Jurnal Kejuruteraan 38(4) 2026: 1847-1864
https://doi.org/10.17576/jkukm-2026-38(4)-24

Deep Learning Approach for Landslide Delineation in Tropical Region of Malaysia

Mohd Asraff Asmadi[a], Muhammad Zulkarnain Abd Rahman[a*], Muhammad Safwan Ruslan[a], Puven Raj P.Chazian[a], Mohd Radhie Mohd Salleh[b], Ahmad Safuan A Rashid[c], Omar Farouk Fauzi[a] & Muhammad Khalid[d]

[a]*Department of Geoinformation, Faculty of Built Environment and Surveying, Universiti Teknologi Malaysia, Malaysia*

[b]*Department of Water and Environmental Engineering, Faculty of Civil Engineering, Universiti Teknologi Malaysia, Malaysia*

[c]*Department of Geotechnics and Transportation, Faculty of Civil Engineering, Universiti Teknologi Malaysia, Malaysia*

[d]*School of Geography and Information Engineering, China University of Geosciences, 430074, Wuhan, China*

**Corresponding author: mdzulkarnain@utm.my*

Received 7 October 2025, Received in revised form 12 March 2026
Accepted 12 April 2026, Available online 30 July 2026

ABSTRACT

Landslides are a signi icant geological hazard, occurring across various spatial and temporal scales and resulting in severe environmental damage and loss of human life. This study presents a rapid framework for landslide detection by using a high-density airborne LiDAR data deep learning approach. The study area is located in the tectonically active area of Kundasang, Sabah, Malaysia. High-density airborne LiDAR data was acquired over the active, dormant, and relict landslides. The airborne LiDAR data was used to generate high resolution of two key inputs: Digital Terrain Model (DTM), hillshade and slope, and Digital Terrain Model (DTM), slope and aspect. The detection process was based on the Mask Region-based Convolutional Neural Network (Mask R-CNN) with the architecture of ResNet-101 and ResNet-152. The R-CNN model was trained and evaluated using a landslide inventory developed by landslide boundary that has been manually digitized on the DTM. The reference data was prepared by the experts, which has been randomly divided into two groups of training (70%) and validation (30%) datasets. The performance of the R-CNN method was evaluated based on the resolutions of input parameters, different landslide states of activities, and architecture of R-CNN. The results show that R-CNN can detect the active landslide more effectively than dormant and relict landslides with the integration of DTM, hillshade, and slope map at 1 m resolution. The R-CNN with 152 layers showed the best F-measure of 50.7% value for active landslide detection. However, the detection results for dormant and relict landslides remain low. The remote sensing-based landslide detection framework showed promising results, though more effort should be focused on detecting historical landslides.

Keywords: Landslide detection; Light Detection and Ranging (LiDAR); Digital Terrain Model (DTM); Deep Learning (DL)

INTRODUCTION

Landslides have become a significant geological calamity globally, often triggered by rainstorms, seismic events, and human interventions (Jiang et al. 2022; Krishna et al. 2021; Wei et al. 2023). In South East Asia countries, the number of landslide incidents is on the rise, which is mainly caused by increasing rainfall intensity (Krishna et al. 2021). As highlighted by the World Health Organization (WHO), from 1998 to 2017, landslides affected approximately 4.8 million people and led to over 18,000 deaths (Dang et al. 2024).

In Malaysia's mountainous regions, historical records show frequent destructive landslides, which underscoring the need for comprehensive hazard assessment. Reliable landslide hazards and risk assessments required considerable effort in data collection, including landslide inventory. A landslide inventory comprises an extensive record documenting the occurrence and specific attributes of previous landslides, serving as historical disaster data. The landslide inventory is crucial in producing landslide susceptibility and landslide hazard maps, which are subsequently used for landslide vulnerability, risk assessment, and other landslide disaster management phases (Krishna et al. 2021; Wei et al. 2023). This effort allows systematic and comprehensive landslide disaster risk reduction strategies to be implemented at different levels of national disaster management (Dang et al. 2024; Krishna et al. 2021). The conventional approach of field-based landslide investigation has limitations regarding cost, time, accessibility, safety, and area coverage (Wang et al. 2023; Wei et al. 2023). Manual identification and interpretation of landslide areas require extensive expertise, which demands a significant amount of time and manpower, particularly when dealing with large geographical areas. Furthermore, apart from individual efforts in detecting the landslide, there is no existing database that offers a complete tally of all landslides on both a global and national level (Dang et al. 2024). In this matter, remote sensing technology has been increasingly applied for landslide detection and inventory that account for different types, scales, and periods of landslide occurrences (Wei et al. 2023).

Identification of relict landslides is still important in understanding the landslide mechanism, causal factors, and evidence for various machine learning landslide susceptibility and hazard modelling (Garcia et al. 2023). Relict landslides detection in tropical regions have several limitations due to the rapid growth of vegetation over landslide areas, which reduces the visibility of the landslide area (Garcia et al. 2023; Wang et al. 2023). Therefore, the identification and characterization of relict landslides become complicated over time. Furthermore, the form and boundary of relict landslides deteriorate over time, constraining their potential for detection.

RELATED WORKS

The conventional approach of manual visual interpretation of remotely sensed imagery is highly subjective, depending on the quality of the data and experience (Jiang et al. 2022). Developments in landslide detection have rapidly evolved from manual visual interpretation to machine learning approaches that require learning and detection processes using computers (Garcia et al. 2023). Various automatic and semi-automatic approaches of landslide detection, such as Object-Based Identification Analysis (OBIA), pixel-based classification, machine learning, and deep learning, have been introduced to increase accuracy and reduce the subjectivity in manual landslide interpretation (Garcia et al. 2023). High-resolution satellite imagery has been used intensively as base data for landslide detection (Conciatori et al. 2024; Jiang et al. 2022; Wei et al. 2023; Yu et al. 2020). The nature of remote sensing data allowed monitoring and identifying landslides across extensive regions, a task frequently unfeasible using conventional ground-based techniques (Wang et al. 2023; Wang et al. 2024). However, optical remote sensing data presents a challenge as many objects are mistaken for landslides, especially since landslides, characterized by exposed soil, can resemble farmland, mountain pits, country roads, etc. (Wang et al. 2023; Wang et al. 2024).

Nowadays, machine learning, especially the deep learning method, has gained much attention for object classification and detection. The deep learning method of Convolutional Neural Networks (CNN) is widely accepted as the most successful network architecture in the field of deep learning (Garcia et al. 2023; Wang et al. 2023; Wang et al. 2024). They are extensively employed to produce spatial features essential for tasks such as detecting objects and segmenting high-resolution images. Previous studies suggested that deep learning has performed very well in landslide detection, which primarily involved two major tasks, namely, landslide detection through bounding box and landslide segmentation that produced a landslide boundary (Wang et al. 2023). Ghorbanzadeh et al. (2022) introduced Landslide4Sense, which utilized optical remote sensing data from Sentinel-2 imagery and slope data obtained from ALOS PALSAR. The evaluation was performed on 11 deep learning segmentation models over different locations and times of landslide occurrences. The result showed that the Res U-Net surpassed the performance of the other models in detecting landslides.

Wang et al. (2023) improved Mask Regional Convolutional Neural Network (Mask-RCNN) algorithm that works with limited landslide samples using high-resolution remote sensing images in China. The loess landslides were detected with an improvement in precision of 16.7% from the original algorithm. Yu et al. (2017) proposed Convolutional Neural Network (CNN) with an improved region-growing segmentation method for landslide detection. The CNN method was employed for landslide detection, and the delineation of the detected landslide's boundary was enhanced using region-growing segmentation.

Garcia et al. (2023) introduced a new CNN framework for the semi-automatic identification of relict landslides in Brazil that employs a dataset created through a k-means clustering algorithm and incorporates a pre-training phase. The method was applied to a medium-resolution, multispectral remote sensing image. The results showed that detecting relict landslides in rainforest-covered areas has limitations, primarily due to similarities in the spectral responses of pastures and deforested regions that are generally used as indicators for landslide scars. Dang et al. (2024) evaluated different deep learning model input sizes on Sentinel-2 images for landslides in Vietnam. Further analysis has been made by the same researcher for input data fusion between Sentinel-1 (SAR) and Sentinel-2 (optical) images. Yu et al. (2020) investigated the performance of vegetation indices obtained from Landsat images with DTM using a deep learning approach for landslide detection in Nepal. The results showed satisfactory performance of the framework for national-scale landslide detection.

Despite this progress, most existing methods have focused on optical or SAR imagery rather than high resolution topographic data. Detection of relict landslide is particularly difficult because their surface expressions become subtle over time. Previous studies on utilizing CNN for landslide detection were hampered by low detection accuracy, which has invoked various strategies, including modifications to the existing CNN framework (Dang et al. 2024; Wei et al. 2023), input data (Dang et al. 2024; Wang et al. 2024; Yu et al. 2020), and post-processing of the steps of the initial detected landslides. Inevitably, deep learning requires a huge amount of data obtained at various scales and data sources. Xu et al. (2024) developed a large-scale and multi-sensor dataset for landslide detection using a deep learning approach. The landslide datasets consistst of 20,865 images, incorporating data from both satellites and unmanned aerial vehicles across nine regions. Previous studies on landslide detection using CNN primarily concentrated on identifying fresh landslides and often relied on multi-spectral imagery captured shortly after the event, when the landslides were more prominently visible in the landscape (Garcia et al. 2023). However, very few studies have leveraged high density of Light Detection and Ranging (LiDAR)-derived terrain models for automated landslide delineation in complex forested environments. LiDAR can generate detailed DTM and relevant terrain parameters over highly vegetated regions by filtering out non-ground point cloud (Choi et al. 2023; Metes et al. 2024; Pellegrino et al. 2024; Zhu et al. 2020). The detailed DTM captures terrain micro-features that may not be visible in optical images. Therefore, identification of relict landslides was often included in DTM as one of the input data (Garcia et al. 2023).

