Mapping of Elements at Risk for Landslides in the Tropics Using Airborne Laser Scanning

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Key words: Building and road extraction; building filter; ALS-derived topography openness

SUMMARY

Mapping elements at risk for landslides in the tropics pose as a challenging task. Aerial-photograph, satellite imagery, and synthetic aperture radar images are less effective to accurately provide physical presence of objects in a relatively short time. In this paper, we utilized an airborne laser scanning (ALS) for extracting elements at risk for landslides, which we emphasized on the buildings and roads extraction in a populated tropical region (Cameron Highlands, Malaysia). We presented the building filter derived from the hierarchical robust interpolation method for building extraction. Meanwhile, the road extraction was performed based on the ALS-derived topographic openness, analyzed in a stereoscopic model. Building and road attributes in relation to landslides were subsequently generated such as perimeter and area of building footprint; number and height of the buildings; road location; length; road gradient, and road-cuts. We quantitatively evaluated the building detection method and measured the vertical accuracy of ALS-derived road. The evaluation showed the building detection rate of 88.6%, the correctness of 90% and the overall quality of 80.7%. The vertical accuracy of the ALS-derived road was about 0.68 m and spatially improved compared to the existing road map. This study illustrates the effectiveness of ALS data for mapping elements at risks in the tropics, which are essential for landslide vulnerability and risk assessment.

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1. INTRODUCTION

Elements at risk is an essential component for vulnerability assessment and one of the main spatial data layers required for a total risk calculation (van Westen et al., 2008). As indicated by Varnes (1984) according to UNDRO (1982), elements at risk are a part of risk equation within a quantitative risk assessment. Fell et al., (2005) determined the conditional probability of landslide risk by taking into account all the potentially affected elements at risk for landslides. Elements at risk is defined as objects which possess the potential to be adversely affected (Hufschmidt et al., 2005). van Westen et al., (2005) refer to the objects by giving emphasis to the buildings, population and infrastructure, which are at particular risk for landslides. As a basic unit for risk analysis, characteristics of elements at risk are required to be properly collected, particularly at the landslide-prone areas in the tropics.

Spatial, temporal and thematic characteristics of elements at risk should be included for a complete risk database. Despite the mapping of elements at risk is not completely different from other types of hazard mapping; more emphasizes should be given to its characteristics which are essential for the landslide vulnerability study (van Westen et al., 2005). A rapid inventory of the elements at risk in the equatorial regions with appropriate mapping techniques is needed.

In the tropics, mapping of elements at risk for instance buildings and roads are rather difficult because of climatic, topographic, and anthropogenic factors over the areas. Often, the spatial characteristics of elements at risk, in the form of location in relation to the landslides, are collected from the cadastral database or thematic maps. Outdated and inconsistently updated elements at risk for landslides are among the major issues in the tropics. A wide coverage of aerial-photography and satellite imagery do not consistently provide reliable images due to constant cloud cover and forest canopy (Brardinoni et al., 2003; Metternicht et al., 2005). Whereas, synthetic aperture radar technique is less effective to reveal physical presence of objects due to geometric noise, temporal signal de-correlation caused by tropical-vegetation, and atmospheric variability in space and time (Rott, 2009).

There is a need to accurately measure the physical presence of objects in a relatively short time for a large area. Over the last few years, airborne laser scanning (ALS) becomes available to provide a highly accurate topography data, particularly in complex landscapes (e.g. urban environment and forested terrain). The ability of ALS to penetrate the gaps between forest foliages and its independence to solar incidence angle makes ALS superior to image-based photogrammetric techniques for extracting man-made features in a rugged forested terrain (Kraus, 2007). Many studies have been conducted for building extraction using ALS data (Matikainen et al., 2003; Pfeifer et al., 2007; Rutzinger et al., 2008). Most of building detection methods have been implemented in a rasterized ALS data. An appropriate tropical-building detection method and its parameterization, which solely performed on point cloud is scarcely well-documented. Extracting the building footprint, from low point density ALS data in the tropics is a challenging task while quantitatively accessing the overall quality of the extracted buildings, coupled with completeness and correctness percentage are hardly accomplished. Road extraction from air-based imageries has been extensively studied (Quackenbush, 2004). ALS has been used for extracting the linear features and characterizing the 3D road attributes in the urban or open terrain (Alharthy et al., 2004; Clode et al., 2007; David et al., 2009). Few studies have been carried out to extract road features in the rugged forested terrain covered with structurally-complex forest types (White et al., 2010). Mapping road features in the tropics is an important step to identify slope stability problems along the transportation route zones. Over the large area in a forested mountainous landscape, mapping and maintaining the road attributes are time-consuming and expensive (Jazouli et al., 1994).

