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A Review Of Detection Technique For Flooding Zone And Landslide Susceptibility Zone

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Abstract

Floods as one of natural disaster can trigger landslides. Floods and landslides generally occur on a small micro scale and usually produced on a large scale map. Several data parameters are used to describe the distribution area of flooding and landslides, such as Topographical, Geological, Land Use/Cover, Floor Area, Rainfall, Soil, River/Stream, Roads/Street, Seismicity, Intense Precipitations, Building Footprint Area, and Population. Prediction of flood zone and landslide susceptibility zones uses data parameters that are analyzed using a quantitative approach. Meanwhile, combination with a qualitative approach is usually used to analyze the data parameters that more influence on the occurrence of floods and landslides based on the frequency of disaster events. This paper is attempts (1) to review methodology used to predict flood event zones and landslide susceptibility zones or floods that trigger landslides with quantitative approaches, qualitative approaches and combinations thereof and (2) to perform eligible data used or material as driven factor and subfactor triggering flooding and landslide. From the acquisition of 109 references paper related to the prediction of flood disaster zones or landslide vulnerability zones, about 87 references paper were obtained that linked flood disaster zones and landslide vulnerability zones and used as input material. Based on selected paper identified particular parameter (12 factors and 17 subfactor) were used to describe the distribution area of floods and landslides.

***Keywords*:** *Flooding, Landslide, approach, methodology, eligible data.*

1. Introduction

Landslide is a natural phenomenon occurring in the mountainous terrain of the world (Lourembam & Oinam, 2021). Landslide is an important geological hazard that causes damage to natural and social environment (Pardeshi, 2013). Landslide is broadly defined as rock and soil movement (Huang et al., 2019). Landslide is commonly regarded as spatially discrete and temporally dynamic phenomena. Detailed understanding of the slope soil geo-technical properties can provide reliable information in connection to landslides (Mandal & Mondal, 2019). Landslide is a major geological hazard worldwide, accounts for a high number of human casualties and an enormous loss of property, and causes severe damage to natural resources, ecosystems and infra-structures (Dai et al., 2002; Guzzetti et al., 2012 in Aditian et al., 2018).

Landslides are major natural hazards that often result in human and economic losses as a consequence of natural forces and human actions (Hadmoko et al., 2017). Landslides are one of the major natural hazards controlled by a combination of factors such as rock type, slope, and land use type that lead to instability in the terrain (Van Westen et al., 1999 in Peñafiel & Rojas, 2021). Landslides are the results of two interacting sets of forces; the precondition factors, naturally induced which govern the stability conditions of slopes, and the preparatory and triggering factors, induced either by natural factors or by human intervention (Mandal & Maiti, 2015). Landslides are a globally serious issue, it is a natural phenomenon that can turn into a natural disaster (Sina et al., 2021). A landslide is defined as: "the downslope movement of soil, rock, and organic materials under the effects of gravity" (Highland & Bobrowsky, 2008, p. 4 in Puente-Sotomayor et al., 2021). Landslide is generally defined as the downward movement and displacement of the material forming a slope with the effect of gravity (Schuster and Krizek 1978, p. 11-33 in Akinci et al., 2021).

A landslide causes serious economic damage, particularly in highly dense urban areas; fallen rocks obstruct highways and sub-roads in urban regions (Omar et al., 2017). Landslides still cause a significant death toll and significant economic losses all over the world (Corominas et al., 2014). Landslides and debris flows are among the most calamitous natural hazards in the world (Pradhan et al., 2019). Landslide velocities have been changing in last 50 years, from landslide activation until today, in range from extremely slow to very slow (Gradiški, 2018). Landslide therefore becomes a priority area for natural disaster management. Various studies that have been carried out earlier have provided information on landslide-prone areas maps, the application of landslide management methods, and the identification of landslide mechanisms (Noviyanto et al., 2020). The term landslide recognition includes all those activities aimed at recognizing past landslide events that occurred in a specific region. All these techniques allow feeding databases and building inventories for landslides (Scaioni et al., 2014). The term landslide comprises almost all varieties of mass movements on slopes, such as rock-falls, topples and debris flows, that involve little or no true sliding (Varnes, 1976 in Kornejady et al., 2015).