The main objective of this paper is to perform semi-automatic detection of different activities of landslides, namely active, dormant, and relict, in the tropical region of Malaysia, particularly in Kundasang, Sabah, by using high-density of airborne LiDAR-derived DTM with a deep learning approach. Unlike prior CNN-based or optical image-based approaches that rely mainly on multi spectral imagery, which provides little direct elevation information, this study will leverage precise LiDAR-derived terrain features. LiDAR technology can produce DTM with sub-meter accuracy under forest canopy, allowing subtle landslide topographic to be detected even where the vegetation is dense. It was noted that the optical satellite imagery obtained from the Unmanned Aerial Vehicle (UAV) measured the reflectance of sunlight from the earth surface object and hardly captured any topographic information of the earth surface (Choi et al. 2023). In this context, the proposed approach is not intended to serve as a fully operational landslide early-warning system; rather, it is designed as a semi-automated framework to support landslide inventory development by enhancing boundary delineation and spatial consistency, thereby complementing expert interpretation and reducing subjectivity and manual effort in inventory mapping. A detailed comparison is performed between different input resolutions of DTM and parameters to determine the effectiveness of deep learning to delineate landslides under varying conditions.

METHODOLOGY

The methodology of this paper, as shown in Figure 1, comprises four (4) main phases:

1. Generation of landslide inventory map: The high-density of airborne LiDAR and field investigation data collected over the study region undergoes pre-processing. The pre-processing includes data filtering and ground point and non-ground point cloud classification from the airborne LiDAR data to produce the landslide inventory.
2. Derivation of multi-resolution digital terrain models (DTMs) and terrain features: We employed the interpolation method to produce high resolution of DTMs at three resolutions (1 m, 5 m, and 10 m) from the airborne LiDAR data. From each DTM we derived some terrain features to be assigned as input parameters in the deep learning method.
3. Landslide delineation by using the deep learning method: The process involves splitting the landslide inventory into training (70%) and testing (30%), and then exporting the training data along with input parameters for the deep learning. Next, we trained a Mask R-CNN model using these

inputs. Two backbone models were compared: ResNet-101 and ResNet- 152, chosen for their strong feature extraction capacity. After training, the models were applied to the test data to segment landslide areas.

4. Validation of landslide detection results: The results were evaluated to observe the impact of multi-resolution DTMs and other terrain features and the difference in landslide sizes and activities on the delineation accuracy.

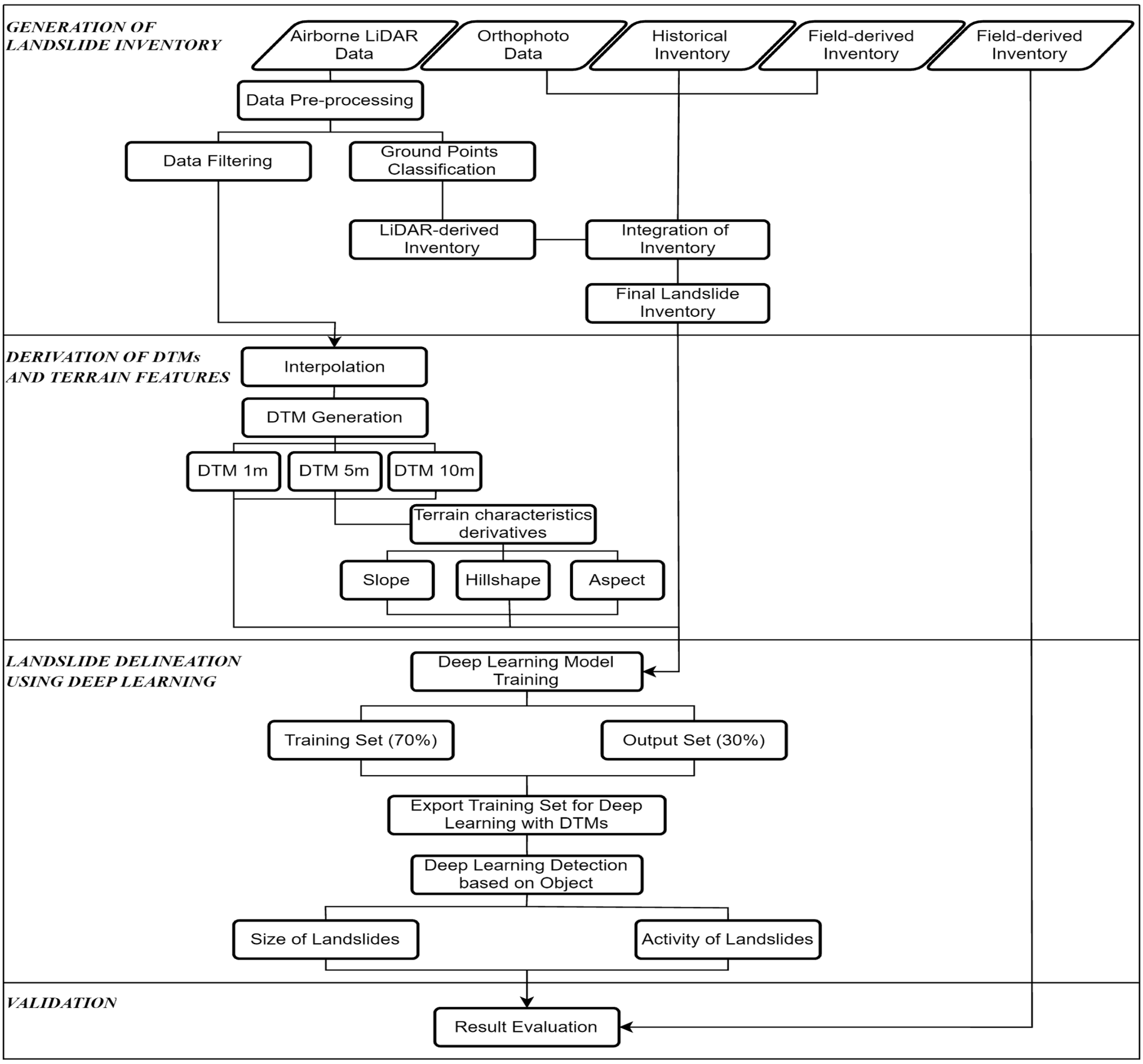

FIGURE 1. Overall methodology used in this study

DESCRIPTION OF STUDY AREA

The study area is situated in Kundasang, a region located in the northwest of Ranau, Sabah. Kundasang is widely known for its undulating geographical topography, characterized by its instability. The study area involves an area of 70.47 square kilometers and is located at elevations ranging from 500 to 2000 meters above mean sea level. The chosen location was based on the prevalence of landslides, which were frequently triggered by both natural factors and human activities that impacted the natural environment. The presence of hilly terrain and ridges, characterized by their significant elevation and the presence of steep slopes, can be attributed to intense tectonic activity in the past (Tating, 2006).

CLIMATE

Kundasang is categorized by a tropical climate, with a minimum monthly precipitation of 60 mm and the mean annual precipitation of 2075 mm, as reported by (Tating et al. 2013) with temperatures fluctuating between 16°C and 24°C. Therefore, this area experiences rainfall akin to tropical climates but with an average temperature that is more temperate.

GEOLOGY AND LITHOLOGY

The Kundasang area is comprised of several lithological formations, namely the Crocker Formation, the Trusmadi Formation, and a number of more recent Quaternary alluvial deposits (Tongkul, 1987). The seismic event that took place in Sabah resulted in the initiation of debris flow, leading to environmental damage along the affected channel. The earthquake occurred as a result of movement along a southwest-northeast (SW-NE) trending normal fault. The epicenter was located in close proximity to Mount Kinabalu, and the seismic activity triggered significant landslide activities in the surrounding area (Tongkul 2017).

GEOLOGICAL HAZARDS OF KUNDASANG, SABAH

The study area was exposed to several geological hazards that have already resulted in natural disasters, causing significant human and economic damages. Given its status as a prominent tourism hub, the repercussions of past disasters were not limited to the local population but also had a significant impact on non-residents, particularly tourists. This situation necessitates the prompt implementation of hazard and risk assessment in the area.