So far, few attempts have been made to utilize ALS data for mapping elements at risk in the populated mountainous regions in the tropics. Herein, we refer elements at risk to the buildings and roads as the objects in the context of landslide risk assessment. Therefore, our first objective of this paper is to highlight the capability of ALS technique for providing accurate physical presence of objects in the relation to the elements at risk for landslides. The second aim of this research evaluates the extraction methods of the buildings and roads, with regards to elements at risk for landslides. For the building extraction, we optimize the filtering and classification method in such a way that the buildings can be automatically extracted from the low point density ALS data and solely works on point clouds. Thus, we revealed an appropriate parameterization for building detection in the tropics, namely as the building filter. The road extraction was performed based on the ALS-derived image, coupled with visualization technique. The semi-automatic approach revealed two types of roads and subsequently identified road cuts which are relevant to landslide occurrences. Road network and building footprints will be quantitatively accessed. This research framework was implemented on the landslide-prone areas in a lowland evergreen rainforest in Malaysia.

2. STUDY AREA

The study area is located within the equatorial belt in the Peninsular Malaysia. It is situated on the south-facing slope of Bertam River Basin, Cameron Highlands. Figure 1 shows the location of study area in the Malaysian Tropical Rainforest. Overview of ALS point cloud at particular areas are given in Figure 1(B)(C). Typically, this area has higher annual rainfall with up to 3500 mm per year. Herein, the tropical rainforest also refers to a lowland equatorial evergreen rainforest. The average mean temperature is about 27°C per day and daily humidity is recorded up to 97%. Two monsoons seasons, which normally takes place from April to October (south-east monsoon) and from October to February (north-east monsoon). The area is characterized by irregular topography with slope gradient ranging between 15 and 80^{o}. Elevation of the study area is up to 2500 m above mean sea level. Geology at the study area is characterized by a megacrystic biotite granite (Krahenbuhl, 1991) and have been weathered to form tropical residual soils. This typical soil can be observed on the side slopes, whereas colluvial soils largely covered the footslopes.

