Evaluation of U-Net transfer learning model for semantic segmentation of landslides in the Colombian tropical mountain region

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Abstract. Landslides in tropical regions, like the Colombian Andean region, pose unique challenges due to factors such as intense rainfall, steep slopes, and complex terrains. Mapping historical and current landslide activity through inventory maps is essential in tropical mountainous regions. While satellite data is commonly used for mapping, it can be time-consuming and manual-intensive, limiting inventory availability. Deep Learning (DL) models, especially Convolutional Neural Networks (CNNs), have shown promise in remote sensing applications with High Resolution (HR) imagery, including landslide detection. Despite advancements, their use in this field is still relatively limited. This study assesses the effectiveness of U-Net model, for automated landslide detection using spectral data from optical satellite imagery (RGB bands), two DEM-derived geo-indices (slope and curvature), and two Synthetic Aperture Radar (SAR) layers (VV amplitude pre- and post-landslide event in May 2015) across three image models (3, 5, and 7 bands). Initially, data is combined into multi-band images, and the model is trained in the "La Argelia" river basin in Colombia's Pacific region. Subsequently, the model is tested in the "La Liboriana" river basin in the western Andean region. The landslide detection results within the inference area are validated by comparing them with the landslide inventory and segmentation results. The U-Net model demonstrates good performance (F1-score around 0.70) for landslide detection, as confirmed in various geographical settings. By utilizing DL models and combining high-resolution satellite imagery, topographical, and SAR data, a comprehensive space-time mapping of landslides can be achieved. This approach has the potential to greatly improve the accuracy and effectiveness of landslide mapping, offering a more holistic view of the temporal dynamics related to these natural hazards.

1 Introduction

In mountainous regions, natural hazards such as landslides, avalanches, floods, and debris flows can cause significant property damage and human casualties [1]. Making their accurate detection and mapping is crucial for risk management and mitigation efforts. This plays a critical role in emergency response and long-term land use planning [2]. Landslides in

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tropical regions present unique challenges due to the interplay of various factors. The combination of intense rainfall, steep slopes, and geologically complex terrains found in some regions, as Andean region of Colombia, can contribute to heightened landslide susceptibility. Considering that landslides occur systematically worldwide, it is essential to develop research on landslide susceptibility and risks in order to support adequate land use planning processes [3]. Semantic segmentation is a computer vision task that aim to classify landslide pixels and non-landslide pixels to delineate locations, extents, and boundaries of landslides [2]. The inventory of morpho-dynamic processes is the most important input to establish the relationship between a factor or combination of conditioning factors and the possibility of the occurrence of mass movements [4]. The knowledge of the spatial extent of the past and present landslide activity, compiled in the form of a landslide inventory (LI) map, is essential for effective landslide risk management, and it has high demand for risk assessment of this natural hazard, particularly in tropical mountainous regions [5] and detailed inventories are crucial for the succeeding phases of landslide risk studies [6]. High-resolution data acquired by satellites are often used to map landslides by identifying morphological expressions that can be associated with past and/or recent deformation [7]. Nevertheless, this process can be slow, difficult, and additionally, it requires extensive manual efforts and time, making landslides inventories not available for all affected regions.

In literature can be found a Machine Learning Approach (MLA) based on multi-temporal satellite and object segmentation processes. From these approaches, extraction features and classification process are carried out under a deep learning model (Convolutional Neural Network - CNN) to obtain the landslides probabilities. Finally, this information feeds an Object-based image analysis (OBIA) segmentation process for landslide detection features. This kind of approach raises good performance and has been used before by [8] considering optical data, while [9] considered also some landcover optical indices. Deep Learning (DL) and, mainly, CNNs have been used in various remote sensing tasks on Very High Resolution (VHR) imagery, such as classification, segmentation, and object detection. Nevertheless, few studies use CNNs for landslide detection [10]. [11] evaluated various MLA on VHR optical data from the RapidEye satellite and topographic factors, and [12] used different CNNs on non-nadiral and crowdsourced optical images for landslides classification. Also, [5] used residual networks for landslide detection using spectral (RGB bands) and topographic information. Regarding radar images, [10] applied CNN methods to landslide detection based on ground range detected (GRD) Synthetic Aperture Radar (SAR) imagery, using both VV (Vertical-Vertical) and VH (Vertical-Horizontal) polarization amplitudes, achieving accuracies comparable to optical data performance.

