Landslide Susceptibility Mapping of Kundiawa Gembogl District in Simbu Province of Papua New Guinea

Mathias Kopail Mond[1] and Sailesh Samanta[2]

[1]*Graduate Student, Department of Surveying and Land Studies, The Papua New Guinea University of Technology, Private mail Bag, Lae, Morobe, Papua New Guinea*

[2]*GIS Section, Department of Surveying and Land Studies, The Papua New Guinea University of Technology, Private mail Bag, Lae, Morobe, Papua New Guinea*

[1]matiinikesmond@gmail.com; [2]rsgis.sailesh@gmail.com

Received: 30 October, 2023 | Accepted: 23 November, 2023

Abstract

A landslide is the downslope and outward movement of earth-forming materials. The study area is Kundiawa Gembogl district, which is one of the six districts of Simbu Province in the highlands region of Papua New Guinea. More often, there are landslides on the roads that affect the traffic for both locals and the tourists who visit Mt. Wilhelm every year and affect the local revenue. This research aims to identify the landslide-prone areas and produce a landslide susceptibility map of the district of Kundiawa Gembogl, and a risk assessment of the properties. A wide variety of parameters or physical factors can affect the earth's stability and cause landslides. In this research, six (6) physical factors were used to generate a landslide susceptibility map. They are rainfall, slope, lithology, soil types, distance from the road, and distance from the river, which were generated either from the Digital Elevation Model (DEM) or through spatial analysis using Papua New Guinea's (PNG) national database respectively. The Weighted Linear Combination (WLC), an analytical method that deals with multi-attribute decision-making (MADM) was used to generate the landslide susceptibility map. The resulting susceptibility map was validated by using fifteen (15) past-recorded landslides in the area and most of them were found to be in the moderate and high-risk zones.

Keywords: *Landslide, Susceptibility, Weighted Linear Combination, Highlands, Papua New Guinea, Geographical information System*

1. Introduction

Landslide refers to the movement of ground or slope materials in a downward and outward direction at a vertical angle (Tandon et al., 2022). The assessment of landslide vulnerability involves the identification of areas that are susceptible to landslides by examining factors or parameters that can trigger such hazards or disasters (Glade, 2003). Landslides are considered to be one of the most perilous, devastating, and expensive natural or human-induced hazards that can occur anywhere on Earth (Svalova, et al., 2019). Conducting landslide risk assessments is of utmost importance as it aids in disaster prevention and facilitates the planning of infrastructure development. However, the assessment of this hazard/disaster is still lacking in some parts of the world (Dai et al., 2002). Without proper assessment of the surrounding environment and no proper planning of the area may put human lives and properties at risk.

The natural landscape is mountainous with rugged terrains, and slope hillsides with lots of creeks and rivers running downhill. Due to the geographical condition of the landscape, there are higher risks of having landslides anywhere (Svalova, et al., 2019). More often, there are landslides along the road in the rugged terrain area, which affects the traffic, causing adverse effects on the local revenue, infrastructure, and properties of those who are living there (Dai and Lee, 2002). It is not uncommon for disasters to result in casualties, particularly in areas where there is a high concentration of people living and farming on mountainous terrain that is susceptible to landslides. To effectively plan for and mitigate the impact of such disasters, it is crucial to conduct landslide susceptibility mapping and zonation of the affected area. This will help identify areas that are most at risk and enable disaster preparedness planning and mitigation efforts to be targeted accordingly.

In the recent past, a wide range of models, algorithms, and techniques have been used for GIS-based landslide susceptibility mapping (Lee, 2019). These models are divided into basic two categories, data-driven and knowledge-driven. Probabilistic, statistical, and machine-learning models are classified under data-driven models (Bordoni et al., 2021; Zêzere et al., 2017). On the other hand, the analytic hierarchy process (AHP) and weight overlay are widely considered under knowledge-driven models (Kaur et al., 2023; Ma et al., 2019). The most frequently used models to analyze landslide susceptibility and their trends are regression models (Kadavi et al., 2019; Zhu et al., 2018), frequency ratio models (Son et al., 2016; Li et al., 2017), artificial neural networks (Ermini et al., 2005; Lee et al, 2006; Tsangaratos and Benardos, 2014), fuzzy logic (Pradhan, 2010; Pourghasemi et al., 2012; Sur et al., 2020; Mallick et al., 2018), support vector machine (Huang and Shao, 2018; Yao et al., 2018), AHP (Pourghasemi et al., 2012; Samanta and Bhunia, 2023), and weight of evidence (Vakhshoori and Zare, 2016; Lee and Choi, 2004). The Weighted Linear Combination (WLC) (Michael and Samanta, 2016) method was used to evaluate the parameters for landslide susceptibility zonation of the district. The weightage of the physical factors was generated through the Analytical Hierarchy Process (AHP). AHP arranges the elements into a hierarchy using subjective judgments in order to assign numerical values based on the relative importance of these elements to the overall goals (Saaty, 1980).

The aim of this research was to identification of the landslide-prone areas and the impact assessment on the local and surrounding infrastructure resources. The study was conducted with three objectives. They are, (i) to identify the parameters, that have a major influence on landslide occurrence, (ii) to identify of landslide susceptibility zone using a multi-criteria approach, and finally (iii) to validate the acceptability of the model by overlaying the historical landslides data on the resulted landslide susceptibility zone. The final output, a landslide vulnerability assessment map will guide respective authorities in disaster mitigation, future district development plans, and helps educate the villagers or public about the hazard/disaster zones. These maps can be used as reference documents for planning land use, and infrastructure such as selecting the most suitable site for buildings and road construction. Lives and properties will remain at risk without such studies and proper dissemination of information to the local authorities and local residents.

