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ORIGINAL ARTICLE

A Geographical Information Systems-Multi Criteria Decision Analysis Integrated Landslide Risk Index For Yatiyanthota Divisional Secretariat Division, Sri Lanka, Using Geospatial Techniques

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ABSTRACT

A landslide is one of the most destructive and frequent environmental disasters on the Earth's surface. They are a common disaster in many districts of Sri Lanka, including Kegalle, particularly during the south-west monsoon season. This research developed a landslide risk index by combining 25 criteria across six main variables (climate, geology, topography, demography, socioeconomic, and coping factors) that contribute to landslide occurrence in the Yatiyantota divisional secretariat division (DSD) utilizing Geographic Information Systems (GIS) integrated Multi-Criteria Decision Analysis (MCDA) approach. This approach incorporated the Analytic Hierarchy Process (AHP) and employed the Weighted Linear Combination (WLC). Factor and criteria weights were determined using AHP, while factor class ratings were assigned based on logical judgment informed by expert surveys. The results found that 3% (5.6 km^2) of the area is prone to very high risk, while 40% (67.9 km^2) falls into the high-risk category. Meanwhile, 18% (29.1 km^2) was identified as very low and low-risk categories. Moderate-risk areas are also significant, accounting for 39% (66.6 km^2) of the total area. The model validation results demonstrated that the resulting map closely aligns with real-world conditions, achieving 72.2% overall accuracy through Receiver Operating Characteristics (ROC) curve analysis. Accordingly, the GNDs of Mattamagoda, Pahala Garagoda, Amanawala, Berennawa Malwatta were identified to be the most vulnerable to landslide occurrences. Planning authorities should implement remedial measures to minimize landslide risks through various short-term and long-term strategies, utilizing the warning signals identified in the survey.

1 Introduction

Landslide is one of the most destructive and frequent environmental disasters worldwide. These geological hazards relate the downward movement of rock, soil, and debris along slopes, often with catastrophic consequences, including loss of life, infrastructure damage, and significant disruptions to communities. Following a landslide, a critical concern is the resettlement of affected populations, as communities may be left in hazardous locations or face the challenge of rebuilding on unstable ground (Perera et al., 2020).

Heavy rainfall, earthquakes, deforestation, and poor land use planning are major triggering factors for landslides (Perera et al., 2020). Climate change has also predicted to increase their rates and severity, with increasing threats of landslides for vulnerable communities (Madushani et al., 2025). Physical factors like terrain steepness, rainfall, and seismic activity, along with human activities such as construction on slopes and mining, contribute to landslides. While they cannot be fully prevented, various measures may support to reduce the risk and effect of landslides (Ahmed et al., 2013; Alam et al., 2019; Hidayat, 2010). Measures to prevent landslides include restricting harmful

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human activities, evacuating and relocating people from high-risk areas, and educating the public on safety during landslides (Perera et al., 2020).

Landslides are common in Sri Lanka, affecting nearly 20,000 km^2 (30% of the land area) across 10 districts, including Badulla, Nuwara Eliya, Kandy, Rathnapura and Kegalle (DMC, 2017). These areas, located in the wet zone, experience landslides due to heavy rainfall from the Southwest Monsoon (Perera et al., 2020). Several factors, including urbanization (Jayasinghe et al., 2024), land cover changes (Wijesinghe et al., 2024; Withanage et al., 2024d), and deforestation (Withanage et al., 2024b) on sloping terrains in the central highlands, have contributed to the issue (Mutale et al., 2024; Ranagalage et al., 2019; Wijesinghe and Withanage, 2021). Various government agencies, including the National Building Research Organization (NBRO), have taken steps to mitigate landslide risks, supported by the Sri Lanka Disaster Management Act of 2005, which provides a legal framework for Disaster Risk Management (DMC, 2017).

Diverse methods have been developed to assess landslide hazard and susceptibility, including inventory methods, expert evaluation, statistical approaches, deterministic methods, probabilistic techniques and Geographic Information System–Multi-Criteria Decision Analysis (GIS-MCDA) (Girma et al., 2015; Raghuvanshi, 2019; Shano et al., 2021). Landslide vulnerability maps (LVMs) detect risk areas of future landslides by considering key contributing factors (Perera et al., 2020; Raghuvanshi et al., 2015). These maps are essential for sustainable regional planning, as well as for landslide risk reduction and management (Raghuvanshi et al., 2014; Withanage, 2018). By displaying the spatial distribution of risk levels, LVMs serve as a foundational tool for land use planning and engineering development (Raghuvanshi, 2019). In the Sri Lankan context, GIS-MCDA has been widely used in recent years for various fields, including flood vulnerability mapping (Nuwanka and Withanage, 2024), human-elephant conflicts (Withanage et al., 2023), life quality mapping (Dissanayake et al., 2020; Withanage et al., 2024a), groundwater potential zones identification (Pathmanandakumar et al., 2021; Wijesinghe et al., 2023; Wimalasena and Withanage, 2021), cropland suitability evaluation (Jayasinghe and Withanage, 2020), residential suitability analysis (Madurika and Hemakumara, 2017), ecotourism suitability (Pathmanandakumar et al., 2023; Withanage et al., 2024c), and wastewater plant location (Bandara et al., 2022).

This study focuses on Yatiyanthota DSD, which is a main landslide risk area in the Kegalle district, where frequencies and severity have shown an upward trend during the last decade due to climate and physical dynamics (Perera et al., 2020). Many new villages have been resettled due to landslides, and measures are being taken to evict and resettle people from areas identified by the NBRO as prone to landslides (NBRO, 2016b). As a result, landslides have become common in Yatiyanthota, particularly during periods of heavy rainfall, and the local population does not always take the hazards seriously. Consequently, the area continues to be at significant risk of landslides, despite warnings for evacuation. However, identifying risk-prone areas remains somewhat challenging due to the lack of up-to-date information. In this context, GIS serves as a time- and cost-efficient tool, enabling the reliable identification of landslide risk areas in Yatiyantota.

However, a notable limitation is the lack of similar research specifically focused on the study area, with only a comparable study covering the entire Kegalle district. Despite this, the originality of this study is preserved through the utilize of scenario analysis and Receiver Operating Characteristic (ROC) curve-based model validation, which ensure that the findings are well-suited to real-world conditions. Several research questions were identified through literature survey during the initial stage of our research design as; (i) what are the different landslide risk zones in DSD? (ii) what are the most common factors that affected to landslides in study area? (iii) how GIS integrated MCDA techniques can be used to derive a landslide risk index?

To address the above questions, the research objectives were aligned as;

(i) Identifying the most influential variable contributing to landslide occurrences through scenario analysis.
(ii) Identifying common factors affecting landslides in the study area
(iii) Developing a landslide risk index aided by GIS-MCDA

2 Literature Review

Numerous studies have employed diverse methodological frameworks to assess landslide susceptibility and risk. For instance, Dhungana et al. (2023) applied the Analytic Hierarchy Process (AHP) to analyze landslide susceptibility, while Gu et al. (2023) examined the influence of factor screening methods on landslide risk prediction using a Random Forest (RF) model. GIS-MCDA has also been widely adopted; Maqsoom et al. (2022) utilized this approach to assess landslide susceptibility along a 236 km section of a specific transportation route. In addition, Singh et al. (2021) proposed a multidisciplinary framework integrating Remote Sensing (RS, GIS, and semi-quantitative techniques to evaluate landslide risks to buildings in the Himalayan region.