Floods and associated landslides are one of the most widespread natural hazards on Earth, responsible for tens of thousands of deaths and billions of dollars in property damage every year (Hong et al., 2007). Rainfall is the primary trigger of landslides, a key solution for landslide prediction is analyzing rainfall thresholds to determine the lower bounds to empirical distributions of rainfall conditions that have resulted in landslides (Althuwaynee, 2018). Changes in displacement rates over time are mostly controlled by hydrometeorological triggers (e.g. rainfalls, rapid snowmelt) and the consequent increase of pore water pressure and by changes in geomorphology (Séverine et al., 2015). By far the most significant and frequent landslide trigger is rainfall (Miller et al., 2009). For rainfall-induced landslides, the probability calculation ties to the return period of a specific triggering rainfall pattern and related slope stabilities and failure probabilities (Xiao, 2020). Floods as one of natural disaster can trigger landslides. Floods and landslides generally occur on a small micro scale and usually produced on a large scale map. A landslide can be influenced by various factors such as slope conditions and slope angle, lithology, soil type, and hydrologic or meteorological conditions. Another potential factor is induced by human activities such as deforestation, changes caused by construction of structures on the slope, undercutting the toe of the slope for road construction, etc (Silalahi et al., 2019).

Landslide susceptibility (LS) determines the probability of landslide based on the earth's surface material's status (Brabb, 1984 in Liu et al., 2020). Landslide susceptibility is the occurrence of landslide probability depending on situations of the surrounding terrain (Brabb, 1984 in Lourembam, 2021) . Landslide susceptibility, in particular, represents the estimation of spatial distribution of landslides that have already happened or will potentially happen in a given area (Kavoura & Sabatakakis, 2020). The primary purpose of a landslide susceptibility map is to spatially depict the relative likelihood of landslides affecting an area under a given set of geo-environmental conditions (Brabb, 1984; Fell et al., 2008; Glade & Crozier, 2005 in Lima et al., 2021). Vulnerability to landslides depends not only on the characteristics of the element(s) at risk but also on the landslide intensity (Li et al., 2010).

2. Workplace Experiences

A wide range of techniques are available for landslide susceptibility mapping and their quantitative validation, which can be classified into inventory, heuristic, statistical, deterministic and probabilistic (Hansen, 1984; Soeters & Van Westen, 1996; Varnes, 2000 in Ghosh et al., 2009). Susceptibility analysis of landslide risk (LRisk) has been broadly studied in case studies at regional scales and mostly covering rural areas, often involving natural conditions and, to a lesser extent, considering anthropic factors, such as road networks and urban areas (Puente-Sotomayor et al., 2021)). Mapping solutions were proposed based on susceptibility or hazard analyses, whose development in the last few decades—significantly favored by the constant improvement over the years of computing facilities and GIS platforms—represent a well-established topic in the scientific and technical communities dealing with landslide risk reduction (Martino et al., 2020). Mapping past and current landslide occurrence, delineating the areas where landslides may occur in the future, and evaluating the associated risk to population, infrastructure and property is of the utmost importance to land use planning, engineering works design and civil protection programmes which aim to minimize human and material losses due to landslides (Hervás & Bobrowsky, 2009). .

3. Workplace Dissonance

Geospatial modelling of landslide susceptibility is useful for monitoring, mapping and formulating proper management plans that will be helpful for future landslide mitigation measures (Kaur et al., 2017). Various geo-structural as well as causative-factor based approaches are already available for landslide susceptibility zoning. But Geographic Information System (GIS) modelling of landslide phenomena has taken precedence in recent time. Geospatial technologies like the use of GIS, Global Positioning System (GPS), and Remote Sensing (RS) are useful in the hazard assessment, risk identification, and disaster management for landslides (Ahmed, 2015).

4. Effects on Subsequent Intentions

This paper is attempts (1) to review methodology used to predict flood event zones and landslide susceptibility zones or floods that trigger landslides with quantitative approaches, qualitative approaches and combinations thereof and (2) to perform eligible data used or material as driven factor and subfactor triggering flooding and landslide.

