Artificial Intelligence to the rescue of the Ecuadorian Amazon: Monitoring changes with Deep Learning

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***Abstract*—Despite the importance of the Amazon region due to its biodiversity, ecosystem services and its enormous contribution to reduce global warming, this region is currently facing critical threats and challenges such as deforestation, urban and agricultural expansion, massive forest fires, illegal/non-regulated mining, among others. Given its vast extension, timely monitoring aimed to mitigate these problems represents a complex task. The lack of adequate tools has hindered environmental monitoring and management in this region, highlighting the need to develop advanced techniques to address these issues. This study focuses on the implementation of methods to detect and classify land cover changes, using an portion of the Ecuadorian Amazon as a case study. Our proposed method combines spectral vegetation indices generated from Sentinel-2 satellite image and deep learning techniques. Multitemporal images have been collected and preprocessed, applying the Bitemporal Adapter Network (BAN) for change detection and ResNet152V2 for land cover classification. The BAN is then re-trained with a specific dataset for the Ecuadorian Amazon. Results attain a good level of accuracy (99.36 unchanged and 89.6 changed) showing that these techniques are effective not only for detecting changes, but also for classifying affected land cover types. These findings provide valuable information for the implementation of conservation and management policies in the Ecuadorian Amazon.**

***Index Terms*—Deep learning, change detection, NDVI, Sentinel-2**

I. Introduction

The growing pressure caused by human activities on natural ecosystems, has intensified the urgency of assessing and mitigating the environmental impact of our interaction with the planet. Tropical deforestation, in particular, stands up as a global problem of alarming proportions, with consequences that transcend national borders and compromise the well-being of future generations [6]. These negative effects can be perceived as the loss of carbon and biodiversity sinks which not only accelerates climate change, but also destabilizes ecosystem services essential for life on Earth.

At the heart of South America, Ecuadorian Amazon is at a critical crossroad. This vast region is recognized for its exceptional biodiversity and crucial role in regulating global climate. Currently, Amazon jungle faces accelerated degradation due to deforestation, forest fires, illegal mining, and uncontrolled expansion of agriculture and urban areas [1]–[3], [18], [38], [39]. The significant magnitude of these challenges demands immediate action and effective monitoring strategies that enable proactive environmental management.

Early detection of land coverage change has become a fundamental pillar of ecosystem conservation. Satellite remote sensing, due to its ability to capture data from large areas of land remotely and periodically, has established itself as a valuable tool towards conservation [25]. Ultimately, the integration of deep learning techniques, such as Convolutional Neural Networks (CNNs), has revolutionized the analysis of satellite imagery, enabling the extraction of detailed and accurate information about changes in land cover [10], [20], [29], [42].

In the scenario describe above, the present work proposes an innovative process aimed to change detection and classification of the Ecuadorian Amazon. Our approach is based on retraining a Bitemporal Adapter Network (BAN) and the use of ResNet152V2. The BAN, a deep neural network architecture designed specifically for Multitemporal image analysis, is specially suited for detecting subtle and complex land coverage changes. Retraining BAN, using a dataset labeled using the Normalized Difference Vegetation Index (NDVI), ensures greater accuracy and robustness in change detection. Once changes are detected, ResNet152V2, a deep convolutional neural network, is used to classify the land coverage types

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affected by those changes, providing valuable information on the nature of the landscape transformation.

The results of this study provide valuable information for environmental management and conservation policy formulation in the Ecuadorian Amazon. The ability to detect, classify and monitor land coverage change in an accurate and timely manner is essential for informed decision making and the implementation of effective conservation strategies. This article is structured as follows: Section 2 reviews the fundamental concepts and state of the art; Section 3 details the methodology; Sections 4 and 5 present and discuss the results; and Section 6 offers conclusions and future perspectives.

II. Background and Related Works

In this section, we present some background information related to change detection on satellite images through the use of deep learning techniques, as well as related works.

A. Background

Satellite imagery, captured by remote sensors, provides a unique perspective of Earth in various regions of the electromagnetic spectrum [8]. Their ability to monitor environmental phenomena and human activities makes them essential tools for natural resource management and conservation [41]. Proper selection of spectral bands, which represent specific ranges of the electromagnetic spectrum, is crucial for applications such as land cover classification [17]. Missions such as Landsat and Sentinel, with their multispectral capabilities, provide valuable data for monitoring vegetation, soil, and ecosystem health [11], [16], [35].

