Monitoring Landslide Progression in Leyte, Philippines using Sentinel-2 Imagery and AI-Based Semantic Segmentation

Recto B.A.B.[1*], Lagria R.F.A.[1], Agapito J.V.C.[1] and Minimo L.G.[2,3]

[1]Department of Industrial Engineering and Operations Research, University of the Philippines Diliman, Quezon City, Philippines

[2]Science and Society Program, University of the Philippines Diliman, Quezon City, Philippines

[3]University of the Philippines Resilience Institute, Quezon City, Philippines

*bbrecto@up.edu.ph

Abstract *Mountainous regions are often devastated by landslides especially following triggering events such as intense rainfall, earthquakes, and volcanic activity. While numerous studies have applied artificial intelligence (AI) for detecting landslides immediately after such events, few have focused on monitoring their spatial and temporal progression over time. This study highlights the potential of AI-based semantic segmentation to monitor landslide progression using multitemporal Sentinel-2 imagery, following the impact of Tropical Storm Agaton in the province of Leyte, Philippines, in April 2022. Sentinel-2 Level 2A images captured immediately after the event, as well as one month, three months, six months, and one year later were acquired and clipped to the municipality of Abuyog in Leyte. From each image, the Red, Green, Blue, and Near-Infrared (NIR) bands, along with the computed Normalized Difference Vegetation Index (NDVI) were extracted and stacked with the elevation values and slope derived from an Interferometric Synthetic Aperture Radar (IFSAR) Digital Terrain Model (DTM) to create multiband inputs for analysis. A U-Net model, trained on labeled landslide polygons which were validated by experts, was then utilized to detect the extent and progression of landslide-affected areas across sequential satellite images captured over time. The model demonstrated consistent segmentation performance across all dates, with F1-scores ranging from 0.684 to 0.821. The results show subtle spatial progression of landslides in certain areas in images taken immediately after the typhoon and those captured one month later, likely due to factors such as prolonged rainfall and terrain instability. In contrast, early signs of vegetation recovery become apparent in some regions between six months to one year after the event. This study provides a starting point for further research on post-disaster recovery monitoring and the identification of areas at risk of subsequent landslides, offering practical value to local government units in planning and decision-making.*

Keywords: Landslide, Change Detection, Sentinel-2, Artificial Intelligence, U-Net

Introduction

Landslides are geological hazards that commonly occur in mountainous and highly elevated regions, where unstable slopes are exposed to triggering events such as intense or prolonged rainfall, seismic activity, or volcanic eruptions (Li et al., 2024). Due to the Philippine archipelago's geographic setting, studies have shown that most landslide occurrences in the country are triggered by heavy or prolonged rainfall, often developing on slopes that are made up of weak, weathered, and fractured materials (Padrones et al., 2017). Beyond their immediate destructive force, landslides also present long-term challenges for disaster management, including the displacement of populations and the recurring instability of affected slopes.

Several studies have focused on methods for detecting landslides from a single satellite image acquired immediately after a triggering event. The identification of landslides using satellite data provides valuable information on the immediate extent of damage without having to go through the traditional and manual methods such as visual interpretation by experts, remote sensing analysis, and field validation, which are usually prone to subjectivity, resource intensive, and time-consuming. However, this approach only presents a static picture of hazard distribution. To gain a more comprehensive understanding, it is also necessary to examine how landslide-affected areas evolve over time, capturing important dynamics such as its persistence on unstable slopes, expansion into adjacent areas, or recovery through vegetation regrowth. Monitoring these temporal patterns is critical not only for understanding the behavior of landslides over time but also for anticipating secondary failures that may occur weeks or months after the initial event. Addressing this gap would significantly contribute to the development of more effective policies and programs that can better support post-disaster rehabilitation, resource allocation, and long-term risk reduction.