5. Theoretical Framework

Landslide susceptibility and hazard zonation techniques obviously divied into 3 (three) layers which are approach layer, analysis layer; method layer. Approach layer consist of (A) Qualitative Approaches; (B) Semi-quantitative Approaches; (C) Quantitative Approaches. Analysis layer related to Qualitative approach layer consist of (A1) Distribution/Inventory Analysis; (A2) Geomorphic Analysis. Analysis layer related to Semi-quantitative approach layer consist of (B1) Multi-criteria Decision Analysis. Analysis layer related to Quantitative approach layer consist of (C1) Statistical Analysis; (C2) Deterministic Analysis; (C3) Probability Analysis and (C4) Artificial Intelligent. Method layer related to Multi-criteria Decision Analysis layer consist of (B1a) Analytical Hierarchy Process/AHP; (B1b) Fuzzy; (B1c) Weighted Linier; and (B1d) Ordered Weighted Average. Method layer related to Statistical Analysis layer consist of (C1a) Bivariate Statistics; (C1b) Multivariate Statistic. Method layer related to Deterministic Analysis layer consist of (C2a) Empirical Approach; (C2b) Limit Equilibrium Approach; (C2c) Numerical Modeling. Method layer related to Artificial Intelligent layer consist of (C4a) Artificial Neural Network/ANN; (C4b) Kernel Based; (C4c) Decision Tree; (C4d) Swarm Optimization; (C4e) Fuzzy Clustering (Shano et al., 2020). Description describe below (Figure 1).

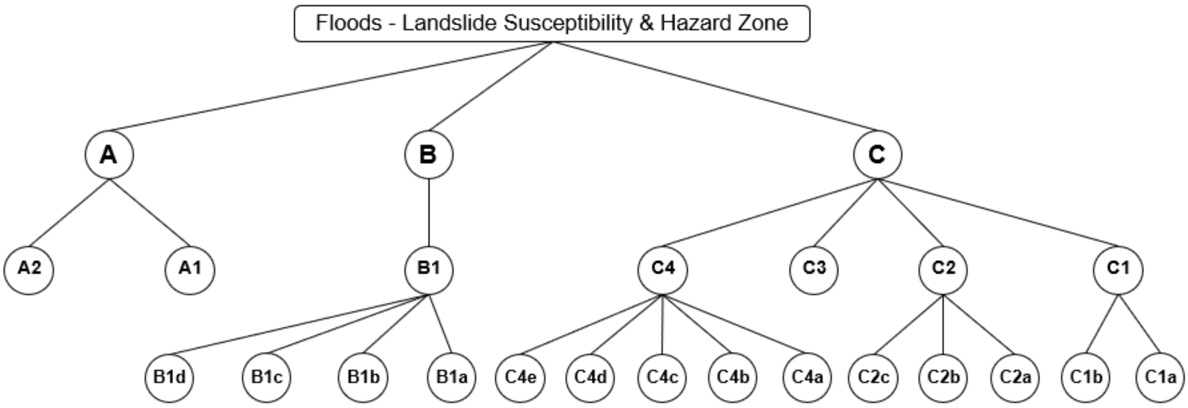

Figure 1. Landslide susceptibility and hazard zonation techniques (modified from Shano et al., 2020)

6. Methodology

6.1 Sample and data collection method

From the acquisition of 109 references paper related to the prediction of flood disaster zones or landslide vulnerability zones, about 87 references paper were obtained that linked flood disaster zones and landslide vulnerability zones and used as input material. Based on selected paper identified particular parameter (12 factors and 17 subfactor) were used to describe the distribution area of floods and landslides, such as Geological, Topographical, Roads/Street, Land Use/Cover, Rainfall, River/Stream (Table 1).

Table 1. Flooding and Landslide susceptibility trigger factor and subfactor (modified)

Factor	Subfactor	Reference
Geological	Lithology	Bhardwaj et al., 2019, Peñafiel & Rojas, 2021, Yang et al., 2019
	Distance to Fault lines	Akinci et al., 2021, Cruden, 2015
Topographical	Altitude	Bui et al., 2019, Halil A, 2021
	Slope	Rahmati et al., 2019, Althuwaynee et al., 2018
	Slope Length	Basri et al., 2021, Halil A, 2021
	Aspect	Dou et al., 2020, Lourembam et al., 2021
	Curvature (Plan, Profile)	Cao et al., 2019, Liu et al., 2020
	Wetness Index	Sema et al., 2017, Liu et al., 2020
	Drainage Distance	El Jazouli et al., 2019, Mandal & Maiti, 2015
Roads/Street	Road Density	Sina et al., 2021, Hadmoko et al., 2017
	Distance to Road	Hong et al., 2019, Hadmoko et al., 2017
Land Use/Cover	Type/LULC	Souissi et al., 2019, Kornejady et al., 2015
	Vegetation Index	Hosseini et al., 2019, Ngandam Mfondoum et al., 2021
Seismicity		Guzzetti et al., 2019, Puente-Sotomayor et al., 2021
Intense Precipitations		Ahmed, 2015, Puente-Sotomayor et al., 2021
Soil	Soil Type	Silalahi et al., 2019, Noviyanto et al., 2020
	Soil Stability	Saputra et al., 2016, Noviyanto et al., 2020
Population		van Westen et al., 2006, Sansare & Mhaske, 2020
Floor Area		Puente-Sotomayor et al., 2021, Hadmoko et al., 2017
Building Footprint Area		Omar et al., 2017, Puente-Sotomayor et al., 2021
Rainfall		Hermle et al., 2021, et al., 2021
River/Stream	River Density	Wan, 2009, Liu et al., 2020, Hadmoko et al., 2017
	Distance to River	Kornejady et al., 2015, Liu et al., 2020

