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Integrated Flood Hazard Vulnerability Modeling of Neluwa (Sri Lanka) Using Analytical Hierarchy Process and Geospatial Techniques

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Abstract: This research aimed to apply the geospatial techniques and Analytical Hierarchy Process (AHP) approach to find vulnerable areas in terms of flooding in the Neluwa area, Sri Lanka. The study incorporated nine relevant criteria for the vulnerability classification under three sub-criteria; the built environment, physical environment, and socio-economic environment. Under the built environment, road networks and buildings were chosen as sub-criteria. The Normalized Difference Vegetation Index (NDVI), slope, elevation, water bodies, and stream density were taken as physical criteria. Land use and population density were considered as socio-economic criteria. All the criteria are set correctly in raster data, and their contents were well adduced. The study consisted of the use of different levels of criteria and combinations of different processes. The analytical results reveal that 14.24% and 30.24% of the total area are at a very-high risk and high risk for flooding, respectively. Only 5.17% of the land was classified as a risk-free area. Eastern, central, and western divisions of the study area are highly vulnerable to floods due to their low slopes. Based on the produced maps, the spatial extents and levels of risk were systematically identified. Data obtained through qualitative judgments related to the field were validated based on the approach used. The potential of this approach is effective in assessing the spatial vulnerability of these flood-affected areas. Using such criteria and a model-based approach will be constructive in identifying different flood scenarios and in providing a remunerative guideline for potential anticipatory measures and better land-based planning in the area.

Keywords: flood hazard; vulnerability; AHP; geospatial techniques; Sri Lanka

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1. Introduction

The frequency of natural disasters has increased manifold in recent years, among other issues that have surfaced in both industrialized and developing nations. Global statistics show that 40% of socioeconomic losses are attributable to natural disasters [1]. This natural phenomenon is mainly due to global warming, which is responsible for changing patterns and intensities of rainfall, resulting in the overflow of rivers and streams. Due to factors such as the inability to cover waterways, the obstruction of drainage channels, climate change, urbanization and population increases, and the construction of physical structures for developmental activities, the frequency of flooding has increased around the world exponentially. A flood is a short-term and occasional rise in the water level of a river or body of water that is caused by heavy rainfall, ocean waves coming onto the shore, such as a storm surge, melting snow and ice, as well as ice jams, dams or levees breaking, and glacial lake outburst flow [2]. Floods are the most widespread natural extreme weather events and can vary greatly, ranging from a few inches to several feet. Floods are one of the disasters feared by people and increase the risk and vulnerability of a society. The aim of flood risk assessment is important in determining the probability and intensity of a long-term disaster. A river floods when the water level rises above its banks. All rivers and canals can be flooded. This includes everything from small streams to the largest rivers in the world. The term "vulnerability" indicates the measurement of potential risk, as well as the socio-economic ability to tackle the worst situation resulting from the disastrous event [3,4]. The concept of vulnerability includes the vulnerability of environmental and human systems to damage or injury, due to exposure to stressors and lack of adaptive capacity [5,6]. The areas that are vulnerable to flooding are more likely to experience socioeconomic and environmental effects. The premise that all vulnerability indicators are equally important is the foundation of several vulnerability indexes [7]. The use of composite proxy indicators is the most popular technique for measuring vulnerability in the context of global change. In more recent times, vulnerability analysis has used the multi-dimensionality notion [8].

Floods have been identified as one of the most devasting natural disasters, ranking highly worldwide [9], and Sri Lanka is not an exception. Although Sri Lanka is a small country, the impact of environmental hazards and disasters has not diminished. For a long time, natural disasters have greatly threatened the survival and functioning of the human environment. Floods, droughts, cyclones, and landslides are the major types of natural disasters. Floods in Sri Lanka have always been a natural phenomenon, affecting humanity and infrastructure. Based on the flood pattern in Sri Lanka, it can be divided into two main zones: wet and dry. With the onset of the southwest monsoon, there is a high tendency of flooding in the wet zone. In some years, the tropical cyclones and depressions, occurring due to the south-west monsoon, have resulted in significant flooding [10]. Thus, the monsoon season receives unusually heavy rainfall over a short period. Such heavy rains have occurred only in certain years. Soil that is saturated with rainwater is less absorbent. This can happen even if there is forest cover. The water then flows down the river valley. It could cause significant flooding in the lowlands of the river valley. To support risk reduction and long-term adaptation strategies, it is crucial to assess vulnerability to climate change and extreme events, such as floods [11]. Disaster management prioritizes crisis response, recovery, and disaster aid in nations such as Sri Lanka that are vulnerable to natural disasters. Numerous studies have demonstrated paradigm shifts, from disaster relief to the reduction of disaster risk and liability. A clear image of the situation on the ground and an indication of how much the danger is expected to affect the population, capital, assets, and location would be provided through vulnerability assessment and mapping [12,13].

According to the Irrigation Department of Sri Lanka, floods between 5 and 8 feet are minor. Conditions between 8 and 11 feet are considered major floods. Floods beyond 11 feet are catastrophic. Studies have revealed that although most of the flooding typically affects the wet zone, the inter-monsoon rains, which fall in the dry zone during the latter part of the year, can be so severe that the areas can become severely flooded. In the last three to four years, significant floods were reported in the country in May. In 2014, flooding has been reported from the Kalu, Kelani, and Gin river valleys. In 2016, floods were primarily observed in Kelani Valley, while in 2017, they were observed in the Kalu, Gin, and Nilwala Valley (www.vidusara.com, accessed on 21 December 2022). Such events reveal a likely increase in rainfall intensity that is in line with global climate change forecasts. However, the use of Geographic Information Systems (GIS) and Multi-Criteria Decision Analysis (MCDA), using the Analytic Hierarchy Process (AHP) method, for flood modeling has not been previously explored in the study area. Therefore, in the present study, these technological strategies have been analyzed, with the main difference being the use of the MCDA–AHP method for the Neluwa region along the Gin River for the first time.

This methodology under the proposed new approach allows for a comparison between parameters; as flood conditions are more prevalent in the studied region, flood risk has been identified in different zones through the proposed approach and methodology. Geo-informatics is considered an obligatory tool for spatial analysis and the identification of interrelationships between multiple criteria, and is widely used for natural hazard risk assessment and management. The use of GIS and remote-sensing techniques is one of the most applicable methods to measure and explore flood vulnerability areas [14]. The use of MCDA techniques with AHP comprises one of the most commonly utilized and accepted methods, and has for several decades in the field of research. Saaty has proposed the AHP methodology to better understand the selected variables and criteria in the study in a hierarchical manner [15]. The variables used are comparatively investigated and after ranking them, appropriate values are assigned to the parameters by following befitting procedures [16]. MCDA and AHP methods have been used successfully in many studies in recent years and have been identified as appreciable technical tools in complex decision-making, criterion selection, and problem analysis. MCDA will enhance the effectiveness of studies by incorporating a wide range of technical, environmental, and socio-economic criteria into successful holistic decision-making through this method. The MCDA method was used to map flood vulnerability areas with geospatial techniques. Admittedly, the Remote Sensing (RS)- and Geographic Information System (GIS)-based spatial data is instrumental [17–19] in facilitating a more accurate representation and visualization of results in the study using MCDA [20]. The sustainability and development of the country or region's physical and socioeconomic climate depend heavily on flood hazard management and mitigation techniques. Risk assessment is very helpful in mitigating the impact of flooding on the community, property, and environment.

Several studies have been conducted using geospatial techniques in order to map flood risk through a variety of approaches, in a national and international context. Nuwanka and Withanage [10] have conducted a GIS-integrated MCDA analysis for the identification and analysis of zoning flood hazard vulnerability in the Nilwala river mouth, in Sri Lanka. Here, they also used three main criteria, including the physical, socio-economic, and built environment. Weights for the major and minor criteria were assigned through the expert judgment method, using AHP. The results highlight that out of the total study area (523 ha), 98.9 ha (18.9%) was at the high-risk level and only 38.9 ha (7.4%) was in a risk-free category. In their research, Ouma et al. [21] have described flood risk vulnerability in an urban area using AHP and GIS techniques. Through the AHP method, the research attempted to create a hierarchical structure that would present the best possibilities for flood risk assessments. The results of the study confirmed that the GIS-based AHP method could be used, in this study, as an effective tool in creating flood hazard maps. The study indicated that these integrated methods can be used efficiently and coherently, with spatial data, to reach definitive outcomes. In their work, Vignesh et al. [22] employed an AHP model based on Multi-Criteria Decision-Making Analysis, in order to identify flood risk zones in the geospatial environment's southernmost district of Tamil Nadu, Kanyakumari. They discovered that the district's risk zones are dispersed throughout a vast area. The study highlighted that unplanned urbanization, in addition to rapid population increases, is an important element that needs to be taken into account in the future management of floods in the studied region. A study conducted at a local scale in Bangladesh aimed to develop the spatial multi-criteria-integrated approach, and to apply this to flood vulnerability mapping, by utilizing geospatial techniques and incorporating sixteen criteria selected under three main vulnerability components, which included physical vulnerability, social vulnerability, and coping capacity. Results showed that including the coping capability has a significant impact on vulnerability [3].

In the Attica region of Bihar, India, Feloni et al. [23] have widely utilized an improved methodology to determine flood susceptibility. The creation and use of a GIS-based multi-criteria analysis approach for identifying locations vulnerable to flooding occurrences are originally reported in this context. Additionally, there have been several significant flood incidents in the area in recent years. According to the transformation procedure, the generated maps show values between the criterion values of zero and one or one and five. The combination of AHP and GIS in the experiment proves to be powerful in its applications for flood vulnerability assessment, in any region. Twenty-one sub-criteria under five main criteria have been applied through Google Earth Engine software, along with the AHP process, in order to create flood risk maps. All criteria required weighting and were present in the form of raster datasets. Thus, based on the opinions of officials involved in soil management and experts in fields such as disaster management, weights for the major and minor criteria were assigned by using AHP. The flood sensitivity map was produced using a range of values for each of the five classes' unique criteria. Using sub-criteria grouped under each of the five criteria, an integrated flood hazard zoning map was created. Flood hazard maps based on basic criteria were used more extensively, in order to develop the final flood zone map. Swain's study will be useful in terms of mapping flood-prone areas, in order to minimize floods and allow designers, stakeholders, and decision-makers to properly monitor areas at risk of flooding, as well as to avouch proper, effective, and sustainable socio-economic development [24].

Eight conditioning factors were utilized to construct redeeming thematic maps by Souissi et al. [25] in their study of GIS-based MCDM–AHP modeling, for flood susceptibility mapping of dry regions, in southeastern Tunisia. The included parameters were elevation, groundwater depth, slope, lithology, land use/cover, rainfall intensity, distance from the drainage network, and drainage density. By assigning different values when creating reclassification maps, and also by considering the flood status of the area and giving an appropriate weight to each theme, the average weight of the factors and the importance of each class were calculated using the Pair-Wise Comparison Matrix (PCM) methodology. As such, the results that were realized after linking the MCDM–AHP–GIS methods in the study area will be a valuable tool for authorities, designers, engineers, hydrologists, and decision-makers, in order to identify flood risk zones and to assess the flood risk index. Decisions are easy to make to reduce the risk of flooding. At present, it is possible to detect an increase in the impact of flood hazards on peoples' lives and property. These floods occur regularly in the Southern Province, Western Province, and Sabaragamuwa Province of Sri Lanka.

