Analysis of deforestation in the Amazon rainforest with segmentation techniques

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Abstract

The main objective of this study is to apply advanced image processing techniques to study deforestation in the Amazon rainforest, paying special attention to the impact of conservation measures in the Jamanxim National Forest, located in Brazil. To this end, the deforested area was analyzed automatically using a series of twenty high-resolution satellite images corresponding to the period between 2000 and 2019, obtained from NASA's Earth Observatory.

The analysis required several stages of processing. First, pre-processing was carried out, which included converting the original GIF file into separate images and automatically removing unwanted elements, such as the year or scale, using transformations to the HSV color space and morphological and median filters. Subsequently, the CLAHE (Adaptive Histogram Equalization) technique was applied to the value channel to enhance contrast and improve the visibility of areas affected by deforestation.

For segmentation, a channel-by-channel adaptive thresholding strategy was chosen in HSV space, using the Otsu method independently on each component (hue, saturation, and value). This approach allowed for better adaptation to variations in light and atmospheric conditions, thus facilitating more accurate discrimination of the color associated with deforested areas. In addition, morphological operations such as closing and opening were applied to the resulting masks to reduce noise, close gaps, and smooth edges.

The results obtained show a sustained and alarming increase in deforested area over the two decades studied. Specifically, in 2019, the area reached 10,239 km², a figure that is almost six times the area recorded in 2000 (1,732 km²). Notable increases were observed, such as the one recorded between 2016 and 2017, with an increase of more than 1,000 km² in a single year. However, the accuracy of the analysis was limited by the quality of the original data, with some errors due to the presence of clouds (as in 2003), detection failures (in years such as 2014, 2015, and 2018), or possible temporal mismatches in the labeling of the images.

Despite these difficulties, the combination of color-based segmentation with morphological post-processing techniques was essential for clearly identifying deforested areas. This temporal study provides valuable information for analyzing the effectiveness of environmental protection policies implemented in the Amazon region and contributes to monitoring their evolution over time.

Key Words

Otsu's Global Thresholding, Threshold Segmentation in HSV Color Space, Adaptive Thresholding Segmentation, Morphological Post-Processing

I. Introduction

The Amazon rainforest, the world's largest tropical forest, plays an essential role in climate regulation, biodiversity, and the water cycle (Fearnside, 1987). However, this ecosystem faces increasing pressure from human activities such as extensive agriculture, livestock farming, illegal mining, and infrastructure construction, which have increased deforestation rates (Ampolini, 2024). This loss not only threatens biodiversity and degrades the soil, but also releases large amounts of CO_2, intensifying climate change (Ampolini, 2024).

In this context, the Jamanxim National Forest, covering some 860,000 hectares, is a strategic area in Brazil due to its value as a biological corridor and refuge for species. Its relevance lies in being a biological corridor and refuge for numerous species, making it a focal point for monitoring and evaluating conservation strategies (Laurance et al., 2010). Studying its conservation status over time is therefore essential to understanding the dynamics of deforestation and evaluating the effectiveness of protection and conservation policies implemented in the region.

The use of satellite imagery has become a key tool for monitoring these changes. These images provide consistent data over time, enabling a detailed analysis of the terrain that is difficult to achieve with traditional methods (Pandey et al., 2022). Automated image processing techniques allow for the objective identification and quantification of affected areas.

In this type of analysis, image segmentation is crucial, as it divides images into regions with similar characteristics (color, intensity, texture), which facilitates the identification of deforested areas (Gonzalez & Woods, 2018). One of the most widely used techniques is thresholding, which classifies pixels according to a predefined threshold. The Otsu method (Otsu, 1979), for example, is effective in images with clear distributions, although it is not always sufficient due to the variability of the Amazonian environment. In these cases, techniques based on color spaces such as HSV or Lab allow for more robust segmentation, as they separate color from intensity, which helps to differentiate more accurately between healthy vegetation and degraded areas (Hema et al., 2020).

The objective of this activity is to apply these techniques to twenty satellite images from the period 2000-2019 (NASA), using a workflow that includes preprocessing, contrast enhancement, and adaptive segmentation. The aim is to quantify deforestation and understand the evolution of forest cover in the Jamanxim National Forest, contributing to the evaluation of conservation strategies in the region.

