legal or illegal logging) requires a more complex process and the involvement of additional resources and expertise.

In the end, deforestation analysis through remote sensing in correlation with GIS represents an efficient and robust scientific approach for extracting quantitative information, allowing for monitoring and evaluation of changes in land use.

6. References

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