This study analyzes the temporal progression of landslides through semantic segmentation using a U-Net model applied to multitemporal Sentinel-2 imagery bands, complemented by elevation and slope information derived from an Interferometric Synthetic Aperture Radar (IFSAR) Digital Terrain Model (DTM). Specifically, the study compares five post-event image dates spanning one year against the baseline event image by generating change maps that classify pixels into persistent non-landslide, persistent landslide, landslide-to-non-landslide indicating recovery, and non-landslide-to-landslide indicating progression. Through this methodology, local government units (LGUs) can be equipped with timely, cost-efficient, and data-driven insights on the persistence and recovery of landslides. The findings of this study, along with future research on this topic, can facilitate the prioritization of high-risk areas, guide resource allocation for post-disaster rehabilitation, and support long-term land-use and development planning. Ultimately, this approach greatly contributes to proactive disaster risk reduction strategies, strengthens resilience in vulnerable communities, and complements existing hazard mapping and susceptibility assessments traditionally used by LGUs.

Literature Review

With the advancement of remote sensing technologies, numerous studies have explored the use of artificial intelligence (AI) based models for landslide detection using satellite imagery. These methods provide faster and more objective assessments of affected areas compared to traditional approaches, which are often time-consuming and highly dependent on the interpretation of experts. In particular, deep learning models have demonstrated potential in processing multiple satellite images to automatically identify areas susceptible to or affected by landslides, offering an effective alternative to conventional methods. By reducing reliance on manual delineation and minimizing the inconsistencies of subjective visual inspections, AI-based approaches provide more consistent and reliable results (Das et al., 2023; He et al., 2024).

The U-Net model has been widely applied in landslide detection studies. It is a convolutional neural network (CNN) designed for semantic segmentation and is particularly effective for tasks requiring precise pixel-level classification. According to Dong et al. (2022), U-Net is well-suited for small datasets due to its efficient use of feature information, achieving high segmentation accuracy with relatively low computational complexity. Compared with other deep learning models such as FCN, DeepLab, and ResU-Net, U-Net offers several advantages, including its simplicity, strong performance in boundary detection, and robustness when only limited training data are available. However, its basic form presents limitations, including difficulty in capturing multi-scale features and in distinguishing landslides from complex backgrounds (Dong et al., 2022). Li et al. (2004) applied the U-Net model for landslide detection using Sentinel-2 imagery. The study used the Red, Green, Blue, and Near-Infrared (NIR) bands, together with elevation and slope data derived from a Digital Elevation Model (DEM), as training and test inputs for the model, achieving relatively good performance with a recall of 62.17, a precision of 79.91, and an F1-score of 69.94.

However, studies focusing on the monitoring of landslide progression over time remain limited. Understanding how landslides change across different periods can provide critical insights for disaster risk reduction and management. For instance, Qu et al. (2020) examined post-failure changes in the Huangnibazi region of China using Sentinel-2 imagery. The study analyzed ten Sentinel-2 images to assess the use of multispectral data in tracking landslide dynamics. By calculating the normalized difference vegetation index (NDVI) to delineate landslide scars and validating the results with unmanned aerial vehicle (UAV) orthoimages, the researchers classified the landslide process into three stages: the startup and acceleration stage, the front and lateral edge expansion stage, and the stabilization stage. Hence, incorporating spectral bands, together with NDVI, as well as elevation and slope data, offers a promising avenue for advancing this line of research by enhancing the ability to capture and monitor landslide progression more comprehensively.

Methodology

The overall workflow of this study (Figure 1) integrates multitemporal satellite imagery with topographic data to detect and monitor landslide progression. Sentinel-2 images acquired immediately after Tropical Storm Agaton and at four subsequent intervals (1 month, 3 months, 6 months, and 1 year later) were combined with elevation and slope information derived from IFSAR DTM. These datasets, consisting of spectral bands (Red, Green, Blue, and Near-Infrared) and topographic variables, were stacked and processed as inputs to a U-Net deep learning model for semantic segmentation of landslides. The model outputs were then compared across different dates to generate change maps and quantify persistence, progression, and recovery of landslide areas through area-based analysis.