2. Methodology

2.1 Study area

The Simbu Province is situated within the highlands geomorphological region. Kundiawa Gembogl district in Simbu (Chimbu) province in the highland region of Papua New Guinea was selected to conduct this research. The district is located in the highland mountain range with steep slopes and rugged terrains with a total land area of 440.4 square kilometers. Total populations of 78,521 are living in this area as per the latest PNG National census data released in 2011. Figure 1 represents the locality map of the study area along with basic infrastructures.

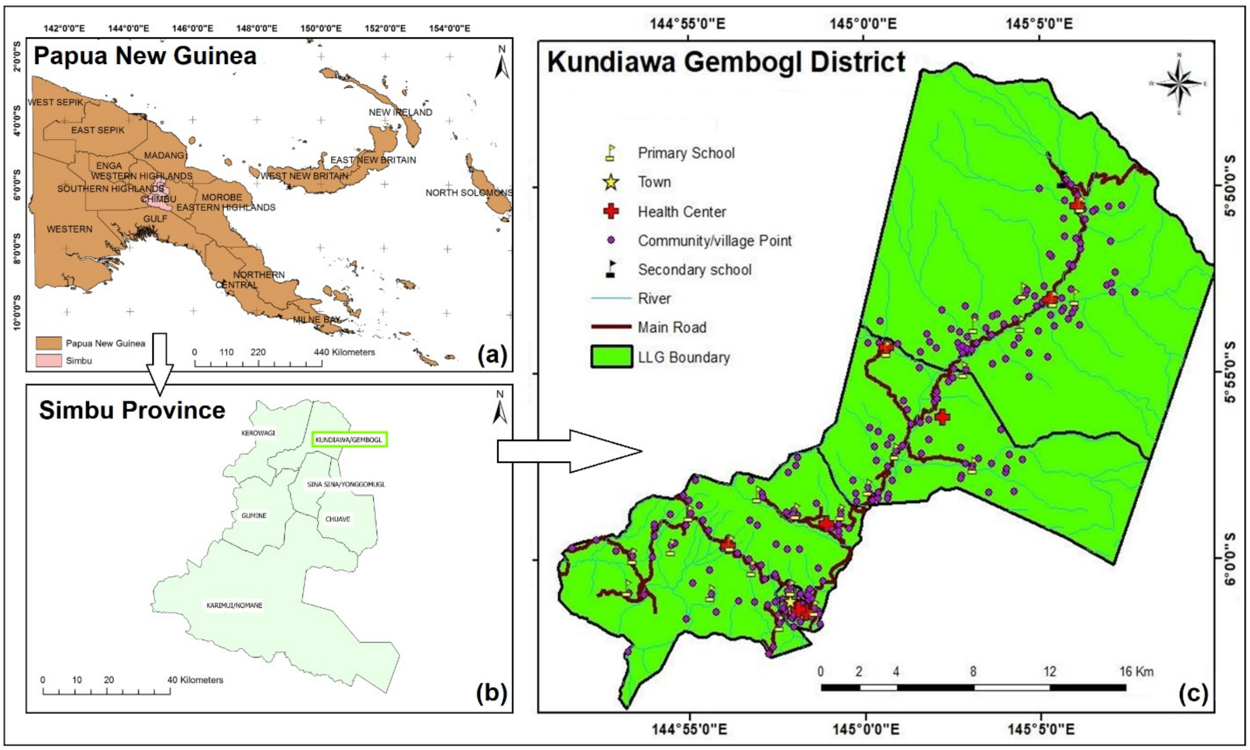

Fig. 1 The location map of the study area; (a) Papua New Guinea, (b) Simbu province and (c) Kundiawa Gembogl district

2.2 Parameters

In this research, six physical parameters were used for the analysis of the landslide susceptibility mapping. They are (i) rainfall, (ii) slope, (iii) soil type, (iv) lithology, (v) distance from the road, and (vi) distance from the river. Rainfall that has a high intensity will influence landslides (Hong et al., 2005). The very high amount of rainfall in tropical and sub-tropical regions may trigger landslides (Kanungo et al., 2009). Intense and/or prolonged rainfall can cause the soil to be unstable and prone to landslides. The slope should be examined in detail, for a steep slope of bare rock can be more stable compared to a slope made of a mixture of rocks and ground (Nathan, 2008). Multiple researches have shown evidence that very high susceptibility zones are more common along river valleys on steep side slopes (Nanehkaran et al., 2023). Therefore, the steeper the slope the more vulnerable the area is to landslide.

Lithology is one of the key factors in landslide susceptibility assessment. The geologic basement has effects on the formation of soil with different cohesion, permeability, texture, and strength and with distinct geotechnical behavior (Segoni et al. 2020). Lithology will show the area that is covered by various rock types or lithological units. It is a frequently used factor in landslide susceptibility analysis (El Jazouli et al., 2022). Soil Type characterizes the mechanical properties of the soil and is particularly important for studying shallow landslides (Bachri et al., 2020). Soil types are one of the key factors for determining the steadiness of slopes. Landslide probability is high over a specific soil type, with a mixture of gravels as a major component. In addition, there was no landslide occurred on the silty soil (Liu et al., 2021). All the soil texture classes were reclassified into hydrological soil groups (HSG) based on the infiltration characteristics.

The proximity to a river is an additional factor that can contribute to the occurrence of landslides. As the distance to the river decreases, the likelihood of a landslide increases. This is because the river can erode the slopes, saturate the lower part of the land, and raise the water level, all of which can negatively impact the stability of the slope (Cellek, 2019). Similarly, the distance to a road is also a significant factor that influences the frequency of landslides (El Jazouli et al., 2019). Landslides associated with roads may occur more frequently compared to those caused by the removal of vegetation (Hosseini, 2011).

2.3Weighted Linear Combination (WLC)

A weighted linear combination (WLC) is an analytical method that can be used when dealing with multi-attribute decision-making (MADM) or when more than one attribute must be taken into consideration. The WLC has three paces, namely (i) deriving and generating parameters from data sets, (ii) Ranking, classifying, and weighting of parameters, and (iii) generation of landslide hazard and risk factor map.