Geological data map (Puente-Sotomayor et al., 2021; Akinci et al., 2021; Sina et al., 2021; Miller et al., 2009; Omar et al., 2017; Corominas et al., 2014; Hervás & Bobrowsky, 2009; Lima et al., 2021; Pradhan et al., 2019; Xiao et al., 2020; Kavoura & Sabatakakis, 2020; Peñafiel & Rojas, 2021; Ghosh et al., 2009; Huang et al., 2019; Liu et al., 2020; Mandal & Maiti, 2015; Hadmoko et al., 2017; Silalahi et al., 2019; Faris & Wang, 2014; Du et al., 2016; Mirzaei et al., 2018; Dandabathula et al., 2021; Knevels et al., 2021; El Jazouli et al., 2019; Hermle et al., 2021; Aditian et al., 2018; Saputra et al., 2016; van Westen et al., 2006; Dou et al., 2020; Kannaujiya et al., 2019) as factor that could be detailed into subfactor as Lithology (Akinci et al., 2021; Sina et al., 2021; Hong et al., 2007; Miller et al., 2009; Omar et al., 2017; Lima et al., 2021; Pradhan et al., 2019) and Distance to Fault lines (Ghosh et al., 2009; Huang et al., 2019; Hadmoko et al., 2017; Silalahi et al., 2019; Faris & Wang, 2014; Du et al., 2016; Mirzaei et al., 2018).

Topographical data map (Puente-Sotomayor et al., 2021; Akinci et al., 2021; Sina et al., 2021; Scaioni et al., 2014; Althuwaynee et al., 2018; Lourembam et al., 2021; Hong et al., 2007; Miller et al., 2009; Xu et al., 2021; Kornejady et al., 2015; Omar et al., 2017; Corominas et al., 2014; Kavoura & Sabatakakis, 2020; Peñafiel & Rojas, 2021; Liu et al., 2020; Mandal & Maiti, 2015; Hadmoko et al., 2017; Ngandam Mfondoum et al., 2021; Silalahi et al., 2019; Faris & Wang, 2014; Mirzaei et al., 2018; Dandabathula et al., 2021; Knevels et al., 2021; El Jazouli et al., 2019; Hermle et al., 2021; Aditian et al., 2018; Saputra et al., 2016; Wan, 2009; van Westen et al., 2006; Hervás & Bobrowsky, 2009; Lima et al., 2021; Ahmed, 2015; Pradhan et al., 2019) as factor that could be detailed into subfactor as Altitude (Liu et al., 2020; Dandabathula et al., 2021; Saputra et al., 2016; Wan, 2009; Sansare & Mhaske, 2020), Slope (Althuwaynee et al., 2018; Miller et al., 2009; Xu et al., 2021; Kavoura & Sabatakakis, 2020; Hermle et al., 2021; Aditian et al., 2018), Slope Length (Mandal & Maiti, 2015; Silalahi et al., 2019), Aspect (Hadmoko et al., 2017; El Jazouli et al., 2019; van Westen et al., 2006), Plan Curvature and Profile Curvature (Sina et al., 2021; Pradhan et al., 2019; Peñafiel & Rojas, 2021; Mirzaei et al., 2018), Topographic Wetness Index (Lima et al., 2021), Drainage Distance (Ahmed, 2015; Knevels et al., 2021). Topographic factor and subfactor commonly derived from Digital Elevation Model (DEM) which produced from satellite (Shuttle Radar Topography Mission) or aerial (LiDAR).