The U-Net model, with its encoder-decoder architecture and skip connections, has shown exceptional performance in various image segmentation tasks. Recent studies have addressed this issue, analysing and validating the potential of some CNN transfer learning architectures as U-Net, Res-Net, Attention U-Net, among others, and ML approaches for automated landslide detection using spectral information from the optical satellite imagery and topographical data, [2]; [6]; [13]; [14]; [15] and [16]. [2] proposed a dual‑encoder U‑Net for landslide detection using Sentinel‑2 and Digital Elevation Model (DEM) data. [1] presented an innovative deep learning strategy employing transfer learning that allows for the Attention Deep Supervision Multi-Scale U-Net model to be adapted for landslide detection tasks. [3] tested the applicability and effectiveness of a U-Net for semantic segmentation of Landsat 8 satellite imagery to the identification of landslide scars. Regarding SAR imagery, [10], [17], have used Sentinel 1 data. Because a space-time mapping landslide is challenging and requires a lot of time and resources to delineate landslide footprints of affected areas, the current advances in DL models and VHR satellite imagery can contribute positively to mapping landslides not just spatially but also temporally. Independently of the adopted approach for landslide detection, a layer (dataset) of past landslide is needed for validation process, hence, it is necessary to delineate landslide footprints of affected areas from visual interpretation of satellite imagery and field survey recognition. This process is the beginning of all automatic or semi-automatic workflows of landslide detection.

In this study, we evaluate the potential of a deep transfer learning architectures as U-Net for automated landslide detection using spectral information from the optical satellite imagery (RGB bands), two DEM-derived geo-indices (slope and curvature), and two Synthetic Aperture Radar (SAR) layers (VV amplitude, pre -and- post landslide event in May 2015), through three image models (3, 5 and 7 bands). In the first place, we stack data in a multi-band images. Then, the deep transfer learning model is trained in the “La Argelia” river basin in the Pacific region in Colombia, and finally, the trained model is evaluated in the “La Liboriana” river basin in the western zone of the Andean region, where around 160 shallow landslides were triggered by the May 18th, 2015 rainstorm and an associated flash flood and debris flow afterwards killed more than 100 inhabitants and caused considerable amount of economic losses and infrastructure damage. Once obtained the landslide, the results were validated considering the conformity between the landslide inventory and the results of segmentation applied method.

2 Materials and methods

2.1 Study area

The study area for deep transfer learning model comprises a training area in the “La Argelia” river basin in the Pacific region in Colombia, and an inference area corresponding to the “La Liboriana” river basin in the western zone of the Colombian Andean region (Fig. 1). Both basins are similar especially in their climatology, both belong to a tropical zone and are strongly exposed to high intensity rainfall cycles. The "La Argelia" river basin is located in the municipality of "Carmen de Atrato" in the department of "Chocó". In this area, a very humid low montane forest is identified, with temperature between 12° and 18° C, with an average annual rainfall between 2,000 to 4,000 mm. The area is a mountainous territory with steep ravines, poorly or moderately evolved soils and generally non-saturated with rocky outcrops and in others with volcanic ash residues. The predominant geologic formation in the basin is the "Barroso" formation, which is part of the "Cañasgordas" group. It contains spillites, diabases, basalts, porphyritic basalts, agglomerates and breccia’s. North of "Carmen de Atrato" there are lenticular bodies of diabases with dark chert intercalations, important for their relation to hydrothermal and volcano-sedimentary mineralization.

The “La Liboriana” river basin is located in the municipality of "Salgar" in the department of "Antioquia", characterized by steep slopes and a humid tropical climate. About 67% of the total basin area has a slope gradient that exceeds 30°. The mean elevation in the basin is 2,487 m.a.s.l. The average annual temperature is 22° C and rainfall about 3,000 mm. Its geomorphology consists of a mountainous region with a rugged morphology, narrow valleys and very steep slopes with forests in the upper part. A sedimentary rock formation of the Cretaceous period (shales, siltstones, sandstones, and conglomerates with some intercalations) and an intrusive body predominate the geological environment of the basin. These rock bodies undergo severe in situ weathering due to the humid tropical climate, forming saprolite and well-developed residual soils. The soils have different textures, with a predominance of clay and limestone. At organic material predominates in the first layer, while the second layer has underlying clayey soil. The soils are well drained and have a low retention capacity. Soil depth depends on the slope, with values varying between 0.2 and 1.0 m [18].