All the parameters such as slope, soil, rainfall, lithology, distance from the road, and distance from the river were prepared from the different primary or other GIS databases. The slope of the area was calculated from DEM using the slope tools in the Arc Toolbox of ArcMap 10.5. All the parameters were reclassified using the “Reclassify tool” under the Spatial Analysis Tools of ArcMap 10.5. The reclassified values are the rank values, which range from one (1) to five (5). The lower rank refers to very little or no influence and the higher rank refers to very high influence in the cause of the landslide probability (Saaty, 1980). In addition, all the parameters were assigned weights based on the importance of their influence on landslide occurrences. The weighted overlay analysis tool in the ArcMap Toolbox was used to produce the landslide susceptibility map. The weightage of each parameter was estimated through the Analytical Hierarchy Process (AHP). The Analytic Hierarchy Process (AHP) is a theory of measurement through Pairwise comparisons and relies on the judgments of experts to derive priority scales (Saaty, 2008). A consistency analysis was through consistency ratio (CR) calculations to check whether the weights were accepted or not and it was recommended that CR should be definitely below 0.2 (Saaty, 1977).

The validation of the risk factor map was done after the risk map production. The past landslide points were overlaid on the landslide susceptibility map to see whether the landslide points fell in the high susceptibility zones or low susceptibility zones. In the general view, if most of the historical landslides come under moderate to very high susceptibility zones, then the model can be accepted to be used. The methodological flow chart is presented in the figure 2.

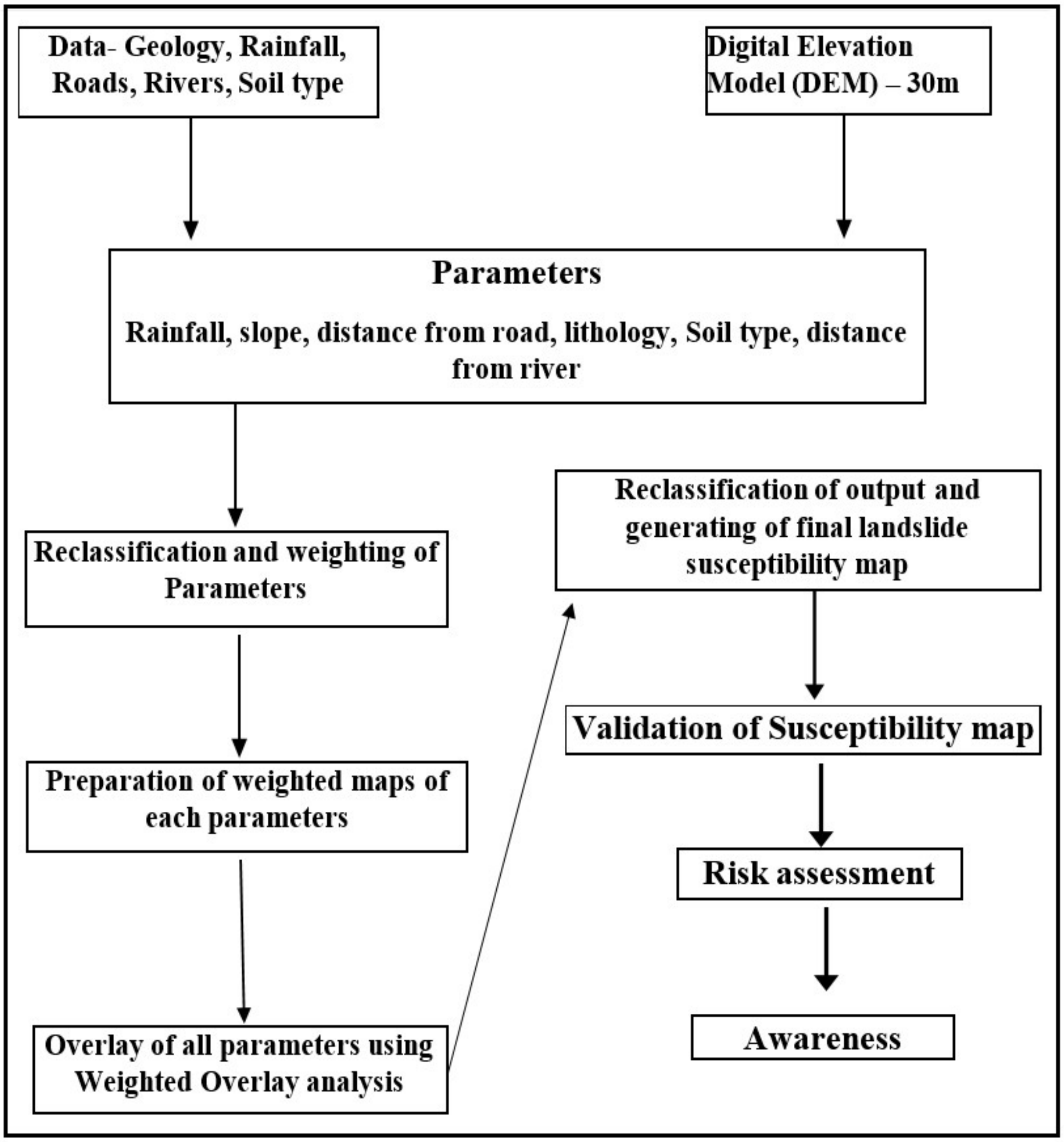

Fig. 2 The methodological framework for landslide susceptibility analysis

3. Result and discussions

A variety of factors and the preparation of consequent thematic data layers are vital components of any model for landslide susceptibility mapping. The features leading to instability in terrain are mainly rainfall, soil type, lithology, slope, and distance from the road and river. However, the importance of an exacting parameter depends on site-specific conditions. The Pairwise comparison in the analytical hierarchy process was used to calculate the criteria weight. The consistency ratio (CR) value was calculated as 0.089 (8.9%), which is a best-fit consistency with the use of six (6) parameters (Figure 3). Table 1 represents all the parameters used for landslide susceptibility mapping with weight and all the sub-classes with their favorable rank.