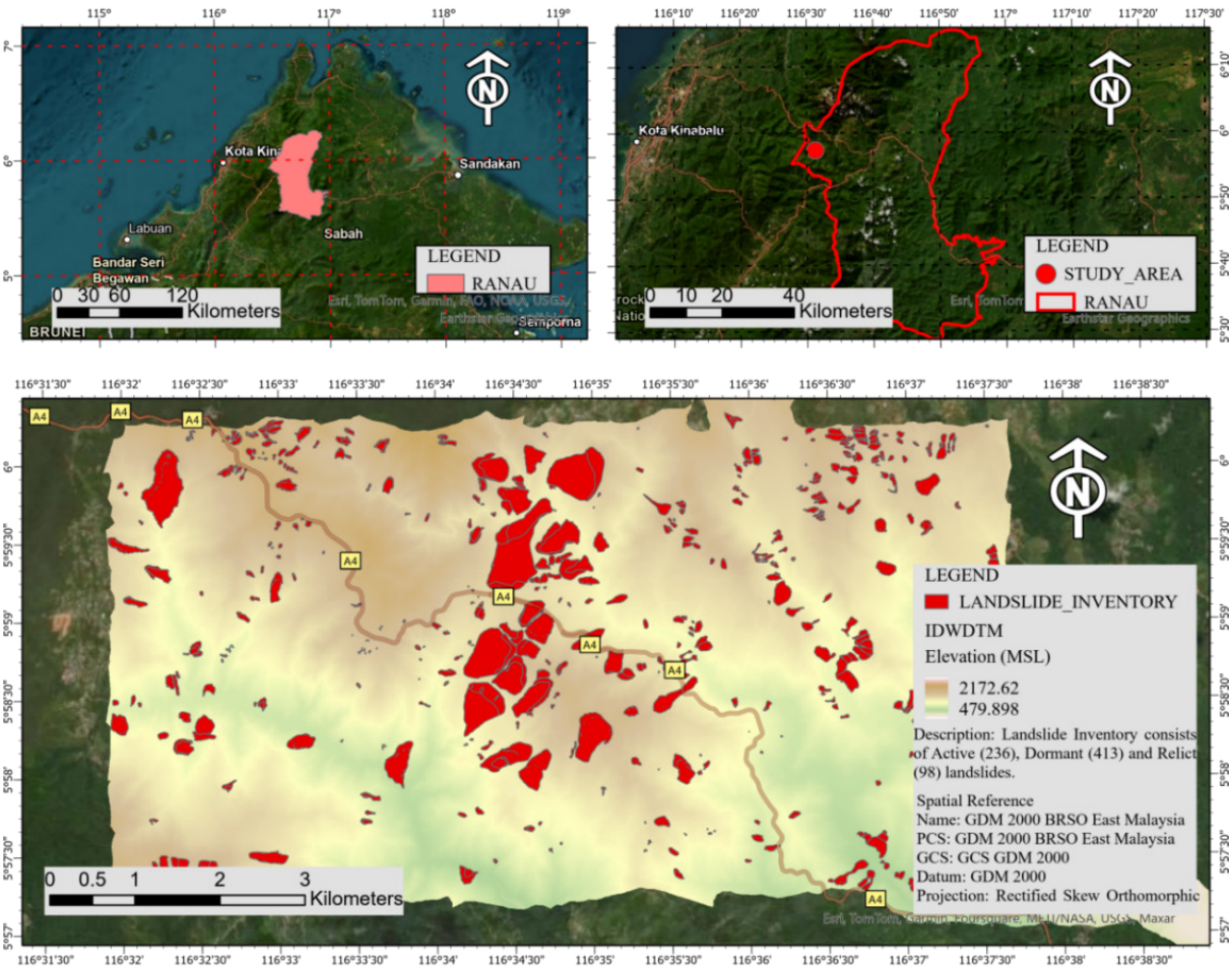

FIGURE 2. Map of study area

GENERATION OF LANDSLIDE INVENTORY MAP

Landslide inventory has played a crucial role in the quality of produced landslide susceptibility, hazard, and associated risks in a complex environment, especially in Kundasang. The process to produce the precise landslide inventory map incorporated data collection and pre-processing, which became the first, fundamental, and important stages of landslide research, which also involved landslide detection and delineation. The important data was obtained from the Department of Mineral and Geoscience (JMG) and Universiti Teknologi Malaysia (UTM), which consists of several types of data: historical inventory, field observation, and geospatial data. The historical inventory contains the ancient landslide incidents database, images, dates of incidents, and causal factors from previous research carried out by the JMG. In addition, traditional field observations were performed in the research area (see Figure 3) to validate the outcomes of the landslide inventory compilation process and closely analyze a range of landslide characteristics. Key parameters such as landslide sizes and activity status were meticulously documented through direct observation and measurement. Obtaining these defining attributes in situ provided crucial insights into the landslides and afforded a holistic view of the inventory.

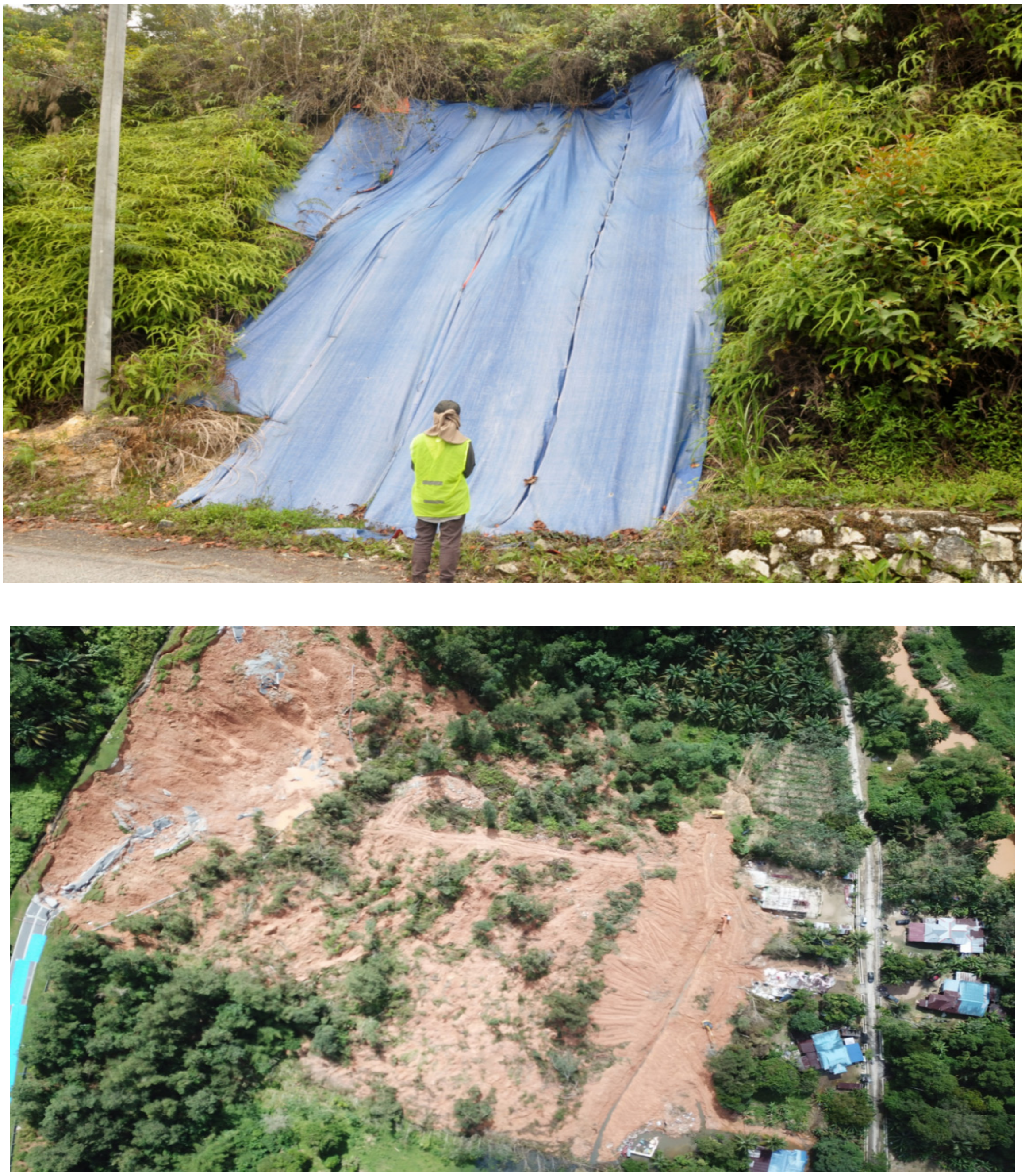

FIGURE 3. Photo captured during the field visit to the area

Meanwhile, the geographical data consisted of high-density of aerial LiDAR data and orthophoto. The study collected airborne LiDAR data from the JMG which reported that the Integrated Geospatial Innovations (IGI) Lite Mapper 6800-400 scanning equipment was installed. Aboard a helicopter, the laser pulse collected several reflections from the ground across the mass of loose rocks and sediment carried by the Mesilau River. The data was collected in August 2015, over two months after the debris flow reached the Mesilau River. The system integrates a Laser Scanner 6800-400 with IMU-Ilf Inertial Measurement, a Trimble R7 GPS Receiver, a DigiCAM H60, and a DigiCAM Lens Cone HC 3.5/50-11. Other than that, the Clear-Protection Filter is a 77 mm filter that is compatible with the LiteMapper system mount, the LiteMapper Data Recorder 680, and the AEROcontrol Sensor Management Unit. The point cloud data were derived from an airborne laser scanner (ALS) called RIEGL LMS-Q680i, to which it was applying full waveform analysis. The RIEGL LMS-Q680i scanner offers scan data collection at an accuracy of 20 mm or precision of 20 mm, a maximum range of 3000 m, and the ability to measure up to 266,000 pulses per second on the ground. Consequently, it generates point cloud data of extremely high density (RIEGL® 2012). The point density inside the study region was determined to be 160 points per square meter (m^2) on average.

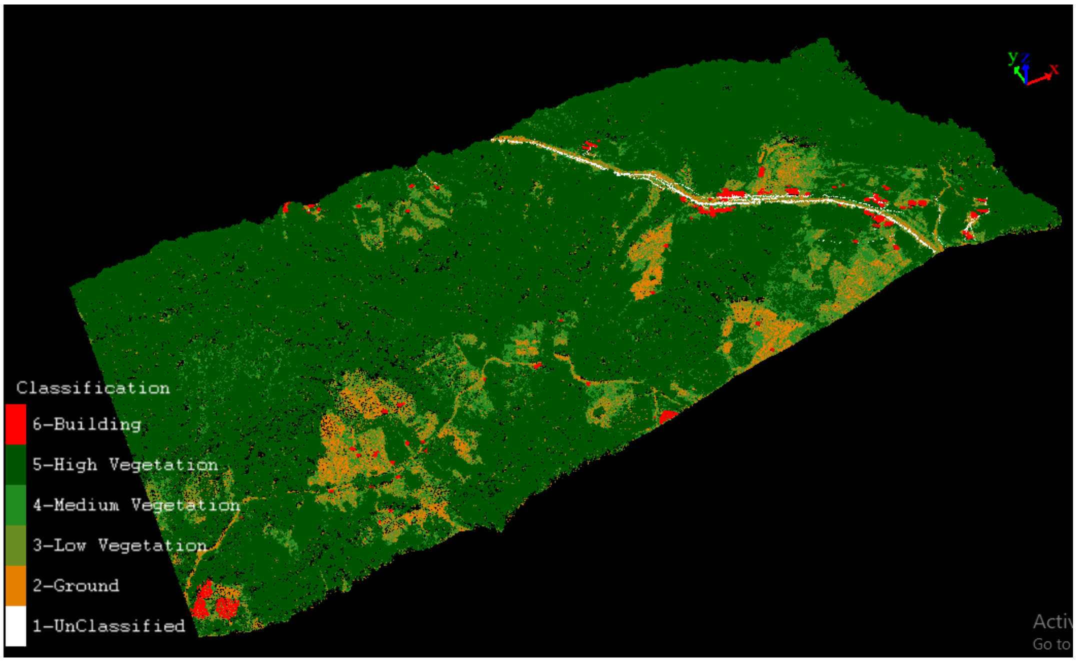

FIGURE 4. Illustration of airborne LiDAR point cloud over part of the study region

The next step was to perform the data pre-processing to convert the raw data source into a format that allows for the delineation of landslides within the study region. One of the primary tasks in the pre-processing of LiDAR data involves the filtering process, generally known as the removal of outliers that are present in the point clouds. There are areas in the LiDAR point cloud datasets that have very low or very high elevations. This could be because of a multipath ray or instrument error during flight missions (Chen et al. 2017). The observed outliers exhibit elevation values that are clearly lower or higher than the elevation values of the surrounding data points. The utilization of an outlier with a very low elevation as a reference point throughout the ground-point categorization procedure introduces significant biases.

