Catena 172 (2019) 435–450

Contents lists available at ScienceDirect

Catena

journal homepage: www.elsevier.com/locate/catena

A novel rockfall hazard assessment using laser scanning data and 3D modelling in GIS

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ARTICLE INFO

Keywords:
Rockfall
Hazard
3D modelling
AHP
GIS
LiDAR

ABSTRACT

Rockfall hazards occur widely in regions with steep terrain such as Kinta Valley, Malaysia. Rockfalls threaten urban areas and the transportation corridors that pass through such areas. This paper proposes a comprehensive rockfall hazard assessment strategy based on high-resolution laser scanning data (LiDAR), both airborne and terrestrial. It provides (1) rockfall source identification by developing a hybrid model based on a bagging neural network (BBNN), which is compared with various machine learning algorithms and ensemble models (bagging, boosting, voting) and a Gaussian mixture model; (2) 3D modelling of rockfall kinematic processes (trajectory distribution, frequency, velocity, kinetic energy, bounce height, impact location); and (3) hazard zonation based on spatial modelling in combination with an analytical hierarchy process (AHP) in a geographic information system (GIS). In addition, mitigation measures are suggested based on the modelling results. The proposed methodology was validated in three study areas to test the applicability and generalisability of the methods. The results show that the proposed hybrid model can accurately identify rockfall source areas at the regional scale. It achieved a 97% training accuracy and 5-fold cross-validation area under curve (AUC) value of 0.96. The mechanical parameters of the developed 3D model were calibrated with an accuracy of 97%, 93% and 95% for Gunung Lang, Gua Tambun and Gunung Rapat areas, respectively. In addition, the proposed spatial model effectively delineates areas at risk of rockfalls. This method provides a comprehensive understanding of rockfall hazards that can assist authorities to develop proper management and protection of urban areas and transportation corridors.

1. Introduction

Rockfalls are a frequent and prevalent phenomenon that can influence isolated homes and entire villages, long stretches of roads and railways and other anthropogenic facilities. Such structures at risk of rockfalls are situated on or close to the base of steep rocky slopes. Rockfalls are a fast mass movement produced by rocks that detach from a slope and free-fall and roll downhill. Because of their high velocities and unpredictability, such events can cause casualties, even with small rock volumes of $< 1\ m^3$ (Gigli et al., 2014; Volkwein et al., 2011).

Most often, rockfall hazards cannot be eliminated due to their frequency and magnitude, which vary both temporally and spatially. The main difference of rockfalls from other unstable slope phenomena is the high mobility of falling rocks (Frattini et al., 2008). Rockfall hazard assessment is restricted by inadequate availability of high-resolution geospatial data on slope topography, rockfall release points, block geometry and rock trajectories (Dorren, 2003). The dependability of rockfall hazard assessments relies on the quantity and quality of available data (Pradhan et al., 2014).

Rockfall hazards are normally assessed by conducting two-dimensional (2D) or three-dimensional (3D) simulations (Fanos and Pradhan, 2016), which evaluate rockfall trajectories, velocities, kinetic energy and the bouncing height of falling blocks. Simulation models mimic boulder kinematics, computing their motion downslope based on Newton's second law while ignoring the friction of air (Pradhan and Fanos, 2017b). Some of these models also explicitly involve the rolling movements of rocks (Lan et al., 2007). However, the study of rockfall impact assessment (the interaction of rocks with the topographic surface during sequential contacts) remains a major scientific challenge in rockfall modelling (Matas et al., 2017).

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https://doi.org/10.1016/j.catena.2018.09.012
Received 27 March 2018; Received in revised form 29 August 2018; Accepted 6 September 2018

Rockfall trajectories are controlled by the locations of the seeder points, slope topography, the mechanical properties of falling rocks and outcropping materials (Ritchie, 1963), and by the rock masses and shapes. Such parameters are usually hard to evaluate. The most frequently used method is based on probabilistic analysis while statistically varying the input parameters (Giani et al., 2004; Fanos et al., 2016).

Quantitative techniques have become common in last decade (Pham et al., 2016; Pradhan, 2011). For the spatial prediction of landslides, machine learning approaches are now considered more efficient than conventional approaches such as analytic and expert opinion-based techniques (Pradhan, 2013; Hong et al., 2015). Basically, the use of machine learning in landslide probability analysis involves assessing the spatial relationship between past landslide events (*inventory data*) and a set of conditioning factors from which the potential probability of the occurrence of a landslide is estimated (Chen et al., 2015). However, machine learning is rarely applied in rockfall source identification.

The current research proposes a methodology that aims at accurately, rapidly and objectively defining detailed slope topography and the 3D positions of features of interest (such as possible existing protection measures, elements at risk, etc.). In addition, it aims to identify rock dimensions and shapes, and main rockfall source regions (through a hybrid model). Numerous studies have already dealt with some of these topics, using either light detection and ranging (LiDAR) or photogrammetric data (Abellán et al., 2010; Ferrero and Umili, 2011; Ferrero et al., 2011; Gigli et al., 2014).