II. Material And Methods

This study was conducted using specific remote sensing data and specialized software for image processing and analysis. The careful selection of these resources was key to ensuring that the results obtained were both reliable and reproducible.

The analysis of deforestation in the Jamanxim National Forest (BNJ) was carried out using a series of twenty multispectral satellite images corresponding to the period 2000–2019. These images, obtained from NASA Earth Observatory (NASA Earth Observatory, n.d.), provide high-quality, open-access remote sensing data, which are essential for large-scale environmental monitoring. The images were in animated GIF format, with each frame representing the forest cover of the BNJ in a specific year. Their spatial resolution allowed us to identify patterns of change related to deforestation. An important aspect was the scale, where 51 pixels are equivalent to 20 kilometers, which was key to converting the data from pixels to metric units (km^2) and facilitating its geographical interpretation.

All processing and analysis of the satellite images was performed using Matlab, a high-level programming environment widely used in science and engineering for its power in numerical computation, data visualization, and algorithm development. This environment provided a solid foundation for handling large volumes of data in the form of matrices, as well as for efficiently implementing complex algorithms in both signal and image processing, while also facilitating rapid prototyping. Although the specific development was carried out in this environment, the techniques explained in the following sections will focus solely on the mathematical foundations that underpin them, without going into detail about specific functions of the platform.

Image segmentation plays a key role in digital processing, as it allows an image to be divided into different regions or areas with similar characteristics. This division facilitates both interpretation and subsequent analysis, making the image more understandable and manageable (Gonzalez et al., 2018). In this work, thresholding-based techniques are used, a fairly common approach that separates pixels according to their intensity level.

A. Otsu's Global Thresholding

The Otsu method (Otsu, 1979) is an automatic and non-parametric global thresholding technique that is frequently used to separate the pixels of an image into two categories: background and main object. What this approach does is search for the threshold value that best differentiates between the two classes, maximizing the variance between them. In practical terms, if the image is represented on a grayscale with L possible levels (for example, from 0 to 255), the algorithm explores all possible threshold values k. This threshold divides the image into two groups: C_0, which contains pixels with gray levels from 0 to k, and C_1, with pixels between k+1 and L−1. For each gray level i, its probability of occurrence is calculated as $p_i = n_i/N$, where n_i is the number of pixels with that level and N is the total number of pixels in the image.

The probability that a pixel belongs to class C0 is defined as:

$$\omega_0(k) = \sum_{i=0}^{k} p_i$$

And for class C1:

$$\omega_1(k) = \sum_{i=k+1}^{L-1} p_i$$

The means of the gray levels for each class are:

$$\mu_0(k) = \sum_{i=0}^{k} \frac{i \cdot p_i}{\omega_0(k)}$$

$$\mu_0(k) = \sum_{i=0}^{k} \frac{i \cdot p_i}{\omega_0(k)}$$

The overall mean of the image is:

$$\mu_0(k) = \sum_{i=0}^{k} \frac{i \cdot p_i}{\omega_0(k)}$$

Otsu's method seeks the threshold k that maximizes the variance between classes, defined as:

$$\sigma_B^2(k) = \omega_0(k)\omega_1(k)\big(\mu_0(k) - \mu_1(k)\big)^2$$

The value of k that maximizes $\sigma_B^2(k)$ is the optimal threshold.

B. Threshold Segmentation in HSV Color Space

Segmentation in HSV (Hue, Saturation, Value) color space is an effective strategy for identifying and separating objects within an image based on their color (Hema et al., 2020). Unlike the classic RGB model, where colors are mixed using red, green, and blue channels, the HSV model clearly separates color information (hue and saturation) from intensity information, making it particularly useful when lighting conditions vary between images or within the same image.

This color space is divided into three key components:

- **Hue (H)**: Indicates the type of color, such as blue, green, or red. It is represented as an angle that runs around the color wheel, typically between 0° and 360°, although in some systems it is normalized between 0 and 1.
- **Saturation (S)**: Reflects how pure or intense a color is. When saturation is high, the color is vivid; when it is low, it tends toward gray. It can also be expressed on a scale from 0 to 1.
- **Value (V)**: This refers to the brightness or intensity of the color. The higher the value, the lighter the color; if it is low, the color appears darker or duller.