AHP Scale: 1- Equal Importance, 3- Moderate importance, 5- Strong importance, 7- Very strong importance, 9- Extreme importance (2,4,6,8 values in-between).

These are the resulting weights for the criteria based on your pairwise comparisons:

Cat		Priority	Rank	(+)	(-)
1	Rainfall	26.1%	1	5.5%	5.5%
2	Soil Type	25.4%	2	15.6%	15.6%
3	Slope	15.3%	3	8.2%	8.2%
4	Distance from Road	12.9%	4	6.3%	6.3%
5	Distance from River	9.7%	6	5.3%	5.3%
6	Lithology	10.6%	5	3.3%	3.3%

Number of comparisons = 15
Consistency Ratio CR = 8.9%

(a)

The resulting weights are based on the principal eigenvector of the decision matrix:

	1	2	3	4	5	6
1	1	1.00	2.00	3.00	3.00	2.00
2	1.00	1	4.00	1.00	2.00	2.00
3	0.50	0.25	1	2.00	3.00	1.00
4	0.33	1.00	0.50	1	2.00	1.00
5	0.33	0.50	0.33	0.50	1	2.00
6	0.50	0.50	1.00	1.00	0.50	1

Principal eigen value = 6.557
Eigenvector solution: 6 iterations, delta = 1.1E-8

(b)

Fig. 3 The Pairwise comparison in analytical hierarchy process to calculate the criteria weight; (a) Priorities and (b) Decision matrix

The mean annual rainfall of the study area ranged from 2400 - 4700mm (Figure 4a). The study area was classified into five different rainfall intensity zones. They are (i) 2400 - 2900mm, (ii) 2900 – 3400mm, (iii) 3400 – 3900mm, (iv) 3900 – 4300mm, and (vi) 4300 - 4700mm. Maximum rain is dominated in the northern side of the study area. There are five (5) categories of rock were found in the study area, namely (i) volcanic rock, (ii) sandstone and siltstone, (iii) sedimentary deposits, (iv) Scree deposits, and (v) limestone (Figure 4b). Limestone rocks were found in the middle of the study area, covered by 12.26% of the study area, and considered to be at higher risk for landslide occurrence. However, some small pockets of sedimentary deposits were observed in the north part of the district, covering only 1.66%. Furthermore, the volcanic and igneous rocks (71.58%) were found in the north, northeast, and southwest parts of the study area, marked to be at lower risk for landslide occurrences. The scree deposits were observed in some pockets of the district, wrapped by 3% of the study area. The remaining part (23.77%) of the study area is enveloped by sandstone and siltstone, allocated in the central and some small pockets in the southern part. Nine (9) types of soil texture were found in the study area, namely Sandy loam, Loamy, Sandy clay loam, Silty clay, Clay, Sandy clay, silty clay loam, Silt, and Peat. These soil texture classes were reclassified into four (4) hydrological soil groups (HSG). They are (i) HSG-A (Sandy loam), (ii) HSG-B (Loamy), (iii) HSG-C (Sandy clay loam), HSG-D (Silty clay, Clay, Sandy clay, silty clay loam, Silt, and Peat). The study area is dominated by soil group D, which covers almost 74.19% of the study area (Figure 4c). The slope map was prepared from the DEM of the study area and divided into five slope categories (Figure 4d). They are (i) Less than 10º, (ii) 10 - 20º, (iii) 20 - 30º, (iv) 30 - 40º, and (v) more than 40º. Five different multiple-ring buffer areas were created on the path of the road to determine the road's effect on the slope's stability. They are (i) Less than 250m, (ii) 250-500m, (iii) 500-1000m, (iv) 1000-2000m, and (v) more than 2000m (Figure 4e). Similarly, five different multiple-ring buffer areas were created on the path of the river to determine the effect of the river on the stability of the slope as well as the landslide occurrences. They are (i) Less than 250m, (ii) 250-500m, (iii) 500 - 750m, (iv) 750 - 1000m, and (v) more than 1000m (Figure 4f).