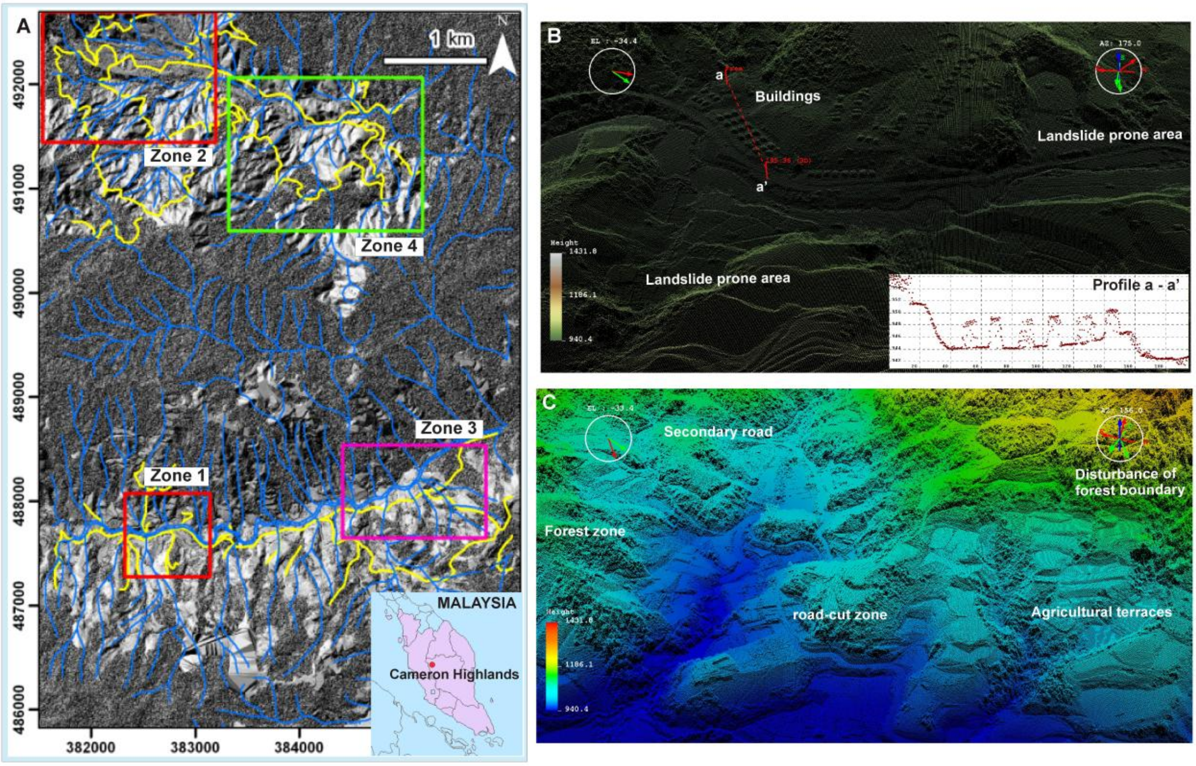

Figure 1: Location of study area in the Malaysian tropical rainforest (Cameron Highlands). A) Digital surface model showing existing road and zonation, B) Buildings shown in point cloud which is enlarged from zone 1, C) Anthropogenic activities, enlarge from zone 3.

The study area is mainly covered by hill dipterocarp, montane oak and montane ericaceous forests (Wyatt-Smith, 1995). Within the tropical climatic, agriculture activity (e.g. vegetable production and tea plantation) is largely dominent in this area. Agriculture terraces on the footslopes and dispersed settlement zones are typical scenario of landscape, where most of these areas are prone to landslides. High demand for agriculture products and increasing number of population leads to high activities of anthropogenic sources. The conversion of forest-land into agriculture-land, without proper guidance on slope stability, good practice on land management and lack of enforcement cause a major problem to the environmental and ecological issues. Due to intense and prolonged rainfall, particularly in the tropical residual soil cut slopes, many unstable slopes are initiated in this region (Othman et al., 1991).

3. METHODS

3.1 Airborne laser scanning measurement

In this study, we used about 40 million point clouds representing as first and last pulse of laser data in a rugged forested terrain of 32 km^2. This data was collected by the Department of

Survey and Mapping (JUPEM) Malaysia in June 2004 over the Cameron Highlands, Malaysia. During the ALS data acquisition, JUPEM used several permanent Global Positioning System (GPS) stations consisting of primary and secondary GPS stations within the flight zones . The Airborne Laser Terrain Mapper (ALTM) 3100 laser scanning system, coupled with ALTM-IMU was used. An oscillating single-axis mirror system was applied to capture the physical presence of the landscape, with a pulse repetition rate of up to 100 kHz. As a result, a very large dataset of point clouds, with point density of 2 points m^{-2} was utilized in this paper.

3.2 Mapping elements at risk in the tropics

In this section, we presented methods to extract objects (buildings and roads), which are relevant to elements at risk for landslides in the tropical rainforest. In order to implement the methods, two zones (1 and 2) were selected in the study area as depicted in Figure 1. These zones were categorized as highly susceptible to landslides by Pradhan and Lee (2009). Local farmers tend to expand these areas for agriculture activities. Besides that, we used landslide inventory from ALS to allocate the landslide prone areas in the study area. Landslide inventory has been prepared by an expert-image interpreter using a stereoscopic-visual interpretation technique. 1m ALS-derived image was used, coupled with various visualization techniques. A high resolution ALS-derived DTM was generated using a modified landslide filter for forested landslides. The landslide filter was revealed by Razak et al., (2011), specifically to deal with complexity of landslide morphology beneath dense vegetation. A detailed description about the quantitative and qualitative assessment of ALS-based landslide inventory, reconstruction of high resolution DTM, its effectiveness for susceptibility mapping in the tropics has been discovered and will be published in the near future.

3.2.1 Building extraction in the tropics

A hierarchical robust interpolation (HRI) method was used in this study. This method is implemented in the SCOP++ environment and capable to filter and classify the point clouds. HRI method is structured by a robust interpolation algorithm (Kraus and Pfeifer, 1998) and Pfeifer et al., (2001) extended into a hierarchical approach. This method was originally developed for ALS data in the forested terrain. The algorithm is empirically based on linear prediction and associated to a weight function (Eq. 1). In order to calculate weight P_i for each point, filter values, f must be properly assigned. Eccentricity, g is determined with a histogram of residuals. Values of a and b are represented in relation to half-width values and the steepness of the weight function. The schematic diagram of the weight function used for the landslide-DTM can be found in Razak et al., (2011). In principal, more weight is given to points which are likely to ground surface and low weight to points likely to non-ground surface (e.g. building and vegetation). The procedure is an automatic, fast and solely works on point cloud. Therefore, we are not dealing with inequality extraction due to point clouds and image conversion.