Machine learning and statistical models have further contributed to advances in landslide assessment. Yin et al. (2020) addressed highway landslide disasters in China using a hybrid model that combined Principal Component Analysis (PCA) for key factor selection with an optimized Support Vector Machine (SVM), achieving strong predictive performance. Similarly, Yu and Gao (2020) developed a Geographically Weighted Regression (GWR) model for landslide susceptibility mapping, while Luo et al. (2019) evaluated landslide risk using SVM techniques. Comparative and semi-quantitative approaches have also been explored, including the comparison of logistic regression, MCDA, and likelihood ratio models by Akgun (2012), as well as the semi-quantitative landslide risk assessment conducted by Biçer and Ercanoglu (2020).

Beyond modeling, several studies have focused on data acquisition and monitoring techniques. Confuorto et al.

(2019) employed synthetic aperture radar (SAR) to monitor landslides, whereas Bacha et al. (2018) developed a landslide inventory using SPOT-5 satellite imagery. Earlier efforts by Dou et al. (2015) assessed landslide risk through the integration of remote sensing data and GIS tools, and Messeri et al. (2015) introduced the weather type flood and landslide risk index (WT-FLARI) to support hazard assessment.

While global research on landslide susceptibility has made significant strides through the application of advanced geospatial techniques and machine learning algorithms, a noticeable research gap persists in their regional adaptation, particularly in Sri Lanka. Studies such as those by Dou et al. (2015), Yin et al. (2020), and Gu et al. (2023) demonstrate the effectiveness of integrating remote sensing, PCA, SVM, and random forest models in enhancing predictive accuracy and optimizing causative factors. However, Sri Lankan studies remain predominantly limited to conventional GIS-based techniques, as seen in the works of Nagamuthu et al. (2024), Wickramasooriya and Dilini (2022), and Kumara and Kanthilatha (2021), without leveraging advanced machine learning or data fusion methods. Furthermore, while some international studies have explored infrastructure-specific vulnerability (eg: Singh et al., 2021) or utilized temporal satellite data (eg: Confuorto et al., 2019), such dimensions are largely absent in Sri Lankan research. There is also limited integration of risk and vulnerability parameters into a single composite index, with the exception of Perera et al. (2020). Additionally, most local studies are geographically constrained and lack scalability or comparative scenario analysis. Therefore, there is a clear need for comprehensive, multi-criteria, and multi-scalar approaches in Sri Lankan landslide risk studies especially those that incorporate machine learning, temporal datasets, and vulnerability mapping to bridge this methodological and contextual gap and better inform disaster risk reduction policies. Various researchers across Asia have employed diverse criteria in GIS-MCDA-based landslide studies, with common factors including slope, LULC, elevation, and geological features such as lithology and faults. Notably, Sri Lankan studies (eg: Nagamuthu et al., 2024; Perera et al., 2020) have considered both physical (eg: slope, rainfall) and anthropogenic (eg: road distance, land use) variables, aligning with global practices but still showing limited integration of dynamic or socio-economic indicators. Only one study has assessed landslide risk in Kegalle district, using just eight variables. To address this gap, we analyzed landslide susceptibility using 25 variables, validated the model with ROC curves, and scenario analysis which did not apply in previous studies in Sri Lanka. The reviewed literature highlighted this research gap and guided to develop a GIS-MCDA based landslide risk assessment.

3 Research Methodology

3.1 Study Area

Sri Lanka, located in the tropics, spans 65,610 km^2 (CB-SL, 2023). This study focuses on Yatiyanthota DSD in Kegalle District, covering 178 km^2 on the eastern border of the central highlands (Fig. 1). The coordinates of the DSD is bounded between 7.0354°N and 7.0233°N latitudes, and 80.2908°E and 80.3613°E longitudes. The area has a population of 60,084 and 18,136 housing units, including 113 temporary houses. It experiences an equatorial climate with an average annual temperature of 27°C and rainfall exceeding 2,500 mm, influenced by monsoons. Key livelihoods include public service (950 workers) and agriculture (240 workers), with tea and rubber as primary crops. The region is multicultural, comprising Buddhists, Hindus, Muslims, and Christians.(Yatiyantota-DS, 2023).

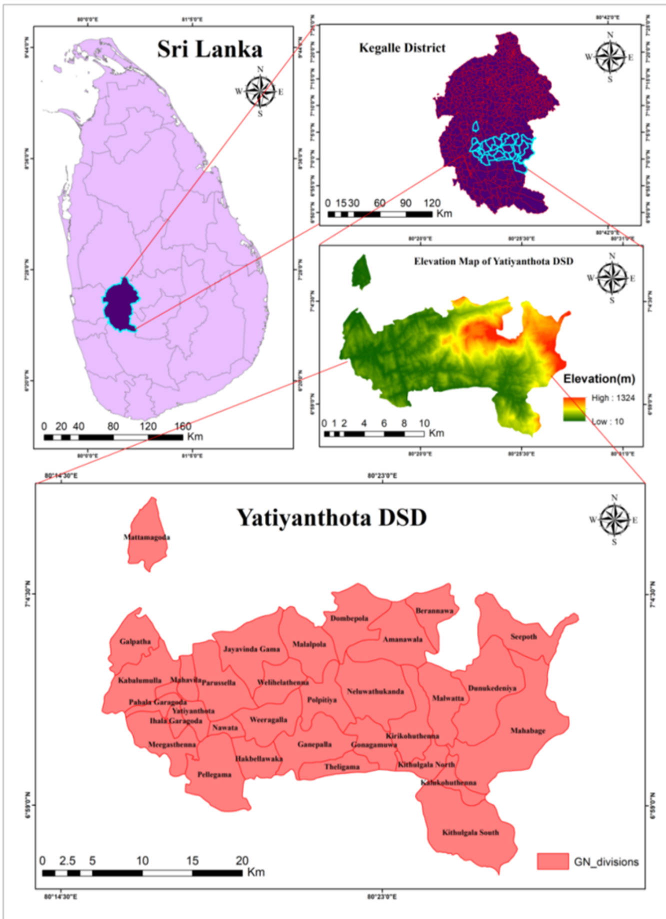

Fig. 1: Geographical location of the study area [*Source:* Survey Department of Sri Lanka].

The study area is situated in the southeastern portion of the Kegalle district, an area identified as highly susceptible to landslides. Studies have shown that this region exhibits a high probability of landslide occurrences due to the agglomeration of causative factors such as rainfall, slope, rubber plantations, and land-use changes. Also, Kegalle district has experienced devastating landslides, notably the Aranayaka landslide in May 2016, which resulted in 127 fatalities and the destruction of 75 houses. This event was triggered by exceptionally heavy rainfall, accumulating to 446.5 mm over three days. Such incidents underscore the area's vulnerability and the need for detailed risk assessments. Research indicates that LULC changes, particularly the conversion of vegetation to agricultural land, have led to an increase in landslide frequency in the Kegalle district. Between 1988 and 2017, thick vegetation decreased from 1,242 km^2 to 945 km^2. Further, a study focusing on five landslide-prone DSDs in the Kegalle district, including Yatiyantota, revealed that 88% of participants recognized landslides as a hazard in their area (NBRO, 2016a). In May 2024, the NBRO issued a landslide risk warning for several DSDs in the Kegalle District, including Yatiyantota.