The procedure of ground point and non-ground point classification from the point clouds is also a crucial step in distinguishing between ground points and non-ground points, which include vegetation, structures, and other things. The significance of this lies in the utilization of ground points for the generation of DTM and other terrain features such as hillshade, slope, and aspect to depict landslides in two- and three-dimensional modelling views. Landslides and man-made slope failure signatures such as hummocky topography, bulging, tension cracks, and crown-shaped scarps were recognized, whereas non-ground points are commonly eliminated as they are considered to be noise. Figure 5 illustrates the procedure flow for generating a final derived landslide inventory map. The data collected was integrated to produce a precise and comprehensive landslide inventory. There were 745 landslides that were captured in the final landslide inventory map that (see Figure 2) was used as a training dataset and testing dataset in the deep learning method.

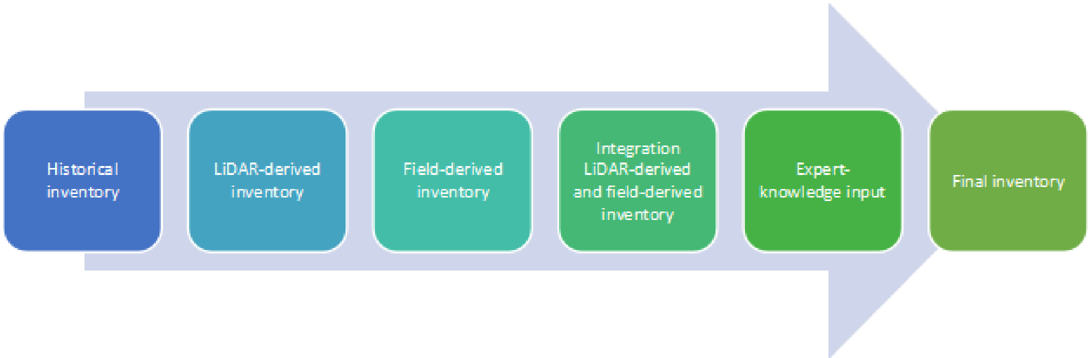

FIGURE 5. A procedural flow for producing a final derived landslide inventory map

DERIVATION OF DTM AND TERRAIN FEATURES

The development of multi-resolution DTMs was crucial to employ as an input parameter in deep learning. Inverse Distance Weighting (IDW) is a widely used interpolation technique for producing DTM. The IDW technique is a deterministic interpolation approach that was often applied in rugged forested terrain (Chen et al. 2017; Razak et al. 2013) and can estimate the value of an unknown point by calculating the weighted average of the values of known points in its proximity. The weight assigned to each known point is inversely related to the distance between that place and the unknown point (Shepard, 1968). The different resolutions of DTM were created at 1 m (high resolution) in Figure 6, 5 m (medium resolution), and 10 m (low resolution).

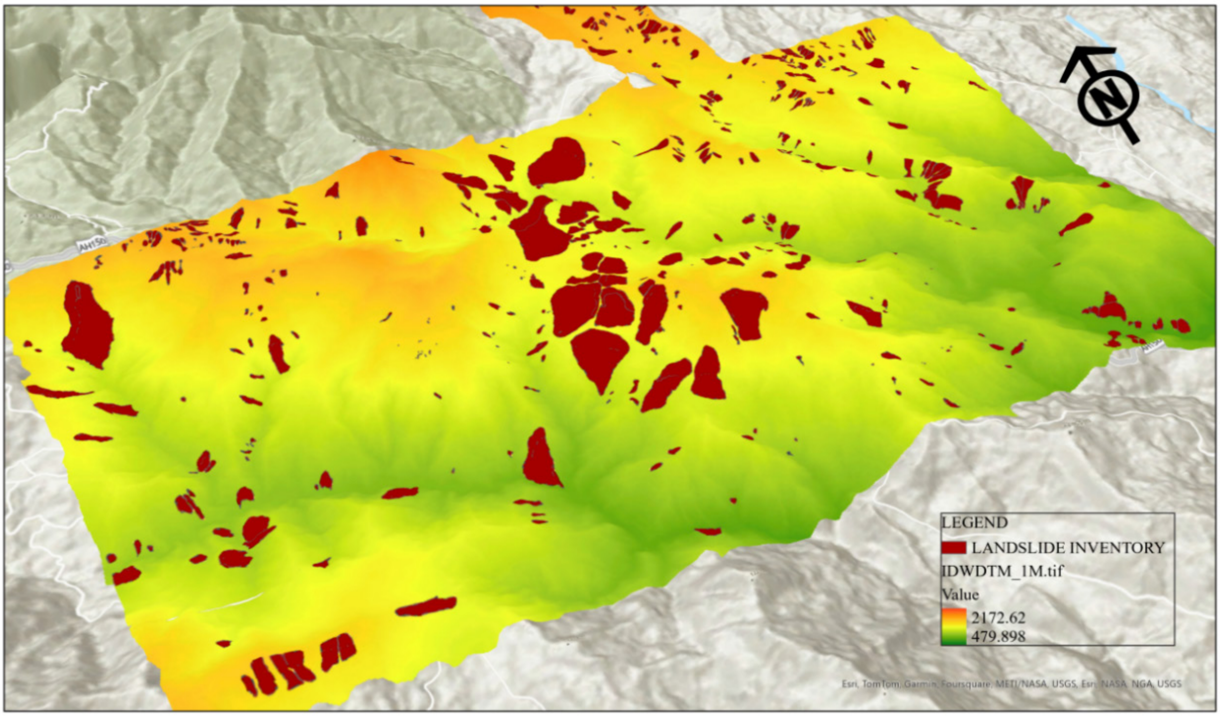

FIGURE 6. Visualization of 1 m resolution of DTM

Next, the derivation of terrain characteristics was obtained from DTMs, as they were highly beneficial for the landslide investigation (as discussed in the previous section). Their contributions facilitate the provision of vital information regarding the physical features of the terrain. The integration of DTM derivative products, including hillshade, slope, and aspect, with a deep learning model was utilized for enhanced landslide identification and delineation (Azarafza et al. 2021; Guzzetti et al. 2012; Jaboyedoff et al. 2012). These derivatives can serve as input characteristics for the deep learning models, allowing them to acquire complex patterns associated with the landslide incidents.

DEEP LEARNING APPROACH FOR LANDSLIDE DETECTION

Deep learning (DL) was introduced to perform landslide delineation based on multi-resolution digital terrain models (DTMs). ArcGIS Pro is a GIS environment software that provides DL detection tools that were employed for this study. To delineate the landslides, this method was employed by initially creating the DTMs at various resolutions: 1 m, 5 m, and 10 m from the pre-processed LiDAR point clouds, as mentioned in Section Derivation of DTM and Terrain Features. The landslide inventory was randomly separated into training (70%) and validation (30%) datasets.

EXPORT TRAINING DATA FOR DEEP LEARNING

The procedure for exporting the training datasets is required to train the deep learning model. The essential input parameters for landslide detection consist of a combination of DTM, hillshade, and slope and combination of DTM, slope, and aspect (Congalton 1991) for each resolution and training (70%) dataset. These terrain-derived layers are employed to capture topographical and morphological characteristics relevant to landslide boundary delineation and are treated as multi-channel image inputs commonly adopted in convolutional neural network architectures rather than as direct physical predictors of landslide processes. This representation enables the deep learning model to learn spatial and morphological patterns associated with landslide features from visually encoded surface information, without inferring subsurface conditions or triggering mechanisms. The training dataset is organized into an output folder that contains image chipsets. Then, the Mask R-CNN metadata format was applied for annotating the training data.

TRAIN DEEP LEARNING MODEL

The input training data comprises picture chips obtained from DTMs, hillshade, and slope and DTMs, slope, and aspect parameters. Every image chip is accompanied by annotations in the Mask R-CNN format, consisting of bounding boxes, masks, and class names for the images. The Mask R-CNN expands upon Faster R-CNN by incorporating an additional branch that predicts segmentation masks for each Region of Interest (RoI), alongside the existing branches for classification and bounding box regression (Jiang et al. 2022). The next step was to employ two distinct backbone models for the purpose of comparison, as they are essential elements of the Mask R-CNN architecture, tasked with extracting features from the input images that consist of: i) ResNet-101 and ii) ResNet-152. These models were selected because residual connections enable effective training of very deep networks, which is essential to capture complex geomorphological patterns present in high resolution LiDAR-derived terrain data. ResNet-101 comprises 101 convolutional layers and approximately 44.5 million trainable parameters, which provides a balance between feature richness and computational efficiency where moderately complex terrain patterns must be captured. Meanwhile, the deeper ResNet-152 includes 152 layers and 60 million trainable parameters. It offers a larger receptive field and greater representational capacity, which it can potentially improves the detection of subtle topographic signatures of landslides. The selection of both backbones therefore allowed us to systematically evaluate whether the additional depth translated into measurable performance gains, especially for active, dormant, and relict landslide classes. The following procedure (see Figure 7) is iterated for every input raster resolution in order to assess the impact of terrain dataset attributes on the delineation of the landslides.

