
Preface

The significant growth of world's population and the rapid expansion of cities generate great challenges for decision makers and put an increasing number of people at hazards. Even though it is impossible for human being to prevent natural disasters, there have been great efforts to create knowledge, design methods, and frameworks to assess, prepare, and mitigate the potential effects of natural hazards. Among natural disasters, landslides pose considerable risks to people's livelihood and to the environment. They cause significant disruption and economic losses by the devastation of major infrastructures such as settlements, transportation, power and communication lines, and other utilities. Several landslide triggering factors such as intense rainfall, earthquakes, volcanic eruptions, hurricanes, and human activities threaten many parts of the world and increase the potential of landslides. Hence, it has been important to put significant efforts to advance landslide studies and design effective and practical tools that could be used by decision makers.

Landslide is defined as “the movement of a mass of rock, debris, or earth down a slope.” They result from the failure of hill slope materials driven by the force of gravity. Landslides are also known as slope failure and they are classified into several types according to the type of mass movement. The basic types of landslide movements are fall, topple, slide, flow, and spread. Landslides occur almost worldwide and cause significant disasters with very great impacts to the society. They are studied in many countries, and scientific and engineering fields and a wide variety of innovations have been proposed to enhance our understanding of their mechanisms. In general, landslides occur in a variety of landscapes characterized by the cliff, steep slopes, and unstable geology. There are many other factors contribute to the landslide occurrence such as slope curvature, weathering, water content, sediment availability, climate, vegetation, and anthropogenic inputs. However, most of the time, landslides are triggered by one factor or combination of factors such as heavy rainfall, earthquakes, or glacial erosions. Thus, it is important for scientists to understand the links between these factors and the concept of landslide risk. This has allowed them to accurately predict the distribution of future landslides, estimate and simulate their extents, and quantify their impacts to the human life and property.

Assessment of landslides usually involves several modeling techniques using a wide range of data sources. Overall landslide assessments comprise detection of landslide scarps, prediction of the spatial distribution of potential future landslides, modeling hazards and vulnerability, and estimating landslides risks and their impacts. For the detection of landslide scarps, the key methods are interpretation of aerial photographs, change detection, topographic and geomorphological analysis of laser scanning data. In addition, a wide range of knowledge-based, statistical, and machine learning methods are used for predicting potential future landslides in a given area. For example, the popular methods are analytic hierarchy process, frequency ratio, logistic regression, and support vector machines. On the other hand, techniques for modeling landslide hazards are generally well documented. Their concepts are based on integrating the spatial and temporal variations of triggering factors with potential landslide zones. Furthermore, to model landslide risks, understanding of the elements at risk including exposure information is considered a critical factor. Exposure information is

produced by obtaining the best available data, statistics, spatial and attribute data about buildings, demographics, community infrastructure, and agricultural commodities. This information allows to model landslide vulnerability through the use of curves that describe a probable damage severity or economic loss for a particular type of infrastructure when it is subjected to some level of hazard. Finally, modeling of landslide risk is based on statistical information about past events and their estimated impacts. Overall, risk models can be used to perform cost–benefit analysis for various forms of mitigation involving short-term solutions, such as early warning and response, along with long-term solution, such as land use planning and improvements to building codes and infrastructure.

The practical development of landslide risk models requires comprehensive data for each step of modeling. In the recent times, LiDAR (light detection and ranging) is widely used for landslide investigations to create accurate digital elevation models which enable extracting several precise topographic, geomorphological, and hydrological factors used in several steps of overall landslide assessments. The key advantages of using LiDAR for landslide studies are high-resolution landslide contours, which permits identifying landslide scarps and displaced materials and delineating geomorphological features of landslides such as scarps, mobilized material, and foot. Other advantages include automating landslide mapping, penetrating vegetation canopies, and supporting simulations of debris flows and rock falls at small scales due to their high-density points collected over the focused area.

Landslides occur worldwide; however, rainfall-induced slides tend to be much greater in tropical hilly areas. Mountainous terrain and heavy tropical rains put dense populations and infrastructures at risk. Thus, monitoring different types of landslides can be useful for mitigating the effects of these disasters and properly plan for potential future events.