3.2 Spatial Data Sources

To derive the landslide risk maps, spatial data layers related to 25 sub-criteria (Table 1) across six variable domains were utilized (climate, geology, topography, demography, socioeconomic, coping factors). The selection of the six primary domains: climate, geology, topography, demography, socioeconomic conditions, and coping capacity, along with the associated 25 sub-criteria, is rooted in well-established literature and global best practices for landslide susceptibility and risk assessment using GIS-based MCDA. Each domain captures critical dimensions influencing both the occurrence of landslides and the vulnerability of human systems exposed to them. Topographical factors play a crucial role in controlling slope stability, hydrological flow patterns, and erosion potential (Ayalew and Yamagishi, 2005; Guzzetti et al., 2005), while geological characteristics further influence terrain stability through their effects on lithology and structural conditions (Dai and Lee, 2002). Precipitation acts as a primary triggering mechanism for landslides by increasing soil saturation and pore-water pressure (Crozier, 2010; Glade, 2003), and the proximity to water bodies can intensify these processes by enhancing soil moisture and erosion rates (Montgomery and Dietrich, 1994). In this context, drainage density is commonly used as a proxy for the hydrological response of terrain to rainfall. Beyond physical factors, human vulnerability is often heightened in areas with high population density or socially marginalized communities, and vulnerability metrics derived from demographic characteristics are therefore widely incorporated into disaster risk assessment frameworks (Cutter et al., 2012; Wisner and Wisner, 2004). These criteria collectively align with the Sendai Framework for Disaster Risk Reduction which promotes integrated risk assessments incorporating natural, social, and infrastructural dimensions (UNDRR, 2015).

In this context, spatial data were sourced from the digital data layers from the Survey Department of Sri Lanka, Open topography data (https://opentopography.org/), and Landsat-8 images (https://earthexplorer.usgs.gov/). The data related to coping centers, hospitals and landslide occurrences were sourced from both secondary and primary sources, including the GPS field survey.

The study calculated slope, elevation, aspect, curvature, topographic wetness index (TWI), normalized difference vegetation index (NDVI), and drainage density using a 30x30 m resolution digital elevation model (DEM) from shuttle radar topography mission (SRTM) (https://www.jpl.nasa.gov/). Soil, geology, and geomorphology maps from the department of agriculture, Sri Lanka were used to assess landslide risk across different units. A land use map from the Survey Department of Sri Lanka (2020) and precipitation data from four meteorological stations provided by the Department of Meteorology, Sri Lanka, were also utilized. For AHP analysis opinions of the experts collected from a structured questionnaire. To data analysis purpose ArcMap 10.3 was used. For AHP based analysis, the spreadsheet developed by Goepel (2012) was used.

Table 1: Data type, resolution/scale, and sources of sub criteria.

Sub criteria	Data type	Resolution / scale	Source
Elevation, slope, aspect, curvature, TWI	Raster	10*10m	https://portal.opentopography.org/datasets
NDVI	Raster	30*30m	Landsat-8
Geology, soil, geomorphology	Vector	1:10000	Department of Agriculture, Sri Lanka
Rainfall, rivers	Vector	1:10000	Department of Meteorology, Sri Lanka, Survey Department of Sri Lanka
Pop density, dependent population, women population, disable population, uneducated population	Vector	1:10000	Resource profile, Urban Development Authority, Sri Lanka
Land use, housing units, houses, temporary houses, roads, landslide locations, hospitals, coping centers	Vector	1:10000	Survey Department of Sri Lanka, NBRO, GPS field survey

3.3 Methods

The study suggests a GIS-MCDA technique to evaluate landslide risk in the Yatiyantota DSD. The approach involved six key steps: (i) selecting and defining criteria, (ii) standardizing the criteria, (iii) assigning weights and scores to the criteria, (iv) checking for consistency, (v) aggregating the final risk map, and (vi) model validation (ROC and scenario analysis).

Table 2: Pairwise comparison matrix for six variables.

Matrix	1 - Topography	2 - Geology	3 - Climate	4 - Demography	5 - Socioeconomic	6 - Coping	Normalized Principal Eigenvector
1 - Topography	1	1 2/9	1 1/6	1	1 1/9	1	18.00%
2 - Geology	5/6	1	1	8/9	1 1/9	8/9	15.83%
3 - Climate	6/7	1	1	8/9	1	1 1/9	16.20%
4 - Demography	1	1 1/9	1 1/9	1	1	1 1/9	17.67%
5 - Socioeconomic	8/9	8/9	1	1	1	1	16.15%
6 - Coping	1	1 1/9	8/9	8/9	1	1	16.46%

3.3.1 Criteria selecting and structuring

Identifying relevant criteria is essential for assessing the landslide risk. In this study, "risk factors" for a landslide index were determined through a literature review and informal interviews with 10 experts. An open random sample technique was used to select experts for the survey considering their expertise, research interests, and academic qualifications. Accordingly, responses from 10 experts were used to derive AHP weights and ratings (5 university academics, 2 Disaster Management Centre (DMC) officials, 2 NBRO officers, and 1 UDA official). By this way, 25 criteria were chosen and classified into six classes as described in material section.

3.3.2 The criteria standardization

MCDA is one of the most widely used approaches for identifying optimal solutions from various options in complex domains including urban planning, environmental management, healthcare, agriculture, energy, supply chain and logistics (Pathmanandakumar et al., 2023; Withanage et al., 2024b). AHP, a common MCDA method introduced by Saaty (1980), was employed in this study. Accordingly, a grading system was applied to rank attribute classes of each factor upon judgement of experts, with values ranging from 1 to 5 (1 = very low, 2 = low, 3 = moderate, 4 = high risk, and 5 = very high risk).

3.3.3 Assignment of weights

Experts used Saaty's 1-9 range to rank the criteria and factors for evaluating landslide risk. The AHP spreadsheet was then employed to calculate the weights and rates for criteria and factors, along with the AHP weights, consistency index, and ratio. A pairwise comparison was conducted to define potential risk zones. The pairwise comparisons matrix defines A = $[Cij]_{nxn}$ as equation (1) (Mahdavi and Niknejad, 2014); in the context of pairwise comparison matrices, the notation Cij represents the relative importance or preference of element i over element j.

$$\begin{bmatrix} C_{11} & C_{12} & C_{1n} \\ C_{21} & C_{22} & C_{2n} \\ C_{1n} & C_{2n} & C_{nn} \end{bmatrix} \quad (1)$$

3.3.4 Consistency checking

In AHP, it is mandatory to assess the consistency of pairs. The consistency ratio (CR) was calculated using equation (2) (Saaty, 1980) ;

$$CR = \frac{CI}{RI} \quad (2)$$

In this context, CR is consistency ratio, CI is consistency index, and RI indicates the random index, which varies depending on the order of the matrix. The consistency index can be calculated using equation (3) (Saaty, 1980) ;

$$\frac{\lambda_{\max\, n}}{(n-1)} \quad (3)$$

Table 3: Final weight and CI and CR values of landslide risk model.

Factor	Weights	+/-
Topography	18.0%	1.0%
Geology	15.8%	1.2%
Climate	16.2%	1.0%
Demography	17.6%	0.8%
Socioeconomic	16.1%	1.1%
Coping	16.4%	1.3%

Eigenvalue	Lambda 6.011	MRE 6.5%
CR 0.37	GCI 0.01	Psi 15.0%

If the CR exceeds 0.10, it indicates that some pairwise values need to be reviewed. Conversely, if the CR is below 0.01, the values are considered acceptable. Here, λ_{max} represents the largest eigenvalue of the matrix, and n indicates the matrix order (Saaty, 1980). The RI was determined upon Saaty's random inconsistency table. The pairwise matrix and the normalized principal eigenvector values for the six variables are presented in Table 2. In this study, the CI for key variables was reported as 0.01, and the CR was 0.2 as shown in Table 3.