Segmentation in HSV is based on setting limits (thresholds) for each of these three components. A pixel will be classified as belonging to the searched object only if its H, S, and V values are within those defined ranges. For example, if we want to identify areas of red color, we will set specific ranges for hue, saturation, and value that match the characteristics of red. In practical terms, this translates into applying mathematical conditions that filter pixels according to their color attributes.

$$H_{min} \leq H_{pixel} \leq H_{max}$$
$$S_{min} \leq S_{pixel} \leq S_{max}$$
$$V_{min} \leq V_{pixel} \leq V_{max}$$

If a pixel satisfies all these conditions, it is classified as part of the segmented object. Otherwise, it is classified as part of the background.

C. Adaptive Thresholding Segmentation Technique in HSV Space with Morphological Post-Processing

This technique combines several approaches to achieve more accurate image segmentation, even under variable lighting conditions or with notable differences in color. It is based on the integration of adaptive thresholding, the use of HSV color space, and subsequent refinement through morphological operations (Sharma et al., 2016). Its purpose is to more effectively isolate relevant regions within an image, minimizing common errors in complex environments. The methodology consists of the following main steps:

- **Conversion to HSV color space**: The first step is to transform the image from the RGB model to the HSV space, which allows the chromatic information (hue and saturation) to be separated from the luminous information (value or brightness), favoring a more stable segmentation in the face of light variations.
- **Adaptive thresholding**: Instead of using a single threshold for the entire image, this approach employs adaptive thresholding. This technique involves dividing the image into smaller sections, to which a specific threshold is then applied. By applying Otsu to each of the three HSV channels, a specific threshold is obtained for Hue, Saturation, and Value, better adjusting to the chromatic particularities of each image or frame.
- **Morphological post-processing**: After applying segmentation, mathematical morphology operations (Erosion, Dilation, Opening and Closing) are used to refine the results obtained. These tools allow the shape and size of the segmented areas to be adjusted, eliminating noise or unwanted details.

  Erosion: This operation is used to reduce the size of objects detected in an image, eliminating small details, isolated points, or noise. It is especially useful when you want to clean up the segmentation of irrelevant elements. The erosion of an image A by a structuring element B is defined as:

  $$A \ominus B = \{z \in E \mid B_z \subseteq A\}$$

  Where B_z is the structuring element B shifted by z.

  Dilation: This has the opposite effect to erosion. It is applied to expand objects, fill small gaps, and connect fragmented regions. The dilation of an image A by a structuring element B is defined as:

  $$A \oplus B = \{z \in E \mid (\hat{B})_z \cap A \neq \emptyset\}$$

  Where $(\hat{B})$ is the reflection of B.

  Opening: This consists of first applying an erosion and then a dilation using the same structuring element. This operation is useful for removing small irregularities or noise without significantly modifying the shape or size of large objects. It is expressed as:

  $$A \circ B = (A \ominus B) \oplus B$$

  Closing: First performs a dilation and then an erosion with the same structuring element. It is suitable for closing small gaps within objects, smoothing broken edges, and joining components that are close together. It is defined as:

  $$A \cdot B = (A \oplus B) \ominus B$$

The combination of adaptive thresholding in HSV color space with morphological post-processing techniques offers more robust and accurate segmentation. This strategy is especially useful in images with variable lighting conditions or complex colors, as it allows for clearer distinction of regions or objects of interest within the scene.

III. Results

This section presents the results obtained after applying the image processing techniques mentioned in the Materials and Methods section. The presentation is organized according to the stages of preprocessing, segmentation, and temporal analysis of deforestation, highlighting both the effectiveness of the methods used and the difficulties or limitations encountered during the process.

A. Visual Analysis of Pre-processed Images

The pre-processing stage was essential for improving the quality of the satellite images and preparing them for segmentation. First, the original GIF file was converted into twenty individual JPG images, which made it easier to handle each year separately and allowed them to be processed in batches. To remove visual artifacts, such as year marks and scale, the images were transformed from RGB space to HSV space, and median filters were applied along with morphological operations. This allowed for the creation of very precise masks for those areas, enabling their replacement with green areas of the same color as the neighboring pixels without damaging important information in the images (see Figure 2).