This book at the first describes the fundamental concept of using LiDAR for landslide applications and assessment. A general overview of laser scanning systems in the context of landslide studies is explained to support understating the followed materials of the book. As a preliminary step, landslide and debris flow inventory mapping and characterization is presented with diverse illustrations. This is followed by a detailed landslide susceptibility mapping procedures including optimization of landslide conditioning factors, effects of spatial resolution of DEM, and detailed comparative analysis of a large number of models used in the literature. Besides, identification of debris flow source areas and its assessment using empirical models will be discussed. In addition, landslide risk assessment using multihazard scenarios will be described. Furthermore, LiDAR techniques in rockfall hazard assessments is also investigated and discussed in details.

This book is organized into 17 chapters.

Chapter 1 briefly discusses about the active remote sensing systems, such as light detection and ranging (LiDAR) which are widely used in landslide disaster management and risk mitigation. The main advantage of these technologies is the production of high-resolution digital elevation models (DEMs). Such models allow detailed mapping of terrain and extraction of geomorphological features, which are extremely important in landslide assessment. Therefore, this chapter provides an overview of the use of LiDAR in landslide investigations. First, it introduces the main components of LiDAR systems and the basic concept of laser measurements and then discusses the accuracy and resolution of typical laser scanning systems. Second, it provides information about LiDAR data processing (i.e., point cloud filtering, geometric calibration). Third, it discusses the main products of LiDAR that are useful for landslide investigation and modeling. Finally, it describes and illustrates several landslide applications where LiDAR data are beneficial.

Chapter 2 proposes a semiautomatic supervised approach for the detection of landslides in man-made slopes. Several techniques have been proposed for landslide mapping using remote sensing data in the literature, especially in unstable slope areas. Generally, cut slopes are created to mitigate the risk of land failure for areas that have high probability of failures. This method creates new challenges for landslide mapping in these areas. Five classifiers were evaluated for object-based landslide detection using airborne LiDAR data coupled with

orthophotos. This chapter aims to: (1) to prepare spectral, spatial, and texture features, as well as LiDAR-derived parameters for landslide detection using supervised classification schemes; (2) to evaluate five well-known classifiers (i.e., Bayes k-nearest neighbor, support vector machine (SVM), random forest (RF), and decision tree) for landslide detection, thereby determining the best algorithms; and (3) to produce an inventory map of landslides and man-made slopes of the study area using the best classifiers found in the second objective. Results of landslide factor and feature analyses showed that landslides and cut slopes are extremely difficult to separate using only LiDAR-derived parameters. Orthophotos are useful information for the separation of landslides from other features, such as grassland, buildings, and water bodies. Spatial and texture features are also important for landslide detection. A field validation was also applied using a landslide inventory map collected from multiple field investigations. This inventory map shows landslide locations, type, geometry, and direction. Landslide inventory was also used to train the classifier, thus improving sampling accuracy. The result of the analysis showed that SVM and RF achieved relatively high user and producer accuracies, and indicated a good classification of landslides and cut slopes simultaneously. In comparison, SVM performed better than RF for landslide and cut slope classification. Overall assessment indicated that the separation between cut slopes and landslides using LiDAR data and orthophotos in supervised classification is possible and can be improved. The resulting landslide inventories are valuable resources for both the geomorphological investigation of landslide events and hazard assessment and susceptibility analysis in landslide-prone regions.

Chapter 3 discusses about a new approach for detection of different types of landslides such as shallow and deep seated. A good landslide inventory map is a prerequisite for analyzing landslide susceptibility, hazard, and risk as well as for studying the evolution of a landscape affected by landslides. Using traditional methods for landslide detection is challenging because of the presence of dense vegetation in landslide locations and the time-consuming large-scale projects that are concomitant with these methods. Data derived from LiDAR can depict ground surface and provide valuable information on the topographic features of locations hidden under dense vegetation. This study presents an automatic LiDAR-based landslide detection method and discusses its capability to differentiate between shallow and deep-seated landslides as well as its transferability. An existing supervised approach was adopted to optimize segmentation parameters (i.e., scale, shape, and compactness). Subsequently, a correlation-based feature selection technique was used to select relevant attributes for developing the set of rules. The rules were developed using a decision tree algorithm. An object-based approach was applied to identify the locations and characteristics of landslides. To validate the method, the area under the curve was used. The accuracy of landslide detection on the test site was 0.82, and the accuracy of detecting shallow and deep-seated landslides were 0.80 and 0.83, respectively. The intensity derived from the LiDAR data and texture significantly affects the accuracy of differentiating shallow from deep-seated landslides. Therefore, the current study demonstrated that LiDAR data are highly efficient in detecting landslide characteristics in tropical forested areas.