3.3.5 Landslide risk index

The overlay method was applied using the Weighted Linear Combination (WLC) approach and variables and criteria were combined through WLC, with the derived weights listed as in Table 3. The WLC method involves the risk maps normalizing, weights assigning, and combine weighted maps into the standardized risk map/s. This includes two steps; the pairwise matrix normalization as $A = [C_{ij}]_{nxn}$ using equation (4) , and the calculation of each criterion weight using equation (5) (Saaty, 1980);

$$C_{ij} = \frac{c_{ij}}{\sum_{j=1}^{n} c_{ij}} \tag{4}$$

$$W_{ij} = \frac{\sum_{j=1}^{n} c_{ij}}{n} \tag{5}$$

where W_{ij} the normalized weight or priority value of element i in column j. In $\sum_{j=1}^{n}$ is the summation symbol, which tells sum over all columns j from 1 to n (the total number of elements). The landslide risk index/map was derived through overlaying six variable maps. Those thematic maps were transformed into raster and then reclassified within standardized risk scales based on different attribute values. The risk zones were identified using the LRI according to the assigned weights and score rankings using equation (6) (Saaty, 1980) ;

$$LRI = \sum_{i}^{n} W_i X_i \tag{6}$$

where LRI stands for landslide risk index, W_i indicates the multiplication of all related weights in the hierarchy of i^{th} factor given for a particular class of the i^{th} factor found on the evaluated spatial unit X_i is factor *i*.

3.3.6 Scenario analysis and model validation

Once the LRI was derived, a scenario analysis was conducted to evaluate the bias of experts on the reliability of the resulted maps. This was done by changing the cluster weights for six different scenarios. In this study, two weighting approaches were employed: the equal weighting method, where all variables were assigned the same level of importance, and the majority weighting method, where each scenario prioritized one primary variable such as topography by assigning it a higher weight, while the remaining five variables were given equal but lower weights. This approach allowed for the exploration of how individual factors influence overall risk, providing a more nuanced understanding of landslide susceptibility across different thematic perspectives.

Validating the landslide risk model is essential to secure the accuracy and scientific validity of the results. To achieve this, ROC curves were generated for each class to validate the model (Saha and Roy, 2021). Each validation point was superimposed on google earth pro images, and cross-validation was performed using ground truth data collected through field verification.

4 Results and Discussion

4.1 Landslide risk distribution for 25 sub variables/criterion

The high-risk zone has concentrated in the southern and eastern parts. The spatial distribution of each risk category for the criteria is visualized in Fig. S 1, S 2, and S 3. Most of the area falls under very low to low risk across criteria, with significant variation based on specific factors. The analyzed criteria indicate that most areas exhibit low to very low risk, with exceptions based on specific factors. Elevation, slope, river proximity, soil, and housing units predominantly fall under very low or low risk. Moderate risk is significant for TWI, NDVI, geology, and land use. High to very high risks are notable for curvature (48.7%), aspect (17%), landslide locations (66%), and distance from roads (87.8%). Vulnerable populations, including women, disabled, and uneducated groups, largely experience low to very low risk (78.5%-94.4%). Risks from hospital distance skew heavily towards very high (81%), while coping center proximity mostly shows low to very low risk (90.8%).

This spatial distribution reflects patterns observed in similar studies across Sri Lanka and other parts of Asia, where terrain-related factors, and proximity to roads often emerge as key contributors to high-risk zones. The predominance of high to very high risk in these criteria aligns with studies conducted in hilly and monsoonal regions, underscoring the influence of topographical complexity and human-induced alterations. Conversely, factors like elevation, slope, and proximity to rivers showing lower risk levels is consistent with findings in regions where these variables have been stabilized through natural vegetation or infrastructural planning. The vulnerability analysis reveals that despite the presence of scenario groups, their exposure remains relatively low, possibly due to spatial separation from hazard-prone zones a trend also noted in earlier studies in central and southern Sri Lanka. The elevated risk linked to distance to hospitals highlights the need for improved emergency infrastructure, mirroring recommendations from disaster resilience research in Nepal, India, and Bangladesh. Overall, the results highlight the necessity for location-specific mitigation strategies that prioritize both physical risk factors and social vulnerabilities.

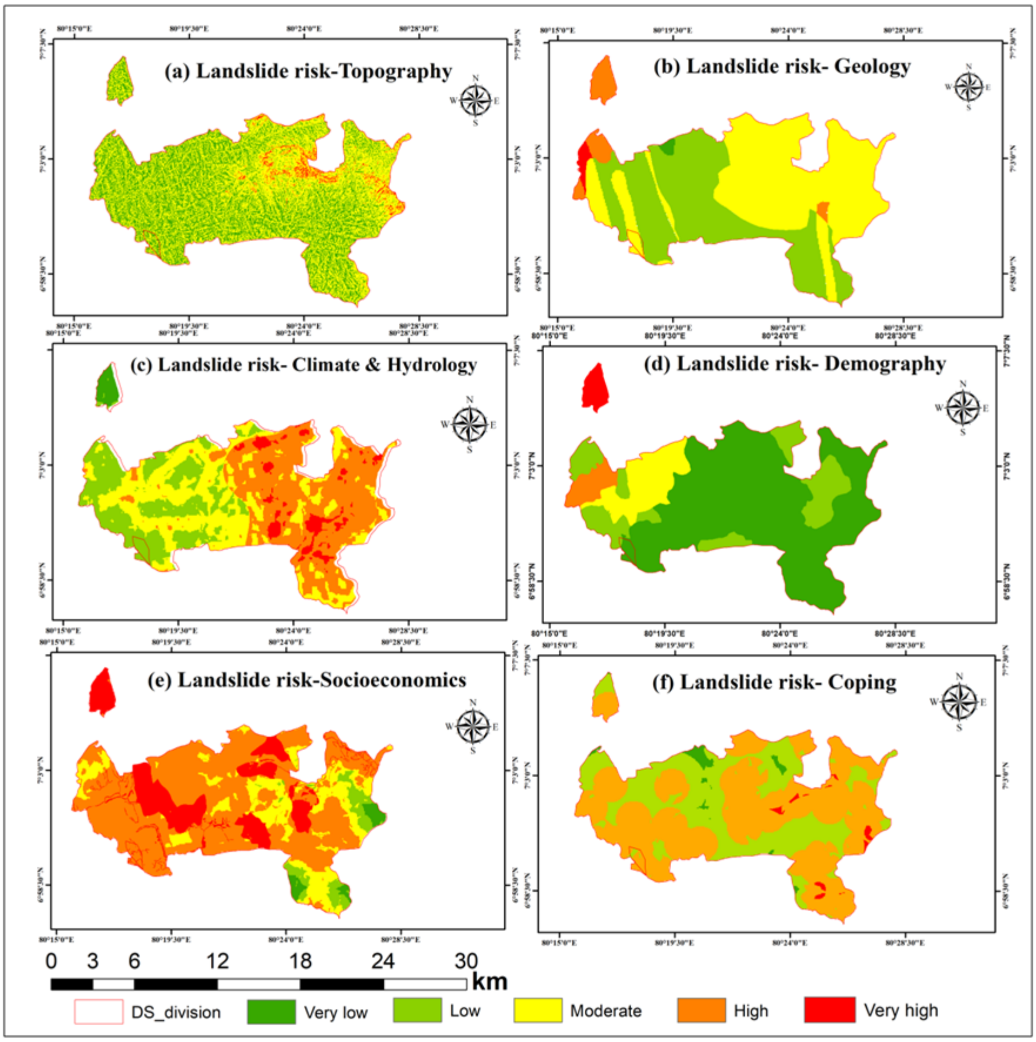

Fig. 2: Landslide risk levels for the selected six main variables; (a) topography, (b) geology, (c) climate and hydrology, (d) demography, (e) socio-economic factors, and (f) coping factors.