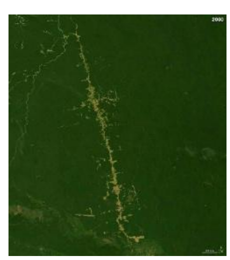


Figure 1: Original image. Source: NASA Earth Observatory. (n.d.)

Figure 2: Preprocessed image. Source: NASA Earth Observatory. (n.d.)

This technique was key in allowing the segmentation algorithms to focus exclusively on identifying deforested areas, without being affected by text or graphics present in the images.
Furthermore, by applying Adaptive Histogram Equalization (CLAHE) to the value channel (V) of the HSV space, a notable increase in local contrast was achieved, facilitating better differentiation of areas in the images (see Figure 4).

Figure 3: Original image. Source: NASA Earth Observatory. (n.d.)

Figure 4: Image after CLAHE application. Source: NASA Earth Observatory. (n.d.) - processed

Thanks to this improvement, it was much easier to visually distinguish between dense forest areas, damaged vegetation, and already deforested areas, which was essential for subsequent segmentation methods to work correctly. By applying CLAHE only to the V channel, the original color information of the image remained intact, avoiding any alteration that could interfere with segmentation based on color tones.

B. Comparison of Segmentation Techniques

Various segmentation strategies were evaluated to identify the most robust and accurate one for detecting deforested areas.

B.1 Global Thresholding (Otsu Method)

The initial application of the Otsu method for global thresholding, which is based on the gray level distribution of the image, showed significant limitations (see Figure 5). Although this method works well with images that have clear bimodal histograms (Otsu, 1979), in the case of satellite images of complex forest areas, it failed to correctly distinguish between different regions of interest, such as forest, deforested areas, or water bodies. The variability in tones and gradients present in the transition zones between the forest and exposed soil caused the segmentation to have many false positives and some false negatives, making it unfeasible to use this method as the main one.

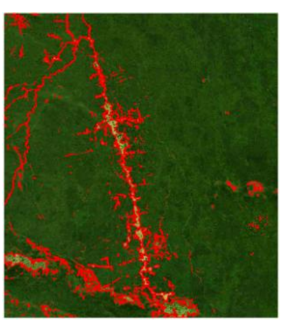


Figure 5: Global Otsu superimposed on the original image. Source: NASA Earth Observatory. (n.d.) - processed

B.2 Thresholding in HSV Space (Manual Adjustment)

A manual thresholding approach in HSV space, focusing on the Hue (H) channel, was also evaluated. Although this conversion allows for better differentiation of tones (Hema et al., 2020), manually adjusted thresholds for one image were not reliable for others due to variations in lighting and terrain. This led to the omission of deforested areas or the inclusion of unaffected areas, making accurate and reproducible quantification difficult (see Figures 6 and 7).

Figure 6: Thresholding in HSV space (year 2000). Source: NASA Earth Observatory. (n.d.) - processed

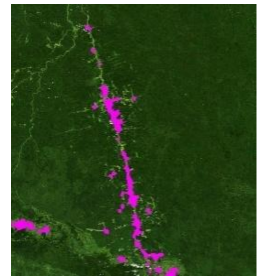


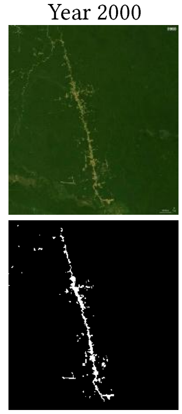
Figure 7: Thresholding in HSV space (year 2001). Source: NASA Earth Observatory. (n.d.) - processed

B.3 Adaptive Thresholding in HSV Space with Morphological Post-Processing

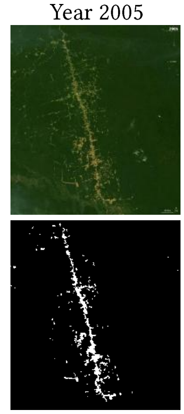
The adaptive thresholding technique in HSV space, together with careful morphological post-processing (Sharma et al., 2016), proved to be the most effective for detecting and measuring deforested areas (see images in Table 1). This strategy took advantage of the HSV space to better distinguish colors and the ability to adjust thresholds locally according to the specific characteristics of each region.