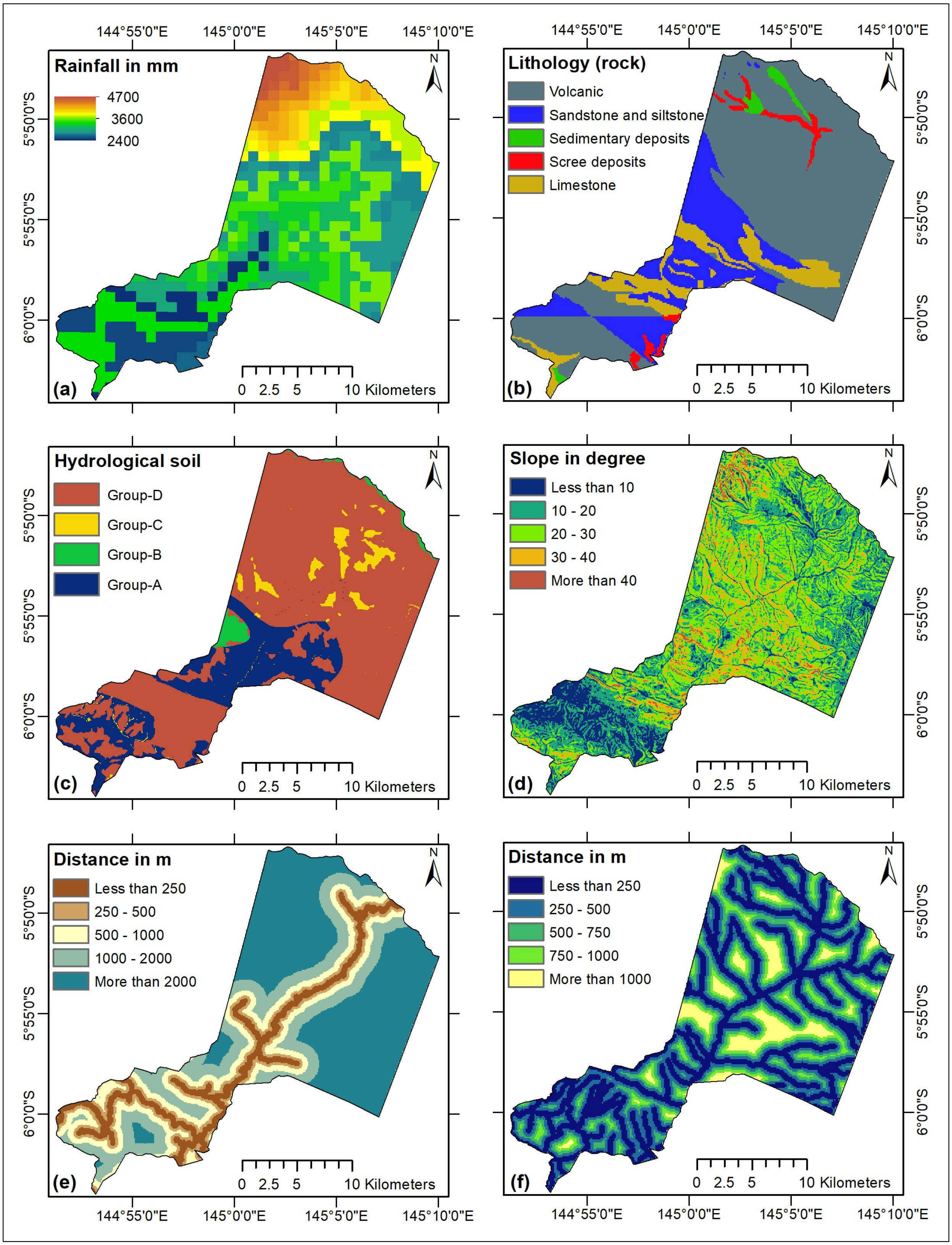

Fig. 3 Parameters used for the landslide susceptibility analysis, (a) rainfall, (b) lithology/rocks type, (c) hydrological soil group, (d) slope, (e) distance from road, and (f) distance from river.

Table 1. Parameters used for landslide susceptibility mapping with weight and rank

Parameters	Sub-class	% Weight	Rank
Rainfall	2400 – 2900 mm	26.1	5 – Very high
	2900 – 3400 mm		4 – High
	3400 – 3900 mm		3 – Moderate
	3900 – 4300 mm		2 – Low
	4300 – 4700 mm		1 – Very low
Soil Type	HSG-A (Sandy loam)	25.4	5 – Very high
	HSG-B (Loamy)		4 – High
	HSG-C (Sandy clay loam)		3 – Moderate
	HSG-D (Silty clay, Clay, Sandy clay, silty clay loam, Silt, Peat)		1 – Very low
Slope	Less than 10	15.3	1 – Very low
	10 - 20		2 – Low
	20 - 30		3 – Moderate
	30 - 40		4 – High
	More than 40		5 – Very high
Distance from road	Less than 250m	12.9	5 – Very high
	250 - 500		3 – Moderate
	500 - 1000		1 – Very low
	1000 - 2000		1 – Very low
	More than 2000		1 – Very low
Distance from river	Less than 250m	9.7	5 – Very high
	250 - 500		4 – High
	500 - 750		3 – Moderate
	750 - 1000		2 – Low
	More than 1000		1 – Very low
Lithology - formation	Limestone	10.6	5 – Very high
	Scree deposits		4 – High
	Alluvium , Sedimentary and fluvio-glacial deposits		3 – Moderate
	Sandstone, siltstone		2 – Low
	Volcanic		1 – Very low

The result of the weightage overlay analysis generates five (5) susceptibility classes ranging from very high with a value of 5 to very low with a value of 1. Figure 5 shows that the northeast zone of the study area is highly susceptible to landslide occurrence. High susceptible landslide areas were portrayed in the north, northeast, and northwest portions of the district because of higher rainfall and group-D soil type. The medium landslide susceptible zone was delineated in the central part of the study area because of the flat terrain. However, some pockets of southern and middle parts of the district were marked as low to very low vulnerable to landslide events. To validate the resulting landslide susceptibility map the legacy database of fifteen (15) past landslide point data was overlaid on the susceptibility map, which was collected from the provincial disaster office. Figure 5 shows that most of the past landslides (14 points out of 15) fall on the moderate to high susceptibility zones.