Chapter 4 presents a Taguchi-based Random Forest technique for landslide detection from LiDAR and QuickBird satellite image. Landslide mapping in tropical regions is challenging because of the rapid vegetation growth. Hence, increasing the performance of landslide mapping with remote sensing skills is essential. This chapter proposes an efficient methodology to detect and map the landslide-prone areas located in Bukit Ma'okil, Johor, Malaysia, using an integration of high-resolution LiDAR with high-resolution QuickBird satellite imagery. An object-based classification method was used to distinguish the landslide-prone areas from non-landslide features. The Taguchi technique and Random Forest (RF) methods were employed to optimize the segmentation process and to select important features, respectively. The rule-based technique was also used for object-based classification. The Taguchi optimization applied in the current research allowed the selection of suboptimal segmentation parameters by conducting 25 experiments, each evaluated by kappa coefficient. The application of the RF method significantly contributed in selecting the most relevant features for

ruleset development and classification. Landslide and non-landslide locations were detected, and the confusion matrix was used to examine the proficiency and reliability of the results. The overall accuracy was 90%. The current research integrated object-based analysis and optimization method as a pioneering landslide detection application to reduce time for image classification. The successful production of a reliable and accurate landslide inventory map confirmed the efficiency of the methodology. Therefore, the results derived from the proposed method can assist researchers and planners in implementing and expediting landslide inventory mapping.

In contrast to Chap. 4, Chap. 5 presents debris flow detection using LiDAR data in a tropical forested area. Debris flow is one of the most destructive mass-wasting events. Debris flow is also referred as mudslide, lahars, or debris avalanche, which is a rapid mass movement mainly triggered by intense precipitation or rapid snow melt that starts on steep mountain channels. The loosen materials are saturated with water-formed debris flows. Debris flow can be catastrophic because it is associated with the loss of human life and property destruction. Given the rapid population growth, especially in mountainous region, source areas prone to debris flow should be identified. In this study, LiDAR, a high-resolution airborne laser scanning data, was used to obtain debris flow-related parameters. First, a digital elevation model (DEM) was generated from the LiDAR point clouds as a primary source of data. The parameters were constructed in GIS environment, which contains slope, plan curvature and flow accumulation derived from a DEM. The datasets were converted to ASCII grids for importation in Flow-R (Flow path assessment of gravitational hazards at a Regional scale) software. Many softwares were developed to understand debris flow behavior. In this research, Flow-R model was used because it can produce significant results based on the quality of the DEM, thereby obtaining reliable results for identification of debris flow sources. Various DEM resolutions (1, 2, 5, and 10 m) were generated for identification of debris flow source areas and consequent determination of an optimized resolution. Landslide inventory map, which was prepared mostly from field investigation, was used for validation. The landslide inventory map was buffered to 20 and 50 m for each DEM resolution. The results from buffered zones were later used to generate the intersection between the buffered zones and the source area produced from Flow-R. Additionally, high-resolution ortho-images were used as supplementary data to visualize the location of debris flow source areas. The results revealed that DEM with 1-m resolution produced the highest accuracies among all DEM resolutions. According to the sources and landslide inventory data, buffering and intersection were 72% and 93% from 20- and 50-m resolutions, respectively. On the contrary, the DEM of 2-m resolution achieved 45% and 79% of buffering and intersection from 20 and 50 m, respectively. The DEM of 5-m resolution achieved the accuracies of 17% and 31%. Finally, the lowest accuracy was produced by DEM with 10-m resolution at 3% for each 20 and 50 m from buffering and intersection methods. The present findings showed a good compromise between landslide inventory location and modeling source resulting from 1-m DEM resolution. Nevertheless, results obtained from 2 and 5 m still produced significant information about debris flow source areas (but not at an optimum detection), whereas DEM with 10 m produced poor result.

Chapter 6 discusses about the optimization of landslide conditioning factors using LiDAR data. Landslide susceptibility modeling (LSM) is the basic step in overall hazard and risk assessment. This chapter presents the optimization of landslide conditioning factors and an analysis of their effects to improve the accuracy of landslide susceptibility models and provide insights into landslide conditioning factors. A landslide inventory map with 132 landslides was prepared based on multisource remote sensing data. A total of 15 landslide conditioning factors were used, including LiDAR-derived and non-LiDAR-derived factors. First, multicollinearity analysis was conducted to remove highly correlated factors from further analysis. Second, ant colony optimization was used to select significant landslide conditioning factors from the initial 14 factors for further analysis. Data mining techniques, including support vector machine (SVM) and random forest (RF), were used to analyze the effects of the selected landslide conditioning factors on the prediction rate accuracy of the susceptibility models.