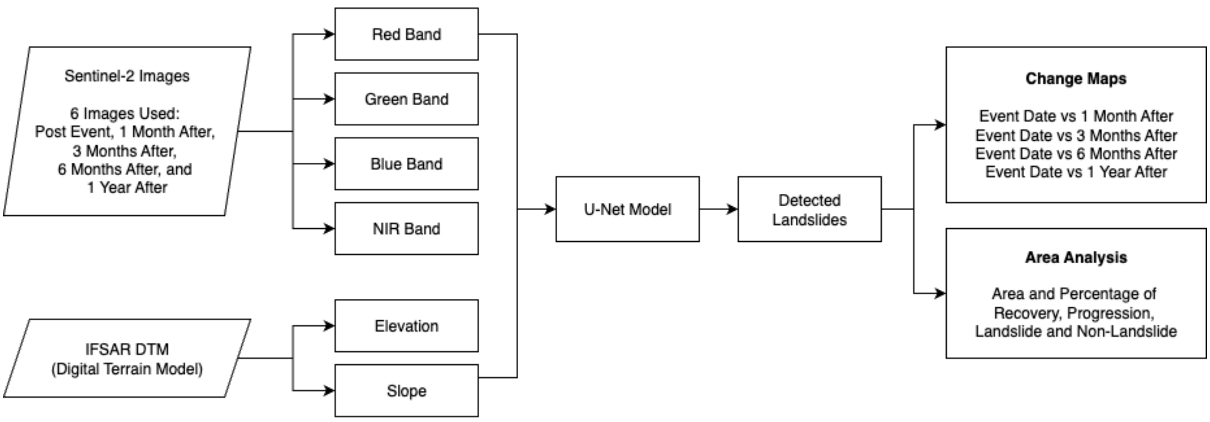

Figure 1. General Workflow for Monitoring Landslide Progression.

a. Study Area

Leyte Island, situated in the Eastern Visayas region of the Philippines, is highly susceptible to landslides due to its steep terrain and underlying geological conditions. Eco et al. (2015) documented 280 landslides across the province between 2002 and 2014, with the majority concentrated in upland areas. More recently, disaster reports have highlighted the continuing severity of such events where the NDRRMC (2021; 2022) recorded a total of 27 landslides during Super Typhoon Odette (Rai) and Tropical Storm Agaton (Megi). Minimo et al. (2023) also reported around 750 landslides and/or erosion sites detected through satellite imagery following Tropical Storm Agaton in 2022.

Figure 2 shows the location of Abuyog, Leyte, which experienced numerous landslides following Tropical Storm Agaton and serves as the study area for monitoring landslide progression using satellite imagery over a one-year period. The areas shaded in red indicate the validated landslide locations immediately after the event.