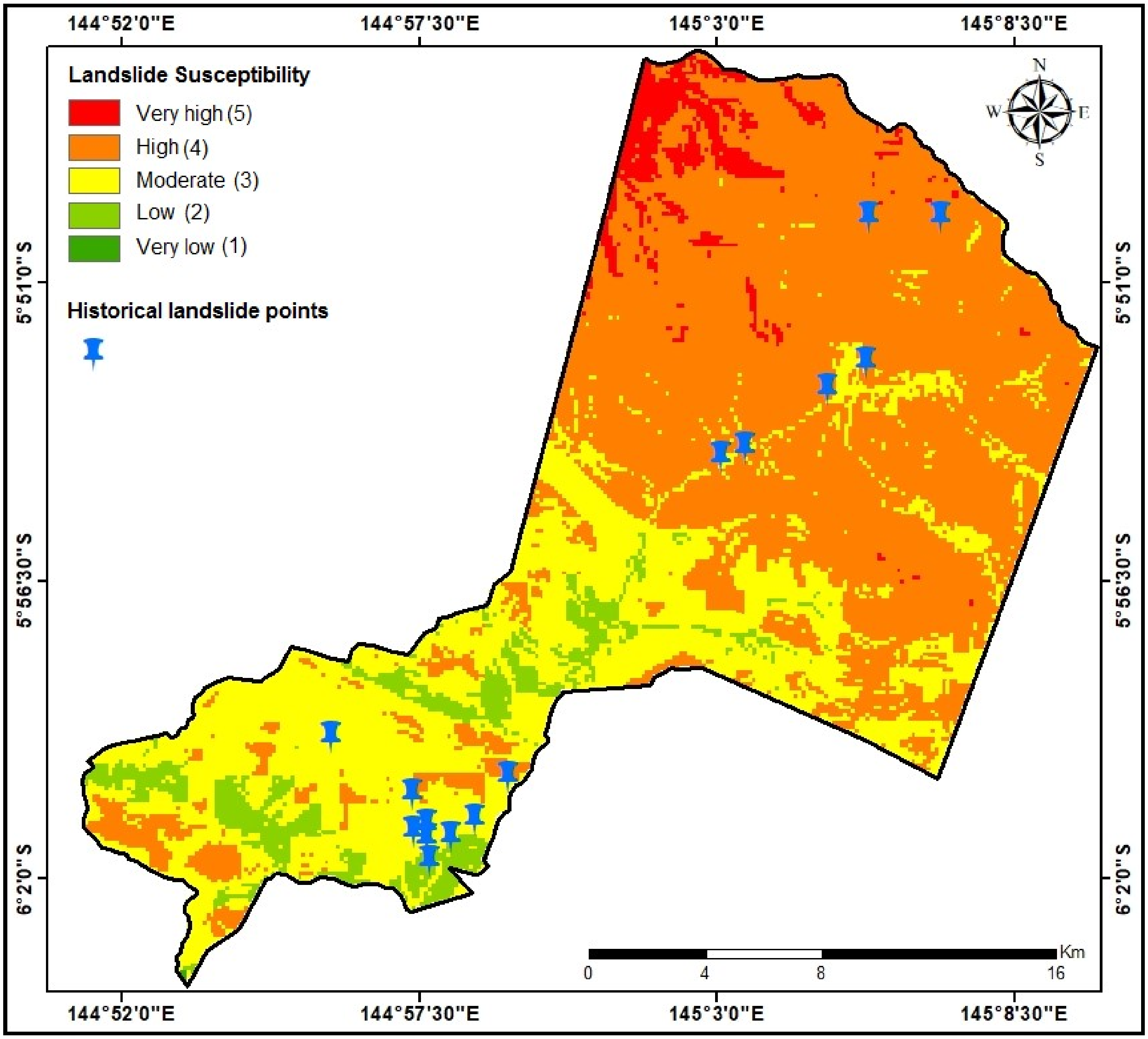

Fig. 5 Resulted landslide susceptibility map overlaid with historical landslide points

Village and infrastructure were overlaid on the resulting output for a vulnerability assessment. Most of the infrastructures are situated within the Moderate and high susceptibility zones (Figure 6 and Table 2).

Table 2. Vulnerability assessment of six immediate infrastructure/facility

Susceptibility Zone	Aid posts	Health Center	Primary School	Bridges	Villages	Village Court
1–Very Low	0	0	0	0	0	0
2-Low	3	3	6	5	39	3
3-Moderate	6	4	12	7	121	16
4-High	2	1	7	0	91	12
5-Very High	0	0	0	0	0	0