Therefore, flood hazard management is an essential factor. The present study has been conducted based on the awareness of how the flood conditions have varied in the study area, that is, around the Gin River, and how to recognize and act on pre-flood hazard conditions. This type of research is not taken into account in the study area. As a result, the current endeavor is topical and novel, in order to implement the quick assessment of flood susceptibility, utilizing the MCDM and GIS. This study tried to prepare flood risk maps in the Neluwa area along the Gin River, since floods are one of the major natural disasters in the Gin River basin, and act as the most devastating natural hazard in the area, resulting in a loss of property and human lives. Henceforth, based on the results, the study will provide a potential flood mapping and assessment methodology for the region, integrated with GIS and AHP. For weighing the major and sub-criteria, AHP was used through a questionnaire method, in order to obtain ideas from experts in the field. Attempts have also been made to rank the flood risk areas through a structured process and extensive use of multiple criteria decision analysis. It was an effective way to analyze the physical, socioeconomic, and built environment as the main criteria, in order to analyze the expected results and outcomes.

2. Materials and Methods

2.1. Study Area

Neluwa Divisional Secretariat (DS) is located in the Northeastern boundary of the Galle District, between 120–140 km in the North and 145–170 km in the East (Figure 1). The total land extent of this division is 15,348 ha, and consists of 34 Grama Niladhari Divisions (*GNDs*). The area is located between the Northern latitudes 80–19/89–29.5 and Eastern longitudes 6–17/6–25.5. Neluwa DS comprises 9% of the total land area of Galle District, and is in fourth place among the Divisional Secretariat Divisions in the district, in terms of size. The average elevation of this division is more than 300 feet. According to the distribution of rainfall in this division, two main zones can be identified: areas receiving 2500–3000 mm and areas receiving between 3000–4000 mm. Overall, this division can be termed as a lowland wet zone that receives more than 3000 mm/year of rainfall, and does not have high temperatures and wind speeds [26]. Neluwa Divisional Secretariat is made up of rocks belonging to the Pre-Cambrian period. The area is especially rich in chanokites and meta sedimentary rocks of the Vijayan complex.

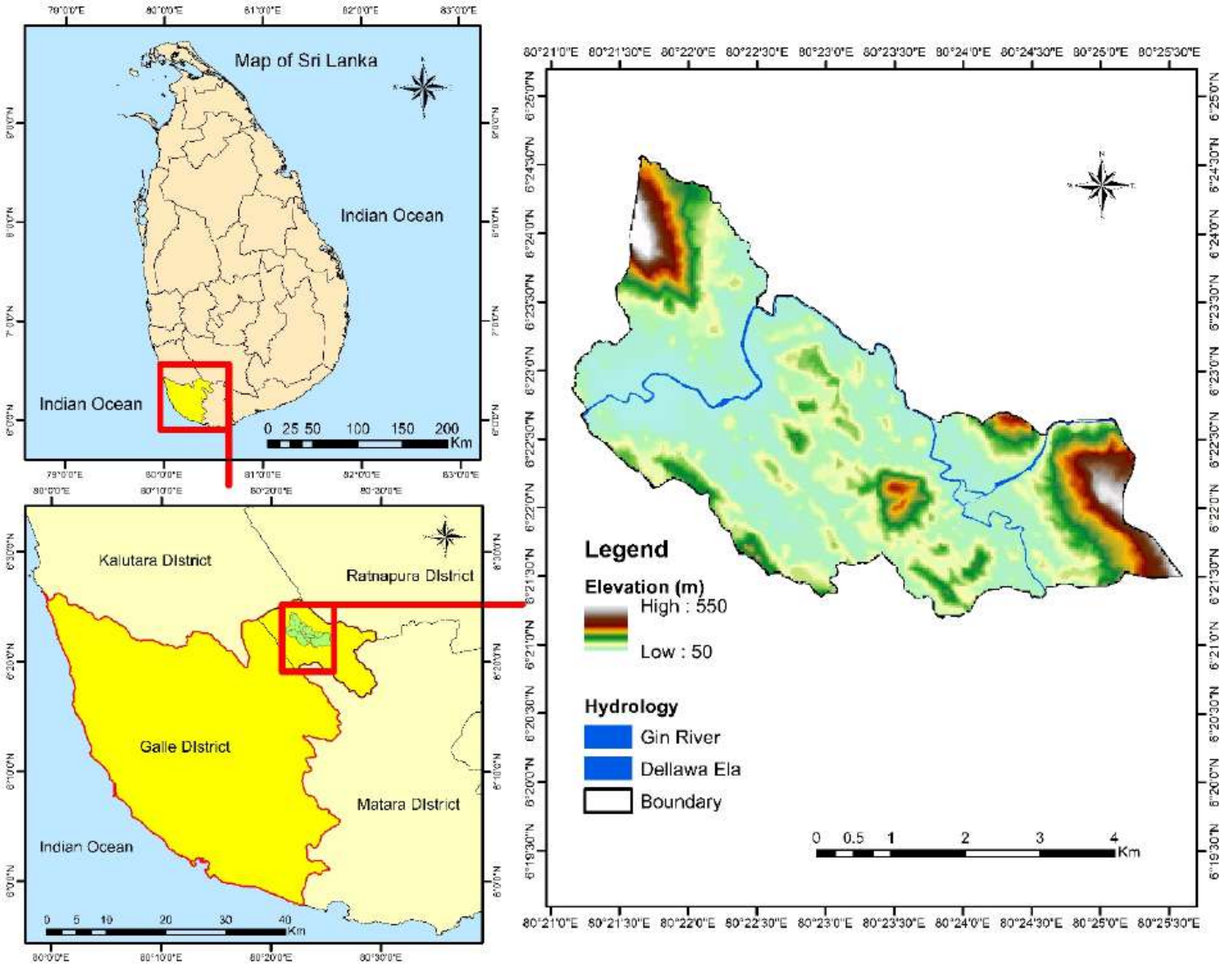

Figure 1. Study area.

2.2. Data Sources

The research has been carried out according to the framework of the AHP, MCDM, and GIS, in the geospatial environment, and using ArcGIS 10.8 software, developed by Environment System Research Institute (ESRI), USA. Based on a comprehensive literature survey and expert opinions, three major criteria have been chosen and those were divided into nine sub-criteria for flood vulnerability mapping. The study was based on different types of data, according to the main criteria obtained from the Survey Department of Sri Lanka, with a scale of 1:10,000. Population census data were gathered from the resource profile of Neluwa D.S.D., as mentioned in Table 1. It was important to collect relevant datasets when mapping flood-prone areas through a geotechnical approach.

Table 1. Vulnerability criteria used in the study.

Main Criteria	Sub Criteria	Data Sources
Built Environment	Buildings	Survey Department Digital data Layers, 2022
	Road network	Survey Department Digital data Layers, 2022
Socio-Economic	Population	Resource profile of Neluwa DSD, 2020
	Land use	Survey Department Digital data Layers, 2022
Physical Environment	NDVI	USGS, Landsat 8, 2022
	Water Bodies	Survey Department Digital data Layers, 2022
	Stream Density	Survey Department Digital data Layers, 2022
Shapefile	Slope	Using Survey Department Contour line, 2022
Shapefile	Elevation	Using Survey Department Contour line, 2022

Note(s): **Source:** Compiled by Author, 2022.

Based on the literature, the available data, and their applicability and impact on flood risk in the current study, the criteria and alternatives were chosen. By mapping the choices for each criterion, the spatial thematic layers of each chosen criterion were created. In this study, we created nine thematic layers, under three vulnerability components. For each raster layer, the spatial resolution was set at a cell size of 30 m × 30 m using ArcGIS 10.8 software. For its use in predicting flood situations and representing vegetation cover, the Normalized Difference Vegetation Index (NDVI) was computed. Here, the NDVI was calculated using the following formula [27]:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}}$$

NIR and R stand for near-infrared band and red band, respectively. The following equation has been used in relation to the LANDSAT 8 data:

$$\mathrm{NDVI} = \frac{\mathrm{Band}\ 5 - \mathrm{Band}\ 4}{\mathrm{Band}\ 5 + \mathrm{Band}\ 4}$$

With the help of ArcGIS, DEM was also used to create the area's elevation map. The line density analysis Tool in ArcGIS was used to generate the drainage density network. Elevation and slope are key factors in determining a terrain's stability when considering the topography of the Neluwa area. The amount and direction of surface runoff or groundwater that reaches a location are influenced by the slope. The main factor affecting how much rainfall contributes to stream flow is the slope. It regulates the duration of subsurface, infiltration, and overland flow. Since its concentrations indicate the type of soil and its geotechnical characteristics, the drainage network is an essential ecosystem for reducing risks. A weight value, corresponding to its relative relevance, was assigned to each element in order to undertake a thorough assessment of the impact of each criteria on flood generation in the research area. Pairwise comparison analysis, a method Saaty introduced in 1980, was used to determine the weight [21].

2.3. GIS Approach

There are some methods that we experimented with, in order to decide on the best alternative. Among them, AHP is one of the most popular methods. The AHP method is used to weigh criteria and sub-criteria by evaluating Disaster Management (DMCs), stakeholders, regional planners, or experts affiliated with the decision-making process. Given that AHP is the easiest decision-making approach to prototype, it has emerged as one of the most popular techniques for combining decision-making processes and geospatial analysis [28]. This indicates that the approach is simple to use and yields effective and precise findings for spatial analysis. AHP has gained popularity as a consequence of its simple deployment and successful outcomes. This method is as widely used as the MCDM method, for considering the flood risk in various regions/countries [29]. Major criteria maps are created based on values at different levels. A comparison is then made of the relationship between each criterion in the standardization process, and potential flood risk is identified and assessed through criteria weights using relevant field experts and their judgments. The comparison between the criteria was most aptly identified using the MCDA method, through GIS technology that applied Satty's [30] AHP scales as pair-wise comparisons, as mentioned in Table 2. However, to reclassify the criterion maps, standardization was done by the pair-wise comparison method. The next step was to establish weights for each criterion. According to the weight calculation, different criteria had different importance levels. In the current research, we report the judgments of experts from the field of hydrology, GIS, and disaster management. Additionally, sub-criteria maps were reclassified and weighted based on the experts' opinions. To calculate AHP weights for the criteria, ten semi-structured questionnaires were collected from experts, including civil engineers, disaster managers, university lecturers, AHP-based researchers, GIS experts, and other researchers in the field. Accordingly, experts' opinions were used to construct a pair-wise comparison matrix and to allot weights as per the importance of each criterion. The experts were selected based on their basic knowledge and research experiences.

Table 2. The AHP scales for paired comparisons.

Numerical Scale	Scale
1	Equally important
3	Moderately important
5	Strongly important
7	Very strongly important
9	Extremely important
2, 4, 6, 8	The importance lies in between two degrees

Note(s): **Source**: Saaty 1990 [30].

In the present study, nine sub-criteria were identified, under three main criteria, the built environment, physical, and socio-economic characteristics, with these three being relevant to the flood vulnerability evaluation for the study area. Under the built environment, road network and buildings were chosen as sub-criteria. NDVI, slope, elevation, water bodies, and stream density were taken under physical criteria and land use and population density were taken under socio-economic criteria. All criteria required weighting and were present in the form of raster datasets. The study consists of different levels of use of criteria and combinations of different processes. When weighing the criteria, it is recommended to quantify the pairs and quantitatively calculate the extent as to which the relationship between them is relevant to the study. The flood risk assessment map was obtained by overlaying all sub-criteria maps, by using weighted overlay technology through the Arc GIS software-aided Weighted Linear Combination (WLC) method. Five risk zones could be identified, based on the standard given in flood risk assessment when creating vulnerability maps, including very high risk, high risk, moderate risk, less risk, and risk-free. On the other hand, based on the range of parameters, the flood risk level was classified into five types (7—very-high risk, 5—high risk, 3—moderate risk, 1—less risk, and 0—risk-free). All criteria were plotted and transformed into values displayed within raster cells, and used in weighting for linear combination.