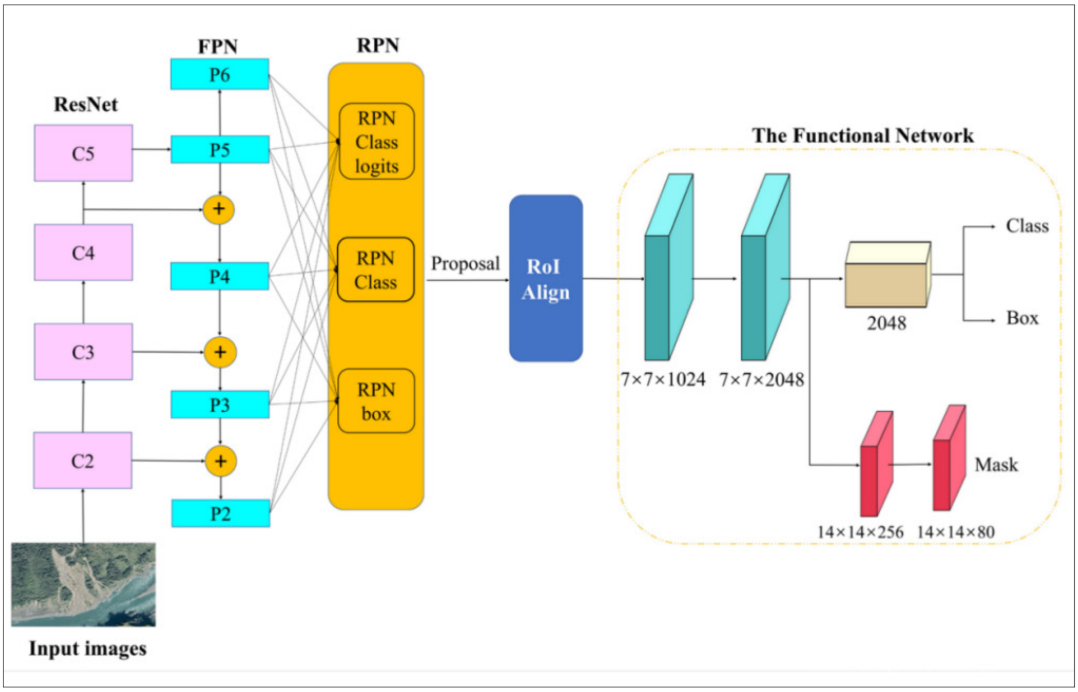

FIGURE 7. Mask R-CNN architecture for landslide detection (Jiang et. al., 2022)

VALIDATION OF LANDSLIDE DETECTION

The accuracy of landslide delineation can be assessed using statistical classification algorithms based on the data feature detection results. By performing an accuracy check, it can be determined how accurate the deep learning is in detecting landslide sizes as well as landslide activity. In order to calculate various accuracy statistics, such as Precision, Recall and F1-score (Congalton 1991), an error matrix was constructed to summarize the correspondence between predicted landslide segments and the manually delineated reference data. Within the context of landslide inventory development, these metrics are used to evaluate spatial agreement and boundary reliability rather than to quantify exhaustive identification of all landslide occurrences. In particular, Precision reflects the degree to which the predicted landslide areas correspond to true landslide features, which is essential for minimizing false delineations that may affect inventory quality, while Recall represents the proportion of reference landslide features that are successfully delineated by the model. The error matrix therefore provides a structured means of assessing how accurately individual landslide segments are delineated relative to their mapped extents.it was essential to utilize an error matrix. A matrix of errors was generated to monitor the progress of individual landslides. This matrix reflects the segments that were allocated to activity for a landslide, as opposed to the actual delineation. The subsequent equations display the whole set of formulas included in the accuracy evaluation procedure, as illustrated in Equations 1-3:

$$\text{Precision} = \frac{\text{TP}}{\text{FP+TP}} \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{FN+TP}} \tag{2}$$

$$F_1 = 2\frac{precision \times recall}{precision + recall} \tag{3}$$

where TP is for true positives, which represents the number of positive samples that are accurately predicted. FP represents the count of negative samples that are incorrectly predicted as positive, while FN represents the count of positive samples that are incorrectly expected as negative (Cai et al. 2021; Li et al. 2021).

RESULTS

PARAMETER LAYERS FOR LANDSLIDE DETECTION

Parameter layers play a vital role as input parameters for landslide detection by using deep learning tools. Multi-resolution DTMs were derived from high-density airborne LiDAR data. The data provided highly precise elevation information and then produced the three different spatial resolutions of DTMs, starting at 1 m (high-resolution), 5 m (medium-resolution), and 10 m (low-resolution). The generated multi-resolution DTMs were supported by the derivation of terrain features, including hillshade, slope, and aspect, for each spatial resolution to enhance the delineation of landslides by using deep learning approaches. Figure 8 illustrates the parameter layers at 1 m resolution that consist of the combination of DTM, hillshade, and slope, while Figure 9 shows DTM, slope, and aspect combination.

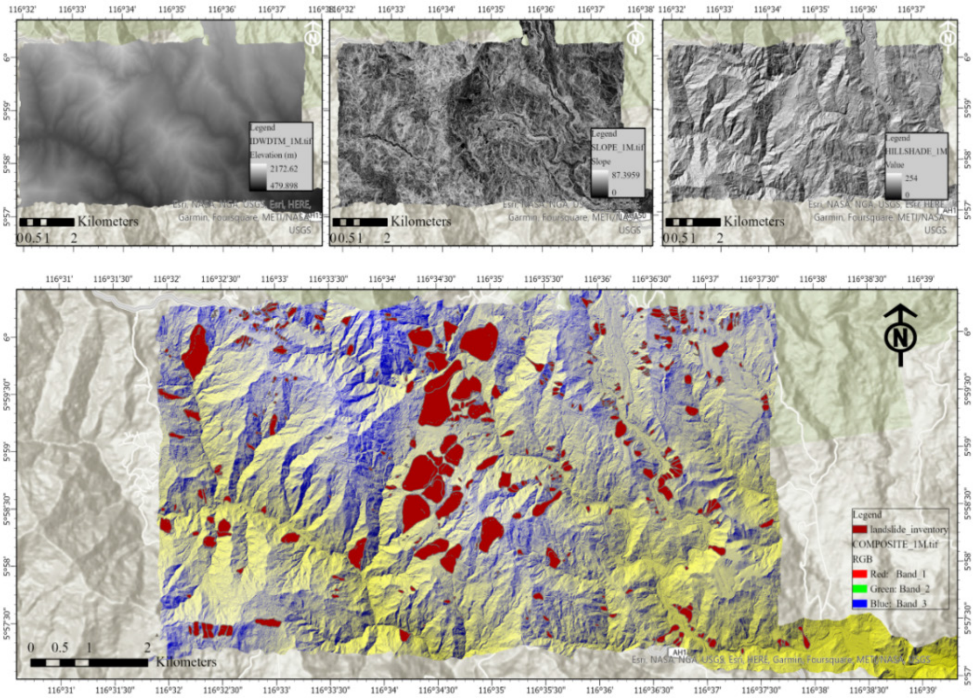

FIGURE 8. Map of DTM, hillshade, and slope at 1 m resolution for the deep learning input parameters

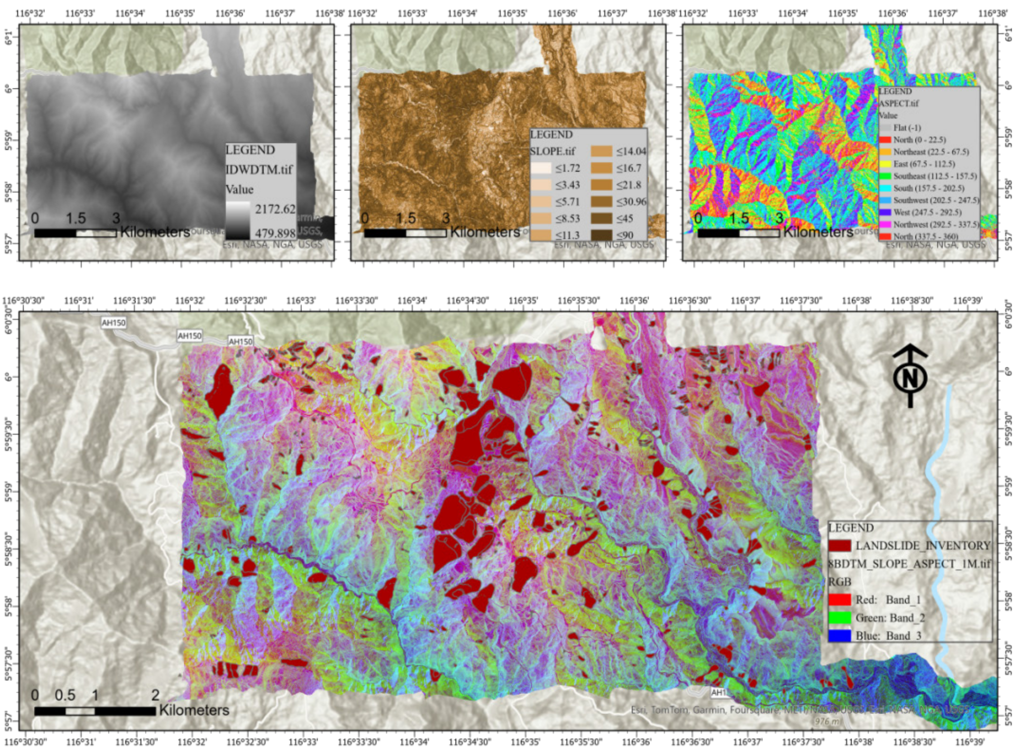

FIGURE 9. Map of DTM, slope, and aspect at 1 m resolution for the deep learning input parameters

LANDSLIDE DETECTION USING DEEP LEARNING

The analysis involved manipulating various parameter settings to assess their impact on the performance of the delineations obtained from the deep learning technique. The results were achieved by systematically altering the resolutions and backbone models, namely ResNet-101 and ResNet-152. Figure 10 depicts the best results of landslide delineation at each resolution, as the utilization of the Mask R-CNN with the combination of the DTM, hill shade, and slope at 1 m resolution with ResNet-152 indicates the best performance compared to other parameter settings.