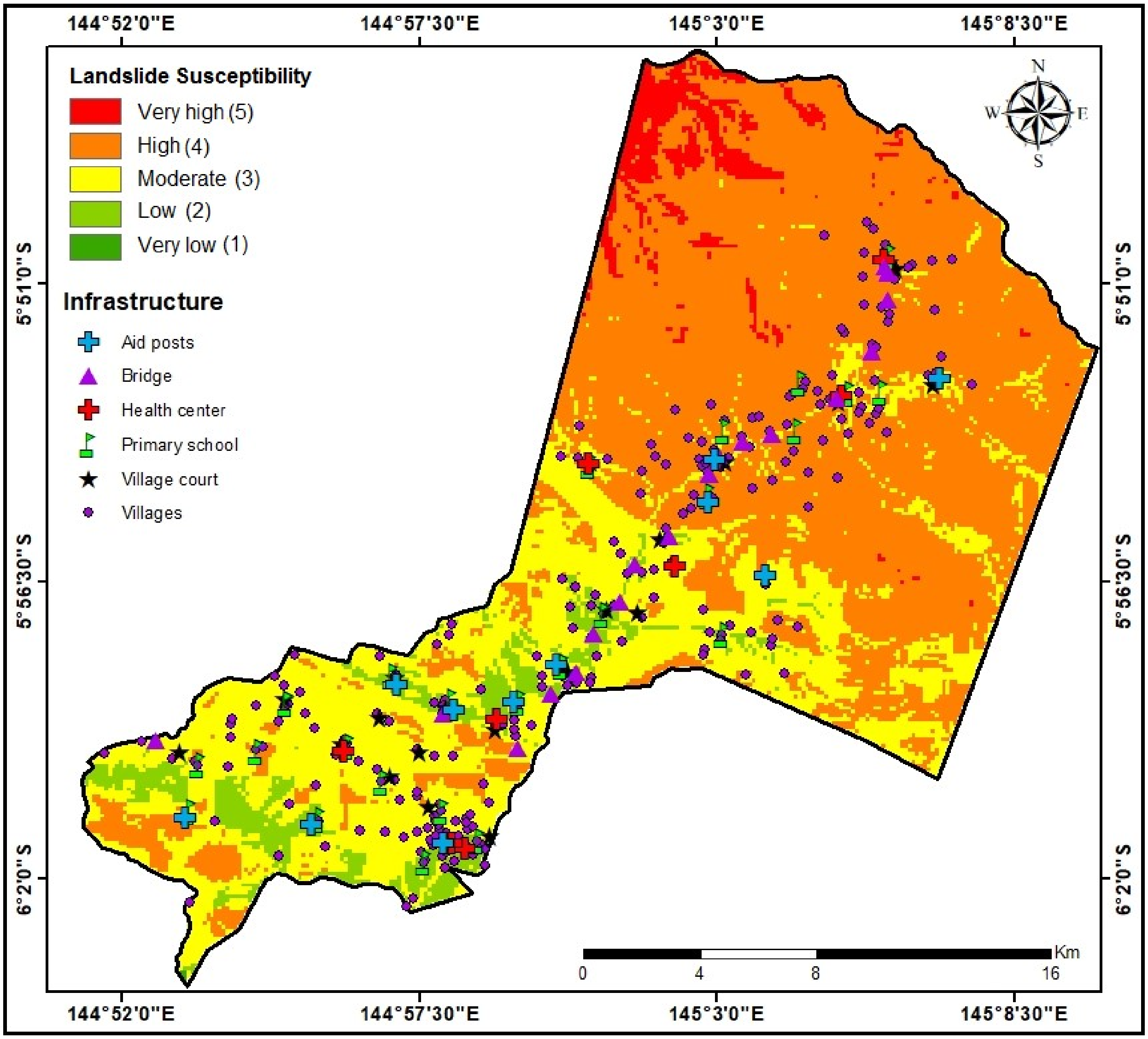

Fig. 6 Resulted landslide susceptibility map overlaid with infrastructure facilities

4. Conclusion and recommendations

The Gembogl road and surrounding district area are prone to frequent landslides, which can cause significant damage to infrastructure and even result in loss of life. The population growth in the area has led to people settling in locations near the road for easy access to basic services, without proper consideration of environmental factors such as unstable slopes and vegetation clearance for road construction. To address this issue, a study was conducted to assess six physical factors and produce a landslide susceptibility map using the weighted linear combination (WLC) method and analytical hierarchy process (AHP). The map was validated using historical landslides and showed a positive correlation with moderate to high susceptibility zones. Landslides pose a greater risk when they affect human lives and infrastructure, while those occurring in remote areas with little human activity may be less dangerous. To better understand the actual risk, a landslide vulnerability assessment was conducted using the location of villages and infrastructure facilities.

Developing countries like Papua New Guinea should demarked landslide susceptibility zones over all the regions, where people are living in high altitude or mountainous areas. This type of study will help local authorities to better plan where there should be developments and where people should settle. In addition, landslide susceptibility will help the district development authority in their development plans and the disaster office in their disaster mitigation and prevention acts. There should be research on landslide susceptibility mapping almost in all regions of this country. Moreover, proper measures to avoid or control this matter should be in place to save damage costs and lives in the future. For future research, more parameters could be incorporated into the WLC-AHP method for better results.

5. References

1. Bachri, S., Shrestha, R. P., Yulianto, F., Sumarmi, S., Utomo, K. S. B., and Aldianto, Y. E. (2020). Mapping landform and landslide susceptibility using remote sensing, gis and field observation in the southern cross road, Malang regency, East Java, Indonesia. *Geosciences*, *11*(1), 4.
2. Bordoni, M., Vivaldi, V., Lucchelli, L., Ciabatta, L., Brocca, L., Galve, J. P., and Meisina, C. (2021). Development of a data-driven model for spatial and temporal shallow landslide probability of occurrence at catchment scale. *Landslides*, *18*, 1209-1229.
3. Cellek, S. (2019). The effect of shape on the linear relationship of maximum and minimum void ratios of various sand types. *Geotechnical and Geological Engineering*, *37*, 3701-3713.
4. Dai, F. C., Lee, C. F., & Ngai, Y. Y. (2002). Landslide risk assessment and management: an overview. *Engineering geology*, *64*(1), 65-87.
5. Dai, F., & Lee, C. F. (2002). Landslides on natural terrain. *Mountain Research and Development*, *22*(1), 40-47.
6. El Jazouli, A., Barakat, A., and Khellouk, R. (2019). GIS-multicriteria evaluation using AHP for landslide susceptibility mapping in OumErRbia high basin (Morocco). *Geoenvironmental Disasters*, *6*(1), 1-12.
7. El Jazouli, A., Barakat, A., and Khellouk, R. (2022). Geotechnical studies for Landslide susceptibility in the high basin of the OumErRbiariver (Morocco). *Geology, Ecology, and Landscapes*, *6*(1), 40-47.
8. Ermini, L., Catani, F., and Casagli, N. (2005). Artificial neural networks applied to landslide susceptibility assessment. *geomorphology*, *66*(1-4), 327-343.
9. Glade, T. (2003). Vulnerability assessment in landslide risk analysis. *Erde*, *134*(2), 123-146.
10. Hong, Y., Hiura, H., Shino, K., Sassa, K., Suemine, A., Fukuoka, H., and Wang, G. (2005). The influence of intense rainfall on the activity of large-scale crystalline schist landslides in Shikoku Island, Japan. *Landslides*, *2*, 97-105.
11. Hosseini, S. A., Lotfi, R., Lotfalian, M., Kavian, A., and Parsakhoo, A. (2011). The effect of terrain factors on landslide features along forest road. *African journal of Biotechnology*, *10*(64), 14108-14115.
12. Kadavi, P. R., Lee, C. W., and Lee, S. (2019). Landslide-susceptibility mapping in Gangwon-do, South Korea, using logistic regression and decision tree models. *Environmental Earth Sciences*, *78*, 1-17.
13. Kanungo, D. P., Arora, M. K., Sarkar, S., and Gupta, R. P. (2012). Landslide Susceptibility Zonation (LSZ) Mapping–A Review.