Satellite image analysis has benefited greatly from advances in deep learning. Object detection, which automatically identifies and locates items such as buildings and vehicles, has achieved remarkable accuracy due to the use of Convolutional Neural Networks (CNN) [7], [24]. Image segmentation, which divides an image into meaningful regions, has also experienced significant improvements due to the use of CNNs [5], [26].

Change detection corresponds to the process that recognizes differences in the state of an object or phenomenon over time, and is fundamental in monitoring deforestation and other environmental changes [4]. Common techniques for change detection include image differencing and post-classification comparison [4]. Deep learning with its multilayer neural networks, has been shown to be effective in learning complex data representations [22]. CNNs and Recurrent Neural Networks (RNNs) are particularly useful in image analysis and temporal sequence modeling, respectively [12], [13], [34].

Ecuadorian Amazon faces critical environmental challenges, such as deforestation, artisanal mining, and forest fires. Accurate and timely detection of land coverage changes is essential to address such problems.

In recent years, several deep learning architectures have been developed for change detection in satellite images. Among them, the Bi-Temporal Adaptor Network (BAN) [23] stands out for its transfer learning approach. BAN uses a pre-trained principal model, such as ViTs, CLIP or RemoteCLIP, which is kept frozen during training. A bi-temporal adapter branch (Bi-TAB) processes images from two different times and integrates with the features of the main model to improve change detection. The asymmetric resolution strategy (ARIS) allows BAN to handle resolution differences between input images.

Contrary to other architectures that require extensive training from scratch, BAN leverages pre-existing knowledge from pre-trained models, which reduces the need for large labeled datasets. Its ability to integrate general and specific features makes it suitable for complex change detection in the Ecuadorian Amazon.

B. Related Work

As discussed in the previous section, the last decade has seen considerable advances in change detection using satellite imagery, driven by rapid technological developments and the increasing availability of spatial data. The ability to monitor changes in Earth's surface with a global perspective has generated great interest in a variety of disciplines, from environmental management to urban planning. In this dynamic context, the current state of the art aims to analyze and synthesize the most recent and effective methodologies employed in change detection, exploring the key innovations that have transformed the field and outlining future research directions.

A search for articles related to change detection from Landsat and/or Sentinel satellite images using deep learning was conducted. This search resulted in a number of articles that address the topic and develop various neural network architectures for this purpose. Highlights of each article reviewed are presented below.

A systematic review with meta-analysis conducted in 2020 by Khelifi and Mignotte on change detection in remote sensing with deep learning covered 160 studies [20]. Among their findings, an increasing trend in the number of studies since 2015 can be identified, with a projection of around 100 studies in 2020. CNNs were the most commonly used networks, followed by stacked autoencoders (SAEs), deep belief networks (DBNs), autoencoders (AEs), recurrent neural networks (RNNs), and generative adversarial networks (GANs). SAR (Synthetic Aperture Radar) images were the most commonly used, along with multispectral, aerial and optical images. Khelifi and Mignotte classify change detection approaches into three main groups: supervised methods (predominantly CNN), unsupervised methods and transfer learning-based methods, providing a structured overview of the diversity of approaches in this field.

CNNs have been widely adopted in supervised approaches, using architectures such as VGGNet, GoogLeNet, U-Net, SegNet, FCN, and DeepLab [42]. These networks have demonstrated high performance in semantic segmentation tasks for change detection. However, they face challenges such as pixel-level accuracy and scarcity of labeled training sets. Several innovations have addressed such challenges, as it is the case of [9] who introduced the OSCD (Onera Satellite Change Detection) dataset of 24 Sentinel-2 image pairs to train and evaluate

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two CNN architectures (early and Siamese fusion), achieving superior performance compared to traditional methods.

In [31], convolutional LSTM modules are added to a U-Net network on the extended OSCD dataset, improving the F1 metric by 1.5% and better distinguishing urban changes from other changes in vegetation or clouds. Other studies have integrated semantic segmentation with change detection using LSTM networks in a multitask learning framework [30], showing improvements on several datasets.

Unsupervised approaches based on Generative Adversarial Networks (GANs) have been applied as well, [37], outperforming some supervised methods on OSCD dataset. In [36], an unsupervised method based on temporal anomaly detection with LSTM model was proposed, demonstrating superior performance on two Sentinel-1 datasets.