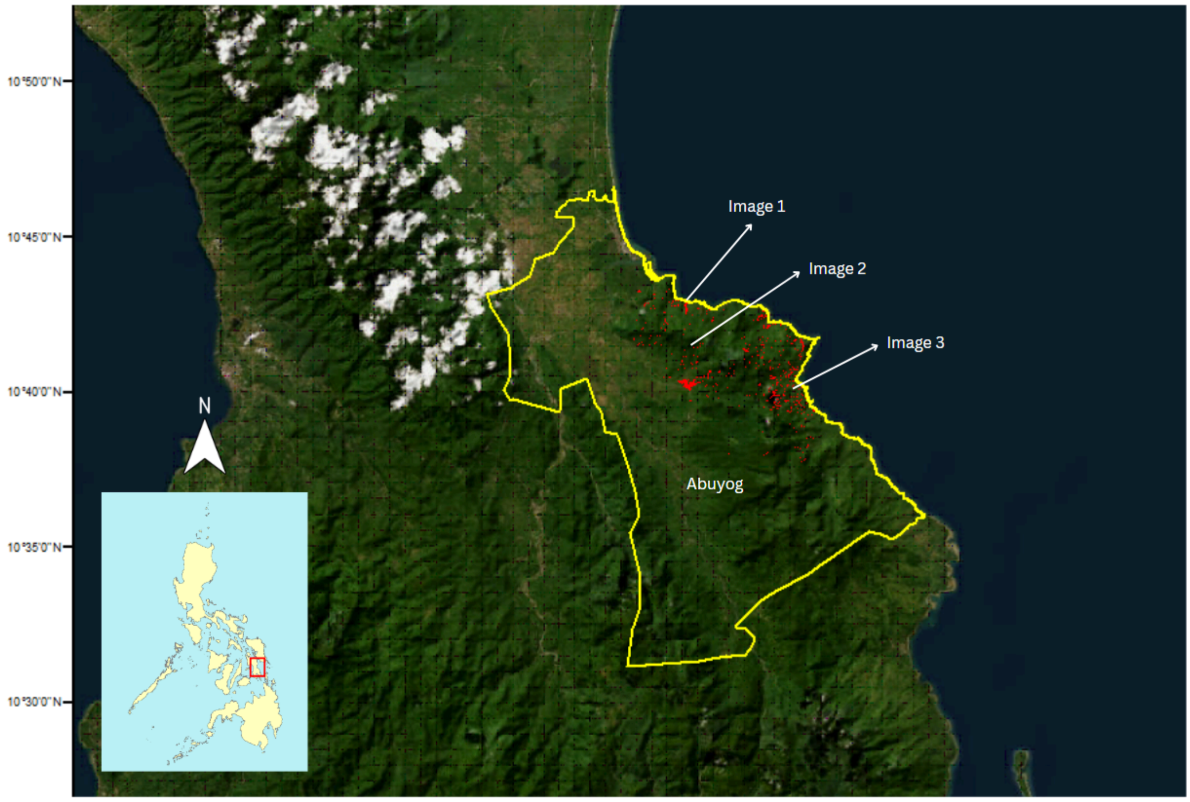

Figure 2. Map of Abuyog, Leyte, Philippines;
Validated Landslides after TS Agaton on April 16, 2022 (Shaded in Red); and
Location of Selected Images for Analysis

b. Data Acquisition and Preprocessing

For this study, satellite images of the area were accessed and visualized through the Copernicus Open Access Hub, where the images with the least cloud cover closest to 1 month, 3 months, 6 months, and 1 year after the event were identified for the landslide-affected areas in Abuyog, Leyte. The Red, Green, Blue, and Near Infrared (NIR) bands from five (5) identified Sentinel-2 Level 2A Surface Reflectance images were then downloaded using Google Earth Engine. Elevation values were derived from an IFSAR DTM grid with a spatial resolution of 5 meters (Rabonza, et al. 2015), while the slope values in degrees were calculated using the Slope tool in ArcGIS. To ensure consistency across all bands, the elevation and slope layers were resampled to a spatial resolution of 10 meters. Downsampling the DTM higher resolution DTM was implemented since upsampling the Sentinel-2 bands to 5 meters would only interpolate spectral values and generate artificial pixels that could mislead the model. No new detail would be gained from such upsampling, since the additional pixels would merely represent estimates based on surrounding values rather than actual measurements.

The Red, Green, Blue, and NIR bands from Sentinel-2, together with the slope and elevation values derived from the IFSAR DTM, were then stacked into a single raster file per image date, resulting in a total of six (6) bands. Each raster file was subsequently divided into image patches of size 128 × 128 pixels, as required by the model for input.

c. Landslide Detection with the U-Net Model

The U-Net model was trained using validated landslide data obtained through on-site assessments, official reports, and expert visual interpretation using Google Earth (MGB, 2022; Minimo et al., 2023; NDRRMC, 2022). These datasets covered several regions in the Philippines, including Abuyog, Leyte, where multiple landslides were triggered by Tropical Storm Agaton between April 1–16, 2022; Sitio Tinabon, Barangay Kusiong, Datu Odin Sinsuat, Maguindanao del Norte, where Severe Tropical Storm Paeng (Nalgae) caused a destructive landslide on October 27, 2022; and Zone 1, Barangay Masara, Maco, Davao de Oro, where continuous rainfall triggered landslides on February 6, 2024. However, the quantity of validated landslide data remained limited, which could affect the ability of the U-Net model to produce highly accurate outputs. To address this, data augmentation was implemented to artificially increase the number of training samples. Using Python, data augmentation was performed by applying horizontal and vertical flips as well as 90°

rotations to the image patches. These transformations expanded the dataset size fourfold, resulting in an overall total of 306 training samples.