As part of the filter strategy, we revealed a parameterization used for building extraction in the tropics. Herein we refer this parameterization as a building filter. First and last pulses of point cloud were used for building extraction. The building filter was considered the low point density of ALS data as data input and its capability to extract a building area as small as 9 m^2. Steps to automatically eliminate or extract the buildings from the point cloud were executed before the filtering steps (thin out – filter – interpolate - sort out/classify) were carried out for DTM generation.

$$P_i = \begin{cases} 1 & f \leq g \\ \dfrac{1}{1+(a(f_i - g))^b} & g < f_i \leq t \\ 0 & t < f_i \end{cases} \tag{1}$$

We utilized the edge detection and region growing technique for a building detection, as implemented in the HRI method. The cell sizes, minimum size of building and minimum slope are the main parameterizations used for the building detection (Table 1). The cell and building size are dependent on the density of point cloud and the minimum number of buildings required to be detected. Minimum slope is used as a threshold to detect the edge and boundary of the building. First, the edge of the building is detected based on computation of the steep gradient. Then the algorithm starts searching and the points grows that are likely to the building geometric. This steps work iteratively in three processing stages. Each stage required different parameterizations. As part of the HRI method, the building filter was executed, while the terrain model was generated and classified the other non-ground points (e.g. vegetation with certain height, below ground surface).

Table 1: Building filter parameterization used for the building extraction in the tropics

Parameters/stages	Cell sizes (meter)	Minimum building size (square meter)	Minimum slope (tangent)
First stage	3.0	9.0	1.1
Second stage	2.0	9.0	1.0
Third stage	2.0	9.0	0.9

Theoretically, three main parameterizations were set at maximum thresholds at the first stage and the values were decreasing at the second and third processing stages. An optimization of the appropriate parameterizations was defined based on trial-and-error strategy. The default settings provided by the software supplier were used as a reference and were then modified, with regards to point density of ALS data, local knowledge on building geometric and topographical elements. The building footprint, with respect to its location, shape, building perimeter, area and height are the primary attributes presented in this paper. They are amongst the essential elements for vulnerability assessment and can be used to link with further attributes such as type of building materials and number of persons inside the buildings. The extracted buildings were spatially analyzed using ArcGIS software in relation to landslides distribution. We calculated the building areas, perimeter and height. For simplifying the building footprint, we applied the Douglas-Pecker algorithm (Douglas and Peucker, 1973), as implemented in GIS environment. This algorithm is capable to remove noise of tropical building footprint.

3.2.2 Road extraction in the tropics

A semi-automatic approach was carried out to extract roads in the tropics. More than 75% of the roads are located in areas that are partly or completely covered by forest. In relation to landslide processes in this area, we differentiate the roads into primary roads and secondary roads. Also, we carefully identified the road cut zones. In this study, we used a new visualization technique, called topography openness which was developed by Yokoyama et al., (2002). This technique was applied into the high resolution ALS-derived DTM, produced in earlier steps. Basically, this technique computes the zenith and nadir angles along the eight azimuth of DTM. As a result, a monoscopic model was derived and visualized in ArcGIS software (Figure 2(A)). The ALS-derived topography openness was unbiased from the solar irradiation. The ILWIS software was used to generate a stereoscopic image of the topographic openness map. This map can be viewed as a stereoscopic or an anaglyph image using a red and blue glass (Figure 2(B)). We then utilized 1 m ALS-derived topographic openness for extracting the roads. Types of the roads were also classified during the detection stages.