Several landslide susceptibility maps were produced for the study area, and the best map was recommended for future land use planning. Results of the multicollinearity analysis showed that the topographic roughness index was highly correlated with the remaining factors, and thus, this factor was removed and not used in LSM. In the factor analysis, 8 underlying factors were extracted from the 15 landslide conditioning factors. All the factors were well represented by the 8 extracted factors because the corresponding communalities (i.e., correlation with the retained factors) were generally high. After multicollinearity and the factor effect were analyzed, 6 experiments classified into 2 main groups were conducted. In the first group, all the 14 factors were examined, whereas the second group included only the LiDAR-derived factors. In the first group, the 3 experiments included 5 factors, 10 factors, and all the 14 factors. In the second group, the 3 experiments involved 3 LiDAR factors, 6 LiDAR factors, and 8 LiDAR factors, which were the total number of LiDAR factors derived from the digital elevation model. These subsets were evaluated using the SVM and RF models. On the one hand, the highest accuracy was achieved using the RF model and 10 factors selected from the 14 initial factors. On the other hand, the lowest accuracy was achieved using the SVM model and only the LiDAR-derived factors. The results showed that LSM should be developed using only significant factors, whereas non-LiDAR factors were important to achieve accurate landslide mapping for a study area.

Chapter 7 discusses about the effect of spatial resolution of DEM in landslide susceptibility mapping. As mentioned previously, landslide susceptibility maps are the main products required for hazard and risk assessments, as well as for land use planning. Spatial data play an essential role in determining the quality of landslide susceptibility maps. Therefore, the spatial resolution of digital elevation models (DEMs) was assessed in this study, and an optimal spatial resolution for landslide susceptibility mapping (LSM) at small-scale catchments was determined. A total of 192 landslide inventories were collected from multisource remote sensing data for the study area. In addition, 13 landslide conditioning factors were derived from a LiDAR-based DEM and existing geodatabases of the study area. Logistic regression was used as the modeling technique to produce landslide susceptibility maps. The accuracy of the susceptibility maps was assessed using several accuracy metrics, namely the area under the curve of a receiver operating characteristic, the kappa coefficient, overall accuracy, and spatial agreement. The spatial agreements were determined using empirical information entropy and average susceptibility values. Results indicated that the importance and multicollinearity of the landslide conditioning factors are sensitive to the spatial resolution and source of the DEM. The optimal spatial resolution was 2 m with a predictive accuracy of 0.963, a kappa coefficient of 0.88, and an overall accuracy that approximates 94.02. The entropy map showed that the produced models generally presented high spatial similarities (entropy value ≤ 0.33), which covered nearly 71% of the study area. Furthermore, the 30-m LiDAR DEM was more capable of predicting future landslides and identifying landslide scarps and flanks than the 30-m DEM based on the Advanced Spaceborne Thermal Emission and Reflection Radiometer. Therefore, a finer spatial resolution does not always guarantee a higher prediction rate. In addition, the selection of DEM spatial resolution and source depends on the objective of the study and the amount of details required in landslide susceptibility maps.

Chapter 8 presents an application of k-nearest neighbor (kNN) and logistic regression (LR) models in landslide susceptibility mapping using LiDAR-derived data. Landslide susceptibility mapping plays an important role in urban planning and disaster management for hilly regions. Such task requires various information on the environmental, geotechnical, and economic aspects of landslides. This paper presents a landslide susceptibility analysis for Bukit Antarabangsa, Ulu Klang, Malaysia, with kNN and LR models. Data on 31 landslide events that occurred in the study area were obtained from different sources. Eleven landslide conditioning factors, including altitude, slope, aspect, curvature, stream power index, topographic wetness index, soil, geology, land use/land cover, distance from rivers, and distance from roads, were considered in landslide susceptibility mapping. The main goal of this study is

to examine the efficiency of the kNN algorithm in landslide susceptibility mapping. This algorithm has seldom been adopted in this field of study. Comparative assessment was conducted by applying an LR model to evaluate the reliability of the proposed kNN algorithm. The results of the two models were compared and validated. Same conditioning factors were employed to build both models. The capabilities of kNN and LR methods were evaluated with the area under curve technique. Results show that kNN performs better than the LR model. The success and prediction rates obtained from the testing results of the kNN algorithm are 86.28% and 82.64%, respectively. The success and prediction rates obtained from the validation results of LR are 75.65% and 72.18%, respectively. kNN algorithm can be used in spatial planning and can help in hazard mitigation.