4.2 Landslide risk for main factors

Results indicated that 0.2% (3.2 km^2) of the area is at high risk based on topography, while very low, low, moderate, and very high risk contribute for 36.6% (65.3 km^2), 61.4% (109 km^2), 0.5% (0.75 km^2), and 0% (0.5 km^2), respectively. High-risk zones are concentrated in the northern, eastern borders, and certain GNDs. For geology, high and very high-risk areas are found in the western and northern boundaries, with moderate risk covering most of the region. Climate factors show higher landslide risks, with nearly half of the area classified as high or very high risk. Demographic factors indicate low landslide risk across most areas, while socioeconomic factors suggest high-risk zones in much of the region, particularly in the central and southern parts. Coping variables reveal that high risk predominates across the entire area, with very low and very high-risk zones being less prevalent. The weighted overlay maps under six variables are shown in Fig. 2.

Several studies across Asia have reported similar spatial patterns of landslide susceptibility influenced by topographic, geological, climatic, demographic, and socioeconomic variables. For example, research in Nepal and northern India found high landslide risks predominantly along steep slopes and fault zones, aligning with this study's observation of high-risk zones along northern and eastern boundaries. In areas like Sri Lanka and Southeast Asia, climate-induced factors, especially heavy rainfall, significantly elevated landslide risks supporting the finding that climate plays a critical role in determining hazard levels. Additionally, studies from parts of Indonesia and the Philippines have highlighted how socioeconomic vulnerability, such as poor infrastructure and densely populated low-income areas, correlates with elevated landslide risk. These parallels reinforce the importance of integrating diverse variables in MCDA for effective landslide risk mitigation.

4.3 Landslide vulnerability in Yatiyantota DSD

The results revealed that very high, high, moderate, low and very low class represents 3% (5.6 km^2), 40% (67.9 km^2), 39% (66.6 km^2), 17% (28 km^2), and 1% (1.1 km^2) respectively (Fig. 3 (a), (b), (c)). According to the results, areas with a very high risk of landslides can be identified in the Mattamagoda, Pahala Garagoda, Kabulumulla, Amanawala, Berennawa Malwatta, GNDs. Only very few landslides risk areas could be observable in Malalpola, Polpitiya, Kithulgala South GNDs. Overall, high risk of landslides could be identified in the area upon the derived composite risk maps. Accordingly, the distribution of areas with high landslide risk is high, and moderate landslide risk areas are also high.

Studies by Dissanayake et al. (2019) and Hewawasam et al. (Hewawasam and Rambukkange, 2018)(2018) have consistently identified LU patterns, steepness, and rainfall as primary factors influencing landslide risk. In particular, steep slopes coupled with deforestation and unplanned agricultural expansion, as seen in Mattamagoda and Kabulumulla GNDs, contribute significantly to very high landslide susceptibility. Additionally, similar vulnerability assessments conducted in the Kegalle district and central highlands confirm that high % of land area often fall under the high and moderate-risk categories (Perera et al., 2020). This pattern can be attributed to the geological structure, soil composition, and human activities, including construction and poor drainage management. Moreover, the relatively low representation of very low-risk areas (1%) echoes findings from Chandrasekara et al. (2018), suggesting that truly stable zones are minimal in such geomorphologically complex terrain. The identification of moderate risk in nearly 40% of the area further supports the idea that while not immediately hazardous, these zones could transition into higher-risk categories under adverse climatic events or due to continued anthropogenic pressure.

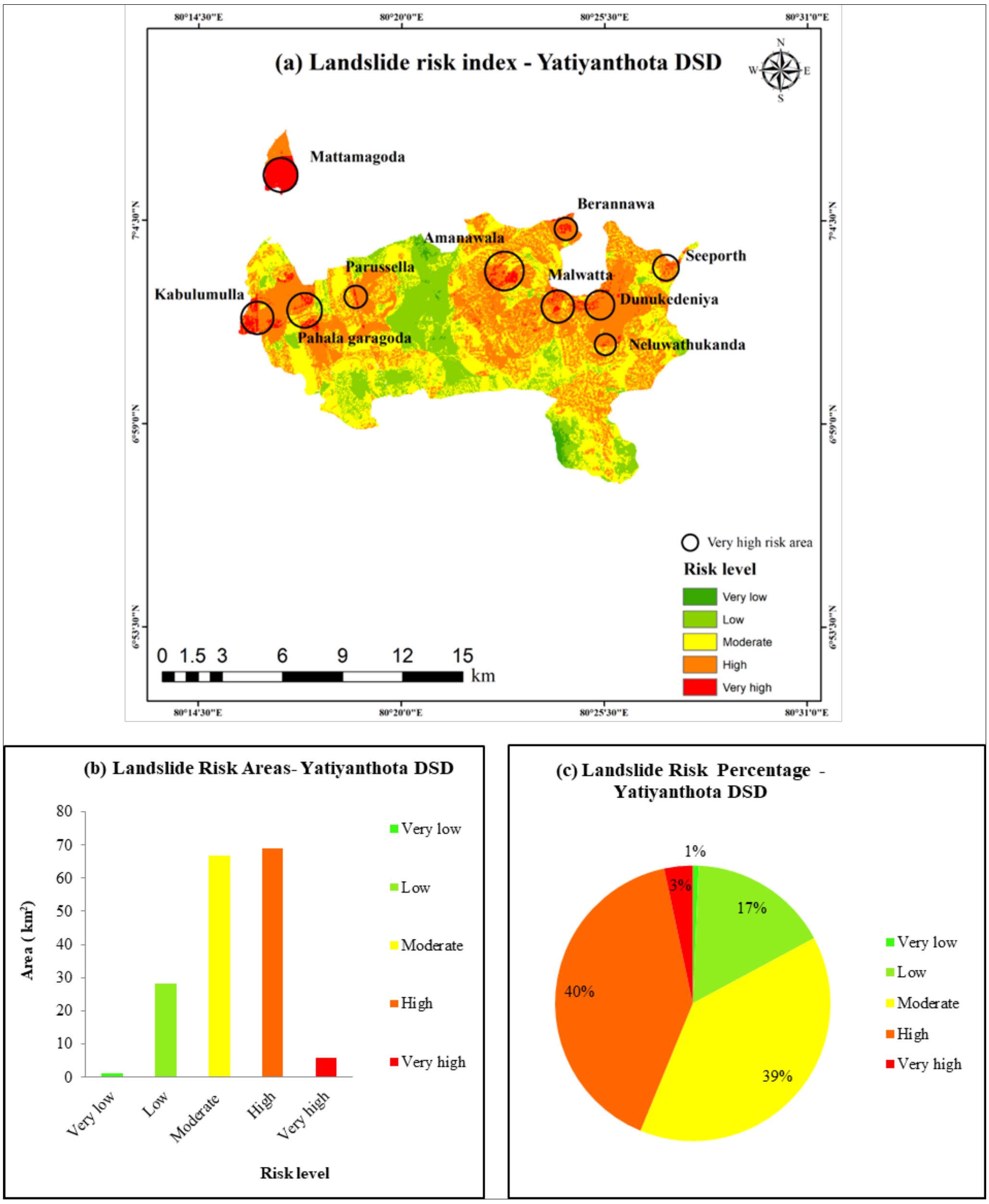

Fig. 3: Landslide risk index in Yatiyantota DSD; (a) risk map, (b) area distribution as km², and (c) area distribution in various risk classes as a percentage (%).