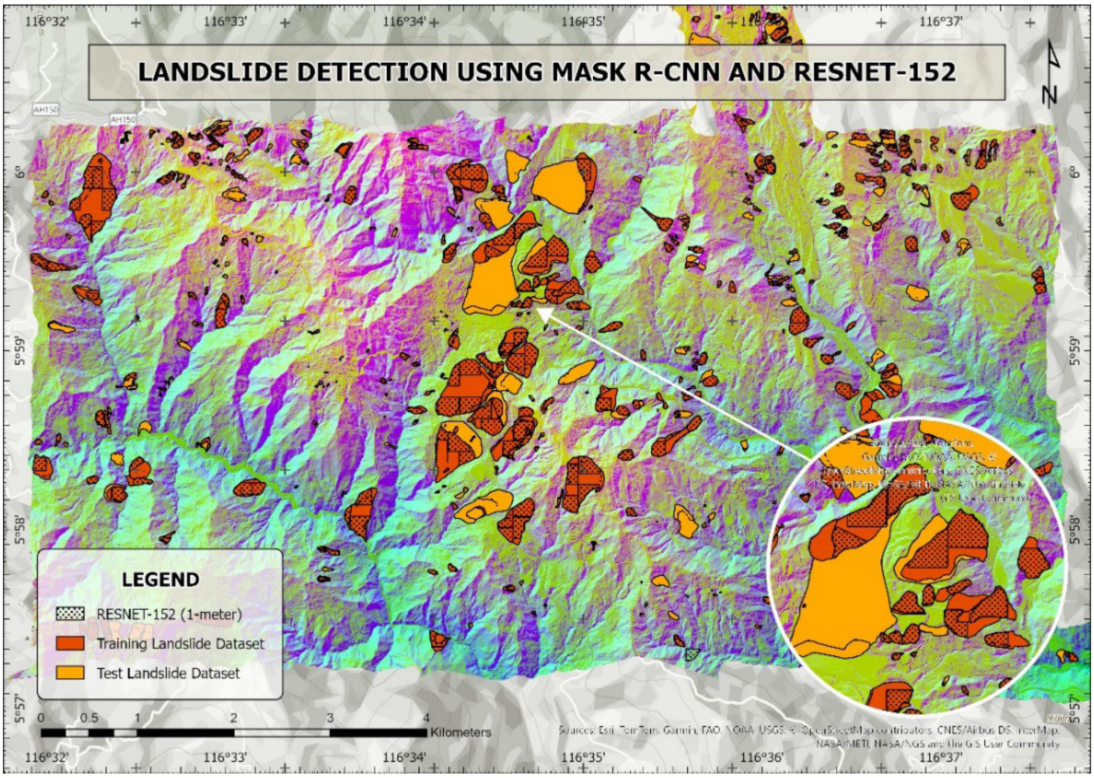

FIGURE 10. Visualization of landslide detection at 1-m resolution using ResNet-152 with the DTM, hillshade, and slope input layers

VALIDATION OF LANDSLIDE DETECTION

The performance of landslide detection by using a deep learning approach for active, dormant, and relict landslides is presented in Figure 11, comparing the architecture of backbone models for the DTM, hillshade, and slope and DTM, slope, and aspect layers, respectively. The deep learning technique classification Mask R-CNN achieved satisfying results for active landslides over dormant and relict landslides.

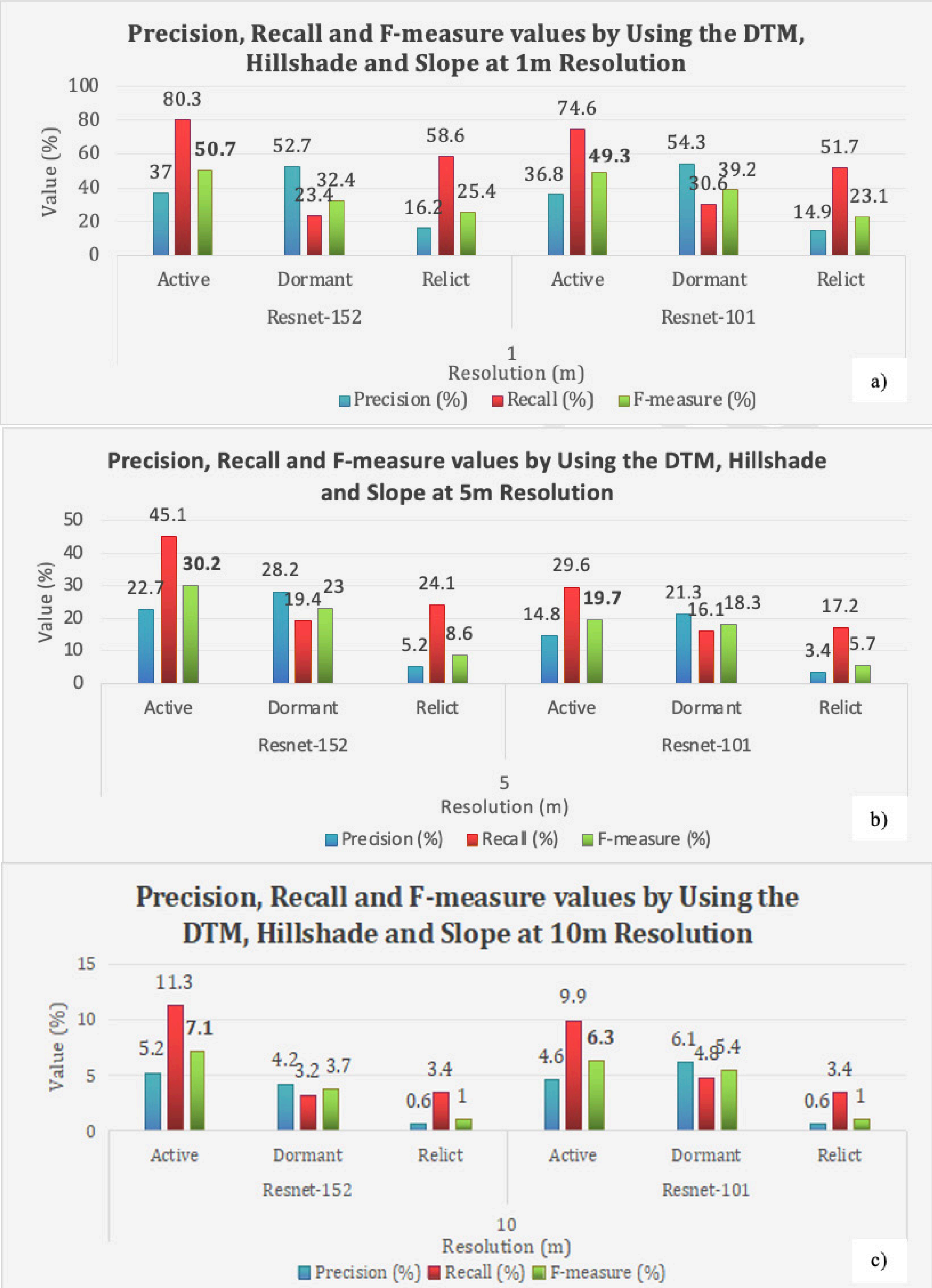

FIGURE 11. Precision, Recall and F-measure values obtained for landslide detection a) at 1 m resolution, a) at 5 m resolution and a) at 10 m resolution by using the DTM, hillshade, and slope input parameters