Chapter 9 presents an application of support vector machine (SVM) and its different kernels in landslide susceptibility mapping. The lack of reliable and comprehensive physical approaches for landslide susceptibility mapping (LSM) has motivated the use of statistical and machine learning techniques, such as the frequency ratio, weights of evidence, logistic regression, and artificial neural networks. However, the support vector machine (SVM) has become increasingly popular because of its capability to deal with high-dimensional spaces and perform high-accuracy classification. In SVM, the model is trained on a training dataset with associated input and target output values. This study illustrates the application of a geographical information system-based SVM modeling for mapping landslide susceptibility along Jalan Kota in Bandar Seri Begawan, Brunei, to evaluate the spatial correlation between landslides and each conditioning parameter. These parameters are altitude, slope, aspect, curvature, stream power index, topographic wetness index, topographic roughness index, geology, soil, land use/land cover, rainfall, and distance from rivers, roads, and faults. Furthermore, four kernel types, namely radial basis function (RBF), polynomial, sigmoid, and linear kernels, were applied to examine the performance of SVM kernels. Finally, the efficiency of the output maps was validated using area under curve, which measured the prediction and success rates for each kernel. Among the applied kernel types, RBF performed better than the others, with a success rate of 88.21% and a prediction rate of 82.90%. Results of the validation process proved the reasonable strength and feasibility of SVM (particularly RBF-SVM) in LSM. The proposed model can assist local managers and government officials in Brunei to formulate landslide mitigation strategies.

Chapter 10 discusses about the quality of landslide inventory by using different approaches. Landslide susceptibility modeling (or mapping) has been extensively explored in research. However, its quality is affected by uncertainties in landslide inventory data. The quality of landslide inventory is examined by experts using aerial orthophotos and field investigations, which are time-consuming and costly given several landslide records in the inventory database. Therefore, the current study developed an ensemble method based on the idea of active learning to overcome the landslide inventory data uncertainties. Integrating active learning modeling into landslide susceptibility assessment can improve the accuracy and generalizability of the models as it automatically removes problematic landslide inventories. The specific objective is to evaluate the ensemble disagreement active learning for the spatial prediction of shallow landslides in Cameron Highlands, Malaysia. The study is conducted using LiDAR data (i.e., vertical and horizontal accuracies are 0.15 and 0.3 m, respectively). Nine landslide conditioning factors are prepared and 192 landslide inventories are collected from various sources such as aerial photographs and high-resolution satellite images (i.e., SPOT 5). Results revealed that the active learning approach combined with common models such as support vector machines (SVM) and logistic regression (LR) can improve the performance of the models. The success rates of the SVM and LR models are 0.81 and 0.84, respectively, whereas the prediction rates are 0.75 and 0.84. After the integration of active learning to the models, the success rates increased to 0.88 and 0.89 for the SVM and LR models, respectively. Furthermore, the prediction rates increased by 0.18 and 0.5 accordingly for the SVM and LR models. Therefore, findings indicate that the use of active learning in landslide susceptibility modeling can improve the success and prediction rates of the SVM and

LR models. In addition, this study suggested that the use of active learning can decrease collinearity among the landslide factors, thereby improving the final models.