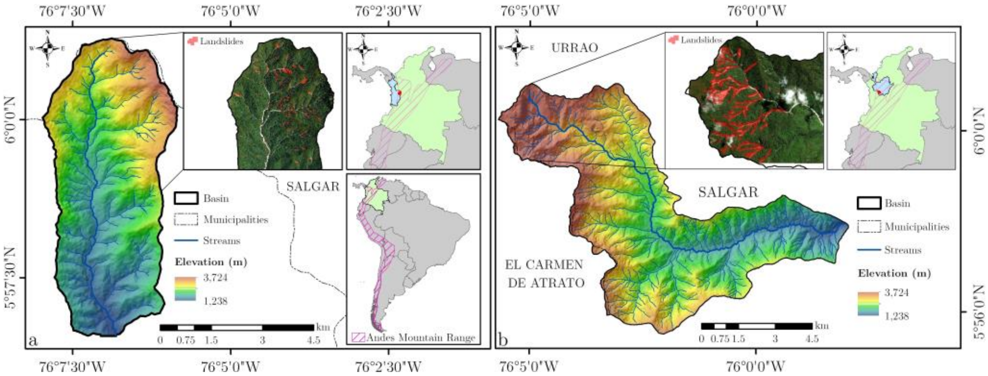

Fig. 1. Geographical location of study area: a) Training and test area: "La Argelia" river basin. b) Inference area: "La Liboriana" river basin.

2.2 U-Net model for semantic segmentation of landslides

In this study was applied a U-Net architecture for landslide segmentation and classification, in Keras library allowing the implementation of neural network models in Python programming language. The Keras library was applied with the open-source TensorFlow backend. The training, validation, testing and inference procedures were performed using a powerful GPU (Graphics Processing Units) with 4 GB of RAM to optimize processing time.

The U-Net model employs a distinctive architecture that effectively captures both low-level and high-level representations. The encoder path of the U-Net model is responsible for capturing low-level representations. It follows a traditional Convolutional Neural Network (CNN) architecture, consisting of a series of convolutional blocks. Each convolutional block includes two convolutional layers with a 3 x 3 kernel size, followed by a 2 x 2 max-pooling layer. To introduce non-linearity, the rectified linear unit (ReLU) activation function is applied to each convolutional layer. Additionally, at the end of each convolutional block in the encoder route, a 2 x 2 max-pooling layer is incorporated to perform non-linear down-sampling.

On the other hand, the decoder path of the U-Net model captures high-level representations and facilitates the reconstruction of the segmented output. In the decoder path, instead of the max-pooling layer used in the encoder path, a 2 x 2 up-sampling layer is employed to perform up-sampling. The up-sampling layer plays a crucial role in restoring the spatial resolution of the feature maps. Following the up-sampling layer, a 3 x 3 convolutional layer is added to process the up-sampled features and extract higher-level information. The combination of the up-sampling layer and the subsequent convolutional layer in the decoder path allows the U-Net model to effectively reconstruct the detailed structures and boundaries of the target objects. This architecture enables precise segmentation of landslides by effectively fusing low-level and high-level representations, resulting in accurate and detailed output masks (Fig. 2).

In order to carry out a training and inference processes using the U-Net, we used two high resolutions (12.5-m pixel) optical satellite images (2014 and 2015 respectively) provided by service HERE from the SAS Planet application, composited by three bands: Blue, Green, and Red. Also, a 12.5-m spatial resolution Digital Terrain Model (DTM) extracted from Alos Palsar data provided by the Alaska Satellite Facility [19]. Finally, two descending orbit Sentinel-1A wide-swath SAR data images (C-band, VV polarisation) [20]. It was used the satellite images to obtain the associated masks of landslide footprint, through to a mask layer indicating the landslide bodies (class label 1) and non-landslide regions (class label 0), respectively. Later, in this approach it was necessary to stack data in a three multi-band images. The next stage was a training and validation processes of transfer learning model U-Net using the inventory of landslides of the study area "La Argelia" river basin. This process involved convolutional, max-pooling and up-sampling process for a semantic segmentation of the landslide class (Fig. 2). In this process, we made a sub-division of images through a patching process, which allowed processing in blocks, which were run on GPU for an optimization of the processing time. With the aim to obtain the best performance in detection process, we used many combinations of hyper-parameters according to the reported values in Table 1.