In standardizing the criteria used, a reclassification was obtained, with areas not susceptible to flooding represented as Number 0 and areas susceptible to flooding represented as a range between 0 and 1 (Table 3). In the pair-wise comparison method, the analyst must specify the values for each pair of criteria that are the most significant in determining the flood risk, and how the relationship between those criteria affects the flood vulnerability. Afterwards, the analyst must qualitatively state as to by how much their value is more substantial than another factor, as well as state the effectiveness of its quantitative expansion. By assigning quantitative weights to determinants and comparing them pairwise to obtain the composite vulnerability maps for the flood risk, weighted criteria were combined to produce a flood vulnerability map. The most significant and common method employed in flood vulnerability mapping is the weighted linear combination method. It uses a linear superposition approach, based on the importance of different factors' weight [31–33]. Linear combination converts multi-factor evaluation into a comprehensive one [34]. The procedures of WLC are expressed by the following formula, as proposed by Mendoza, [35].

$$S = \sum Wi\, Xi * \prod c\, J$$

where, ***S*** = vulnerability; ***Wi***—the weight of factor ***i; Xi***; ***Xi***—criterion score of factor ***i***; ***cj***—criterion score (false/true) of constraint j; **Π**—produce.

Table 3. Score values assigned to reclassify each sub-criterion map used for the stud.

Flood Criteria	**Vulnerability Class Ranges and Ratings**					
	Unit	Risk Free (0)	Less Risk (1)	Moderate Risk (3)	High Risk (5)	Very High Risk (7)
(A) Physical Environment						
NDVI	Levels	0.47–0.56	0.42–0.46	0.36–0.41	0.25–0.35	0.12–0.24
Slope	Degrees	30–57	21–29	13–20	5–12	0–5
Elevation	m	91–155	50–91	-	-	-
Distance from River	m	400–768	200–400	100–200	50–100	0–50
Stream Density	km^2	0–3.73	3.74–7.45	7.46–11.2	11.3–14.9	15–18.6
(B) Built Environment						
Distance from Road	m	600–1135	300–600	200–300	100–200	0–100
Distance from Buildings	m	800–1374	400–800	200–400	100–200	0–100
(C) Socio Economic Environment						
Land use	Class	Rock	Rubber/Dense forest/Tea	Coconut	Homestead	Paddy
Population Density	Person/km^2	48–129	129–240	240–401	401–631	631–1085

This process, known as the Analytical Hierarchy Process (AHP), is one of the most appropriate techniques for pair comparison and weight development for criteria, developed by Satty [30], in the context of multi-criteria decision-making and criterion-building relationships [36–38]. Many of the criteria in the study were chosen based on previous literature surveys, and were used in particular contexts when obtaining relevant data [39,40]. Whether the flood risk in the area is directly or indirectly determined is clear from the criteria used in the present study. Nine thematic maps (Figure 2) have been created under three main criteria. The study was carried out to generate a final flood risk map using the spatial analysis procedure (Figure 3).

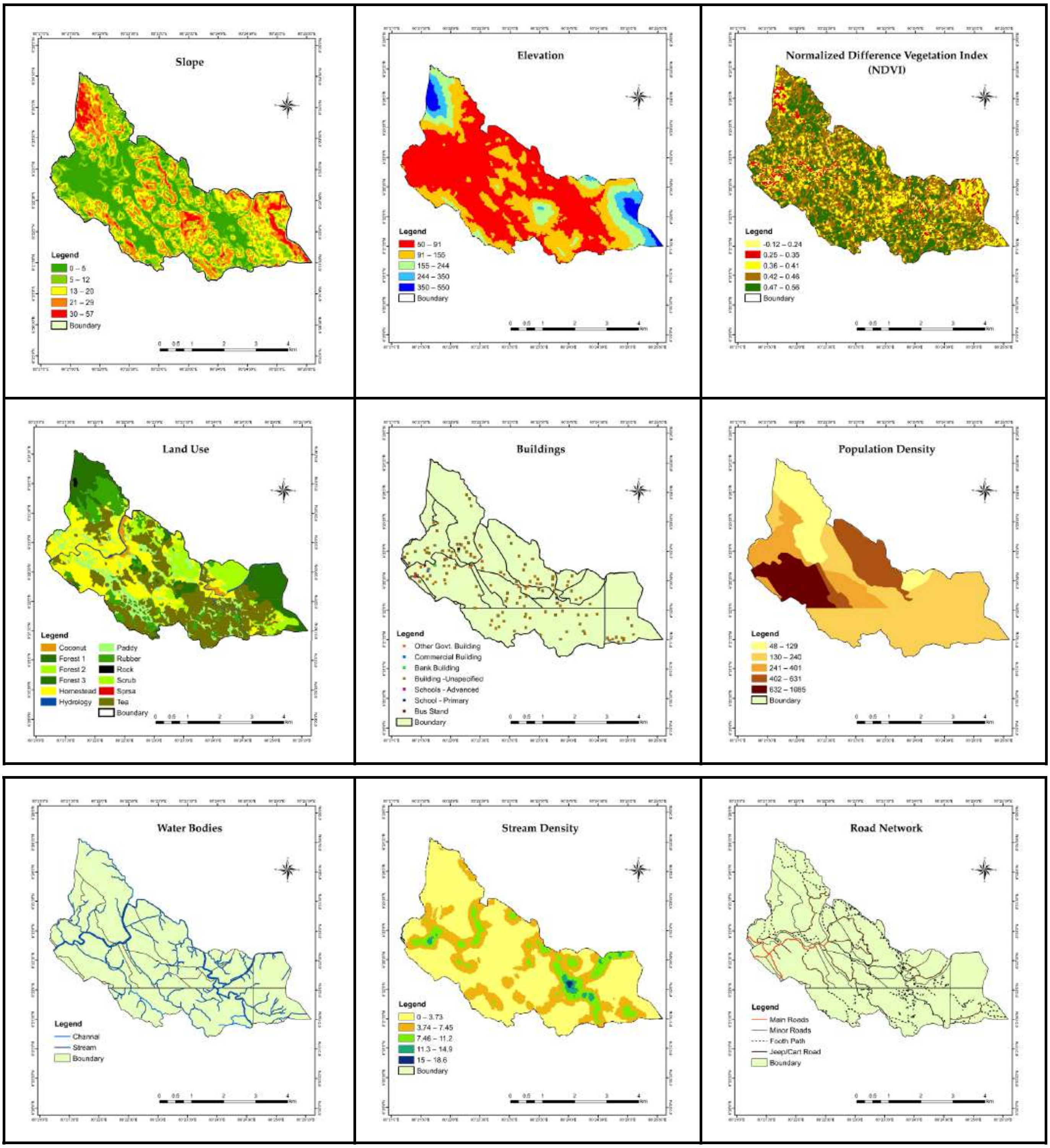

Figure 2. Sub-criterion maps used for the study.

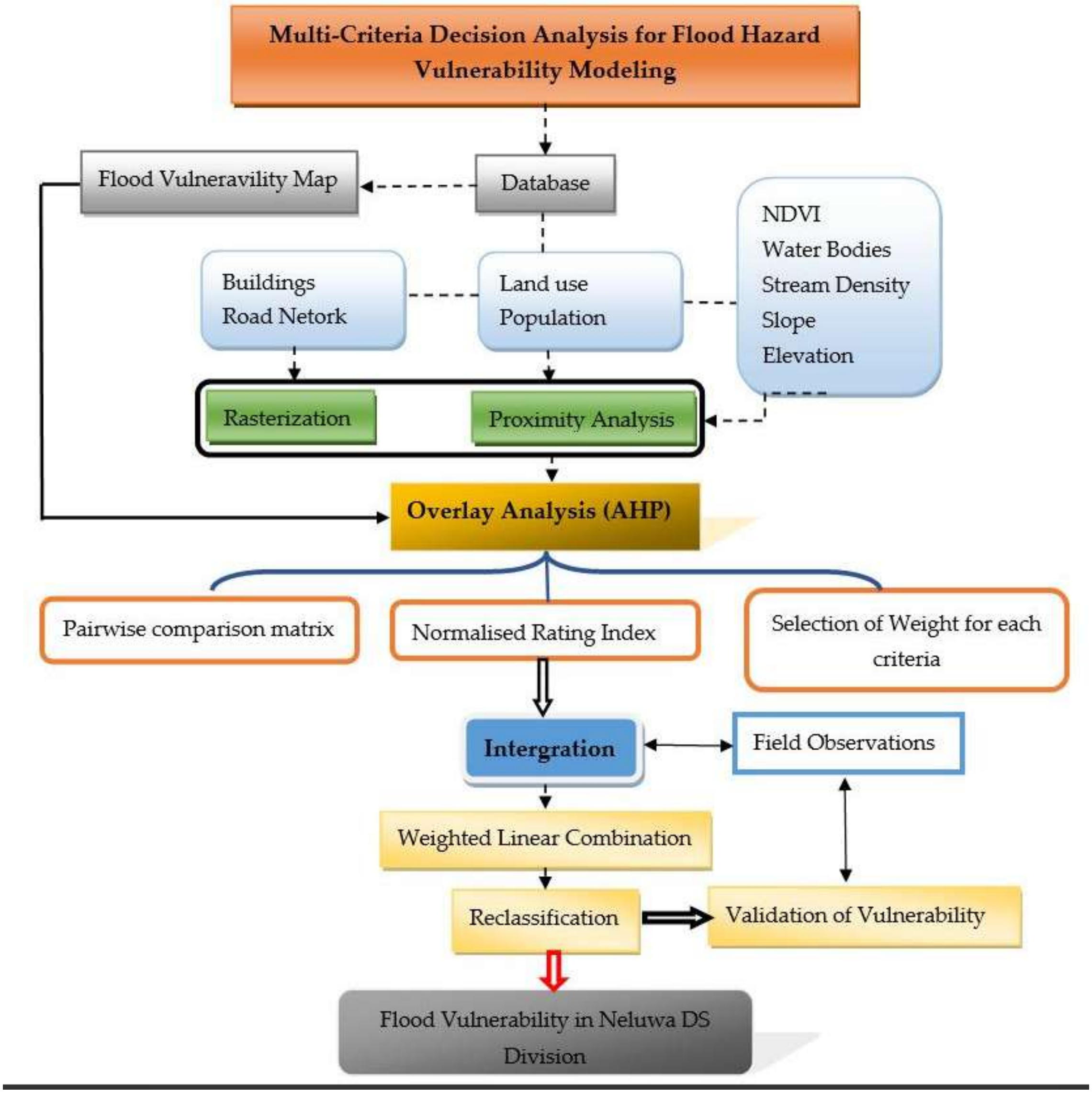

Figure 3. Spatial analysis procedure of the study.

2.4. Developing GIS Model

Model Builder has a systematic technology that can be used to edit and manage the required model. Arc GIS 10.8 version, developed by the ESRI, USA, was utilized. As a GIS analyst, anyone can use the model builder, for a variety of applications. Additionally, a model builder is used for constructing simple workflows. It is an easy and significant application for creating and running workflows, and has a simple, neat interface. When creating a model builder for any study, it is essential to pay attention to areas such as the model canvas, model diagram, model elements, variables, and tools. It also should provide advanced methods for extending ArcGIS functionality, by allowing one to create a model as a tool. Not only that, the ArcGIS model builder offers several advantages, particularly in terms of progressive processing, and easier database management. Using spatial analysis techniques in Model Builder (Figure 4), flood risk vulnerability was evaluated by applying different analytical GIS techniques, including overlaying, buffering (Euclidian), reclassifying, and Raster-to-Vector conversion based on multi-criteria decision analysis.