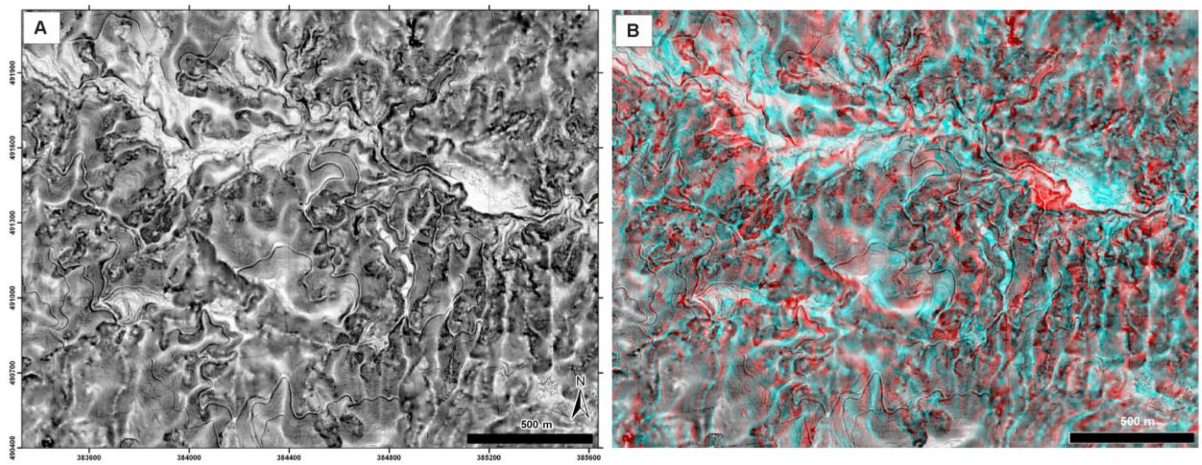

Figure 2: ALS-derived topographic openness. A. Monoscopic image, B. Stereocopic image

3.2.3 Quality assessment

The quality assessment was conducted by a statistical comparison between the extracted objects with reference datasets. For building extraction, we used a reference data generated from a stereoscopic-based visual interpretation of ALS-derived DSM and further validated using a dynamic 3D point cloud visualization. See Figure 3(A)(B) for examples of data sources used for generating a reference dataset. A stereoscopic model was produced with combination of a shaded-relief of DSM and the ALS-derived DTM. Further detail about an artificial stereo image technique can be found in van Westen et al., (2004). The 3D point cloud is capable to provide a geometrically accurate dataset and much better than the one provided by photogrammetric products (Leberl et al., 2010). A large number of point clouds can be dynamically visualized in 3D model using the Quick Terrain Modeler software. A reference dataset derived from a stereoscopic visualization was simultaneously evaluated with

3D point cloud. Therefore, a reliable reference dataset is sufficient to access the performance of building extraction method. Furthermore, the road extraction was quantitatively accessed based on the vertical accuracy of the extracted roads. The positional errors of the ALS-derived road were not carried out in this paper. It is because of the inavailibility of the reference dataset and the existing road map is not comparable due to different techniques applied for road measurements, period of data acquisition, and improper map generalization techniques.

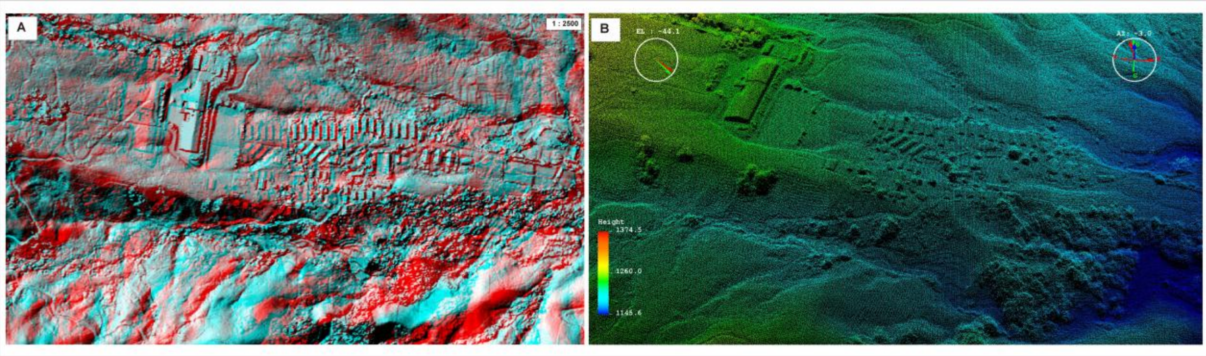

Figure 3: Data sources used for constructing reference dataset in the tropics.
A) Stereocopic model visualized as blue-red anaglyph image, B) Dynamic 3D point clouds

To evaluate the performance of the building filter, we employed the quantitative assessment of building extraction (Lee et al., 2003; Rottensteiner et al., 2005; Sohn and Dowman et al., 2007) and particularly used the building footprint area on the following measures (Eqs.2,3,4):-

$$\text{Completeness} = \left(\frac{TP}{TP+FN}\right)\times 100 \qquad (2)$$

$$\text{Correctness} = \left(\frac{TP}{TP+FP}\right)\times 100 \qquad (3)$$

$$\text{Quality percentage} = \left(\frac{TP}{TP+FN+FP}\right)\times 100 \qquad (4)$$