14. Kaur, H., Gupta, S., Parkash, S., and Thapa, R. (2023). Knowledge-driven method: a tool for landslide susceptibility zonation (LSZ). *Geology, Ecology, and Landscapes*, *7*(1), 1-15.
15. Lee, S. (2019). Current and future status of GIS-based landslide susceptibility mapping: a literature review. *Korean Journal of Remote Sensing*, *35*(1), 179-193.
16. Lee, S., and Choi, J. (2004). Landslide susceptibility mapping using GIS and the weight-of-evidence model. *International Journal of Geographical Information Science*, *18*(8), 789-814.
17. Lee, S., Ryu, J. H., Lee, M. J., and Won, J. S. (2006). The application of artificial neural networks to landslide susceptibility mapping at Janghung, Korea. *Mathematical Geology*, *38*, 199-220.
18. Li, L., Lan, H., Guo, C., Zhang, Y., Li, Q., and Wu, Y. (2017). A modified frequency ratio method for landslide susceptibility assessment. *Landslides*, *14*, 727-741.
19. Liu, Y., Deng, Z., and Wang, X. (2021). The effect of rainfall, soil type and slope on the processes and mechanism of rainfall-induced landslide.
20. Ma, Z., Qin, S., Cao, C., Lv, J., Li, G., Qiao, S., and Hu, X. (2019). The influence of different knowledge-driven methods on landslide susceptibility mapping: A case study in the Changbai Mountain Area, Northeast China. *Entropy*, *21*(4), 372.
21. Mallick, J., Singh, R. K., AlAwadh, M. A., Islam, S., Khan, R. A., and Qureshi, M. N. (2018). GIS-based landslide susceptibility evaluation using fuzzy-AHP multi-criteria decision-making techniques in the Abha Watershed, Saudi Arabia. *Environmental Earth Sciences*, *77*, 1-25.
22. Michael, E. A., and Samanta, S. (2016). Landslide vulnerability mapping (LVM) using weighted linear combination (WLC) model through remote sensing and GIS techniques. *Modeling Earth Systems and Environment*, *2*, 1-15.
23. Nanehkaran, Y. A., Chen, B., Cemiloglu, A., Chen, J., Anwar, S., Azarafza, M., and Derakhshani, R. (2023). Riverside Landslide Susceptibility Overview: Leveraging Artificial Neural Networks and Machine Learning in Accordance with the United Nations (UN) Sustainable Development Goals. *Water*, *15*(15), 2707.
24. Nathan, F. (2008). Risk perception, risk management and vulnerability to landslides in the hill slopes in the city of La Paz, Bolivia. A preliminary statement. *Disasters*, *32*(3), 337-357.
25. Pourghasemi, H. R., Pradhan, B., and Gokceoglu, C. (2012). Application of fuzzy logic and analytical hierarchy process (AHP) to landslide susceptibility mapping at Haraz watershed, Iran. *Natural hazards*, *63*, 965-996.
26. Pradhan, B. (2010). Application of an advanced fuzzy logic model for landslide susceptibility analysis. *International Journal of Computational Intelligence Systems*, *3*(3), 370-381.
27. Saaty, T.L., (1977). A Scaling Method for Priorities in Hierarchical Structures. The Journal of Mathematical Psychology, Vol. 15(3), 234-281.
28. Saaty, T. (1980, November). The analytic hierarchy process (AHP) for decision making. In *Kobe, Japan* (Vol. 1, p. 69).
29. Saaty, T. L. (2008). Decision making with the analytic hierarchy process. *International journal of services sciences*, *1*(1), 83-98.
30. Samanta, S., and Bhunia, G. S. (2013). Landslide susceptibility zone identification of Markham Watershed, PNG A study based on remote sensing and GIS technology. *International Journal of Physical and Social Sciences*, *3*(1), 307-322.
31. Son, J., Suh, J., and Park, H. D. (2016). GIS-based landslide susceptibility assessment in Seoul, South Korea, applying the radius of influence to frequency ratio analysis. *Environmental Earth Sciences*, *75*, 1-16.

32. Sur, U., Singh, P., and Meena, S. R. (2020). Landslide susceptibility assessment in a lesser Himalayan road corridor (India) applying fuzzy AHP technique and earth-observation data. *Geomatics, Natural Hazards and Risk*, *11*(1), 2176-2209.
33. Svalova, V. B., Zaalishvili, V. B., Ganapathy, G. P., Nikolaev, A. V., and Melkov, D. A. (2019). Landslide risk in mountain areas. *Geology of the South of Russia*, *9*(2), 109-126.
34. Tandon, R. S., Gupta, V., Venkateshwarlu, B., and Joshi, P. (2022). An assessment of Dungale landslide using remotely piloted aircraft system (RPAS), ground penetration radar (GPR), and Slide & RS2 Softwares. *Natural Hazards*, *113*(2), 1017-1042.
35. Tsangaratos, P., &Benardos, A. (2014). Estimating landslide susceptibility through a artificial neural network classifier. *Natural hazards*, *74*, 1489-1516.
36. Vakhshoori, V., and Zare, M. (2016). Landslide susceptibility mapping by comparing weight of evidence, fuzzy logic, and frequency ratio methods. *Geomatics, Natural Hazards and Risk*, *7*(5), 1731-1752.
37. Yao, X., Tham, L. G., & Dai, F. C. (2008). Landslide susceptibility mapping based on support vector machine: a case study on natural slopes of Hong Kong, China. *Geomorphology*, *101*(4), 572-582.
38. Zêzere, J. L., Pereira, S., Melo, R., Oliveira, S. C., and Garcia, R. A. (2017). Mapping landslide susceptibility using data-driven methods. *Science of the total environment*, *589*, 250-267.
39. Zhu, A. X., Miao, Y., Wang, R., Zhu, T., Deng, Y., Liu, J., Lin, Y., Qin, C.Z., and Hong, H. (2018). A comparative study of an expert knowledge-based model and two data-driven models for landslide susceptibility mapping. *Catena*, *166*, 317-327.

Author's Bibliography

Mr. Kopail Mathias Mond has recently completed in Bachelor of Science from the PNG University of Technology. He will be graduating next year 2024.

Dr. Sailesh Samanta is presently working as Associate Professor and GIS Section Head in the Department of Surveying and Land Studies at The Papua New Guinea University of Technology, Papua New Guinea. His research profile can be accesses through https://scholar.google.com/citations?user=vd3ddccAAAAJ