Figure 4. ArcGIS model for creating flood vulnerability map of the Neluwa DSD using Model Builder.

Accordingly, the knowledge of experts was used to construct a pair-wise comparison matrix, and the contribution of each criterion was examined. Then, the values in each cell were divided by the sum of each column. The process took place based on the three major criteria. Main criteria weights were constructed regarding the results of ten experts in the disaster management and GIS fields. According to the questionnaire survey, the main criteria matrix was filled as below (Tables 4 and 5).

A—Physical Environment
B—Socio-economic Environment
C—Built Environment

Table 4. Main Criteria Weight Matrix (one expert).

Criteria	A	B	C
A	1	7	1/5
B	1/7	1	1/7
C	5	7	1

Note(s): **Source**: Author calculation based on AHP and Questionnaire Survey, 2022.

Table 5. Normalized Criteria Weight Matrix for Main Criteria (one expert).

	A	B	C	Criteria Weights	Final Criteria Weight
A	0.1	0.8767	0.0588	1.0355/3	0.3451
B	0.8	0.1095	0.4705	1.38/3	0.46
C	0.1	0.0136	0.4705	0.5841/3	0.1947

Note(s): **Source**: AHP weights' calculation based on experts' opinion and Questionnaire survey, 2022.

3. Results

The research aimed to create flood vulnerability maps of the Neluwa using geo-informatics. Results of vulnerability levels and area calculations for major criteria such as the physical, socio-economic, and built environment parameters differed from each other based on their criterion values, which were assigned based on experts' opinions.

3.1. Weights for the Criteria

When using the pairwise comparison matrix and factor maps, weighting and ranking procedures are followed. Representing weight values between zero and one is based on priority. Accordingly, using the weighted linear combination, the sum of the weights is calculated as one. This then allows assigning weights to the major criteria and sub-criteria, and a standardized eigenvector is then extracted from the comparison theorem by entering each criterion. The final flood vulnerability map is the outcome of the overlaying major criterion maps. The results of the AHP weight calculation are shown in Table 6. Higher weight values of criteria indicate greater impact and propensity for disasters. We observed that the criteria used for the study revealed a high priority for flood risk. It can be identified that the physical environment affects flood risk the most, as the most weighted criterion. The subsequent risk maps will be created depending upon the manner in which the ranking decision is derived, and the quantitative values will be obtained for each criterion.

Table 6. Weights assigned for each major and minor criterion of the study.

	Main Criteria	Weights	%	Sub Criteria	Weights	%
A	Physical Environment	0.4081	40.8	NDVI	0.1421	14.2
				Stream Density	0.2507	25.0
				Elevation	0.1638	16.3
				Slope	0.2027	20.2
				Water Bodies	0.2445	24.4
B	Socio-economic Environment	0.2956	29.5	Land use	0.2705	27.0
				Population Density	0.7293	72.9
C	Built Environment	0.2940	29.4	Buildings	0.6293	62.9
				Roads	0.3706	37.0

Note(s): **Source**: AHP weight calculations using experts' opinions.

3.2. Flood Vulnerability Levels for Minor Criteria

The best available proxies for catastrophic occurrences must be explicitly chosen as indicator variables, as per the approach of the study. Any form of thorough vulnerability assessment requires the indicators chosen for each of these components to be crucial factors. The composite vulnerability index approach was used to map the Neluwa areas that are vulnerable to natural and climate-induced disasters. Vulnerability indices were calculated by using data from selected vulnerability areas. The highest and lowest vulnerability regions have been classified using the vulnerability index in the Neluwa area. All of the selected sub-criteria are the most significant criteria in flood risk assessment. The NDVI criterion was used in terms of physical characteristics and is currently being used in many studies. Values obtained from the NDVI map, created by region-based satellite imagery, range from −0.12 to 0.24. After re-classification, four vulnerability areas were identified, with the −0.12–0.24 zone being labeled the very-high-risk zone and the 0.47–0.56 being the risk-free area. The area has minor hilly features, and after reclassifying the elevation map, it was divided into two zones: risk-free and less-risk areas. The elevation of the area ranges from 0 to 155 m. The reclassified slope map identified five classes: risk-free, low risk, moderate risk, high risk, and very-high risk. Low-slope areas have been identified as very-high-risk areas and exalted slope areas were identified as risk-free areas. The majority of the study area has water bodies.

The Gin River, Dellawa Ela, and other tributaries have caused flooding in the area. According to the reclassified hydrology map, the majority of the area was classified as very-high risk. On the other hand, when reclassified in terms of the stream density map, four classes were realized: low risk, moderate risk, high risk, and very-high risk. In the reclassified distance from the building map, four vulnerability levels have been considered: risk-free, low risk, moderate risk, and high risk. There is an extensive road network in the area, extending from 0 to 1374 m. The area between 0 and 100 m is a high-risk area and the zone between 600 and 1374 m has also been identified as a risk-free area. Population density and land use have been identified under socio-economic criteria. Land use was a significant factor that determines the flood situation in the area. In this study, there are eleven types of land use that have been considered. Paddy and water areas were observed as very-high-risk areas for flooding. Among them, roads and forest areas were identified as risk-free areas. Apart from that, the study area has a sizeable population, and densely populated areas were identified as very-high-risk zones.

3.3. Flood Vulnerability Levels for Major Criteria

The final flood vulnerability map in the study area has been generated, overlaying three major criterion maps, which include those of the physical environment, socio-economic environment, and built environment. The final analysis revealed five vulnerability classes for flooding in the study area (Figure 5). The final results obtained from the flood vulnerability modeling revealed that 0.69% (0.15 km^2) and 6.84% (1.48 km^2) of land in the area is very-high risk and risk-free, respectively, in terms of flood vulnerability. After comparing all the criteria in the physical environment, it was found that there is a moderate-risk area (10.8 km^2). After overlaying all socioeconomic criteria maps, it was revealed that there are four vulnerability levels. Based on population density and land use, 0.41% (0.09) of the area has been indicated as very-high risk, 30.61% (6.62 km^2) as a high-risk area, and 48.19% (10.42 km^2) as a low-risk area. Under the built environment, the highest risk area was identified as comprising 25.12% (5.15 km^2) of the area, and 6.34% (1.30 km^2) was risk-free. The results obtained upon combining the main criteria maps reveals the distribution of flood risk in the area.