In addition, data augmentation techniques [27], combinations of CNN and RNN [21], and transfer learning from pre-trained models [19], [28], [33] have been explored to improve performance. For example, [27] combined data augmentation and deep architectures in SZTAKI AirChange, achieving 95.1% accuracy.

III. Change Detection Process

For the development of the satellite image change detection system in the study area, a methodology based on MLOps (Machine Learning Operations) has been implemented and adapted to optimize the selection, retraining and evaluation of deep learning models. Initially, an exhaustive selection of pre-trained models was performed, focusing on those with proven performance in detecting changes in satellite images. Subsequently, the training phase was adapted to focus exclusively on the retraining of the selected model, taking advantage of pre-existing knowledge and adjusting it to the specific characteristics of our dataset. After evaluation and validation of the retrained model, an additional phase was incorporated to classify the detected changes, providing detailed information on the nature of land cover transformations (Figure 1). The choice of MLOps is based on its ability to automate and merge the various stages of the machine learning lifecycle, facilitating the efficient management of large volumes of data and the precise configuration of neural networks [40].

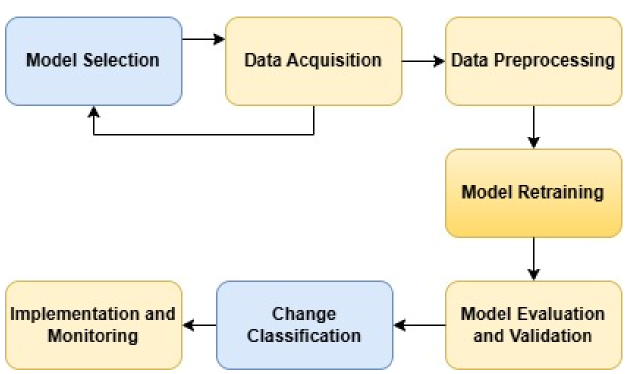

Fig. 1: Diagram of the phases of the MLOps methodology adapted to this study.

A. Model Selection

An exhaustive review of deep learning models for change detection in satellite images has been carried out in first place, discarding those unsuitable for implementation or having data quality problems. Finally, two main models were selected:

BAN (Bitemporal Adapter Network) [23]**:**

The BAN network corresponds to a change detection framework based on a universal baseline model. Its goal is to extract knowledge from base models and use it for change detection. BAN comprises three parts: a frozen base model (e.g., CLIP), a bi-temporal adaptive branch (Bi-TAB), and bridging modules between them. BAN extracts general features through the frozen base model and injects them into Bi-TAB through the bridging modules. Bi-TAB, a model-independent concept, extracts task- or domain-specific features and can be any existing change detection model or stacked blocks. BAN improves the performance of existing change detection models with only few additional learnable parameters. This model will take care of finding changes between two dates in the same area.

ResNet152V2 [32]**:** This model is used to classify land cover and land use into 10 classes, which include: Forest, Annual Crop, Industry, Herbaceous Vegetation, among others. This model has been trained with imagery from the EUROSAT dataset [15] [14] and will be used to classify regions where there exist changes between the before and the after date.

B. Data Acquisition

Data have been obtained from the Sentinel-2 satellite via the Copernicus Browser website. Six areas were selected for training purposes, whereas two other areas, each covering 1.05 km^2, were reserved for validation. Special care was taken to ensure that all images used in the study were cloud-free. Satellite images were taken at an approximate interval of six months to capture significant vegetation changes over time. Specifically, bands 2, 3, 4 and 8 were downloaded in TIFF format, and each image was stored as a 32-bit float file.

To ensure Sentinel-2 images are geometrically well-calibrated and free from translation or rotation offsets, ESA applies a rigorous calibration and validation process. The satellite's orientation (roll, pitch, yaw) is corrected, and images are coregistered using global reference imagery and high-resolution DEMs. This achieves sub-pixel accuracy, with absolute geolocation errors under 8m and multi-temporal alignment within 5m (CE95). Quality is continuously monitored by the Mission Performance Centre (MPC), and processing chains are updated to avoid geometric drifts over time.

C. Data Preprocessing

The data preprocessing phase was of paramount importance for the preparation of the dataset used to train the neural network. This stage was carried out by means of a Python script using the Rasterio library, specialized in remote sensing data management.