Where, TP (True Positive) is the number of building areas classified by both dataset, FN (False Negative) is the number of building areas classified only by the reference dataset, FP (False Positive) is the number of building areas classified only by the building filter. The completeness is referred to building detection percentage, whereas the correctness are the ratio of the correctly classified building areas (TP) with respect to the total building areas classified by the reference dataset and by the automatic method (TP+FP), respectively. In order to acquire a perfect quality, the method must correctly classify buildings, without missing any building and without over-classifying the buildings. These factors indicate a measure of building extraction performance. The vertical accuracy of LIDAR-derived road was measured based on 32 field-surveyed GPS points in this area. The validation data was collected in July 2009. The terrain heights of these points were measured using a Topcon Hiper Pro, using a real-time kinematic technique with horizontal and vertical accuracy of about 10 mm + 1ppm and 20 mm + 1ppm, respectively. The statistical measurement of *root* *mean square* (*RMSE*) is sufficient for an analysis of height differences as depicted in Eq. 5. The gradient of ALS-derived road was calculated and analyzed in this paper, in which road gradient is one of essential parameter for estimating rates of road erosion (Luce et al., 1999).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(Z_{GPS\ i} - Z_{ALS\ i}\right)^2}{n}} \tag{5}$$

4. RESULTS AND DISCUSSION

4.1 Building maps and quantitative assessment of the building filter

We extracted 137 buildings with height of up to 20 m. Figure 4(A)(B) show the height of ALS-derived buildings in the landslide prone zones. The perimeter of the buildings was about 40 m and the area ranging between 9 and 3875 m^2. The classification results, in the form of building area show that the TP, FP and FN are 11242, 1240 and 1442 m^2, respectively. Based on these results, the evaluation of the extracted buildings were computed using Eqs. 2, 3, 4. The building filter indicates that the buildings were detected at the rate of 88.6% (completeness) and 90.0% in correctness. We attained higher correctness performance than the completeness due to the tendency of the building filter to produce less false positive than false negatives. The overall success of the building filter, also described as quality percentage to extract the buildings in the tropics was 80.7%.

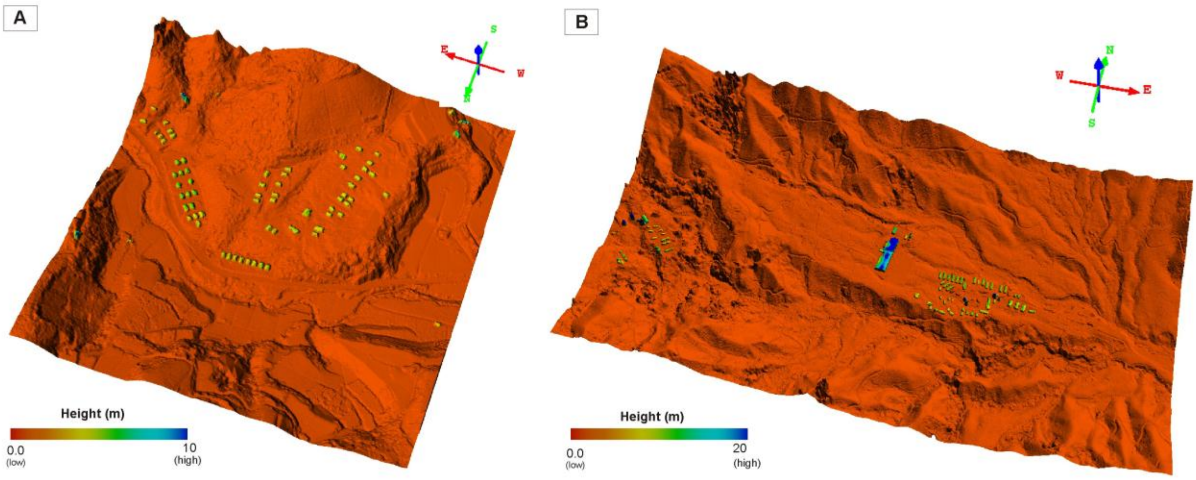

Figure 4: Building height in the landslide prone areas. A) zone 1, B) zone 2

Previous studies have developed methods to extract buildings with building detection rate within the range of 60 and 94%. Within the similar environment of the landscape, Chen et al., (2009) produced 60.5% user accuracy for building classification; with total accuracy was about 69.1% and kappa coefficient of 0.62. Ma (2005) found in average of 86.5% buildings were correctly detected in the areas of low topographic roughness. With combination of multi-spectral band dataset and high resolution orthophoto, Rottensteiner et al., (2005) achieved 94 and 80% for completeness and correctness, respectively. Sohn and Dowman