The input data, consisting of 128 × 128 image patches with six (6) bands each, were converted from TIF to HDF5 (H5) format to ensure compatibility with the TensorFlow/Keras deep learning framework used by the U-Net model. The H5 format enables efficient storage and rapid access to multidimensional arrays during training and inference. Each image patch serves as an input sample to the U-Net, which processes the data through successive convolutional and pooling layers to learn spatial and contextual features relevant to landslide detection. The model then generates a probability map for each patch, where every pixel is classified as either landslide or non-landslide.

d. Change Detection and Temporal Analysis

After the model detection of landslides in each image patch, the result can be merged to reconstruct the landslide prediction map for the entire study area. However, since the landslides in Abuyog, Leyte are generally small in size and dispersed across the region, only three (3) images were selected for analysis. This process allowed the study to focus on specific areas, as the resolution of the satellite images used could only capture small changes at the pixel level.

Two types of analysis were performed to monitor landslide progression in the selected images. First, a change map was generated by comparing the event date, which served as the baseline image, with images taken 1 month, 3 months, 6 months, and 1 year after the event. This map highlighted changes relative to the original landslide scars and visually illustrated areas that persisted, revegetated, or expanded over time. In all images, non-landslide pixels were assigned a value of 0, while landslide pixels were assigned a value of 1. Categorical colors were then used to represent three (3) classes of change. Red indicates new landslides, referring to areas that were previously stable or non-landslide but were later classified as landslide in the succeeding images. Green represents recovery areas, or landslide-affected zones during the event date that showed signs of vegetation regrowth or stabilization in later images. Brown signifies stable landslides, which corresponded to areas consistently identified as landslides across all time periods, showing little to no change in extent. Second, area metrics were calculated to quantify the observed changes. The total landslide area for each image date was computed and expressed both as an absolute value (in hectares) and as a percentage relative to the baseline event date. The quantitative evaluation of landslide progression and vegetation recovery through the comparison of metrics across the 1 month, 3 month, 6 month, and 1 year intervals, provides an objective complement to the visual interpretation from the change maps.

Results and Discussion

The U-Net model, trained on validated landslide data with augmentation, successfully delineated landslide-affected areas from multitemporal Sentinel-2 imagery, achieving an F1-score of 72.97, a precision of 79.54, and a recall of 67.46. The detected landslides for the selected image patches at each date are presented in Figure 3.

Figure 4 presents the change maps generated from the comparison between the event image and subsequent dates. A gradual contraction of landslide boundaries in scarred areas, consistent with vegetation recovery and slope stabilization, can be visually observed, along with isolated cases of expansion in unstable zones, particularly within one to three months after the event. In the 6 months and 1 year post-event images, the dominance of green pixels, representing the areas that have recovered, over brown or red pixels, representing the areas where landslides have persisted and expanded, is evident, highlighting the progressive regrowth of vegetation.

Across all selected images, as presented in Tables 1–3, the stable non-landslide class (0→0) consistently occupied the largest proportion of the area, with values exceeding 85%, showing that most of the terrain remained unaffected throughout the monitoring period. This indicates that the U-Net model was able to focus on the localized changes within the broad landscape.

For instances of landslide expansion (0→1), it showed the least extent across all images, with generally remaining below 3%. In Image 1, modest expansion was observed immediately after the event at 1.01%, but these values stabilized to less than 0.6% in the later dates. Similar patterns were seen in Images 2 and 3, where expansions were occasional and limited in scale. These results suggest that while slope instability persisted in the month immediately following the event, the overall risk of widespread secondary failures diminished within the 1 year period. This can be attributed to the fact that these landslides were primarily induced by intense rainfall, and without a subsequent event of similar magnitude, repeated or further large-scale landslide re-occurrence was unlikely.