Landslide susceptibility maps help to understand the spatial distribution of landslide probability, and they also improve landslide risk assessment and land use planning. The advancement in computer hardware and software has improved the accuracy of many landslide susceptibility models. These models are grouped into five categories: expert, bivariate statistical, multivariate statistical, machine learning, and hybrid methods. Each category has several models and possesses respective advantages and disadvantages. The advantage of expert-based models is that they do not require landslide inventory data for model training; however, their disadvantage is the subjectivity of the judgment of the importance of landslide conditioning factors. Bivariate statistical models compute the contribution of landslide conditioning factors for landslide occurrence; however, their main drawback is the assumption of conditional independence. Multivariate statistical models analyze the interaction of all parameters in controlling the occurrence of landslides; their drawback is the collection of data over a large area regarding landslide distribution and factor maps. Machine learning models account for nonlinear relationships and handle uncertainty in landslide inventory data; their drawback is their time-consuming nature and their susceptibility to overfitting of the data. Hybrid models can overcome several of the disadvantages of the individual models, but the complexity of hybrid models is often high. Given the various advantages and disadvantages of the aforementioned methods, today's land use planners face the challenge of selecting the most appropriate model for their needs. Therefore, the main objective of Chap. 11 is to evaluate the performance and sensitivity of 14 models, frequency ratio (FR), statistical index (SI), weights of evidence, logistic regression (LR), partial least squares, discriminant analysis, analytic hierarchy process, fuzzy AHP, support vector machine (SVM), random forest, decision tree, FR-SVM, LR-RF, and SI-LR, to provide clear guidelines for land use planners in selecting the most appropriate model. A test site in Cameron Highlands was selected. The results showed that the best model is the hybrid FR-LR model, with a prediction rate of 0.83. This model could predict over 75% of the landslide inventories in the very high susceptible class. It also demonstrated good spatial agreements with several other models.

In contrary to the previous chapters, Chap. 12 presents a detailed landslide hazard, vulnerability, and risk assessment along a stretch of North-South Expressways in Malaysia. Landslides result in high economic and social losses in Malaysia, especially for highway concessionaries such as the PLUS Expressways Berhad. This study aims to perform landslide vulnerability and risk modeling for cut slopes along the Gua Tempurung area on the North-South Expressway in Malaysia. This area was selected because of the frequent occurrences of landslides along the expressway. Highway concessionaries such as the PLUS Expressways Berhad allot a large portion of their annual budget to ensuring the safety of this expressway and making it resilient against natural hazards. Landslide hazards, vulnerability, and risk zoning maps are considered in the decision-making process involving land use/land cover (LULC) planning and overall road management in prone areas. The accuracy of the results is directly related to the spatial data and the methods for obtaining such data. In the present work, we produced a landslide inventory map depicting the 17 landslide locations identified through a field survey. The landslide inventory data were randomly divided into a training dataset: 60% (10 landslide locations) for training the models and 40% (7 landslide locations) for validation. In the first step, a susceptibility map was constructed using the logistic regression method, in which weights were assigned to each conditioning factor according to its correlation with landslide occurrence. High-resolution LiDAR was used to derive the landslide conditioning factors for the spatial prediction of landslide-prone regions. Eight conditioning factors, namely altitude, slope, aspect, curvature, stream power index (SPI), topographic wetness index (TWI), terrain roughness index (TRI), and distance from river, were used for the weight calculation. The susceptibility mapping results were validated with the area under the curve (AUC). The assessment showed 84.91% and 83.00% success and prediction rates, respectively. In the second stage, a hazard map was calculated using the average of the

triggering factor (rainfall) for 2014 because most of the landslides in the inventory took place during this year. Overall landslide susceptibility and hazard maps were prepared for the 5-km corridor of the highway. However, only the cut slopes were considered in the vulnerability and risk analysis because they pose a threat to highway users as a result of their frequent reoccurrence. In the third step, elements at risk, such as risk to road users, relative risk of failure, likely effect on traffic, and likely repair costs, were considered in the vulnerability assessment. Each cut slope was examined under these said elements at risk. Subsequently, a value representing the sensitivity of each slope was assigned and considered as the vulnerability value. Finally, a risk map for each cut slope was produced using the derived vulnerability and hazard information. The map of the risky cut slopes may assist PLUS Expressways Berhad in improving highway management.

Landslide hazard and risk maps are essential for hazard mitigation, risk management, and effective land use planning. Chapter 13 presents a multihazard scenario-based landslide risk maps for the Ringlet area located in Cameron Highlands, Malaysia. The main source of data is a digital elevation model (DEM) produced from a high-resolution LiDAR data. In addition, detailed land use maps, adequate landslide inventory data, and rainfall information were used to implement the proposed method. First, the landslide susceptibility map was produced by the logistic regression (LR) model with 12 landslide conditioning factors: altitude, slope, aspect, curvature, stream power index (SPI), topographic wetness index (TWI), terrain roughness index (TRI), distance from a river, distance from roads, distance from lineament, sediment transport index, and geology. Next, landslide hazard maps were produced using five different scenarios: (1) the average intensity of rainfall in any day in a year, (2) the abnormal intensity of rainfall recorded in a day, (3) 5-year return period, (4) 10-year return period, and (5) 15-year return period with average intensity of rainfall per day. Then, the landslide vulnerability map was produced using an exposure-based method by utilizing the detailed land use map and information from experts and previous works. Finally, five risk maps were produced for the study area using the five hazard scenarios. The results indicated that the LR model could predict the future landslides with an accuracy of 84.87%. The average annual economic risk for landslides was MYR 5,981,379.00 in the study area.