TABLE I. ORIGINAL VS. SEGMENTED IMAGES WITH ADAPTIVE THRESHOLDING IN HSV AND MORPHOLOGICAL POST-PROCESSING. SOURCE: NASA EARTH OBSERVATORY. (N.D.)

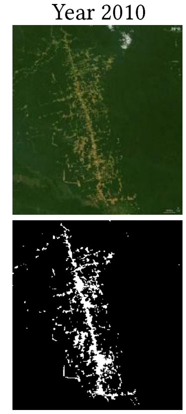
Year 2000



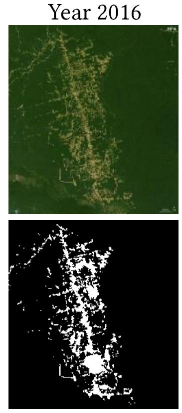
Year 2005



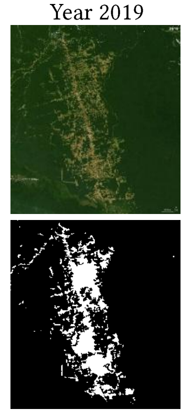
Year 2010



Year 2016



Year 2019



By applying Otsu's method independently to each channel of the HSV space (Hue, Saturation, and Value), binary masks were generated that accurately captured the color and brightness variations characteristic of deforested areas in each image (see Figures 8, 9, 10). Then, by combining these masks with a logical AND operation, only areas that met the criteria in all three channels were considered deforested (see Figure 11), thus reducing the occurrence of false positives and negatives.

Figure 8: Binary mask for channel H (year 2019). Source: NASA Earth Observatory. (n.d.) - processed

Figure 9: Binary mask for channel S (year 2019). Source: NASA Earth Observatory. (n.d.) - processed

Figure 10: Binary mask for channel V (year 2019). Source: NASA Earth Observatory. (n.d.) - processed

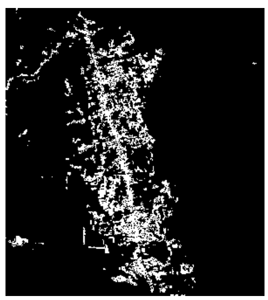


Figure 11: Combination of binary masks for the H, S, and V channels with a logical AND operation. Source: NASA Earth Observatory. (n.d.) - processed

Morphological post-processing played a key role in improving the quality of these masks. The removal of small disconnected objects, filtering areas smaller than 4 pixels, helped to clean up noise and other unwanted artifacts. Opening and closing operations, performed with a disc-shaped structuring element with a radius of 1 pixel, were essential for closing small gaps within deforested areas and eliminating unwanted irregularities or thin connections. In addition, filling holes ensured that internal areas were completely solid, an essential step for accurately measuring the deforested area.

Although this method proved to be very robust, two important limitations were detected. The first was the inclusion of natural features, such as mountains or rivers, which had similar tones to the deforested areas. To resolve this, an additional spatial mask was applied that excluded these areas from the analysis (see Figure 12).

Figure 11: Spatial mask to exclude mountain and river reliefs. Source: Own elaboration.

The second limitation was related to the occasional inaccuracy of the generated masks, where deforested areas were not delineated with the desired accuracy (see Figure 14). This was addressed by fine-tuning the parameters of the morphological operators (e.g., the size of the structuring elements), which allowed for better adaptation to the peculiarities of each image and greater precision in the delimitation of deforested areas (see Figure 15).