Initially, the Normalized Difference Vegetation Index (NDVI) was calculated for each satellite image. The NDVI

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is an indicator that facilitates the evaluation of the presence and state of vegetation, and was calculated using the formula: NDVI = (Band 8 - Band 4) / (Band 8 + Band 4), where Band 8 represents near-infrared reflectance and Band 4 represents visible red reflectance. NDVI values range from -1 to 1, where values close to 1 denote a high presence of healthy vegetation, whereas values close to 0 or negative suggest the absence of vegetation.

To detect changes in land coverage, the absolute difference between NDVI values of two images of the same area, taken on different dates, is calculated. Subsequently, a threshold of 0.2 is applied to determine the significance of a change. If the absolute difference in NDVI between two dates exceeded the 0.2 threshold, the corresponding pixel was considered to show a significant change. This threshold was selected after a process of testing and adjustment, with the objective of maximizing the agreement between the changes detected by NDVI and visual observations. Values higher than 0.2 reduced the extent of the areas of change detected, whereas lower values resulted in the detection of more extensive changes. This process was applied to every pixel in the images, generating a change mask (label) indicating the areas where significant changes have been occurred.

In generating color PNG images from the spectral bands, bands 2 (blue), 3 (green) and 4 (red) were normalized to the range [0, 1] by linear interpolation (see Figure 2). Next, normalized bands were stacked into a three-dimensional matrix, which was converted to an RGB image using the numpy.dstack() function. Finally, the RGB image was saved in PNG format using the Rasterio library. This process was replicated for all the images of the different zones, generating two sets of images: one for earlier dates (folder A) and one for later dates (folder B).

The final dataset consisted of three folders: A (images of the areas at the earlier date), B (images of the same areas at the later date) and Label (change masks indicating areas with significant changes). The images in the Label folder contained two values: white to indicate significant change and black to indicate no change (see Figure 3). This data set was the input for training the BAN neural network.

It is important to note that the use of the Rasterio library facilitated the efficient processing of the remote sensing data, and that the choice of the 0.2 threshold in the NDVI difference is crucial, since this value defines the sensitivity of the change detection. The process to obtain a threshold of 0.2 took a long time. As specified for each BAN network retraining it takes between three to four hours. Future work will consider improving the results of the network predictions and will also implement validations and more processes to support that the chosen parameters are the best. Also, the normalization of the RGB bands ensures that the images possess a range of values suitable for visualization and processing by the neural network.

We must emphasize that the use of Ban's network although the initial training of the neural network requires time and resources, but the bitemporal processing of the image with the trained model is immediate. Furthermore, it is an alternative to change detection using traditional methods.

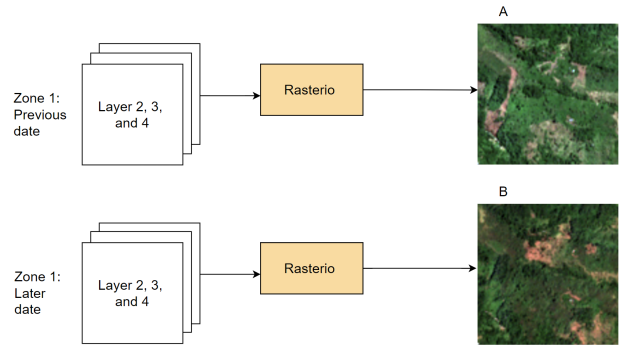

Fig. 2: Generation of color images using layers 2, 3, and 4 of the different zones through the Rasterio library

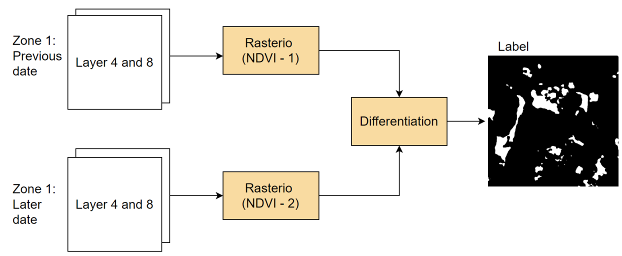

Fig. 3: Generation of the change mask using the calculation of the vegetation index through layers 4 and 8.

D. Model Retraining

The BAN network was retrained with the generated data set, using an High Performance Computer (HPC) with the following specifications: one compute node with an idle time of 600 seconds with no VNC connections, one CPU core, 19,968 MB of total memory, and a 40 GB Nvidia A100 SXM4 GPU, in the gpu-dev partition. Training duration was approximately four hours and was carried out for 40 000 epochs, obtaining satisfactory performance metrics, as can be seen in Table I (in %).