Table 1. Used values for hyper-parametrization and setting of the U-Net models.

Item	Values
Filters	16, 32, 64
Learning rate	5e-4, 10e-4, 5e-5, 10e-5, 5e-6, 10e-6
Batch size	16, 32, 64
Epochs	150
Optimizer	Adam
Lost function	Dice loss
Performance metric	Precision, Recall, F1-score

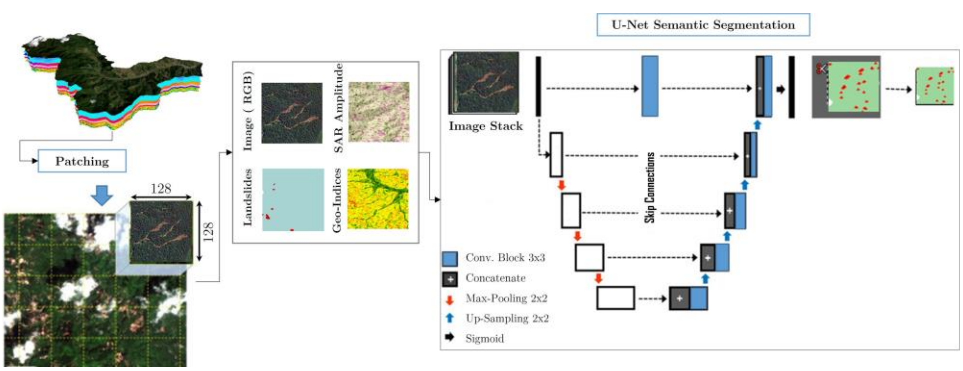

Fig. 2. U-Net model for semantic segmentation of landslides in study area. Adapted from [15].

Once detected the landslides within the study area, it was necessary to validate its accuracy and quality. For this validation we considered some quantitative accuracy assessment methods, commonly used in literature for evaluating the DL methods, [11], [12], [17], considering the conformity between the landslide inventory layer and the results of segmentation applied method. The comparison of accuracies is based on the F1-score, recall, and precision. These metrics are based on true positives (TP), false positives (FP), and false negatives (FN). TP are pixels correctly classified as landslides. FP represents the pixels incorrectly classified as landslides, and FN the pixels incorrectly classified as the background [16]. The precision (P) metric is used to discover how many landslide areas are correctly detected. The recall (R) metric is applied to determine how much of the landslide inventories were detected in the images. The balance between precision and recall is calculated through the F1-score for this aim [9]. These metrics can be calculated by mean of equations:

$$Precision\ (P) = \frac{TP}{TP + FP} \quad (1)$$

$$Recall\ (R) = \frac{TP}{TP + FN} \quad (2)$$

$$F1 - score = 2 \times \frac{P \times R}{P + R} \quad (3)$$

Finally, once trained the U-Net models and accepted its performance levels, we used the transfer learning process for landslide detection in the inference area "La Liboriana" river basin, obtaining the results shown in Fig. 3.

3 Results and discussion

As presented in Table 2, the considered U-Net models achieved the best landslides detection performance results according to hyper-parameters values.

Table 2. Best configuration performance of each training model.

Image U-Net model	Bands	Hyper parameters
RGB	3	Filters: 64, Learning rate: 5E-4, Batch size: 16
RGB + Slope + Curvature	5	Filters: 64, Learning rate: 5E-4, Batch size: 16
RGB + Slope + Curvature + VV Amplitudes	7	Filters: 32, Learning rate: 5E-4, Batch size: 32

According to the results shown in Fig. 3a, it can be noticed that the 3-band image model detects landslides in areas corresponding to cloud cover and in other areas where, according to the landslide inventory, there is no record of movement. Although the 5-bands image model (Fig. 3b) improves performance through fewer false positives in free landslide areas according to inventory, landslide detection in cloud cover persists. Finally, with the 7-bands image model (Fig. 3c), we can observe the significant potential of SAR data, particularly in areas where optical sensors are limited due to cloud cover. With its ability to penetrate through clouds, SAR data has the potential to greatly improve the effectiveness of landslide detection using a remote sensing approach, obtaining a better performance detecting areas correctly classified as landslide class (Table 3). The confusion matrix elements in Table 3 are given in number of pixels.