Figure 12: Mask before adjusting the parameters of the morphological operators (and before applying the spatial mask to exclude mountain reliefs and the river). Source: NASA Earth Observatory. (n.d.) - processed

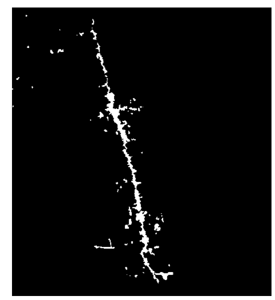


Figure 13: Mask after adjusting the parameters of the morphological operators (and after applying the spatial mask to exclude mountain reliefs and the river). Source: NASA Earth Observatory. (n.d.) - processed

C. Temporal Analysis of Deforestation

The deforested area was quantified using a scale of 51 pixels equivalent to 20 km, which allowed us to construct a detailed time series showing how forest cover in the Jamanxim National Forest has changed over the years. The values for the deforested area, both in pixels and square kilometers for each year, are presented in the table in Table 2.

TABLE II. ANNUAL DEFORESTED AREA IN THE JAMANXIM NATIONAL FOREST (2000-2019). SOURCE: OWN ELABORATION.

Year	*Deforested Area (px²)*	*Deforested Area (km²)*	*Comment*
2000	11.260	1.732	
2001	11.554	1.777	
2002	14.318	2.202	
2003	22.901	3.522	There are many false positives due to clouds.
2004	16.533	2.543	
2005	22.104	3.399	
2006	27.767	4.270	
2007	30.027	4.618	

2008	41.236	6.342	This photo was taken after the one from 2009, as the deforested area is larger. Perhaps there was an error when labeling the year on the photo.
2009	37.613	5.784	This photo may have been taken after the one from 2010, as the deforested area is larger. There may have been an error when labeling the year on the photo
2010	36.155	5.560	
2011	44.842	6.896	If we look at the original images from 2011 and 2012, we can see that the 2012 image has a slightly larger deforested area. This is not correctly reflected in these measurements, possibly due to differences in the tone/saturation of the deforested area in both images.
2012	44.508	6.845	
2013	46.031	7.079	
2014	41.079	6.317	There are some false negatives due to clouds.
2015	41.049	6.313	There are some false negatives due to clouds.
2016	53.840	8.280	
2017	60.418	9.292	
2018	56.773	8.731	There are some false negatives due to clouds.
2019	66.577	10.239	

An analysis of the data in Table 2 reveals a clear and worrying trend: deforestation in the Jamanxim National Forest has been increasing steadily between 2000 and 2019. For example, in 2019, the deforested area reached 10,239 km², almost six times more than in 2000, when it was 1,732 km². This reflects strong and sustained pressure on the region's forests.

In addition, several significant peaks in the annual deforestation rate have been identified, indicating periods of particularly intense activity (see table 3).

TABLE III. TEMPORAL VARIATION FOR THE DEFORESTED AREA IN THE JAMANXIM NATIONAL FOREST (2000–2019). SOURCE: OWN ELABORATION.

Year	*Deforested Area (km²)*	*Variation (km²)*	*Comment*
2000	1.732	-	
2001	1.777	45	
2002	2.202	425	
2004	2.543	170	(2004 value-2002 value)/2
2005	3.399	857	
2006	4.270	871	
2007	4.618	348	
2010	5.560	314	(2010 value-2007 value)/3
		642	(2012 value-2010 value)/2
2012	6.845		
2013	7.079	234	
2016	8.280	400	(2016 value-2013 value)/3
2017	9.292	1.012	
2019	10.239	474	(2019 value - 2017 value)/2

Notable increases include 857 km² between 2004 and 2005, and 871 km² between 2005 and 2006. However, the most marked increase was between 2016 and 2017, with a jump of 1,012 km², the largest recorded in the entire period. These peaks could be related to external factors, such as changes in environmental policies, variations in agricultural commodity prices, or an increase in illegal activities in the area.

It is important to note some limitations in the data that may affect the accuracy of the analysis. For example, in 2003, an anomalous increase of 1,320 km² was detected, probably caused by many false positives related to the presence of clouds, which led to an overestimation of actual deforestation that year. In 2014, 2015, and 2018, false negatives were also recorded, also due to clouds.

Similarly, in 2008 and 2009 there are possible problems with the chronology of the images, which creates uncertainty about the exact timing of some changes. Another particular case is 2011, when an image with apparent increased deforestation was not reflected in the calculations, pointing to a limitation of the algorithm in detecting subtle changes in image quality.