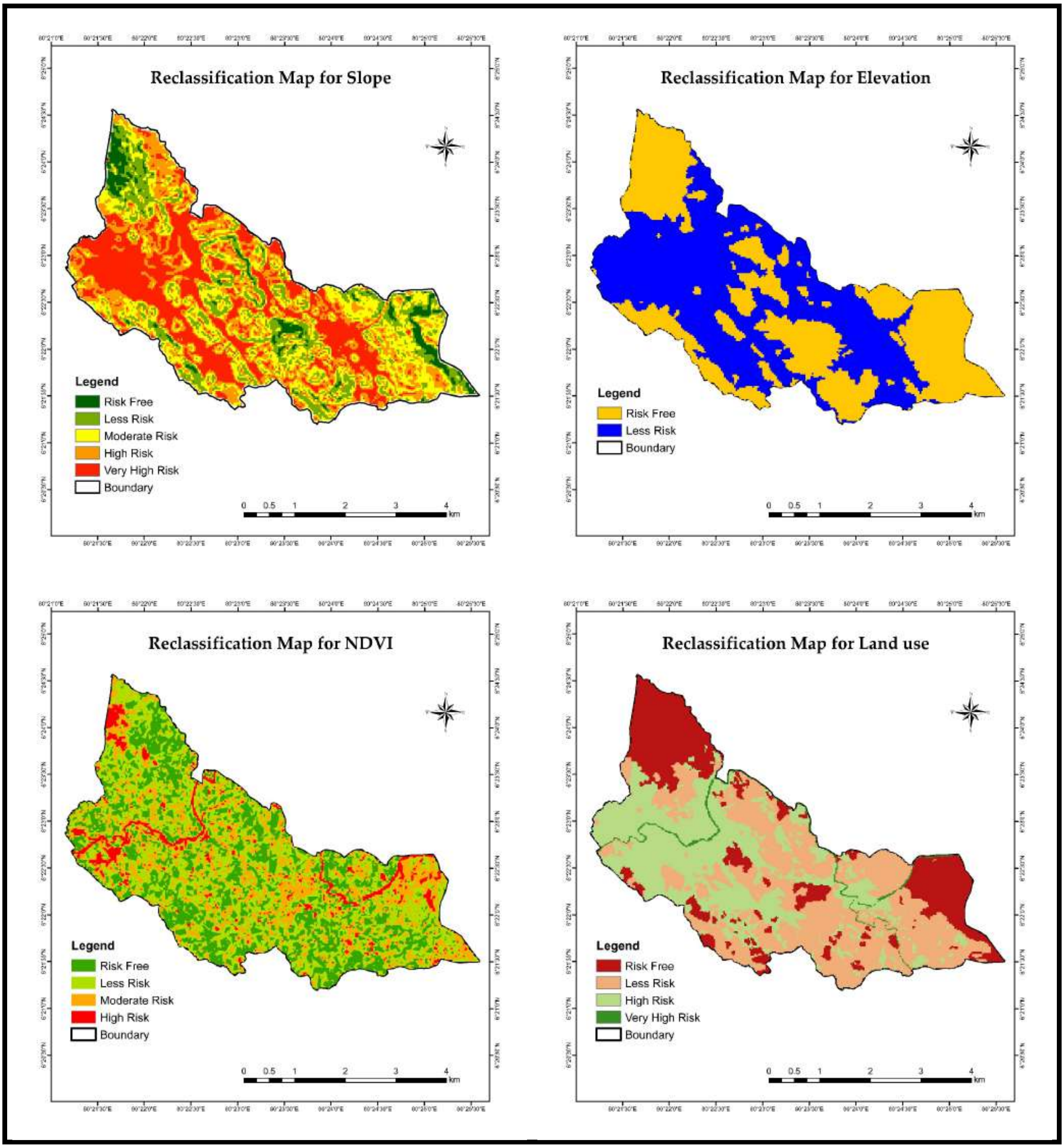

Figure 5. *Cont.*

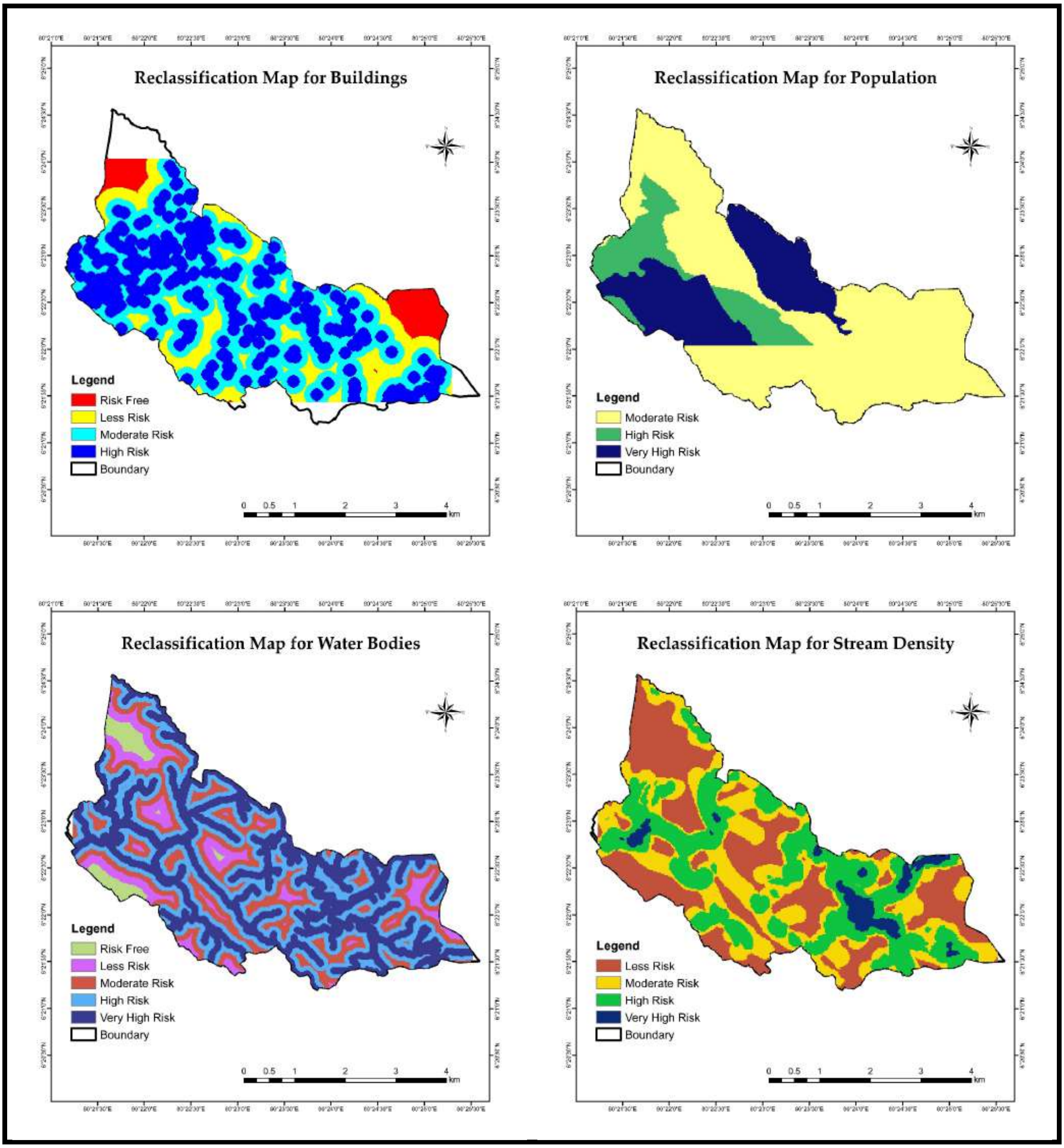

Figure 5. *Cont.*

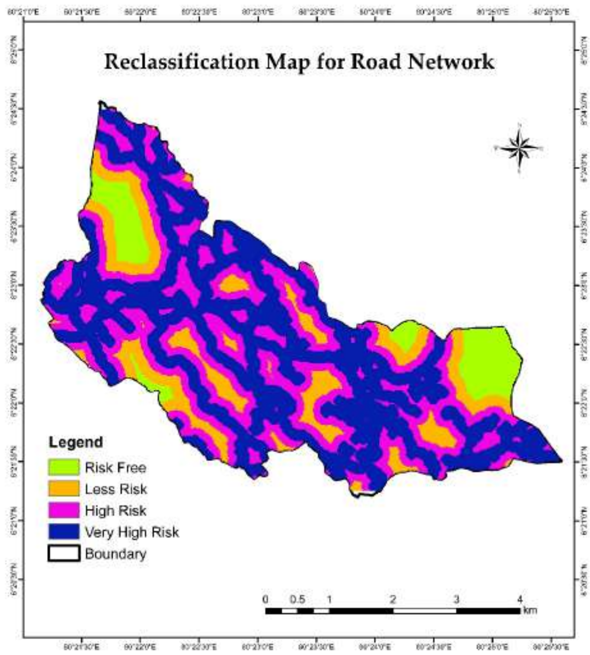

Figure 5. Reclassified Flood Vulnerability potential maps.

After overlaying the final weights for each major criterion map, it was revealed that 14.24% (2.92 km^2) was very high risk and 5.17% (1.06 km^2) of the study area was risk-free for flood hazards. Out of 21.62 km^2, 30.24% (6.20 km^2) is at high risk for flood in the area. The results also indicated that 22.58% (4.63 km^2) of the total area is a moderate risk prone area as demonstated in Figures 6 and 7 and Table 7. The risk of flooding is very high in the western part (Neluwa, Mavita East, and Koswatta) of the study area as the population and buildings associated with those areas are also extensive. Kosmulla and Ehelapitiya areas in the eastern parst of the area have also been identified as very high-risk areas. The Gin River flows through the area as the main source of water and there is a risk of associated flood hazards.

Table 7. Area coverage of flood vulnerability classes.

Criteria	Vulnerability Classes									
	Very High Risk (Sq.km)	%	High Risk (Sq.km)	%	Moderate Risk (Sq.km)	%	Less Risk (Sq.km)	%	Risk Free (Sq.km)	%
Physical Environment	0.15	0.69	3.58	16.5	10.8	50.1	5.56	25.71	1.48	6.84
Built Environment	5.15	25.12	5.78	28.19	6.61	32.2	1.41	6.87	1.30	6.34
Socioeconomic Environment	0.09	0.41	6.62	30.61	4.49	20.76	10.42	48.19	-	-
Overall	2.92	14.24	6.20	30.24	4.63	22.58	5.69	27.75	1.06	5.17

Note(s): **Source:** Arc Map 10.8 based area calculations, 2022.

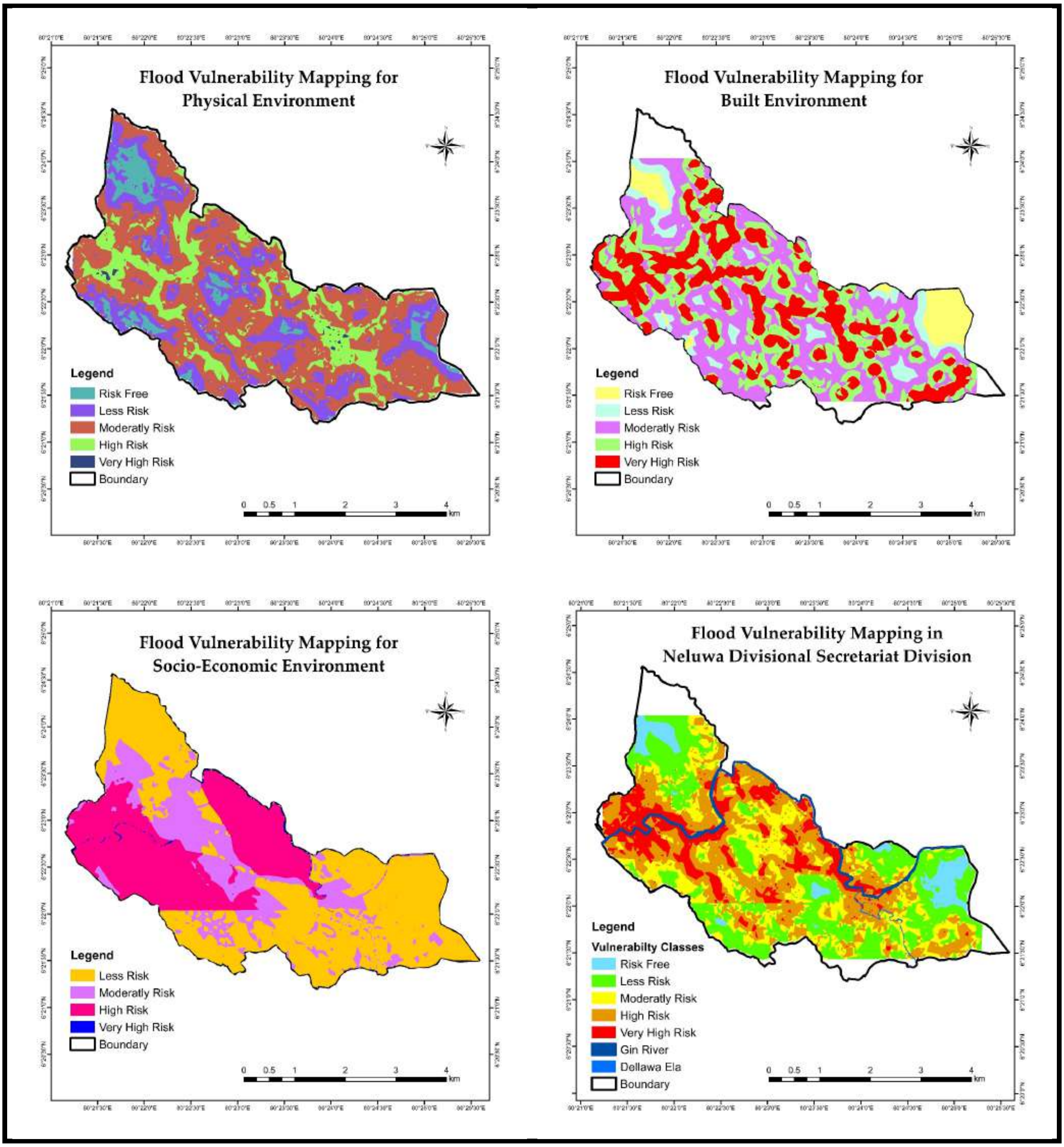

Figure 6. Flood Vulnerability Mapping in Neluwa area.

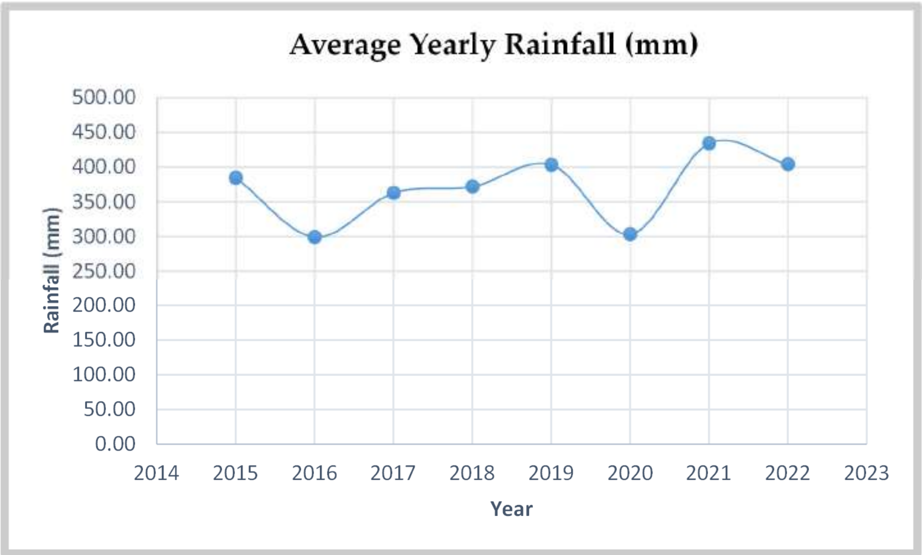

Figure 7. Annual Rainfall Distribution in Neluwa Area from 2015 to 2022. **Source:** Meteorological Department in Sri Lanka, 2022.