Class	Fscore	Precision	Recall	IoU	Acc
unchanged	99.58	99.36	99.8	99.16	99.8
changed	80.56	89.6	73.18	67.45	73.18

TABLE I: Training performance metrics of the model: it can be seen that the results are good, being better in detecting ”no change”.

E. Model Validation

For validation, new images that had not been previously trained on the network were used. For this, the two areas designated for validation, which were downloaded in the data acquisition phase, were used.

Two validations of the model were performed. For the first validation, all available images (two zones) were used (see

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Table II)). In the second validation, only the images of the first zone were used (see Table III). It can be seen in Table III that the metrics are better than those presented in Table II. This is due to the fact that in the second validation, zone two was excluded, as it contained low quality images and this caused the model to under predict correctly.

Class	Fscore	Precision	Recall	IoU	Acc
unchanged	99.1	99.5	98.71	98.22	98.71
changed	71.37	63.38	81.66	55.48	81.66

TABLE II: Results of the metrics using the two zones downloaded for validation.

Class	Fscore	Precision	Recall	IoU	Acc
unchanged	99.49	99.31	99.68	98.99	99.68
changed	86.14	90.77	81.97	75.66	81.97

TABLE III: Validation using only the first zone for validation shows that the metrics improve because zone 2 contains low-quality images and causes the model to fail in prediction.

F. Change Classification

A pre-trained ResNet152V2 model was used to classify areas before and after change detection. The model was trained with images from the EUROSAT dataset. This dataset contains approximately 27 000 examples distributed in 10 categories. These categories are permanent crops, pastures, residential areas, annual crops, roads, rivers, marine lakes, industrial areas, forests and herbaceous vegetation.

Using code, the changes in the boxes for both images A and B are extracted. It is then resized to 64x64 pixels and sent to the model to determine the label. Figure 4 illustrates the flow to perform the sorting of the changes.

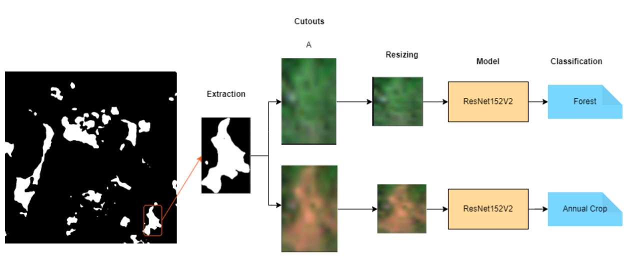

Fig. 4: Flow followed for the classification of the different changes detected with the BAN model.

We should emphasize with reference to the tables, that the difference is that Precision measures overall performance, whereas Accuracy focuses only on predicted positives and is especially sensitive to false positives (FP). This means that an unbalanced class (as in change detection, where the majority of pixels have not changed) makes Accuracy appear high even though the model fails significantly in the minority (changed) class. In addition, the Accuracy penalizes more when the model detects changes where there are none (i.e., many PFs). Regarding the fact that Recall and Accuracy are identical, we must point out that all the values of the metrics shown in the tables are provided by the BAN model. As explained above, this model is reused, therefore, the values that appear to be duplicated will be reviewed in the internal structure of the model to define which of the values is miscalculated and if both are correct.

G. Implementation and Monitoring

After creating the models, a web application was developed using Streamlit.io to display the results of the changes detected in the analyzed areas.

The website lists the analyzed areas and for each of them, shows the respective dates of the color images. The system offers two change detection modes: the first using artificial intelligence (BAN and ResNet152V2 neural networks) and the second based on pixels (NDVI). To use it, two dates have to be selected, which allow the system to load the two images together with their labels. Subsequently, polygonal cropping is performed and the changes are classified.

IV. Evaluation

After training and validating the BAN model, the performance metrics were calculated and showed good results in both training and validation. In both cases, the model has higher accuracy in detecting "no change". This may be caused because the "no change" class has higher pixel coverage in all cases. The metric with the lowest percentage is IoU, which is explained by its relation to the accuracy with which the change or no change prediction overlaps with the actual mask.

As mentioned above, when validation was performed on the entire data set, the performance metrics were inferior compared to using only the first zone. This can be attributed to the poor quality of the second zone images, which caused the model to fail. As seen in Figure 5, validation zone 1 shows similar prediction to the ground truth; it is observed that the model tends to predict almost all changes accurately. However, in zone 2 (Figure 6), it is observed that image B is of poor quality, causing the model to fail in prediction. Therefore, it is recommended to check the quality of the images in the zone where the change is to be predicted to avoid these problems.