(2007) found an overall quality of up 80.5% with detection rate of 88.3% and more than 90% for correctness. Although it is difficult to perform the comparison due to different landscape complexity and primary data sources, the building filter indicated an improvement in the building detection rate and overall extraction quality for the low point density of ALS data in the tropics. The extraction quality will be improved significantly when the data fusion (e.g. oblique and sequence airborne images) is utilized in such a way that it can be used to detect different complexity of buildings in a lowland equatorial evergreen rainforest.

4.2 ALS-derived road map and its attributes in the tropics

We improved the road network based on the high resolution ALS-derived image. Figure 5(A)(B) indicate the existing road network and ALS-derived road, respectively. The location of the road as depicted in Figure 5(A) can be seen in Figure 1 (zone 4). Road positions, length and road-gradient were well-determined from the ALS-derived road map. The topographic openness map revealed from a high resolution ALS-derived DTM provides an effective way to extract the tropical roads in the rugged forest regions.

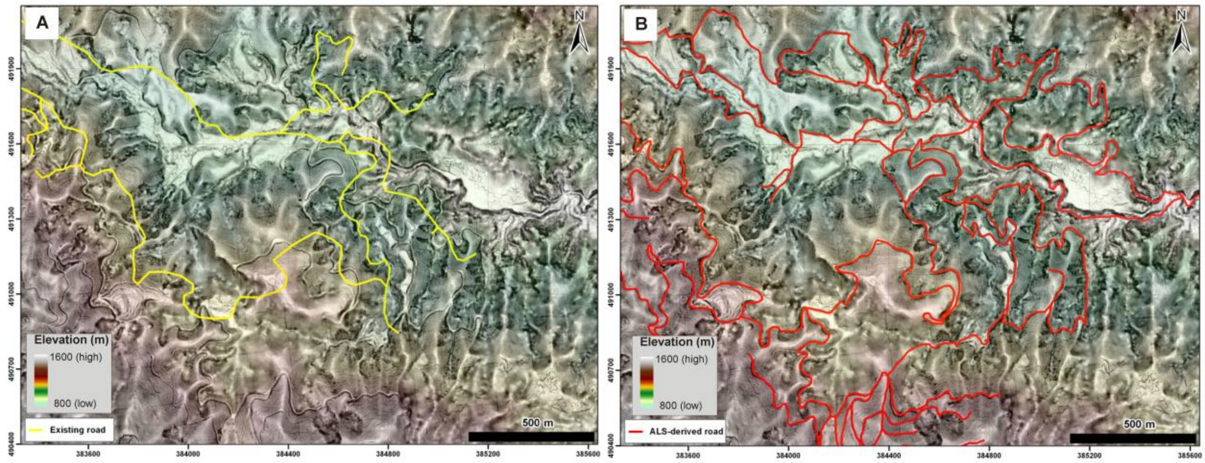

Figure 5: Existing road and ALS-derived road overlaid on the topographic openness with elevation variation. Note: the location of road (A) can be seen in Figure 1 (zone 4).

The vertical accuracy of the ALS-derived road was about 0.68 m compared to the field data. White et al., (2010) found the differences between the ALS-derived DTM and 126 roads surveyed elevation was up to 0.61 m, with a better *RMSE*. They also found a positional accuracy of 1.5 m within 0.53% mean absolute difference. Our accuracy was slightly lower because of the field-surveyed points were collected after five years of the ALS data acquisition where in most cases the areas have higher topographic changes due to agricultural activity, local transportation routes, and high anthropogenic disturbances.

From the ALS-derived road map, we found about 58% of increment of the total road length compared to the existing road network. The average road length for ALS-derived road and existing road map were about 811 and 640 m, respectively. The mean gradient of ALS-derived road was in the range of 4 to 32^0, with standard deviation of 13.6^0 (Figure 6). We calculated that about 28% of total road length was classified as road cuts, where usually landslides initiated and took place in these zones. We also classified the roads into primary and secondary roads. We found only 10% of the total length of ALS-derived road are identified as the primary roads, whereas the other roads are categorised as the secondary roads. Often, the secondary roads are used for agriculture activity and their condition are easily affected by heavy or over-loaded vehicles. We also observed on the field that local farmers have tendency to cut the slopes to construct the roads and many road cuts are located on the secondary roads which are not well-maintained by the local government agencies. This scenario revealed a high certainty to landslide occurrences over the areas.