Despite numerous studies in rockfall hazard assessment, information about impact locations has not been discussed in the literature. However, the impact location is the most significant factor in rockfall risk assessment and the design of mitigation processes. Moreover, the temporal element has not been considered in existing studies, despite it being a key element in early warning processes. Some researchers have utilized 2D modelling approaches for rockfall kinematic process modelling (Keskin, 2013; Papathanassiou et al., 2013). In 2D rockfall models, obtaining realistic assessment results depends critically on the selection of a 2D slope profile. Such models are limited in their capability of providing a spatial representation of rockfall trajectory distributions and characteristics (velocity, energy, bouncing height; Lan et al., 2007). Another group of researchers have performed 3D rockfall modelling based on a lumped mass approach (Palma et al., 2012), which ignores the shapes and sizes of falling blocks. On the other hand, landslide studies have been widely conducted in Malaysia (Pradhan and Lee, 2010; Pradhan et al., 2014); however, they lack comprehensive investigation of rockfall hazard assessment.

2. Study area

Kinta Valley is one of the main districts in Malaysia. The district and surrounding areas have a bedrock geology of mine, limestone bedrock, and granitic hills. Consequently, many geology-related engineering issues, such as rockfalls, landslides and land subsidence, have been encountered in Kinta Valley and its immediate surroundings. The limestone bedrock in this area rises over alluvial plains, forming limestone hills with vertical to sub-vertical slopes.

Kinta Valley is located within the state of Perak in eastern Malaysia (Fig. 1) and was selected for large-scale rockfall source identification. Three of the highest rockfall probability locations (red box, Fig. 1) were selected for rockfall hazard assessment. Kinta Valley district has an area of approximately 370 km^2, and it is located approximately 225 km north of the capital city of Kuala Lumpur. In addition, it is considered one of the richest tin mining areas in the world (Pradhan et al., 2014). The study area was rectangular in shape with its north-western corner located at 4° 38′ 50″ N, 101° 02′ 40″ E and its south-eastern corner at 4° 31′ 45″ N, 101° 11′ 10″ E. The main land use types include non-operational tin-mining areas, peat swamp forest, oil palm plantations, shrubs, grassland and urban areas. Furthermore, the lithology of the area has a high percentage of igneous rock coverage (acid intrusive). Both metamorphic (marble) and sedimentary (limestone) rocks are abundant in the area.

The mean maximum temperature of the area ranges between 24 and 34 °C with relatively high humidity (~83.2%). Regarding rainfall, Kinta Valley receives heavy rainfall throughout the year except May–July, which is the dry season. The mean annual rainfall can reach 321 mm (Meteorological Service Department of Malaysia).

3. Materials and methodology

3.1. Datasets

On January 15, 2015, LiDAR point clouds were collected by a laser scanning system deployed on an aircraft flying at an altitude of 1000 m and using a scanning frequency of 25,000 Hz with multi beams. On average, there were eight data points per square meter. Summary statistics show that there was an absolute vertical accuracy of 0.15 m and a horizontal accuracy of 0.3 m (root mean square error). The raw data was processed to remove outliers and noise and used to generate surface models that were used to derive the rockfall conditioning factors.

In addition, rockfall inventory data was obtained from various sources including remote sensing data, field measurements and historical records. High-resolution aerial photos were used to visually inspect previous rockfalls in the study area. Some rockfalls may occur under vegetation or in areas that are obscured from aerial orthophotography. Such rockfalls were observed via field measurements (for new rockfalls) or historical records (for old rockfalls). Field measurements were conducted using precise Global Navigation Satellite System (GNSS) data that was subjected to real-time correction by the Malaysian Survey Department. In field surveys, the locations of fresh rockfall scars were identified and mapped. A total of 126 rockfalls and their associated attributes were prepared for analysis (Fig. 1). Then, the inventory data were divided into two sets; 70% of the data was utilized to create models, while the rest was utilized for validation and testing.

3.2. Data collection

The laser scanning survey was carried out utilizing a 3D terrestrial laser scanning (TLS) sensor (FARO Laser Scanner Focus 3D) with an accuracy of 5 mm. The TLS scanning outputs a point cloud (an array of points) that is a set of vectors defined by a 3D coordinate system (x, y, z), and is capable of constructing a highly detailed 3D terrain model.

First, TLS surveys (Fig. 2) were carried out from easily reachable locations in three different areas, namely, Gunung Lang, Gua Tambun and Gunung Rapat (red boxes, Fig. 1). The main goal of the TLS survey was to construct 3D terrain models of entire slopes (for evaluation of rockfall modelling) and to characterise the geomechanical properties of block masses (for evaluation of the volume and shape of falling rocks). Therefore, the angular resolution used at each scanning location was selected according to the best arrangement of distances between adjacent points on the rock slope. This was related to the minimum number of features dimension to be extracted (anthropogenic structures, discontinuity surfaces, and Digital Terrain Model DTM resolution) and the number of points (to avoid the dataset becoming too large).

Because of slope roughness and scanning location constraints, and with the objective of eliminating shadowed areas as much as possible, each slope was observed from various scanning locations. A total of 28 scan locations were used to cover the investigated sites and > 600 million points of data were gathered.

The obtained point clouds were aligned by utilizing a geodetic GNSS receiver (Fig. 2) to locate the positions of a number of scanning points and tie points represented by spheres (Morelli et al., 2012). This process usually requires the merging of two or more scans of the same feature obtained from various viewpoints, and also allows proper