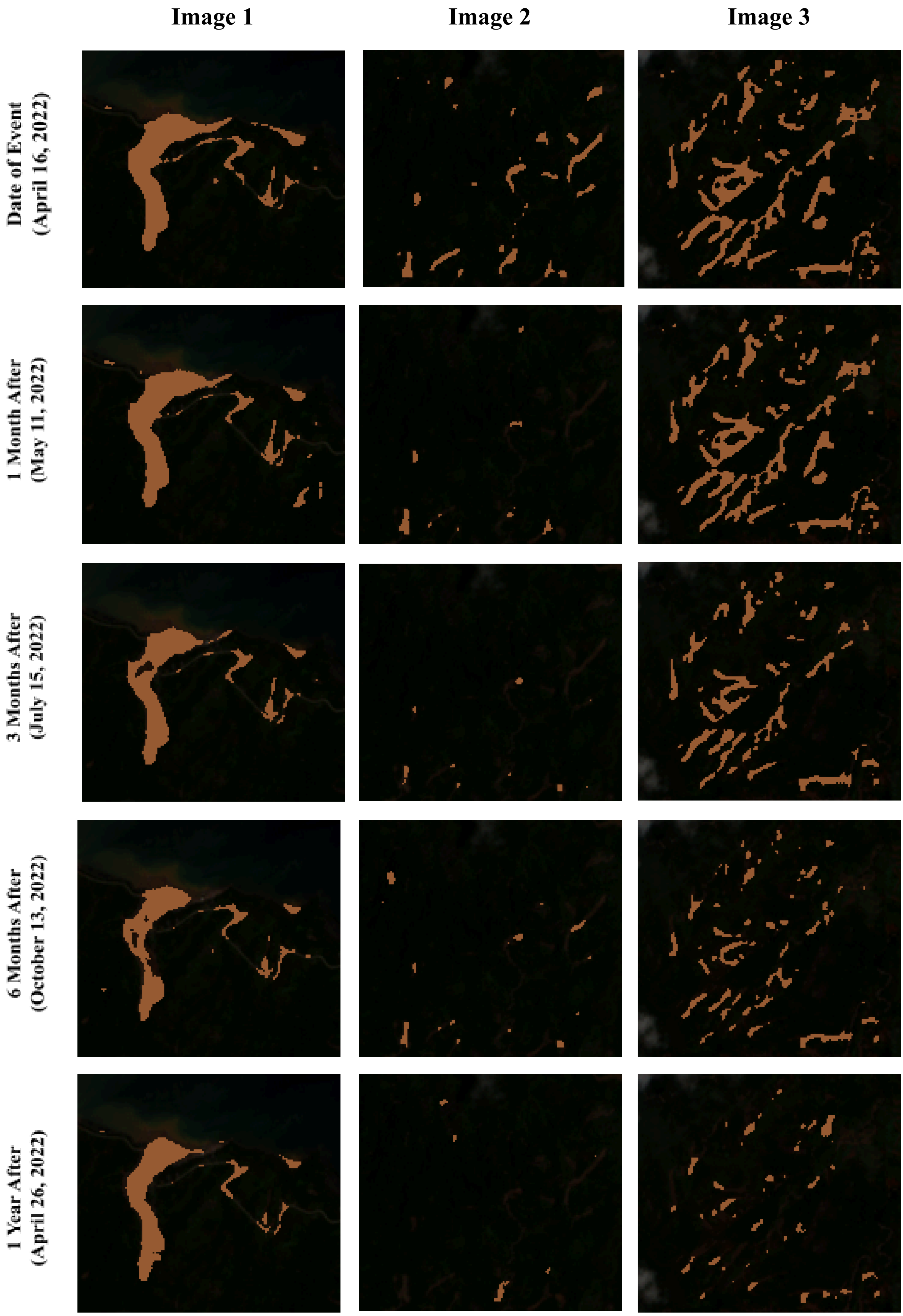

Figure 3. Detected Landslides from U-Net Segmentation on Sentinel-2 Images:
Event Date, 1 Month, 3 Months, 6 Months, and 1 Year after Tropical Storm Agaton.