3.4. Rainfall Distribution in the Area

The Neluwa area is unique in identifying flood risk areas in Sri Lanka. Flooding can be identified as an inherent natural hazard in the region, and flooding situations occur whenever there is heavy rainfall. Based on monthly rainfall values from 2015–2022, the area was identified as a high rainfall area. Heavy rainfall is the main cause of floods. Flooding occurs when the natural water bodies are unable to carry the excess water of the heavy rainfall in the area. In the upper catchment areas, there is very heavy rainfall. According to the rainfall data obtained from the Batuwangala Meteorological Center, this region shows very heavy rainfall (Figure 7). An average monthly rainfall of over 250 mm/year is recorded every year. In the year 2022, a rainfall of 434.72 mm/year has been detected, which means that in May, with the onset of the southwest monsoon, a very large flood occurred in the Neluwa area. During that month, the monthly rainfall was recorded to be 934.7 mm. A gradual increase in rainfall intensity can be detected, and although it decreased by 2020, an average monthly rainfall value of 303.45 mm was recorded. One of the major flood zones in Sri Lanka, the Neluwa area, has been facing major flood conditions for several years now. Due to this, the society, economy, and infrastructure of the area are affected by the disaster.

Role of traditional knowledge in water management, monitoring of climatic changes and productivity of land is to be focused while planning the flood in the study area [41–43]. Recently, role of drones and other techniques have also been widely used in assessing the information and decision support for sustainable management of flood hazard [44–46].

4. Discussion

4.1. Validation of Vulnerability Assessment

AHP was based on risk assessment in verifying and evaluating the consistency of the theoretical results. This helped us to ascertain the relevance of each criterion in flood risk. A better analysis of the risk index could be achieved, and it was possible to obtain the specific and real weight of each criterion. This allows for the reliable mapping of flood-prone areas. In the study, a qualitative validation method was adopted in the assessment of the spatial risk maps and the evaluation of the results. By seeking people's opinions on the risk maps, created under the qualitative approach, observations and discussions were conducted with 50 people, consisting of local people, meteorological station officials, town planners, land-use planners, and experts. Their opinion was asked for regarding the accuracy of the risk map, and through the qualitative approach, it was possible to identify the vulnerable areas through those maps. Discussions with the residents of the area revealed that the area constantly faces floods. The discussions also highlighted that continuous floods in the Neluwa area, including the recent flood in May 2022, have huge negative ramifications on the residents of the area.

Accordingly, the areas where the past floods occurred regularly were observed, and the respondents were classified under five categories while obtaining information in the field. About 29 (58%) of the 50 respondents were highly satisfied with the proposed results, and 14 (28%) respondents were satisfied with the results. Seven (14%) of the respondents were not satisfied with the results obtained from the flood risk maps (Table 8). The Neluwa urban area, i.e., the central part of the map, can be identified as a very high-risk zone and is vulnerable to floods, with rainfall exceeding 100 mm every year. It is not possible to identify very high slope angles in that region, and the flood conditions are constantly increasing, with the rain falling on the hilly regions of the area that join the river, with a large body of water along the slopes. With the flood situation in 2017, this region was also revealed as a high-risk area. Low-risk and moderate-risk areas were largely unaffected during the recent floods. The vulnerability can be further confirmed when the risk map is compared with the divisional secretariat disaster reports. In those reports, a zone, with a buffer of 100 m around these identified areas, has been detected as a flood-prone areas by the institute disaster officials also. According to the people, Neluwa area is prone to flood hazards often once or twice a year.

Table 8. Feedback from the people during the field verification of vulnerability assessment.

Category of People	Total Number of Respondents	Comments of Respondents		
		Highly Satisfied	Satisfied	Not Satisfied
Land Use Planners	02	01	01	0
Experts	04	02	01	01
Meteorologists	02	01	01	0
Town Planner	02	01	0	01
Local people in the area	40	24	11	05
Total	50 (100%)	29 (58%)	14 (28%)	07 (14%)

Note(s): **Source**: Field Verification, 2022.

4.2. Local Community's Experience of Flood Hazards

The distance from the river to the house determines the impact of the flood hazard. When investigating the distance from flood-prone houses to the river during the field study, more houses within a distance of 100–200 m from the river were identified. As the distance from the river to the house decreases, the impact of flooding increases. People living within this zone can be identified as belonging to a high-risk category. The responses of the local people also revealed that the existing houses in the region between 200–250 m were more affected. The nature of the impact of the hazard can be investigated and identified in several ways. It can be divided into full damage, partial damage, and minor damage. Overall, partial damage is more common than full damage in the study area. Apart from that, minor damage can also be seen. During the 2017 flood situation, there was a large rise of 6 to 10 feet. Almost all the buildings in the Neluwa urban area were damaged (Figure 8). The responses of the people regarding their coping mechanisms during such events were that they moved to safe places, such as relatives' houses, displacement camps, and temples. They also revealed that people who had two-story houses stay in their houses. Awareness of the people can be specified as one of the main actions in flood hazard management. To minimize the impact on the people, making them aware of flooding has become an essential factor. Subsidies and compensations are provided as post-event measures in case of flood hazards. The residents revealed that they received subsidies, such as rations, educational equipment, medicines, soft goods, sanitary materials, and kitchen equipment. Compensation under post-flood hazard management is based on an assessment of the damage caused by the flood. The interviews conducted with the people in the study area revealed that the floods that occurred in May 2003 and 2017 were large, catastrophic events and resulted in a high amount of damage.

Figure 8. Flood Situation of Neluwa Area in 2022/2017, (**A**)—26.05.2017 flood situation, (**B**)—26.05.2017 flood situation, (**C**)—26.05.2017 flood situation, (**D**)—27.05.2022 flood situation, (**E**)—27.05.2022 flood situation, (**F**)—27.05.2022 flood situation.

5. Conclusions

In this study, the effectiveness of providing accurate and detailed flood risk and flood vulnerability analysis has been demonstrated along the Gin River, by using GIS, AHP, and MCDA. The main criteria used included, the socio-economic environment, built environment, and physical environment, were very useful in identifying the overall spatial flood risk assessment in the area. This study presented an effective method for spatial risk assessment of flood impacts by integrating multi-criteria using geospatial techniques at the local scale. A qualitative validation approach was used in validating the developed risk maps and this was done based on direct observations from the field, as well as feedback from the community, disaster management officers, meteorologists, and land-use planners. The results of flood hazard map showed that 14.24% (2.92 km^2) was under very-high risk, 30.24% (6.20 km^2) is at high risk and 5.17% (1.06 km^2), area was risk-free for flood hazards. The results also indicated that 22.58% (4.63 km^2) of the total area is a moderately flood-prone area, as demonstrated in Figure 6 and Table 7. The results indicated that very-high- and high-risk areas cover an area of 9.12 km^2 from the central, southern, and eastern portions of the study area. Based on temporal and spatial perspectives, this area shows great variability in the probability and occurrence of inundation. The very-high-flood-risk area is characterized by low elevation and slope, the presence of the Neluwa urban area, high rainfall intensity, and proximity to water bodies.

The results of the study, if implemented well, shall provide an opportunity to control the flood situation in the Neluwa area. Apart from that, other measures, such as the proper implementation of flood monitoring and early warning systems, restricting the expansion of residential zones in high-risk areas, planting of riparian vegetation on both sides of banks of the river to control flood flow velocity, and use of structured and semi-structured measurement methods, are suggested. Awareness and information dissemination about flood at community level should be prioritized. Proper use of such recommendations and suggestions will be a guide to control future flood situations scenarios. The results obtained after linking MCDA–AHP–GIS methods in the study area can be identified as an effective tool in flood risk assessment for engineers, land-use planners, urban policymakers, and disaster managers. Such decision-making techniques can be used successfully in other fields of geography and any area.

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Research Article

Indexing habitat suitability and human-elephant conflicts using GIS-MCDA in a human-dominated landscape

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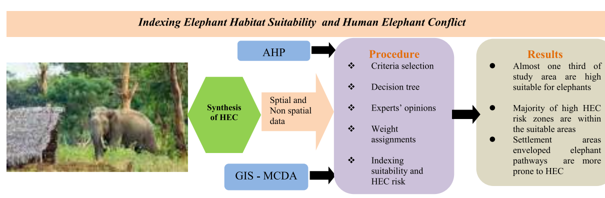
HIGHLIGHTS

- The study area is one of the key elephant pathways in Sri Lanka.
- Human-elephant conflict (HEC) is a result of habitat fragmentation and encroachment.
- Habitat suitability and HEC risk zones were assessed using AHP and GIS-MCDA.
- Elephant habitats are found in locations that are at high risk for HEC.
- The findings serve as a benchmark for future HEC mitigation.

GRAPHICAL ABSTRACT



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ABSTRACT

Concerns for biodiversity loss, wildlife conservation, and habitat destruction have dominated the policy agenda worldwide for decades. Unsustainable human-induced development and negative interaction between humans and wildlife have emerged as predominant issues globally. The present study deals with human and elephant conflicts (HEC) in the Polpitigama Divisional Secretariat, Sri Lanka, which is located in the Kahalla-Pallekele elephant corridor and connects Wilpattu and Kaudulla wildlife sanctuaries. The research objectives are identifying spatial patterns of elephant habitat suitability and probable risk zones for HEC. The elephant habitat suitability and HEC risk zones were identified on spatial and temporal scales using Geographic Information System integrating Multi-Criteria Decision Analysis. Different factors, including habitat suitability, distance to roads, distance to croplands, distance to forests and protected areas, settlements, and population density, were considered to determine HEC risk zones in the area. Topography, water, and vegetation criteria are considered when determining elephant habitat suitability. The results of the Analytic Hierarchy Process run the spatially explicit model. The results revealed that of the total area, 15.3% is very highly suitable for elephant habitats, while the least suitable areas contribute only 4%. About 33.8% of the area is moderately suitable for elephants. The risk map indicates that 23.7% of the total area is under very high risk for HEC, and the least risk areas only account for 5.4%. About 26.2% of the area falls under the moderate risk zone for HEC. Since the model considered three aspects of HEC, it will help policymakers in wildlife conservation to avoid and minimize the HEC.

1 Introduction

As a gregarious animal and a flagship species, the Asian elephant (*Elephas maximus*) lives in 13 different countries ranging from the Indian subcontinent in the west to Indo-China in the east, including islands such as Borneo, Sumatra, and Sri Lanka (IUCN, 2017). According

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to the statistics, around 15% of agricultural products are damaged by wild elephants affecting human security and well-being (Kitratporn and Takeuchi, 2019). India is one of the significant habitats of wild Asian elephants, and about 400 people and 100 elephants die because of human and elephant conflicts (HEC) yearly (Rangarajan et al., 2010). Sri Lanka is home to about 4,400 elephants, accounting for around 10% of the wild Asian elephant population (Fernando, 1997, 2015; Jackson, 1990). Unfortunately, the elephant population in Sri Lanka has dropped by over 85% since the turn of the century, owing to a rise in human population from 2.5 million at the beginning of the century to 21.6 million today, and a decline in forest cover from 70% to less than 22% (Fernando et al., 2005, 2011). According to the latest information from the Department of Wildlife Conservation (DWC) of Sri Lanka, the elephant population is falling, with only 5,879 elephants on the island according to the 2011 elephant census (Dela, 2014; Rathnayake et al., 2022a, 2022b). Most studies have indicated habitat loss and land fragmentation as significant causes of HEC in Sri Lanka. As a result of HEC, approximately 250 elephants and 70 people die in Sri Lanka each year (Fernando et al., 2011). The largest numbers in recorded history for elephant deaths were reported in 2019 and 2020, with 405 and 407 HEC deaths, respectively (Rathnayake et al., 2022a). The northwestern region in Sri Lanka is a threatened area because humans and elephants become victims during the dry and crop-raiding period (Weerakoon et al., 2003).