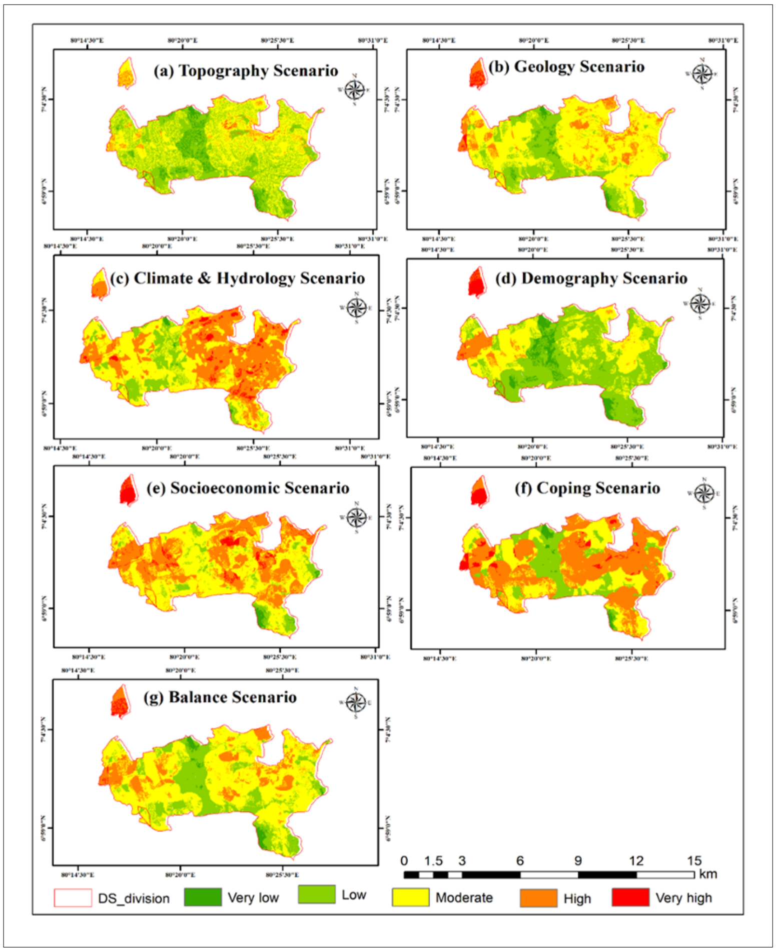

Fig. 4: Landslide risk for various sensitivity scenarios; (a) topography, (b) geology, (c) climate, (d) demography, (e) socioeconomic, (f) coping, and (g) balanced.

4.4 Findings of scenario analysis

Landslide risk maps for various scenarios were generated by adjusting the cluster weights (Fig. 4). Hence the DSD is most sensitive to the climate scenario. The second one is the coping variable scenario and the third one is the socioeconomic scenario. The analysis revealed that scenario (c) (climate) demonstrated a high level of geographical coherence when compared to the overall risk map.

4.5 Model validation results

Validating the landslide risk model is essential to ensure the scientific validity of the results (Dashti et al., 2013; Mahdavi and Niknejad, 2014; Saha and Roy, 2021). Although, previous studies have applied a range of techniques to verify their outcomes, the ROC curve approach most widely adopted. This method illustrates the relationship between false positives (Y-axis) and false negatives (X-axis) (Saha and Roy, 2021). The accuracy of the landslide risk index was validated through field checks and google earth pro images using 50 sample points as 10 per each class (Fig.5). These samples were obtained using ArcMap equal random sample technique. The accuracy values were 83.2% for very low risk, 66.7% for low risk, 54.8% for moderate risk, 76.3% for high risk, and 80.3% for very high risk. Then overall accuracy of the index for was 72.26% (Fig. 6).

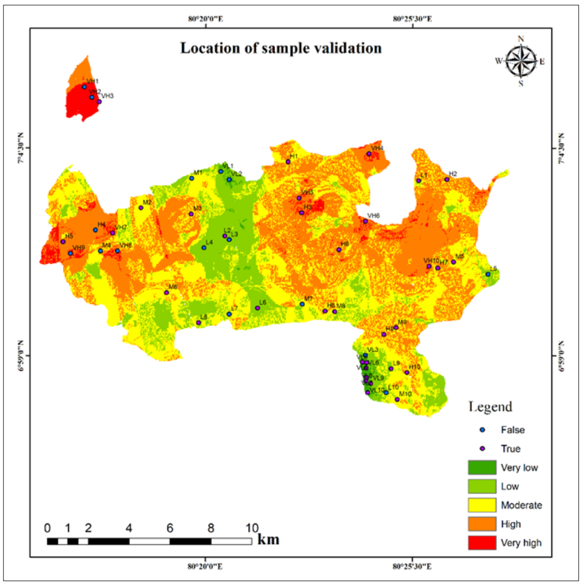

Fig. 5: Spatial distribution of model validation samples.

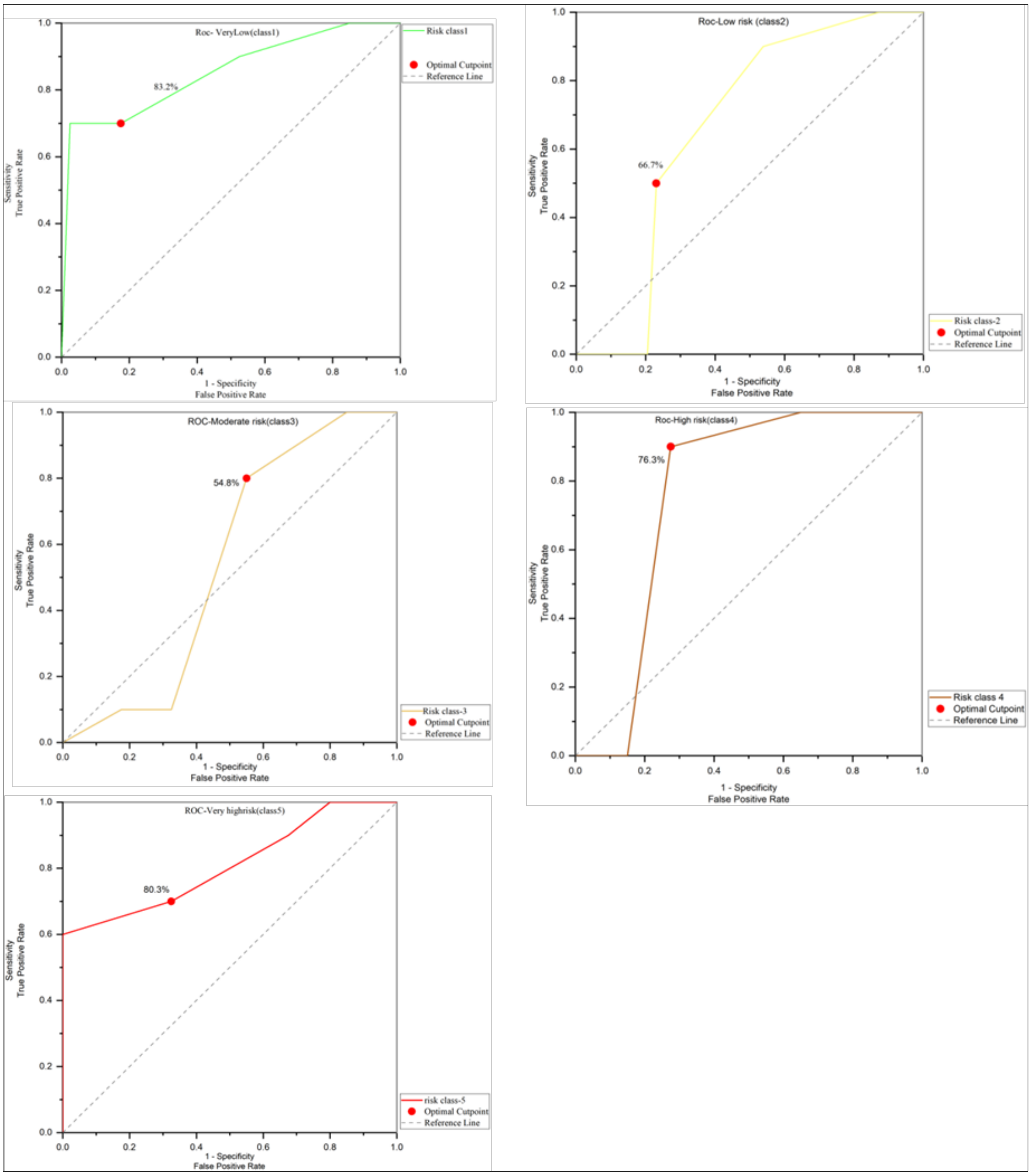

Fig. 6: ROC curves for different risk classes.