Roads/Street data map (Puente-Sotomayor et al., 2021; Akinci et al., 2021; Corominas et al., 2014; Ahmed, 2015; Mirzaei et al., 2018; El Jazouli et al., 2019; Aditian et al., 2018) as factor that could be detailed into subfactor as Road Density (Xiao et al., 2020; Mandal & Maiti, 2015; Hadmoko et al., 2017) and Distance to Road (Sina et al., 2021; Omar et al., 2017).

Land Use/Cover data map (Puente-Sotomayor et al., 2021; Akinci et al., 2021; Sina et al., 2021; Omar et al., 2017; Corominas et al., 2014; Kavoura & Sabatakakis, 2020; Mandal & Maiti, 2015; Mirzaei et al., 2018) as factor that could be detailed into subfactor as Type/LULC (Hong et al., 2007; Miller et al., 2009; Lima et al., 2021; Hadmoko et al., 2017; Noviyanto et al., 2020; El Jazouli et al., 2019; van Westen et al., 2006; Kannaujiya et al., 2019; Sansare & Mhaske, 2020) and Vegetation Index (Althuwaynee et al., 2018; Lourembam et al., 2021; Ahmed, 2015; Ngandam Mfondoum et al., 2021; Silalahi et al., 2019; Hermle et al., 2021; Wan, 2009). Land use/cover factor and subfactor commonly derived from image interpretation or classification and indices which produced from satellite (optical or Radar) or aerial (UAV).

Seismicity data map (Akinci et al., 2021; Sina et al., 2021; Scaioni et al., 2014; Althuwaynee et al., 2018; Lourembam et al., 2021; Hong et al., 2007; Hervás & Bobrowsky, 2009; Lima et al., 2021; Ahmed, 2015; Mandal & Maiti, 2015; Hadmoko et al., 2017; Ngandam Mfondoum et al., 2021; Noviyanto et al., 2020; Silalahi et al., 2019; Mirzaei et al., 2018; Dandabathula et al., 2021; Knevels et al., 2021; El Jazouli et al., 2019; Hermle et al., 2021; Wan, 2009; van Westen et al., 2006; Kannaujiya et al., 2019; Sansare & Mhaske, 2020).

Intense Precipitations data map (Puente-Sotomayor et al., 2021; Lourembam et al., 2021; Hong et al., 2007; Séverine et al., 2015; Omar et al., 2017; Corominas et al., 2014; Ahmed, 2015; Kannaujiya et al., 2019).

Soil data map (Omar et al., 2017; Corominas et al., 2014; Li et al., 2010; Peñafiel & Rojas, 2021; Ghosh et al., 2009; Liu et al., 2020) as factor that could be detailed into subfactor as Soil Type (Lourembam et al., 2021; Hong et al., 2007; Noviyanto et al., 2020) and Soil Stability (Puente-Sotomayor et al., 2021; Ahmed, 2015; Ngandam Mfondoum et al., 2021; Saputra et al., 2016). Population data map (Omar et al., 2017; van Westen et al., 2006; Diakakis et al., 2017; Muis et al., 2015; Jibrillah et al., 2019). Floor Area data map (Puente-Sotomayor et al., 2021; van Westen et al., 2006; Alimohammadlou et al., 2013; Puente-Sotomayor et al., 2021). Building Footprint Area data map (Corominas et al., 2014; Li et al., 2010; van Westen et al., 2006; Dou et al., 2020; Diakakis et al., 2017; Samanta et al., 2018).

Rainfall data map (Sina et al., 2021; Althuwaynee et al., 2018; Lourembam et al., 2021; Séverine et al., 2015; Miller et al., 2009; Omar et al., 2017; Corominas et al., 2014; Hervás & Bobrowsky, 2009; Ahmed, 2015; Peñafiel & Rojas, 2021; Ghosh et al., 2009; Liu et al., 2020; Ngandam Mfondoum et al., 2021; Noviyanto et al., 2020; Silalahi et al., 2019; Mahmood & Rahman, 2019; Diakakis et al., 2017; Hong et al., 2019; Morea & Samanta, 2020; Paliaga et al., 2019; Basri et al., 2021; Handayani et al., 2019; Gutiérrez-Martín, 2020; Fan et al., 2020; Huang & Zhao, 2018).