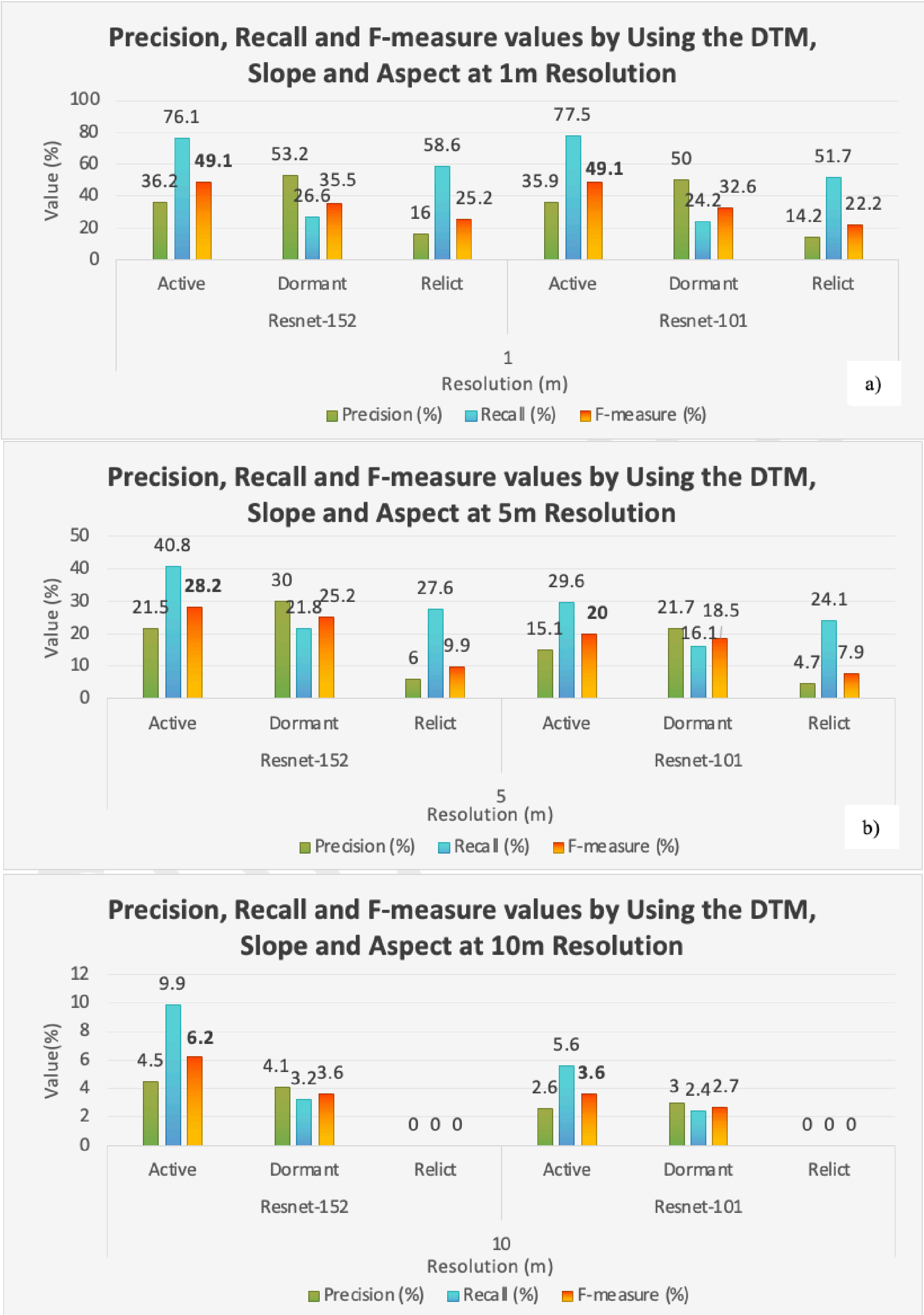

FIGURE 12. Precision, Recall and F-measure values obtained for landslide detection a) at 1 m resolution, a) at 5 m resolution and a) at 10 m resolution by using the DTM, slope, and aspect input parameters

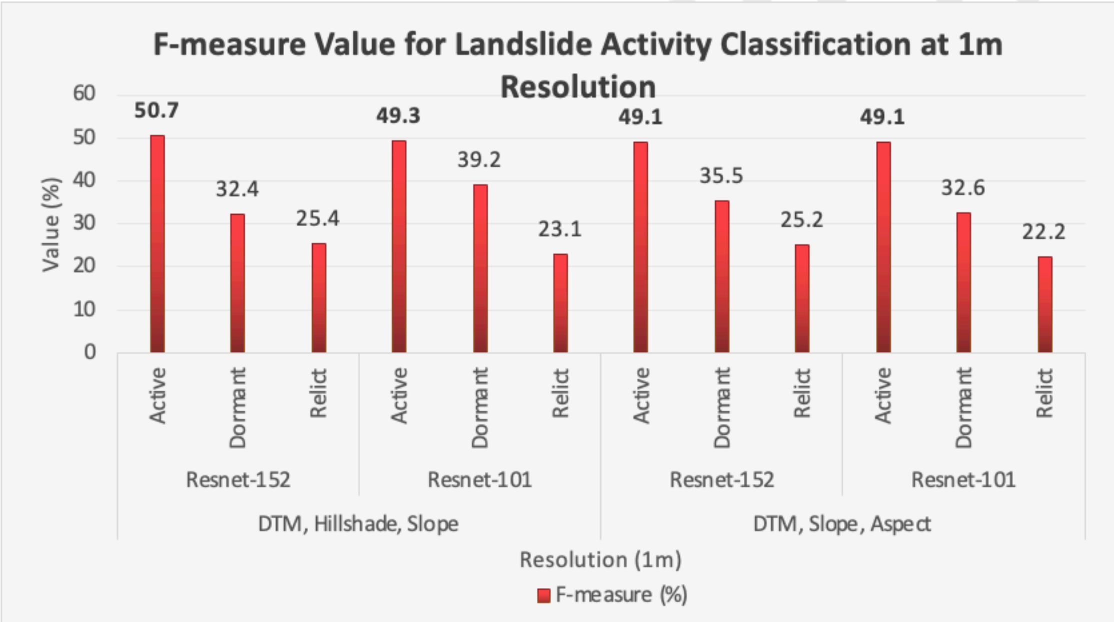

FIGURE 13. F-measure value for landslide activity classification by using both input parameters

DISCUSSION

IMPACT OF DTM PARAMETER RESOLUTION ON SIZES OF LANDSLIDE DETECTION

The 1 m resolution data in Figure 10 provide a detailed representation of terrain morphology that is particularly advantageous for landslide boundary delineation. The high-resolution DTM enables the model to effectively detect and outline complex structures of small landslides by capturing detailed topographic elements with both ResNet-101 and ResNet-152 architectures. The model effectively detects multiple smaller landslides that are not distinguishable at coarser resolutions (5 m and 10 m). At lower resolutions, terrain generalization leads to the loss of subtle morphological cues, resulting in reduced delineation accuracy and increased boundary ambiguity. In contrast, the precise delineation achieved at 1 m resolution reduces uncertainty in defining landslide extents, which is a fundamental requirement for developing reliable landslide inventories (Guzzetti et al. 2012). Implementing detailed terrain variables such as hillshade and slope layers enhances the model's ability to distinguish even subtle variations in slope and aspect. These variations are important indicators of landslide risk (Alimohammadlou et al. 2021; Hosseini et al. 2011). This reinforces the suitability of high-resolution LiDAR-derived terrain data for semi-automated landslide inventory delineation in complex tropical environments.

IMPACT OF DTM PARAMETER INPUT ON CLASSIFICATION OF LANDSLIDE ACTIVITIES

Figure 11 shows the result of landslide activity classification by using the DTM, hillshade, and slope input parameters. The ResNet152 model, at a 1 m resolution, achieved the highest F-measure of 50.7% for active landslides. In contrast, the detection accuracy for dormant and relict landslides was significantly lower, with the ResNet101 achieving an F-measure of 39.2% for dormant landslides, while the ResNet152 received 25.4% for relict landslides at similar resolution. Among the evaluated R-CNN architectures, ResNet152 consistently achieved the highest accuracy for detecting active landslides across various resolutions. Specifically, ResNet152 achieved the highest F-measures for active landslides at resolutions of 1 m, 5 m, and 10 m, with values of 50.7%, 30.2%, and 7.1%, respectively. The accuracy of detection was influenced by the resolution of the input data, with higher resolution data improving detection performance. However, the F-measure for detecting active landslides decreases as the resolution increases, underscoring the importance of high-resolution data for accurate landslide detection. This performance pattern reflects the strong morphological expression of active landslides, which present clearer scarp boundaries and surface disruption that can be effectively captured by high-resolution terrain representations and deeper convolutional feature hierarchies.

For the DTM, slope, and aspect input layer (Figure 12), the F-measure for active landslides reached 49.1%

when utilizing the ResNet-152 model with a 1 m resolution, while the ResNet-101 model also achieved an F-measure of 49.1%. On the other hand, the accuracy of detecting dormant and relict landslides was also considerably lower. The ResNet-152 model achieved the greatest F-measure of 35.5% for dormant landslides, using a 1 m resolution. Relict landslides do even worse, with a maximum F-measure of only 25.2% under identical circumstances. At lower resolutions, these statistics significantly decrease. At a resolution of 5 m, the F-measure for dormant landslides using the ResNet-101 model is 18.5%, whereas for relict landslides it was only 7.9%. When the resolution was set at 10 m, the ability to detect dormant landslides decreased even more. The F-measure for ResNet-101 is 2.7%, and for ResNet-152, it was 3.6%. For both models, the detection performance for relict landslides was as low as 0%. The pronounced decline in delineation performance at coarser resolutions indicates that essential morphological cues required for boundary definition are lost through terrain generalization. For dormant and relict landslides, where surface signatures are already subdued, this loss of spatial detail further limits the ability of vision-based models to distinguish landslide features from surrounding terrain. These results underscore that spatial resolution, rather than network architecture alone, is a primary controlling factor for delineation performance in complex tropical environments.

However, Figure 13 illustrates the accuracy value of F-measure using both input parameters. The best F-measure value of 50.7% of active landslides was captured by using the input parameters of DTM, hillshade, and slope, which indicates that the combination of these terrain features has outperformed the DTM, slope, and aspect layers, especially at 1 m resolution, which was able to visualize detailed topography and landslide evidence over the study region compared to other resolutions. The DTM, hillshade, and slope layers also stand out as the best input parameters to acquire higher F-measure values of dormant and relict landslides compared to other inputs, despite the fact that the values achieved were significantly low. Hillshade enhances local contrast and illumination-related terrain texture, which improves the visibility of subtle surface discontinuities for convolutional feature extraction, whereas aspect primarily encodes directional information that contributes less directly to boundary discrimination.

Comparing to related methods, the Mask R-CNN achieved reasonable detection of active landslide (around 50% of F-1 score). Prior work using optical data has achieved high accuracy in certain contexts. For example, Ghorbanzadeh et. al (2022) found ResU-Net gave superior segmentation results with Sentinel-2 and slope inputs, and Wang et. al (2023) significantly improved Mask R-CNN precision on very high resolution images. However, those approaches rely on spectral cues and may not generalize to dense forest or old scars. Garcia et. al (2023) specifically noted that detecting relict landslides in rainforest regions is challenging due to vegetation and soil cover. Our finding of low F-1 for relict landslides, including at 1 m resolution is consistent with the muted of terrain signals by relict scars due to years of regrowth. In other words, LiDAR-derived elevation models may not fully distinguish very old landslides from the surrounding terrain. This suggests a need for specialized strategies such as multi-temporal analysis of repeated LiDAR or the integration of additional sensors that can penetrate vegetation, which can highlight the subtle signs of aging landslides. Within this context, the observed performance levels are consistent with existing deep learning-based landslide delineation studies in forested regions and reflect current methodological limits rather than underperformance of the proposed framework.