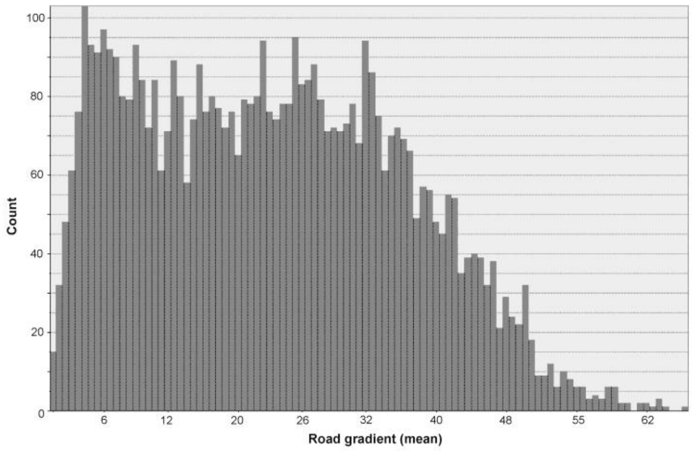

Figure 6: Histogram of the mean gradient of ALS-derived road

In the near future, a proper quantitative assessment of extracted road methods for tropical area is required. Many existing algorithms on line detection previously applied on the images can be tested and implemented on the point cloud. The forested road detection methods should be automatically operated in such a way that their capacity to be applied for a larger area and be working on a national scale. Road grade, cross-sectional slopes, and road prism geometry are among the secondary attributes, which can be derived from our primary ALS derived road map. A higher point density coupled with full waveform with high resolution digital images have more potential to produce more reliable and accurate detection results. As reported by Johansen et al., (2010), cost of ALS mapping for a larger area was lower than the others air-based platform technology. Therefore, it can be intensively used for the tropical regions since topographic mapping in these areas have difficulty in dealing with complexity of the environment, rapidly-re-vegetated issues, prevalent cloud coverage and high anthropogenic activities.

5. CONCLUSION

This paper presented the extraction methods of elements at risk for landslides in which we addressed the buildings and roads extraction in a tropical rainforest region. Spatial characteristics and geometric attributes derived from these two objects are essential for landslide vulnerability assessment. The tropical building attributes are represented in the form of building distribution, perimeter and area of building footprint and height of the buildings.

Meanwhile, tropical road attributes represented as road positions, length and gradient. For the building extraction, we used a hierarchical robust interpolation method and revealed the building filter parameterization, particularly to extract buildings in the tropics from a low ALS point density and capable to detect as small as 9 m^2 of buildings. The building filter was implemented in the three stages of point cloud processing, which works solely on point cloud. We automatically extracted 137 buildings with overall quality building detection of 80.73%. The completeness and correctness of the extracted buildings were about 89% and 90%, respectively. The building detection rate is significantly improved using this method compared to similar study carried out by Chen et al., (2009) in Malaysian tropical environment. In the near future, the works should be addressed towards the data driven approach for 3D building models over the hazardous areas and possibility to extend the workflow to roof shape reconstruction, model generation, regularization and model quality analysis (Dorninger and Pfeifer, 2008).

The total road length as revealed by ALS-derived road map shown about 58% of increment compared to the existing road map. The vertical accuracy of the road derived from ALS-derived topographic openness was about 0.68 m. About 90% of the ALS-derived roads was found and classified as the secondary roads in this study. Almost 30 % of road cuts were identified from ALS data, which can be used for the susceptibility and hazard mapping in the tropics. We observed on the field that this scenario has a direct relationship with the frequent slope failures that occurred in the areas, where mostly road cuts has taken place and many of the landslides had failed to be properly reported. Thus, it seems to take a longer time before the national target for completing a landslide database can be reached, towards which the monitoring, maintaning and predicting landslide prone areas can be perfomed. We noticed that ALS is capable for a rapid mapping, which is one of the essential elements for emergency response in dealing with hazard and risk assessment in the mountainous landscape. We therefore propose to the local and national government agencies in Malaysia to utilize this topographic mapping technology, especially in the context of disaster management and we believe that it should be part of the risk management and prevention policies.

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