River/Stream data map (Omar et al., 2017; Corominas et al., 2014; Hervás & Bobrowsky, 2009; Hadmoko et al., 2017; El Jazouli et al., 2019; Wan, 2009; van Westen et al., 2006; Dou et al., 2020; Sansare & Mhaske, 2020; Mahmood & Rahman, 2019; Hong et al., 2019; Morea & Samanta, 2020; Handayani et al., 2019; Muis et al., 2015) as factor that could be detailed into subfactor as River Density (Xu et al., 2021; Ahmed, 2015; Peñafiel & Rojas, 2021; Dandabathula et al., 2021; Saputra et al., 2016; Paliaga et al., 2019; Jibrillah et al., 2019) and Distance to River (Sina et al., 2021; Pradhan et al., 2019; Huang et al., 2019; Mirzaei et al., 2018; Aditian et al., 2018; Diakakis et al., 2017; Huang & Zhao, 2018).

6.2 Instrumentation

In general qualitative approaches are entirely based on the expert knowledge and experiences of the persons carrying out the susceptibility or hazard assessment (Kaur et al., 2017). Qualitative approaches mainly include heuristic methods, whereas quantitative methods generally comprise numerical analysis of landslide inventories, statistical models and physically based models (Hervás & Bobrowsky, 2009). Quantitative landslide risk assessment uses numerical values and mathematical methods to usually estimate objective probabilities such as the probability of loss of life or of damage to structures or infrastructure due to landslides (Guzzetti 2005 in Hervás & Bobrowsky, 2009). The bivariate statistical approach is relatively simple compared with the multivariate ones, since the bivariate statistical analysis incorporates one dependent variable and one independent variable (Hadmoko et al., 2017). In multivariatt methods for landslide susceptibility analysis, percentage of landslides for each pixel is determined and data layer on landslide presence or absence is developed through statistical analysis (Shano et al., 2020). Multi-criteria decision analysis (MCDA) is a collection of techniques that aid decision-makers in properly structuring multi-faceted decisions and evaluating the alternatives. AHP is a tool under MCDA that is used for dealing with complex decision-making and helps decision-makers set priorities and draw better decisions (Morea & Samanta, 2020). ANN method facilitates to obtain, represent and perform mapping of landside susceptibility and hazard from one multivariate space of information into another by providing a set of data or information relating to representative mapping (Pradhan and Lee 2010; Nefeslioglu et al., 2008; Garrett 1994 in Shano et al., 2020).

The Analytical Hierarchy Process (AHP) is a multi criteria decision making process of measurement through pair wise comparisons and relies on the judgements of the experts to derive priority scales (Saaty 2008 in Pardeshi et al., 2013).The analytic hierarchy process (AHP) is a semi-qualitative method based on weighting and ranging different factors that affect landslide occurrence (Huang & Zhao, 2018). Analytical hierarchy process (AHP) is one of the most popular and satisfactory methods in disaster modelling like flood monitoring, mapping and analysing complex problems (Billa et al. 2006; Yalcin 2008; Chen et al. 2011 in Samanta et al., 2018). The AHP method, suggested by Saaty (1980), has become a popular tool for multi-criteria decision-making. It supports decision-makers to make the best decision, by reducing complex decisions to a series of comparative pairs and synthesizing the results (El Jazouli et al., 2019). The effectiveness of the AHP model as a knowledge-based model is inevitable due to its subjectivity (Althuwaynee et al. 2016 in Lourembam & Oinam, 2021). AHP method is still adopted for regional or large-scale assessments and for areas having no detailed landslide inventory. But the factor ranking process adopted in AHP is associated with uncertainties due to its subjective approach (Zhou et al. 2016 in Lourembam & Oinam, 2021). The multi-criteria evaluation of AHP approach has been applied using the theoretical basis of SMCE method. In this case, these factors are classified in a hierarchic layer and assigned numerical values based on the relative importance of each factor. Subsequently, these factors are synthesized and assigned according to their importance (Sahnoun et al. 2012 in Hong et al., 2019).

7. Finding & Discussion

7.1 Reliability analysis

Based on the results of identification and in-depth assessment of the approach used from 120 reference papers, it shows that 15% papers use a purely using qualitative approach, followed by 37% papers using a combination of a qualitative approach and a quantitative approach, then almost half of the reference papers using a quantitative approach only (see Table 2).