The application of GIS technology (Mishra et al., 2020, 2021, 2023) in ecological studies of elephants has increased rapidly in recent decades (Prakash et al., 2020; Prasad et al., 2011; Shaffer and Bishop, 2016; Kitratporn and Takeuchi, 2019). In addition, Multi-Criteria Decision Analysis (MCDA) is used to evaluate and compare multiple, often conflicting criteria to make the best possible decision. In evaluating the criteria, MCDA considers geographical data models, the spatial dimension of the evaluation criteria, and decision substitutes with identifying interrelationships between criteria (Greene et al., 2011; Wijesinghe et al., 2023). Because of its ability to recognize and balance the significance of complex aspects, researchers typically utilize Analytic Hierarchy Process (AHP) to examine vulnerable areas supporting decision-making in the process of environmental planning and natural resource management (Malczewski, 2006; Mondal et al., 2022a; Jayasinghe and Withanage, 2020; Malliyawadu and Withanage, 2023; Withanage, 2023; Acharya et al., 2022).

Many studies have tried to evaluate socioeconomic impacts, human-elephant interaction, and locations of conflict incidents (Sitati et al., 2003; Palei et al., 2013; Hazarika and Saikia, 2013; Van de Water and Matteson, 2018; Lande, 2000; Pastorini et al., 2010; Sukumar, 1989) while some researchers analyzed the spatial-temporal dimensions of HEC (Li et al., 2018; Prasad et al., 2011; Sanare et al., 2022; Tripathy et al., 2021; Areendran et al., 2011; Kitratporn and Takeuchi 2019; Mondal et al., 2022b). Some Studies (Babu et al., 2018; Khanal, 2022) used machine learning techniques to predict the risk of HEC and then predict HEC risk zones with the random forest method. Thant et al. (2023) identified factors that influence the spatial movement, distribution, and suitable habitats of wild Asian elephants, to examine the relationship between HEC incidents in Myanmar. Yang et al. (2023) identified HEC hotspots in China and possible factors using remote sensing and UAV data. Chiranjib et al. (2022) examined spatiotemporal LULC changes and their impact on HEC by deriving HEC probability zoning maps. Ram et al. (2022) also examined the landscape predictors of HEC in Nepal using multivariate analysis and risk maps. Thant et al. (2021) assessed the pattern and distribution of HEC in three different HEC hotspots in Myanmar and identified local factors that contribute to HEC. Ahmed et al. (2022) analyze spatiotemporal patterns of elephant-train collisions and fatalities and linked them to land cover change (LCC) over time and space from 1988 to 2018 in the Assam region. Results show that large-scale LCC and increased elephant-train crashes and fatalities occur when railways are extended into forest areas. Sulistiyono et al. (2019) used Principal Component Analysis to determine the HEC. Wilson et al. (2013) investigated the links between elephants and human communities and the factors that influence their spatial and temporal occurrences of HEC.

In Sri Lanka most of the previous studies have focused on the socioeconomic impacts of HEC (Kopke et al., 2021; Edirisooriya and Bandara, 2022; Rathnayake et al., 2022; Campos-Arceiz et al., 2009; Ekanayake et al., 2011; Haturusinghe et al., 2012; Santiapillai et al., 2010; LaDue et al., 2021), and elephant movement analysis (Perera, 2009; Fernando et al., 2011). However, spatial analysis of habitat suitability and zoning HEC risk remains limited. Still, those studies are crucial for local-level planning, especially in dry zone where HEC is a major threat to both humans and elephants. Compared to other Asian and African countries, spatial analysis of elephant habitats and HEC are relatively new research areas in Sri Lanka. No comprehensive study is available in Sri Lankan context except for the country-wise GIS-based elephant survey conducted by Fernando et al. (2018).

Our study aims to bridge the knowledge gap by applying GIS technology as a spatial decision support tool for ranking habitat suitability and HEC in Sri Lanka, using Polpitigama DS (the third administrative level of the country) as a case study area. Specific objectives were to identify the spatio-temporal patterns of human-elephant conflict in the study area using incidence and occurrence data and to provide maps for elephant habitats and HEC risk for local-level decision-makers in wildlife conservation and resource allocation. Thus, the study paves the way for other researchers in Sri Lanka to carry out GIS-integrated HEC and habitat suitability modeling using a similar approach but with more criteria and factors in other areas, as well as modeling Human-Lepoard (*Panthera parades*) conflict in Sri Lanka's central highlands.

2 Materials and methods

2.1 Study area

The Polpitigama Divisional Secretariat (DS) is located in Kurunegala District, North Western Province, Sri Lanka, between 7°40′ N to 7°79′ N and 80°20′ E to 80° 32′ E, with a total area of 389.9 km^2. The elevation of the DS ranges from 77 m to 506 m above mean sea level. The study area comprises 294 villages and 82 Grama Niladhari Divisions (GNDs) , totaling 38,995 ha. The DS has a mix of dry and intermediate climate features, with an average annual temperature of 23.4 °C. The Southern half of the DS typically receives 1,750 mm of yearly rainfall, whereas the northern part receives 1,500 mm. Since the DS is bordered to the north and east by the Kahalla-Pallekele (KPK) wildlife sanctuary, the DWC is responsible for most of the territory in the DS. The DS is in an ecologically sensitive zone with a mosaic of different land use practices. Land use and land cover includes paddy fields, homesteads, riparian forests, dry forests, scrub forests, and forest plantations (Fig. 1).

The land use patterns in DS have changed significantly over the past three decades due to population growth, putting forests and conservative areas at risk. Forest areas have been experiencing illegal human settlements and housing developments for decades. In addition, *Chena* (slash and burn) agriculture is also widespread, leading to changes in the landscape. Farmers grow cash crops, fruits, and legumes as their primary sources of revenue using nearby forests. In addition, deliberate forest fires, cattle grazing, and illegal felling of trees pose a significant risk to the forest resources and animals in the KPK sanctuary, which is close to the DS. As a result of the significant changes in LULC patterns, HEC has increased in recent years. The major surface water resources are Kibulwana Oya, Siyabalngamuwa Oya, Hakwatuna Oya, and Mee Oya, all flowing along the DS. In addition, the DS also has 488 tanks of varying sizes fulfilling the area's water demand. In the western part of the DS, the groundwater level is high, and water is available close to the ground surface. The tanks and streams in the KPK sanctuary provide surface water resources for villagers and wild animals, including elephants. Most of the water resources remain low or dry between May and

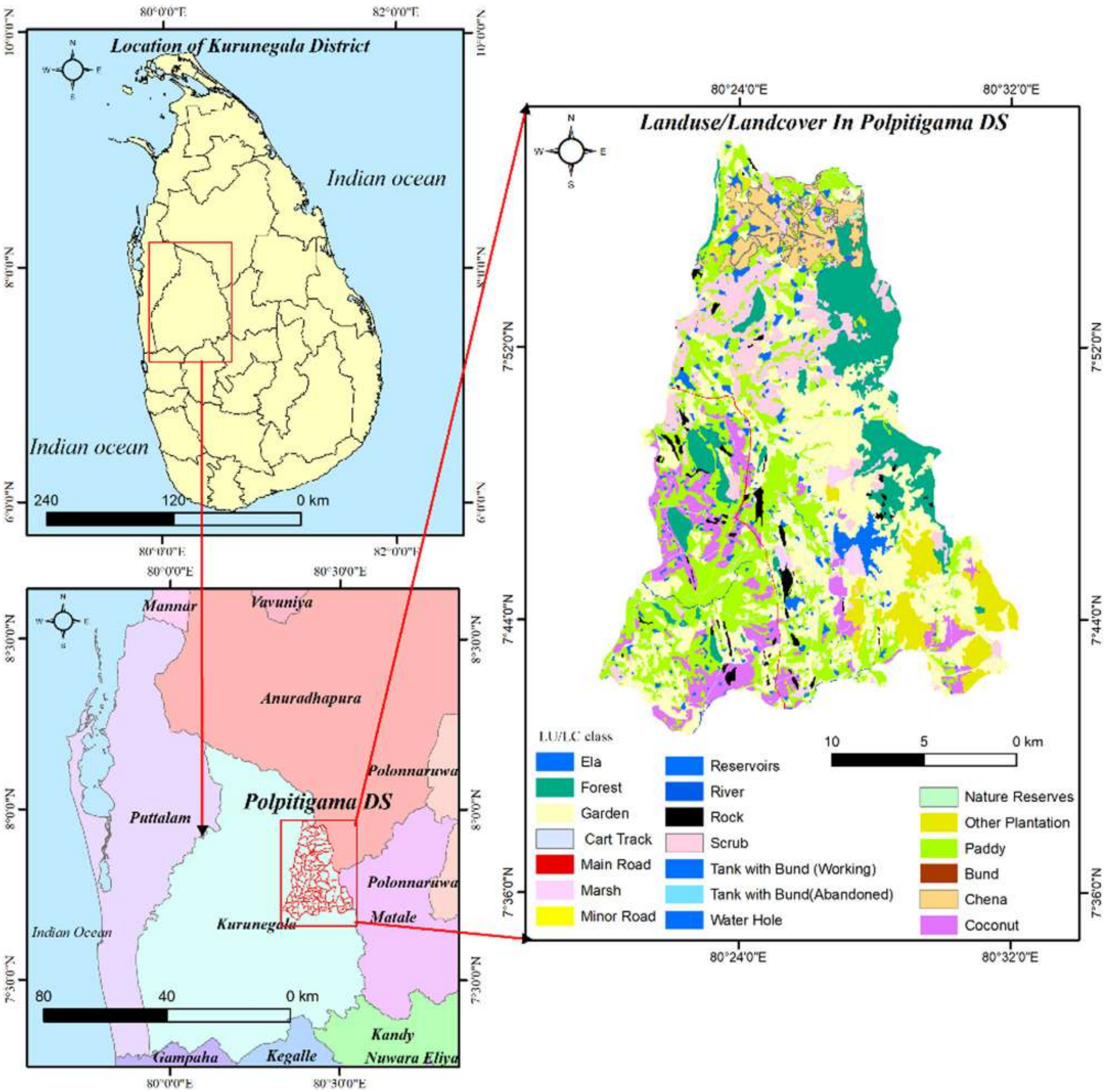

Fig. 1. Map of the study area.

September. Wild elephants regularly visit the homesteads and croplands during the dry season in search for food and water, which has led to an increase in HEC. Dry zone elephants, a meta-population in the country, are the source of most of the HEC incidents. Having altered their foraging patterns, now elephants prefer to eat many domesticated food items. Around 2,844 elephants were killed by farmers, and 1,138 people were killed by elephants between 1991 and 2010. A loss of 1,000 elephants occurred during the previous decade (Dela, 2014; Fernando et al., 2018). In the past ten years, Kurunegala District has seen increased HEC incidences. Male elephant species showed a higher mortality rate, indicating a serious threat to elephant populations. Thirty-nine elephant deaths were reported between 2013 and 2016 in the Kurunegala district, nine of which were in Polpitigama DS (Ministry of Mahaweli Development and Environment, 2017). Mahawa, Polpithigama, and Galgamuwa were responsible for the deaths of elephants through purposeful killing, including gunshots, electric shock, and poison. Villages within the KPK sanctuary encroach on animal territories resulting in more HECs in adjacent areas.