The entire area is prone to landslides, except for a small central and southern region. Topography contributes significantly, with uneven terrain marking high-risk zones, particularly along the western boundary due to rock and soil composition. Graphite mining in Mattamagoda GND also increases landslide risk. Climate further exacerbate the issue, with plantations and human activities identified as contributing factors. Previous works (Perera et al., 2020; Ranasinghe et al., 2005; Wijesinghe et al., 2024) highlight the influence of physical and geographical factors. This research aids in reducing landslide risks and managing disasters effectively.

5 Conclusion

This study developed a comprehensive LRI utilizing a GIS-MCDA framework. Through the integration of the AHP and WLC, 25 criteria were systematically evaluated to assess landslide vulnerability. The findings revealed that 3% (5.6 km^2) of the area is classified as very high risk, 40% (67.9 km^2) as high risk, and 39% (66.6 km^2) as moderate risk, while low and very low-risk zones collectively account for 18% (29.1 km^2). Several GNDs, including Mattamagoda, Pahala Garagoda, Kabulumulla, Berennawa, and Amanawala, were identified as high-risk areas requiring immediate mitigation measures. These outcomes have significant implications for disaster risk management and land-use planning in landslide-prone regions. The study underscores the necessity of incorporating risk assessment into policy and planning frameworks to support both immediate and long-term mitigation strategies. It is recommended to conduct awareness programs and use this study as a guideline. The findings can assist NBRO, the DMC, and the LUPPD in effectively allocating resources and designing targeted interventions. Despite its contributions, the study acknowledges several limitations. The model's accuracy, assessed through ROC analysis, yielded a validation score of 72.2%, suggesting room for improvement. Future research should consider employing higher-resolution spatial datasets and expanding the number of sampling points. Moreover, engaging a broader range of domain experts could further enhance the methodological robustness. Addressing these limitations and applying advanced geospatial techniques will be essential for refining future landslide risk assessments. Notwithstanding these constraints, the present study offers valuable insights for policymakers and researchers aiming to mitigate landslide hazards and strengthen disaster resilience in the region.

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Author Contributions

Conceptualization, methodology, analysis, writing - original draft preparation, M.D.D.L. Writing - review and editing, M.D.D.L., K.P and A.W.G.N.M. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest

The authors declare no conflict of interest.

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Supplementary Materials

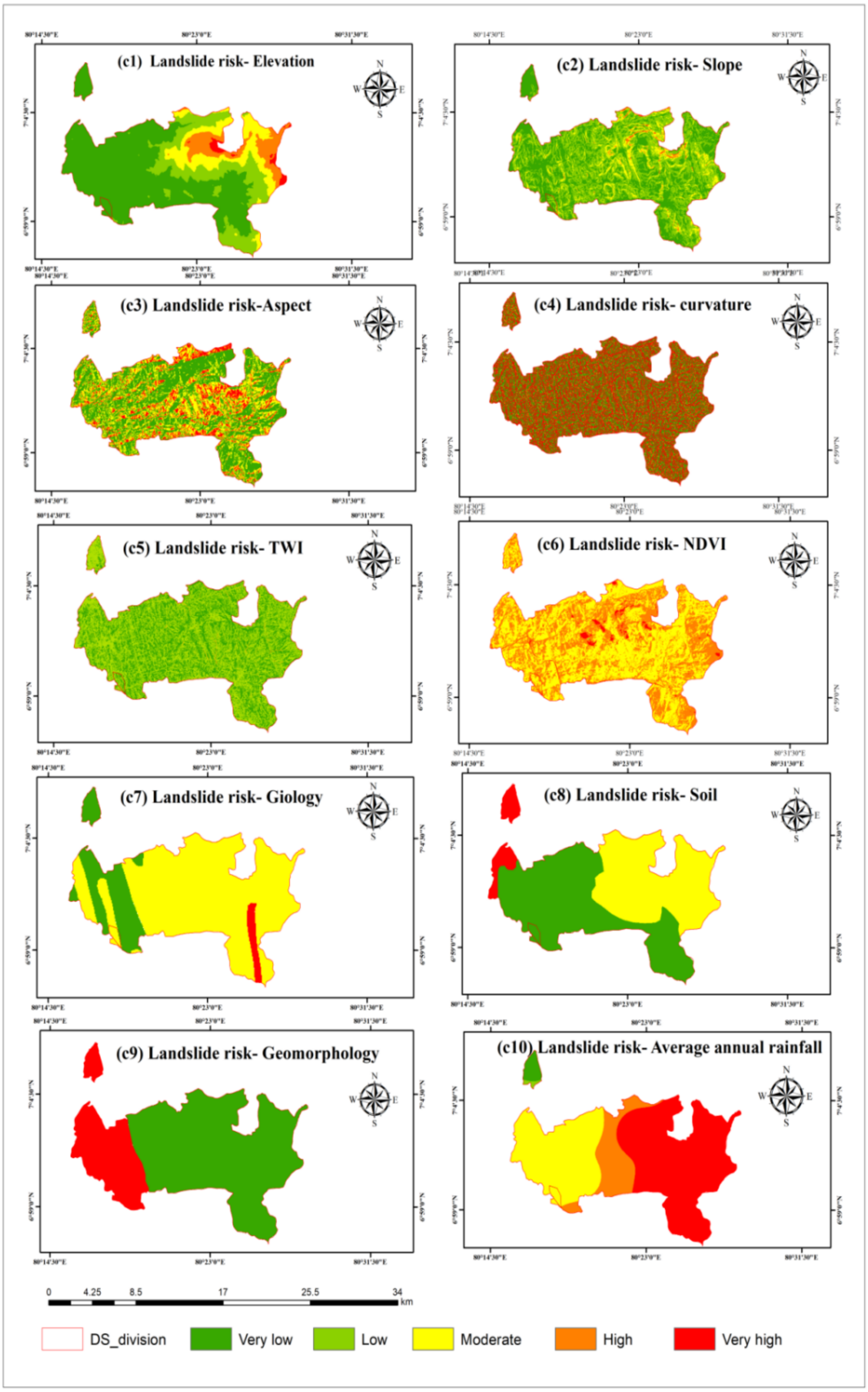

Fig. S 1: Landslide risk (c1) Elevation, (c2) Slope, (c3) Aspect, (c4), Curvature, (c5) TWI, (c6) NDVI, (c7) Geology, (c8) Soil class, (c9) Geomorphology class, (c10) Rainfall.