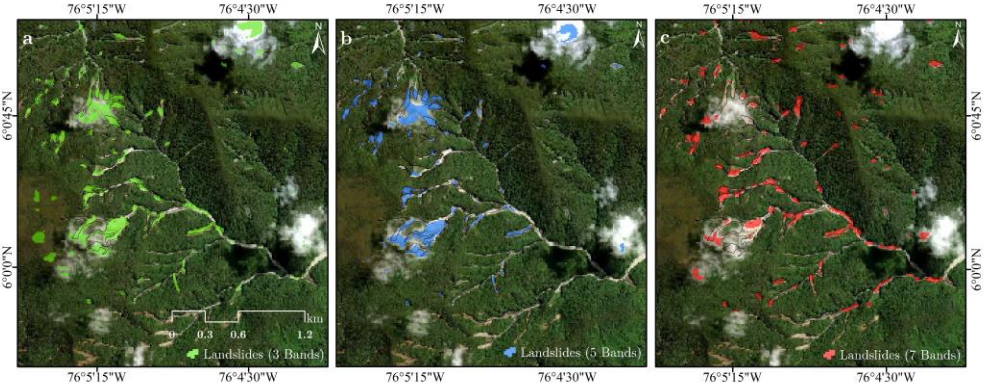

Fig. 3. Landslide detection results generated by U-Net models in "La Liboriana" river basin.

Table 3. Best performance model of U-Net models in training zone.

Image model	Precision	Recall	F1-score
RGB	0.67	0.73	0.70
RGB + Slope + Curvature	0.70	0.65	0.67
RGB + Slope + Curvature + VVs	0.65	0.75	0.70

The obtained results are according and similar to results of other studies in some tropical areas as Rio Grande do Sul (Brazil) (F1-score: 0.65), and Myanmar (F1-score: 0.74) for rainfall-induced landslide detection using the HR-GLDD globally distributed dataset presented by [13], Rio de Janeiro (Brazil) (F1-score: 0.53) [21], and Philippines (F1-score: 0.60) [15], Taiwan (F1-score: 0.64) [22] and south-eastern areas of China with tropical climate analyzed by [13] (F1-score: 0.68). Because obtained values of precision and recall are similar, our predictions can be considered balanced. Fig. 4 and Table 4, present the predicted results according to the true positives, true negatives, false positives and false negatives identified based on the areas detected as landslides by U-Net models and reference images (masks).

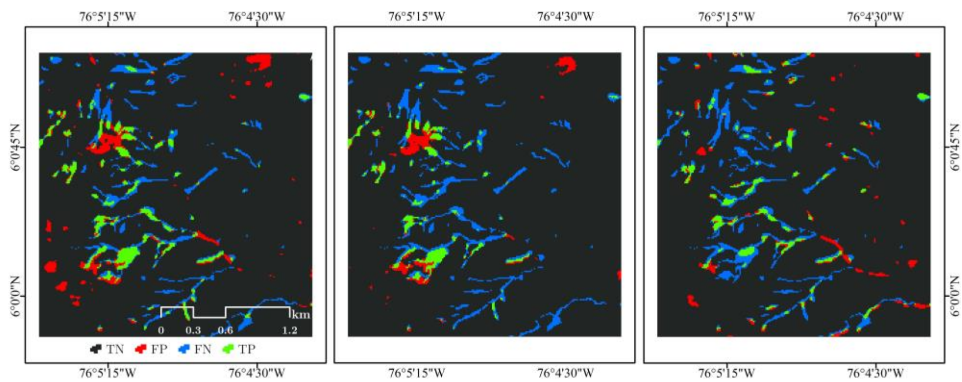

Fig. 4. Detected landslides by U-Net models in "La Liboriana" river basin in terms of confusion matrix elements.

In this case, accuracy indicator was not used since it is not considered a relevant performance evaluation measure for neural networks trained under datasets that have class imbalance [3]. The measurement of accuracy, based on the proportion of correctly classified pixels, can present a distorted representation of the training process due to the predominant presence of non-landslide areas. As a result of this limitation, U-Net models can be directly impacted by the scarcity of training samples and the inherent class imbalance within the dataset. These factors pose significant obstacles to achieving optimal performance and accurate segmentation results. Addressing these challenges and mitigating their impact is crucial for advancing the effectiveness of DL techniques for landslide detection.

Table 4. Confusion matrix values obtained in the inference zone.