The mapping of debris flow risk areas is an important concern because debris flows could result in social losses in hazardous regions, especially in mountainous areas. However, debris flow risk assessment through procedure-based modeling at a medium scale is complex because of several reasons, such as the complex nature of the phenomenon, the inconsistency of local conditioning factors, and the variability of modeling factors. A wide range of debris flow modeling methods has been explored in literature. An effective modeling approach should provide debris flow susceptibility zonation using only minimum data requirements. In Chap. 14, distributed empirical models are used for medium-scale debris flow susceptibility assessments with a light detection and ranging-derived digital elevation model. For debris flow modeling, Flow-R (Flow path assessment of gravitational hazards at a Regional scale) is applied for path assessment of debris flow at regional and medium scales. The Flow-R model requires minimum data input and is flexible to use because of its simple user interface. The second model, rapid mass movement simulation, is used to simulate the run-out of mass movement on a 3D terrain. Although only a preliminary assessment of debris flow effects is presented, the assessment can be useful for land planners and government agencies in their modeling of debris flows and assessment of further effects. The procedure provided in this work can also be replicated in other areas through detailed analyses based on available input data.

Chapter 15 presents a thorough review on rockfall susceptibility, hazard, and risk assessment using different approaches. Rockfalls occur worldwide and annually cause considerable damage to human life and properties. Therefore, comprehensive research is required to understand the triggering and auxiliary elements of the hazards of rockfalls as well as to assess and identify mitigation processes for these calamities. Such research can be used as a reference for managing future rockfall disasters. Rockfall hazard has recently attracted significant attention and has motivated numerous studies. Moreover, such studies have gained importance in various

disciplines with the developments of remote sensing and geographical information system technologies. Current geoinformation techniques have been used to gather information for rockfall analyses. This chapter primarily explains the general principles of and the methodologies for rockfall analyses, including rockfall types, causes, and mechanisms, as well as data sources, modeling approaches, and light detection and ranging techniques for rockfall assessment.

Rockfall magnitude and frequency vary both spatially and temporally. Therefore, eliminating such phenomenon is a challenge. Proper modeling and assessment can aid defining the areas at risk thus remedial the effect of rockfall catastrophe. Chapter 16 describes the location and rockfall characteristics of the study area. The materials used in this study also have been described. Multicriteria method for rockfall source areas identification has been applied in this research. Rockfall trajectories modeling and the velocity associated with them have been explained. Raster modeling using geostatistical method has been applied in this research to represent the spatial distribution of rockfall. Finally, spatial modeling with AHP method has been performed in this study to produce rockfall hazard map. As a result, rockfall trajectories and their characteristics were derived and rockfall hazard map for each scenario was obtained. In addition, barrier location was suggested and its efficiency eliminating rockfall hazard was demonstrated.

In general, this book presents the use of LiDAR in landslide assessments providing useful information and recent findings which will be useful for researchers, graduate and postgraduate students, and decision makers both in government and private agencies. This book describes the main applications of landslides such as supervised/machine learning-based detection and characterization of landslide scarps, spatial prediction of the landslide. It gives a detailed discussion on factor optimization and effects of the spatial resolution of DEM on landslide susceptibility mapping. This book also demonstrates identification of the source of debris flow and its susceptibility assessment by LiDAR data. In addition, this book gives a space for multisenario landslide hazard assessment using airborne laser scanning data, landslide vulnerability, and risk assessment for multihazard scenarios. Finally, this book describes the LiDAR techniques in rockfall hazard assessment in tropical regions. Many case studies presented in this book help decision makers to follow as guidelines for comprehensive landslide hazard and risk assessment using very high-resolution laser scanning data. This book can be helpful and valuable for new students/researchers to understand the concept and use of LiDAR in many landslide applications. The contribution of each chapter of this book advances the landslide studies, opens new areas, and generates new ideas for better landslide assessment.

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