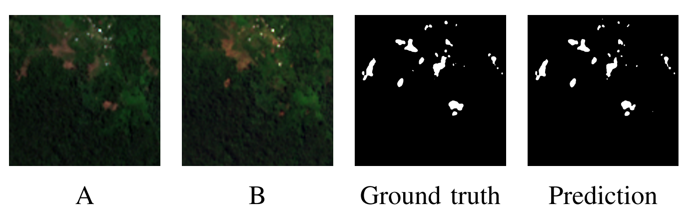

Fig. 5: Validation with data similar to the training data. Two images, A and B, were used, where A corresponds to an earlier date and B to a later date. They were compared with the Ground Truth and the prediction made by the BAN network.

For change classification, a pre-trained model was used; however, it does not always perform optimally due to the quality of the images. This is due to the fact that the clippings are resized to 64x64 pixels.

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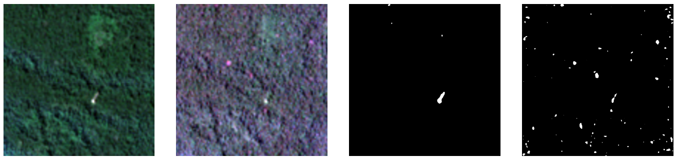

A B Ground truth Prediction

Fig. 6: Validation with low-quality images. As shown in the figure, the model predicts many more changes than actually exist.

To verify the accuracy of the satellite imagery and the change detection process, an in situ validation was performed. This involved taking the coordinates of the areas shaped and evaluated by the model to visit them in person. During these visits, the technicians confirmed that the color changes evidenced in the images are due to cattle grazing, which causes the grass to take on a brownish hue. Over time, these areas recover a green color due to vegetation growth.

V. Conclusions and Future Work

This study has demonstrated the effectiveness of deep learning techniques, specifically BAN network retraining, for land coverage change detection in the Ecuadorian Amazon using Sentinel-2 satellite imagery. The BAN network, adapted with a region-specific dataset, demonstrated a remarkable ability to identify patterns of vegetation change. However, the lack of comparable models for detecting vegetation change in the Amazon limits the possibility of direct comparisons with other studies.

Classification of detected changes was performed using the ResNet152V2 network, applied directly without retraining. Although the results were adequate, it is recognized that the performance of this network could be significantly optimized by retraining it using local data. This finding underlines the importance of adapting deep learning models to the specific characteristics of the study region to improve their accuracy and reliability.

The results of this research have significant implications for the conservation and environmental management of the Ecuadorian Amazon. The ability to monitor land cover change in an accurate and timely manner provides decision makers with a valuable tool for the protection of this critical ecosystem. The information generated can be used to more effectively address deforestation, habitat degradation, and other environmental challenges.

Nonetheless, this study also recognizes several limitations. The quality of satellite imagery and the availability of Amazon-specific datasets are crucial factors that may affect the accuracy and generalizability of the results.

In future research, it is proposed:

- Retrain BAN and ResNet152V2 networks with larger and more diversified local datasets to improve their performance and adaptability.
- Explore and compare the performance of other deep learning architectures used for change detection to identify the most suitable for the region.
- Apply and adapt the developed methodology to other areas of the Amazon, evaluating its generalizability and robustness.
- Develop new specific datasets for change detection and land cover classification in Amazonia, thus enriching the resources available for research.
- Investigate the use of image quality enhancement techniques and alternative data sources to mitigate limitations imposed by the quality of satellite imagery.
- Explore the use of all available spectral bands in satellite imagery to improve the accuracy of change detection and classification.
- Deepen the analysis of the types of change detected, relating them to human activities and the ecological processes that generate them.

These lines of research will allow us to deepen our knowledge of land cover changes in the Ecuadorian Amazon and to develop more effective tools for its conservation and sustainable management.

Acknowledgment

El proyecto ”GEOF-02/2024:Monitoreando el cambio de cobertura arbórea con sensores remotos y Deep Learning” fue cofinanciado por: el Instituto Panamericano de Geografía e Historia (IPGH); la Universidad Tecnológica del Uruguay; la Cooperativa Multiactiva de Jóvenes del Guaviare, Colombia; y el Vicerrectorado de Investigación e Innovación de la Universidad de Cuenca, Ecuador.

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