Image model	TP	FP	FN	TN
RGB	1258	1113	2021	38441
RGB + Slope + Curvature	873	683	2406	38871
RGB + Slope + Curvature + VVs	922	682	2357	38872

DL models typically demand a substantial amount of training data to enhance their robustness. However, the application of this technique in landslide detection, particularly in remote sensing, faces significant challenges due to the scarcity of ground truth landslide data, the laborious process of acquiring accurate samples, and class imbalance issues. Obtaining precise labelling data for model training often necessitates extensive efforts and resources, including manual interpretation of multi-temporal imagery, even field surveys. The acquisition of such data is a time-consuming task that requires expert knowledge. Unfortunately, these challenges restrict the availability of a large and diverse dataset, hindering the full potential of deep learning models in landslide detection.

The prevalence of clouds, shadows, atmospheric noise, and image artefacts like haze makes difficult at times to accurately and regularly map landslides. [1] stated that a possible solution to the problem of cloud coverage is to complement the optical image mapping with a parallel landslide detection procedure based on SAR imagery. This was corroborated and validated in this study since the results of 7-bands image model which consider RGB data, geo-indices (slope and curvature) and VV amplitude pre- and -post landslide events, showed better performance and adjustment detecting landslides respect to ground truth landslide footprints. In our study, the use of the topographical data as an additional bands helped improve the performance of the models, differing from the results obtained by [5] and [11]. Nevertheless, although 5-bands image model (RGB + geo-indices) improve the landslide detection regarding landslide segmentation in cloud areas considering geomorphologic characteristics, it does not completely correct this situation as model that consider SAR data, with its consequent relevant benefits cited by [10]. It is convenient to analyze spatial resolutions and the architectures of models to address the most effective ways to use DEM-derived indices and SAR data with deep learning models. Future studies should explore multi-input models that can be trained with different input sizes; and evaluate different post-processing segmentation techniques to increase the quality of the results [23].

The U-Net model has shown promise in detecting landslides from remote sensing imagery worldwide [6], [10], [13], [24–26]. However, the method has limitations. One limitation is the subjectivity and uncertainty in manually delineating landslides that are used as reference for the training process. This can lead to the detection of only visible landslide bodies, without considering landslides zones masked by local disturbance factors such as vegetation cover or relief shadows. Therefore, the model may still underpredict the areas affected by landslides, even if it achieves high accuracy according to performance metrics [1].

There are some challenges of accurately mapping landslides using remote sensing imagery. Vegetation cover can significantly affect the detection of landslides, with areas covered by dense vegetation proving particularly challenging to map. Similarly, relief shadows can also pose a challenge to landslide mapping. These findings suggest that the limitations of the U-Net model may be a common issue in landslide mapping using remote sensing imagery.

4 Conclusions

Integrating topographical data as an additional band in the models has shown promise in improving accuracy, and the inclusion of SAR data in the 7-bands image model demonstrated its significant potential in improving landslide detection, particularly in areas affected by cloud cover. The ability of SAR data to penetrate through clouds addresses the limitations of optical sensors and enhances the effectiveness of remote sensing approaches. This finding aligns with previous studies conducted in various tropical regions, emphasizing the value of SAR data for rainfall-induced landslide detection.

This study evaluated the applicability of a convolutional neural network architecture as U-Net model for the identification and semantic segmentation of landslides from free satellite imagery (optical and radar) in two basins of the Colombian tropical mountain region. The proposed methodology considers a U-Net model trained with optical imagery joined to geo-indices (DEM-derived) and SAR data, with the potential to be applied for dynamic landslide mapping for the generation and/or updating landslide databases and inventories. Nonetheless, some improvements are still needed to increase the performance of the proposed methodology to detect landslides in tropical complex environments as Colombian Andean region.

Deep learning models, such as U-Net, face challenges in landslide detection due to the scarcity of training samples and the inherent class imbalance within the dataset. The limitation of using accuracy as an evaluation measure for neural networks trained on imbalanced datasets is acknowledged, as it can provide a distorted representation of the training process. The scarcity of landslide samples compared to non-landslide areas can adversely affect the performance and segmentation accuracy of U-Net models. Therefore, addressing these challenges and mitigating their impact is crucial for advancing the effectiveness of deep learning techniques in landslide detection. Although, we consider our proposal as a cost-effective method because consider the use of free satellite imagery under a relative low pre-processing, detecting landslides in a quick way. Hence, we consider this methodology with a huge potential for the improvement of landslide mapping in similar geographical contexts.

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