Despite these challenges, our use of LiDAR does improve over purely optical methods in terms of capturing topography. It provides detailed 3D information of ground points and non-ground points. Our results are promising for a first demonstration of high resolution LiDAR-based landslide delineation in a tropical forested area. Notably, the ResNet-152 backbone consistently outperformed ResNet-101 for active landslide detection, which ensuring that the additional depth helped to capture complex landslide patterns. These findings confirm that high-resolution LiDAR combined with deep convolutional architectures is well suited for semi-automated landslide boundary delineation, particularly for inventories in densely vegetated tropical terrain where manual mapping is challenging.

CONCLUSION

The conclusion section summarizes the key findings and outcomes of the research project. The analysis focused on the accuracy of the landslide detection and delineation by utilizing high-density airborne LiDAR data and deep learning tools with reference landslide inventory. Among the methods evaluated, the input parameters at 1 m resolution depicted the most detailed delineation of landslides compared to 5 m and 10 m resolution, indicating that the higher the resolution, the higher the precision of the landslide inventory. In addition, the ResNet-152 architecture revealed the best performance with parameters of DTM, hillshade, and slope with the highest accuracy of F-measure on active landslides over dormant and relict landslides. The findings emphasize the importance of utilizing the high density of airborne LiDAR data to generate DTM and other terrain features to be used in deep learning to accurately delineate the landslides. Among the evaluated configurations, the combination of DTM, hillshade, and slope, together with the ResNet-152 architecture, achieved the highest delineation performance, particularly for active landslides, reflecting the strong surface expression and morphological contrast associated with recent failures.

Nevertheless, the reduced delineation performance observed for dormant and relict landslides represents an inherent limitation of single-epoch, vision-based approaches in densely vegetated tropical terrain, where surface signatures are progressively obscured by vegetation regrowth and long-term geomorphic processes. Rather than indicating a deficiency of the proposed framework, this outcome delineates the practical boundaries of morphology-driven landslide delineation and underscores the continued importance of expert interpretation for highly degraded or visually ambiguous features. By explicitly quantifying performance differences across landslide activity states, this study contributes empirical insight into the strengths and limitations of LiDAR-based deep learning methods for landslide inventory applications. For further work, we propose integrating multi-sensor and temporal data to address more details of subtle clues of old landslides. Additionally, exploring advancements in deep learning algorithms and enlarging the training dataset could improve the the landslide delineation accuracy. Overall, this study demonstrates that high resolution LiDAR combined with Mask R-CNN can substantially advance landslide mapping in tropical regions. It can provide a foundation for improved hazard monitoring and mitigation. Continued refinement along these lines will further enhance its utility for disaster management in Malaysia.

ACKNOWLEDGEMENT

The authors extend their sincere gratitude to the Ministry of Higher Education (MOHE), Malaysia, and Universiti Teknologi Malaysia (UTM) for their invaluable financial support, which was instrumental in facilitating this research. This study was generously funded through the Fundamental Research Grant Scheme (FRGS), under the grant reference FRGS/1/2020/TK02/UTM/02/1 (UTM Vote No. R.J130000.7852.5F396). The authors acknowledge the pivotal role of this funding in advancing the scope and depth of the research undertaken.

DECLARATION OF COMPETING INTEREST

None.

REFERENCES

Alimohammadlou, Y., Tanyu, B. F., Abbaspour, A. & Delamater, P. L. 2021. Automated landslide detection model to delineate the extent of existing landslides. *Natural Hazards* 107: 1639–1656.

Azarafza, M., Azarafza, M., Akgun, H., Atkinson, P. M. & Derakhshani, R. 2021. Deep learning-based landslide susceptibility mapping. *Scientific Reports* 11(1): 24112. https://doi.org/10.1038/s41598-021-03585-1

Cai, H., Chen, T., Niu, R. & Plaza, A. 2021. Landslide detection using densely connected convolutional networks and environmental conditions. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 14: 5235–5247. https://doi.org/10.1109/JSTARS.2021.3079196

Chen, Z., Gao, B. & Devereux, B. 2017. State-of-the-art: DTM generation using airborne LiDAR data. *Sensors* 17(1): 150.

Choi, S.-K., Ramirez, R. A. & Kwon, T.-H. 2023. Acquisition of high-resolution topographic information in forest environments using integrated UAV-LiDAR system: System development and field demonstration. *Heliyon* 9(9).

Conciatori, M., Valletta, A. & Segalini, A. 2024. Improving the quality evaluation process of machine learning algorithms applied to landslide time series analysis. *Computers & Geosciences* 184: 105531.

Congalton, R. G. 1991. A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment* 37(1): 35–46.

Dang, K. B., Giang, T. L., Phan, T. T., Truong, Q. H., Do, T. H., Dang, N. V. & Forino, G. 2024. Deep learning models integrating multi-sensor and-temporal remote sensing to monitor landslide traces in Vietnam. *International Journal of Disaster Risk Reduction* 105: 104391.

Garcia, G. P. B., Soares, L., Espadoto, M. & Grohmann, C. H. 2023. Relict landslide detection using deep-learning architectures for image segmentation in rainforest areas: A new framework. *International Journal of Remote Sensing* 44(7): 2168–2195.

Ghorbanzadeh, O., Xu, Y., Ghamisi, P., Kopp, M. & Kreil, D. 2022. Landslide4sense: Reference benchmark data and deep learning models for landslide detection. *arXiv preprint* arXiv:2206.00515.

Guzzetti, F., Mondini, A. C., Cardinali, M., Fiorucci, F., Santangelo, M. & Chang, K.-T. 2012. Landslide inventory maps: New tools for an old problem. *Earth-Science Reviews* 112(1–2): 42–66.

Hosseini, S. A., Lotfi, R., Lotfalian, M., Kavian, A. & Parsakhoo, A. 2011. The effect of terrain factors on landslide features along forest road. *African Journal of Biotechnology* 10(64): 14108–14115.

Jaboyedoff, M., Oppikofer, T., Abellán, A., Derron, M.-H., Loye, A., Metzger, R. & Pedrazzini, A. 2012. Use of LiDAR in landslide investigations: A review. *Natural Hazards* 61: 5–28.

Jiang, W., Xi, J., Li, Z., Zang, M., Chen, B., Zhang, C., Liu, Z., Gao, S. & Zhu, W. 2022. Deep learning for landslide detection and segmentation in high-resolution optical images along the Sichuan-Tibet transportation corridor. *Remote Sensing* 14(21): 5490.

Krishna, P. S. V. R., Shivakoti, B. R., Dewi, A., Arambepola, N. M. S. I., Kartiko, R. D., Jayasinghe, S., Basnayake, S., Towashiraporn, P. & Keaokiriya. 2021. On integrating climate change projection into landslide risk assessment and mapping at the river basin level. Jakarta, Indonesia.

Li, X., Liu, C., Wang, Z., Xie, X., Li, D. & Xu, L. 2021. Airborne LiDAR: State-of-the-art of system design, technology and application. *Measurement Science and Technology* 32(3): 032002. https://doi.org/10.1088/1361-6501/abc867

Metes, M. J., Miller, A. J., Baker, M. E., Hopkins, K. G. & Jones, D. K. 2024. Remotely mapping gullying and incision in Maryland Piedmont headwater streams using repeat airborne LiDAR. *Geomorphology* 455: 109205.

Pellegrino, V., Godard, V. & Fleury, J. 2024. Investigation of the use of topographic data derived from Pléiades imagery for high-resolution hillslope-scale morphometry. *Geomorphology* 454: 109162.

Razak, K. A., Santangelo, M., Van Westen, C. J., Straatsma, M. W. & de Jong, S. M. 2013. Generating an optimal DTM from airborne laser scanning data for landslide mapping in a tropical forest environment. *Geomorphology* 190: 112–125.

Shepard, D. 1968. A two-dimensional interpolation function for irregularly-spaced data. In *Proceedings of the 1968 23rd ACM National Conference*.

Tating, F., Hack, H. & Jetten, V. 2013. Weathering and deterioration as quantitative factors in slope design in humid tropical areas: Case study Northern Kota Kinabalu, Sabah, Malaysia. *Newsletter* 33(1): 22–28.

Tating, F. F. 2006. Geological factors contributing to the landslide hazard area at the Tamparuli-Ranau Highway, Sabah, Malaysia.

Tongkul, F. 1987. Sedimentology and structure of the Crocker Formation in the Kota Kinabalu area, Sabah, East Malaysia. PhD thesis, Royal Holloway, University of London.

Tongkul, F. 2017. Active tectonics in Sabah: Seismicity and active faults.

Wang, J., Chen, G., Jaboyedoff, M., Derron, M.-H., Fei, L., Li, H. & Luo, X. 2023. Loess landslides detection via a partially supervised learning and improved Mask-RCNN with multi-source remote sensing data. *Catena* 231: 107371.

Wang, K., He, D., Sun, Q., Yi, L., Yuan, X. & Wang, Y. 2024. A novel network for semantic segmentation of landslide areas in remote sensing images with multi-branch and multi-scale fusion. *Applied Soft Computing* 158: 111542.

Wei, R., Ye, C., Sui, T., Zhang, H., Ge, Y. & Li, Y. 2023. A feature enhancement framework for landslide detection. *International Journal of Applied Earth Observation and Geoinformation* 124: 103521. https://doi.org/10.1016/j.jag.2023.103521

Xu, Y., Ouyang, C., Xu, Q., Wang, D., Zhao, B. & Luo, Y. 2024. CAS Landslide Dataset: A large-scale and multisensor dataset for deep learning-based landslide detection. *Scientific Data* 11(1): 12.

Yu, B., Chen, F. & Xu, C. 2020. Landslide detection based on contour-based deep learning framework in case of national scale of Nepal in 2015. *Computers & Geosciences* 135: 104388.

Yu, H., Ma, Y., Wang, L., Zhai, Y. & Wang, X. 2017. A landslide intelligent detection method based on CNN and RSG_R. In *2017 IEEE International Conference on Mechatronics and Automation (ICMA)*.

Zhu, J., Nolte, A. M., Jacobs, N. & Ye, M. 2020. Using machine learning to identify karst sinkholes from LiDAR-derived topographic depressions in the Bluegrass Region of Kentucky. *Journal of Hydrology* 588: 125049.