Table 2. Flooding and Landslide approach percentage used

Approach Layer	Percentage Used
Qualitative Approaches (A)	15%
Semi-quantitative Approaches (B)	37%
Quantitative Approaches (C)	48%

Based on the results of identification of the analysis used from 120 reference papers, it shows top three analysis as 29% papers using deterministic analysis, followed by 21% papers using multi-criteria decision analysis, then 19% reference papers using statistical analysis (see Table 3).

Table 3. Flooding and Landslide analysis percentage used

Analysis Layer	Percentage Used
Distribution/Inventory Analysis (A1)	8%
Geomorphic Analysis (A2)	10%
Multi-criteria Decision Analysis (B1)	21%
Statistical Analysis (C1)	19%
Deterministic Analysis (C2)	29%
Probability Analysis (C3)	4%
Artificial Intelligent (C4)	9%

Based on the results of identification of the method used from 120 reference papers, it shows top four method as 22% papers using empirical approach, followed by 15% papers using AHP method, then 12% papers using Numerical modeling and 11% reference papers using Multivariate Statistic (see Table 4).

Table 4. Flooding and Landslide method percentage used

Analysis Layer	Percentage Used
AHP (B1a)	15%
Fuzzy (B1b)	3%
Weighted Linier (B1c)	10%
Ordered Weighted Average (B1d)	7%
Bivariate Statistics (C1a)	10%
Multivariate Statistic (C1b)	11%
Empirical Approach (C2a)	22%
Limit Equilibrium Approach (C2b)	3%
Numerical Modeling (C2c)	12%
Artificial Neural Network (C4a)	1%
Kernel Based (C4b)	1%
Decision Tree (C4c)	2%
Swarm Optimization (C4d)	1%
Fuzzy Clustering (C4e)	2%

7.2 Descriptive statistics & analysis

The deterministic techniques are most suitable when applied at large scale, as these techniques require considerable field data on geological and geotechnical parameters (Chimidi et al. 2017; Negassa and Kala 2015; Kanungo et al. 2006 in Shano et al., 2020). The landslide is a vital natural hazard, and therefore, the recognition of areas at risk of landslides and the mapping of the susceptibility to landslides are the interest of responsible organizations and researchers. Landslide susceptibility analysis can be done under the circumstance of having few existing data about the factors causing landslides using AHP method (El Jazouli et al., 2019).

Table 5. Flooding and Landslide susceptibility factor

Factor	Percentage Used
Geological	10%
Topographical	16%
Roads/Street	6%
Land Use/Cover	18%
Seismicity	3%
Intense Precipitations	7%
Soil	9%
Population	2%
Floor Area	5%
Building Footprint Area	3%
Rainfall	13%
River/Stream	8%

Based on the results of identification and in-depth assessment of the parameter used (data factor) from 120 reference papers, it shows that top five parameters as 18% papers remain land use/landcover factor, followed by 16% papers remain topographical factor (slope, aspect, curvature), followed by 13% papers remain rainfall factor, then 10% papers remain geological factor, and 9% papers remain soil factor (see Table 5). Based on the results of identification and in-depth assessment of the parameter used (data subfactor) from 120 reference papers, it shows that type of land use/landcover (14% reference papers) and slope (12% reference papers) remain as majoring parameter (see Table 6).

Table 6. Flooding and Landslide susceptibility subfactor

Subfactor	Percentage Used
Lithology	7%
Distance to Fault lines	6%
Altitude	5%
Slope	12%
Slope Length	3%
Aspect	8%
Curvature (Plan, Profile)	6%
Wetness Index	9%
Drainage Distance	5%
Road Density	3%
Distance to Road	2%
Type/LULC	14%
Vegetation Index	3%
Soil Type	5%
Soil Stability	2%
River Density	6%
Distance to River	4%

8. Conclusion and Future Recommendation

Floods as one of natural disaster can trigger landslides. Floods and landslides generally occur on a small micro scale and usually produced on a large-scale map. Several data parameters are used to describe the distribution area of flooding and landslides, such as land use/landcover, topographical, geological, rainfall, soil, river/stream, roads/street, intense precipitations, floor area, Seismicity, building footprint area, and population. Prediction of flood zone and landslide susceptibility zones uses data parameters that are analyzed using a quantitative approach. Meanwhile, combination with a qualitative approach is usually used to analyze the data parameters that more influence on the occurrence of floods and landslides based on the frequency of disaster events.

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