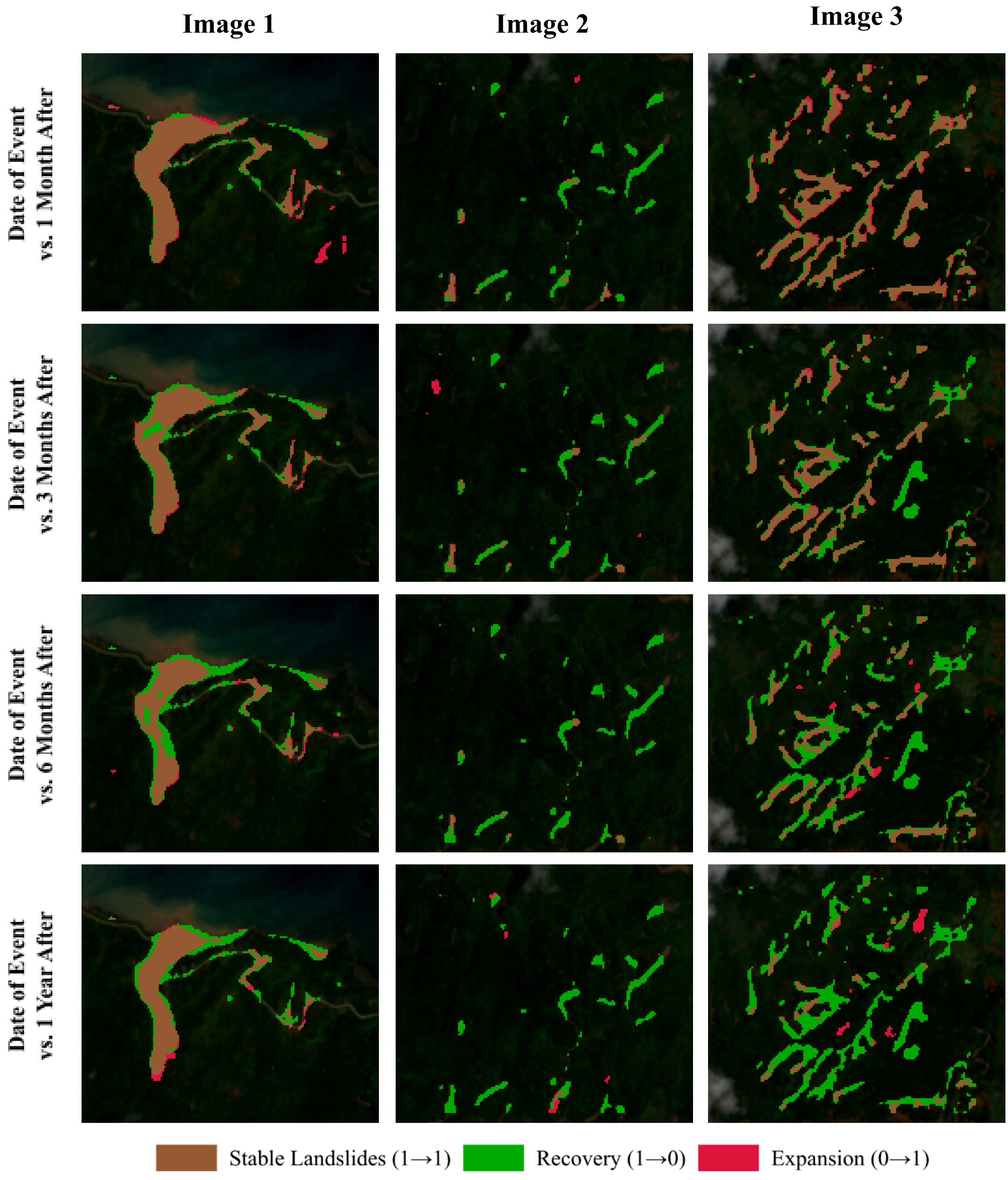

Figure 4. Change Maps Derived from (a) Image 1, (b) Image 2, and (c) Image 3, Illustrating Landslide Progression By Comparing the Baseline (Event Date) with Each Subsequent Post-Event Image.