Despite these difficulties, the overall trend toward increased deforestation is clear, and the data provide a solid basis for understanding how forest loss has evolved in the Jamanxim National Forest.

IV. CONCLUSIONS

This study focused on analyzing deforestation in the Jamanxim National Forest between 2000 and 2019, using digital image processing techniques on satellite data. The results not only confirm that deforestation in this important Amazonian area has been constant and increasing, but also show both the effectiveness and limitations of the methods applied.

A. Summary of Key Findings

The most alarming trend is the steady and marked increase in the deforested area in the Jamanxim National Forest. By 2019, the affected area had reached 10,239 km², almost six times more than the 1,732 km² recorded in 2000. This reflects growing and sustained pressure on the forest, with particularly pronounced peaks, such as the increase of more than 1,000 km² between 2016 and 2017. These periods of acceleration could be related to external factors, such as changes in land use policies, increased economic activity, or fluctuations in the agricultural market.

B. Evaluation of Technique Accuracy

The implementation of a workflow that integrated preprocessing, contrast enhancement, and adaptive segmentation was essential for the identification and quantification of deforested areas. The automatic removal of visual artifacts, such as the year and scale, together with contrast enhancement using CLAHE, proved to be effective steps in optimizing image quality and facilitating subsequent segmentation by clearly highlighting areas of interest (Gonzalez et al., 2018).

Regarding segmentation strategies, global thresholding using the Otsu method was not sufficient due to the chromatic complexity and intensity of the satellite images, which made it difficult to correctly discriminate between different land cover classes (Otsu, 1979). Similarly, manual thresholding in HSV space lacked the adaptability and robustness necessary to handle the variability present between images.

In contrast, the technique based on adaptive thresholding segmentation in HSV space, combined with morphological post-processing, proved to be the most efficient strategy. Conversion to HSV space allowed for better color discrimination, separating chromatic information from intensity (Hema et al., 2020). The adaptive application of the Otsu method to each channel (H, S, and

V) allowed for dynamic adjustment of thresholds according to the particular characteristics of each image, significantly improving segmentation accuracy. Subsequently, the use of morphological operators, such as the removal of small components, closing, opening, and filling holes, was essential to refine the binary masks, reducing noise and artifacts and ensuring the solidity and continuity of the deforested regions. This combination of techniques successfully overcame the limitations of simpler methods, achieving a more accurate, though not perfect, delimitation of the affected areas.

C. Limitations and Challenges

In the field of image processing for deforestation detection, the reliability and accuracy of the analysis can be affected by various factors. Image quality is a crucial aspect, as cloud cover can cause false positives or negatives, compromising the accuracy of the deforested area estimate. In addition, variability in characteristics such as hue and saturation between different captures can lead to an underestimation of deforestation, probably caused by variations in lighting or in the sensors used. On the other hand, errors in the temporal labeling of images introduce uncertainty in the precise chronology of deforestation events, making it difficult to correctly assign changes to specific years. Finally, the effectiveness of the Otsu method depends on the existence of a clear bimodal distribution in the histograms and an adequate configuration of the morphological operators, which limits its general applicability without prior adjustments or recalibrations.

D. Recommendations for Future Work

To mitigate the identified limitations and improve the robustness and reliability in representing deforestation dynamics, several lines of research and improvement are proposed. First, to reduce the incidence of false positives and negatives, it is advisable to use images captured in cloud-free conditions or, failing that, to apply advanced atmospheric correction and cloud removal techniques prior to processing, in order to ensure a more accurate representation of the Earth's surface. Second, it is essential to carry out a thorough verification of the chronology of satellite images and, when possible, apply radiometric normalization methods between different dates to minimize the impact of variations in observed hue and saturation (Song et al., 2001). In addition, the exploration of hybrid segmentation algorithms that integrate spectral information and textural characteristics, as well as the use of machine learning techniques such as convolutional neural networks, are promising alternatives for increasing the accuracy and robustness of deforested area discrimination in complex and variable landscapes (Lillesand et al., 2015). Finally, the incorporation of field validation data, whenever feasible, would allow for a more accurate assessment of the accuracy of classifications and quantified areas, complementing and strengthening remote sensing analysis.

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