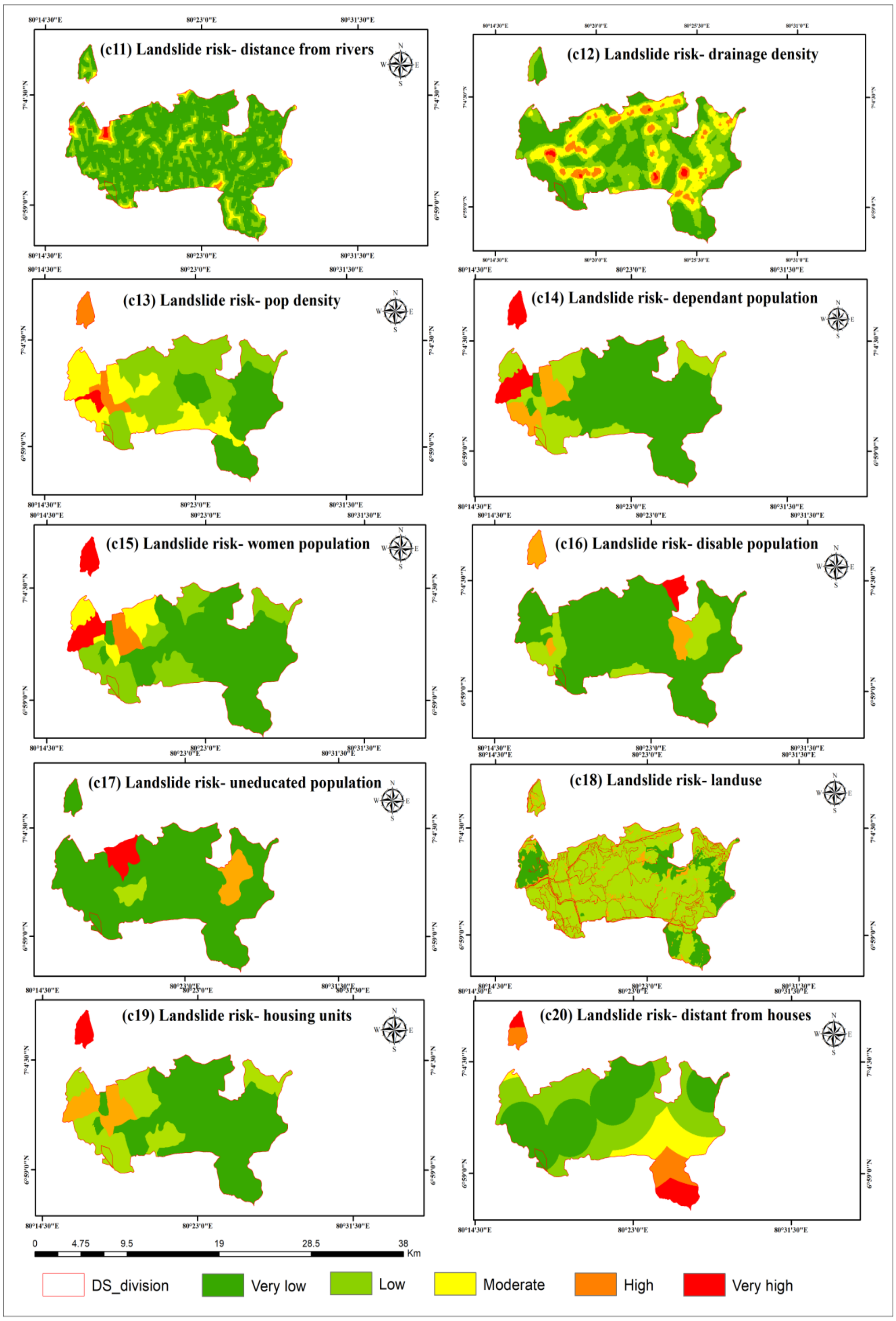

Fig. S 2: Landslide risk (c11) Distance from Rivers, (c12) Drainage density, (c13)Population density, (c14) Dependent Population, (c15) Women Population, (c16) Disable population, (c17) Uneducated population, (c18) Land use, (c19) Housing units, (c20) Distance from houses.

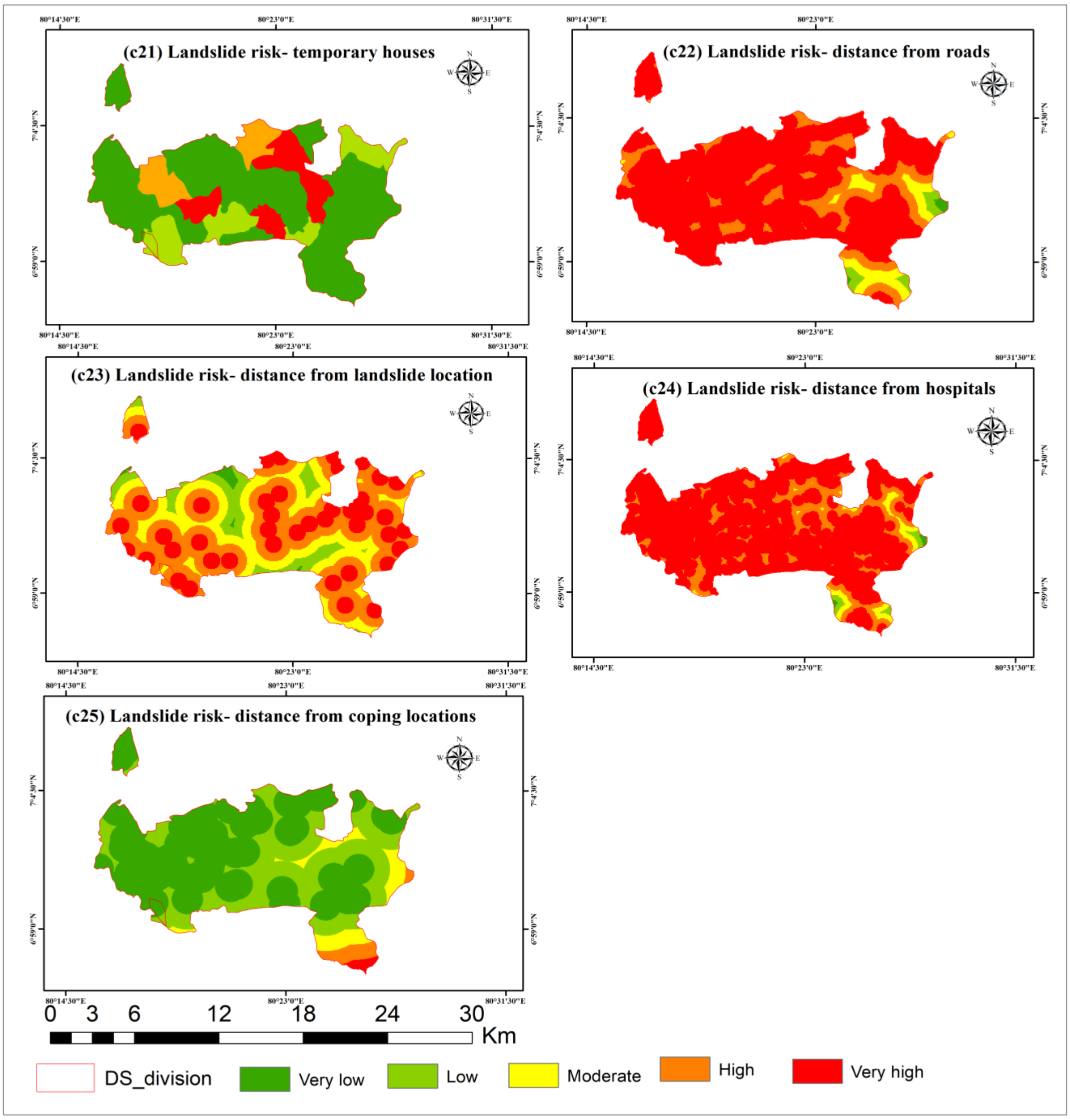

Fig. S 3: Landslide risk (c21) Temporary houses, (c22) Distance from roads, (c23) Landslide locations, (c24) Distance from hospitals, (c25) Distance from coping centers.