IMAGE 1	Area (Hectares)				Percentage (%)			
	ED v 1M	ED v 3M	ED v 6M	ED v 1Y	ED v 1M	ED v 3M	ED v 6M	ED v 1Y
Stable Non-Landslide (0 → 0)	144.48	145.73	145.61	145.53	88.1836	88.9465	88.8733	88.8245
Recovery (1 → 0)	2.23	4.19	6.43	5.55	1.3611	2.5574	3.9246	3.3875
Expansion (0 → 1)	1.65	0.4	0.52	0.6	1.0071	0.2441	0.3174	0.3662
Stable Landslide (1 → 1)	15.48	13.52	11.28	12.16	9.4482	8.252	6.8848	7.4219

Table 1. Quantitative Results of Landslide Persistence, Progression, and Recovery (Image 1) From the Comparison of the Event Date with Subsequent Post-Event Images.

IMAGE 2	Area (Hectares)				Percentage (%)			
	ED v 1M	ED v 3M	ED v 6M	ED v 1Y	ED v 1M	ED v 3M	ED v 6M	ED v 1Y
Stable Non-Landslide (0 → 0)	96.051	95.9412	95.972	96.173	157.37	157.19	157.24	157.57
Recovery (1 → 0)	3.0945	3.6682	3.0518	3.418	5.07	6.01	5.0	5.6
Expansion (0 → 1)	0.1343	0.2441	0.2136	0.0122	0.22	0.4	0.35	0.02
Stable Landslide (1 → 1)	0.7202	0.1465	0.7629	0.3967	1.18	0.24	1.25	0.65

Table 2. Quantitative Results of Landslide Persistence, Progression, and Recovery (Image 2) From the Comparison of the Event Date with Subsequent Post-Event Images.

IMAGE 3	Area (Hectares)				Percentage (%)			
	ED v 1M	ED v 3M	ED v 6M	ED v 1Y	ED v 1M	ED v 3M	ED v 6M	ED v 1Y
Stable Non-Landslide (0 → 0)	83.545	85.1074	84.90	84.7351	136.88	139.44	139.1	138.83
Recovery (1 → 0)	2.0325	5.603	9.3384	12.384	3.33	9.18	15.3	20.29
Expansion (0 → 1)	1.9348	0.3723	0.5798	0.7446	3.17	0.61	0.95	1.22
Stable Landslide (1 → 1)	12.488	8.9172	5.1819	2.1362	20.46	14.61	8.49	3.5

Table 3. Quantitative Results of Landslide Persistence, Progression, and Recovery (Image 3) From the Comparison of the Event Date with Subsequent Post-Event Images.

The observed patterns in both the change maps and area metrics are consistent with the expected behavior of shallow rainfall-induced landslides. The initial expansion in the weeks following the typhoon may be attributed to prolonged soil saturation. However, the images from 3 months, 6 months, and 1 year post-event were dominated by recovery, indicating that vegetation regrowth plays a significant role in slope stabilization within a year.

Conclusion and Recommendation

This study demonstrates the potential of AI-based semantic segmentation using a U-Net model to monitor landslide progression and recovery through multitemporal Sentinel-2 imagery. By integrating the spectral bands of the satellite images with topographic information from IFSAR DTM, the model effectively delineated post-event landslide areas which was used to monitor the changes from immediately after Tropical Storm Agaton in April 16, 2022, up to one year later.

The results showed three main patterns. First, the stable non-landslide areas dominated the landscape, confirming the ability of the model to detect a localized extent of landslide activity. Second, persistent landslide scars declined over time, indicating gradual slope stabilization and vegetation regrowth over time. Lastly, the expansion of landslide areas was minimal and irregular throughout the dates, suggesting that there were no widespread secondary failures within the study period.

In conclusion, the proposed approach provides practical applications for local disaster management. Identifying areas where the soil has recovered or where landslides are most likely to reoccur can guide field validation, prioritize slope rehabilitation efforts, and provide information for long-term land-use planning. For future research, it is recommended to explore the use of satellite imagery with higher spatial resolution to improve the delineation of landslide-affected areas, as finer detail may reveal smaller or fragmented scars not captured in Sentinel-2 data. In addition, implementing a stepwise comparative approach across the multiple post-event dates can offer a clearer understanding of landslide progression, highlighting periods of peak expansion and subsequent recovery. Integrating additional factors such as rainfall intensity, land cover, and soil characteristics could also strengthen the analysis.

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