2.2 Data sources

There were 107 HEC incidences (24 elephant occurrences, 13 human deaths, 30 elephant deaths, and 40 cases of property damages) between 2010 and 2022 in the study area, based on DWC reports and local people's knowledge. Location data of these incidents were collected using Global Positioning System (GPS) survey. These location data created the HEC density maps categorizing incidences into high and low zones. Spatial data on elephant habitat suitability and HEC risk was acquired from different sources. Digital elevation model (DEM) data was taken from NASA SRTM (https://www.earthdata.nasa.gov/). Vector data for land use, roads, and water features were obtained from digital data layers of the Survey Department of Sri Lanka (SDSL). The en-

Table 1
Description of factors and criteria used for elephant habitat suitability.

Factor	Criteria	Raw data type	Processing method	Resolution/scale	Year
Land	Elevation	SRTM (DEM)	Elevation function in ArcMap10.6	90 m	2021
	Slope	TIN and DEM	Slope function in ArcMap10.6	90 m	2021
	Land use	Polygon features	Polygon to raster	1:20,000	2020
	Land area size	Polygon features	Polygon to raster and	1:20,000	2020
Environment	Distance to rivers	Polyline feature	Euclidean distance function in arc Geo-processing	1:20,000	2020
	Distance to tanks/reservoirs	Polygon feature	Euclidean distance function in arc Geo-processing	1:20,000	2020
	Land surface temperature (LST)	Raster	Raster calculator in map algebra	30 m	2022
	Enhanced normalized difference vegetation index (ENDVI)	Raster	Raster calculator in map algebra	250 m	2020
	Rainfall	Rainfall station point feature	IDW	1:20,000	2021

hanced normalized difference vegetation index (ENDVI) was extracted from Moderate Resolution Imaging Spectroradiometer (MODIS) data which has a high biomass sensitivity capability due to the study area's location within the tropical biome. Image mosaicking, re-projection (WGS 84/UTM44N), subset, and resample tools were used to process extracted information from raster data sources. The land surface temperature was calculated using Landsat 8 operational land imager (OLI) data from the USGS data server (https://earthexplorer.usgs.gov/). Based on the digital data, the settlement density layer came from the Global Human Settlement Layer prepared by the European Commission (https://ghsl.jrc.ec.europa.eu/s1_2017.php). The digital data layer of population density was created using 2022 statistical data from the Department of Census and Statistics. All other land use data layers related to HEC risk were extracted from the survey department's digital database. Since all spatial data layers come from different sources, resampling, re-projection and clipping functions were performed to maintain the same spatial resolution and extent.

2.3 Methods

The methodological flow to create habitat suitability and HEC risk index followed four main steps: selecting criteria, constructing decision hierarchy, collecting expert opinion, assigning weights using AHP, and evaluating elephant habitat suitability and HEC risk. The research flow is depicted in Fig. 2.

2.3.1 Selecting criteria

The initial step of GIS-MCDA is selecting the criteria and factors. The criteria were selected based on the previous GIS HEC research, especially in Asian countries, including India, Nepal, and China (Khanal, 2022; Baskaran et al., 2013; Chen et al., 2016). The study used nine relevant criteria (Table 1) for the elephant habitat suitability analysis. An acceptable set of criteria was chosen after analyzing those employed by similar studies in India and Nepal (Khanal, 2022; Baskaran et al., 2013), considering the environmental and socioeconomic context of the study area. These nine habitat suitability criteria were grouped as either land or environmental factors. The land factors included elevation, slope, land use, and size of the land area. The environmental factors included rainfall, ENDVI, distance to rivers, distance to tanks and reservoirs, and LST. Since HEC are mostly caused by human activities, to predict the HEC risk in the area, eight criteria (Table 2) were used, including population density, settlement density, habitat suitability, distance to elephant occurrences, distance to forests, distance to croplands, distance to roads, and distance to fences. Those criteria were grouped into i) proximity to risk and ii) risk exposure.

2.3.2 Constructing decision hierarchy

Integrating AHP with a GIS environment is crucial for processing available information further to assess the suitability of elephant habitats and predict the risk of HEC. Different MCDA models are used by decision-makers, such as the Dominance-based Rough Set Approach (DRSA), which explores knowledge holistically upon inferences (De Figueiredo et al., 2022). MCDA is an effective knowledge synthesis method that has been utilized in conservation to help identify suitable alternatives by integrating information from surveys, modeling, and stakeholders. The MCDA objectives and criteria are organized in a hierarchical structure known as "*decision tree*" (Adem Esmail and Geneletti, 2018). After defining the objectives, possible alternatives and criteria are established to achieve the objectives (Adem Esmail and Geneletti, 2018). The second stage is to perform the actual analysis, and criteria assessment, weighting, criteria aggregation, and sensitivity analysis, including quantification of alternatives. It can be based on either raw information or inputs from relevant stakeholders. The AHP approaches the issue indirectly by asking stakeholders to do a pairwise comparison of alternatives against each criterion, and then stakeholder results are summarized in a normalized matrix (Adem Esmail and Geneletti, 2018).

Accordingly, criteria are grouped into the hierarchical structure/decision tree (**Fig. S1**) when finding suitable habitats for elephants and HEC risk. Thus, in the decision hierarchy finding elephant habitat suitability was on the first level, and environmental, and land factors were on the second. Each criterion under these factors is represented in

Table 2
Description of factors and criteria used in HEC risk prediction.

Factor	Criteria	Raw data type	Processing method	Resolution/scale	Year
Proximity to risk	Distance to elephant occurrences	Point feature	Euclidean distance function in arc Geo-processing	1:20,000	2010–2022
	Distance to forests	Polygon feature	Euclidean distance function in arc Geo-processing	1:20,000	2020
	Distance to fences	Polyline feature	Euclidean distance function in arc Geo-processing	1:20,000	2022
	Distance to roads	Polyline feature	Euclidean distance function in arc Geo-processing	1:20,000	2020
	Distance to croplands	Polygon feature	Euclidean distance function in arc Geo-processing	1:20,000	2020
Exposure to risk	Habitat suitability	Raster data	Raster reclassify	30 m	2022
	Population density	Vector data	Calculate geometry in arc GIS	1:20,000	2020
	Settlement density	Raster	Feature to point and Raster reclassify	10 m	2018

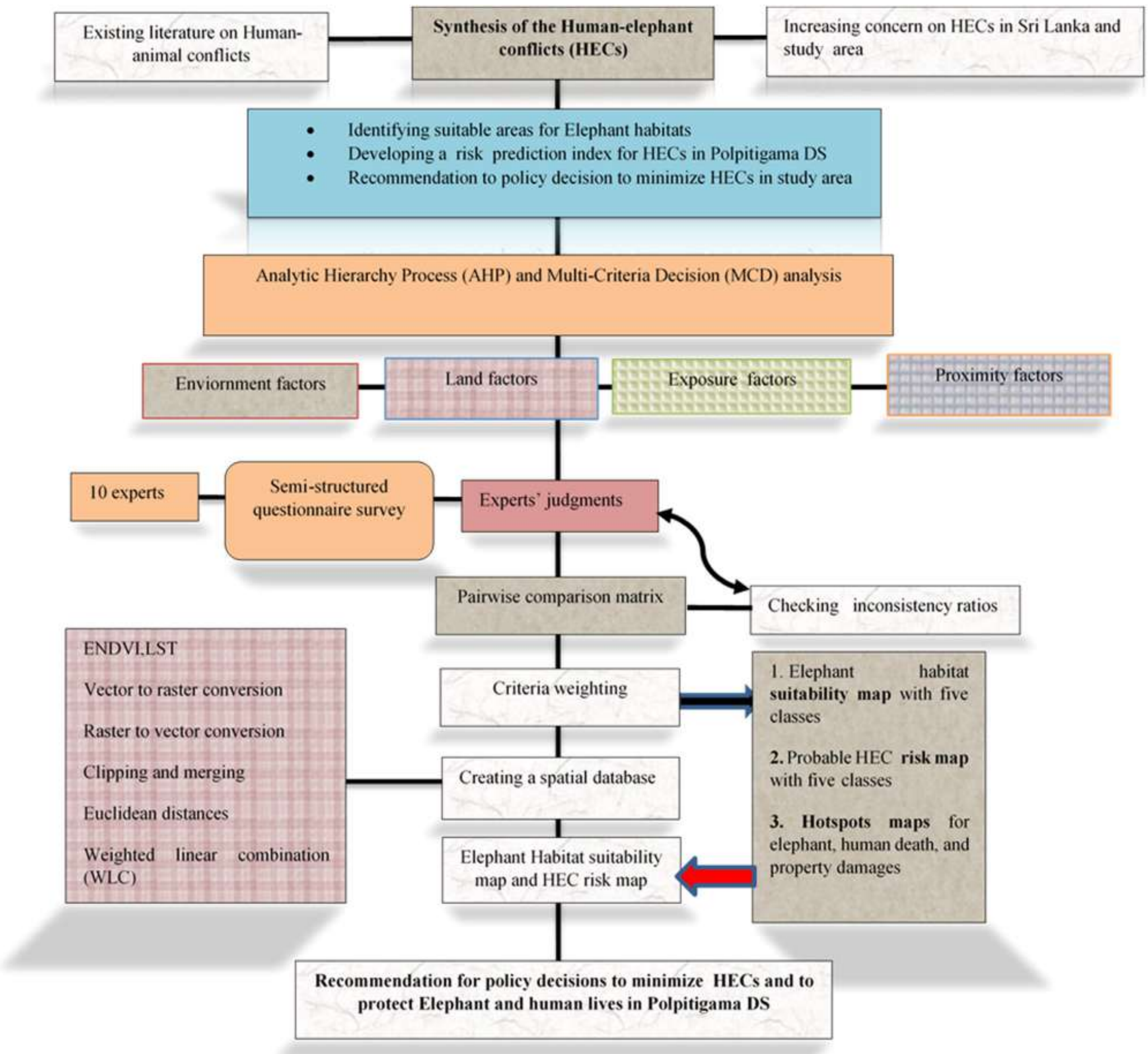

Fig. 2. Methodological flowchart of the study.

level 3. In the case of the HEC risk prediction, the first level was the objective of the HEC risk analysis. Level 2 comprised two factors, including proximity and risk exposure **(Fig. S2)**. Eight criteria considered to find HEC risk in the study area were under level 3.

2.3.3 Collecting expert opinions

Weights for each criterion were determined using expert judgments on ten questionnaire responses from geo-informatics, conservation biology, ecology, forestry, and biogeography experts. At first, face-to-face interviews were done when experts were available despite their busy schedules, with each expert outlining the scope and major objective of the study. Following that, criteria weighting and ranking suitability and HEC risk were received using semi-structured questionnaires. The first section of the semi-structured questionnaire comprised the 16-comparison matrix for habitat suitability and 14 matrices for HEC risk prediction constructed to assign weights for criteria and factors on Satty's 1–9 scale. The second section is allocated to rank each criterion using attribute values as a range from 1 to 5 (1=least suitable/least risk, 2=low suitable/low risk, 3=moderate suitable/moderate risk, 4=high suitable/high risk, and 5=very high suitable/very high risk).

2.3.4 Assigning weights using AHP

The AHP is a globally accepted subjective technique used to assign weights for different criteria in multi-criteria decision analysis. Based on Satty's 1–9 scale the experts were asked to rank the factors and criteria for habitat suitability and HEC risk prediction. The GNU Octave 7.3 software calculates the criteria and factors, AHP weight, consistency index, and consistency ratio.

The influence of one criterion over another was determined by expert comparison judgment; if the two criteria had equal influence, the score was one. If one criterion had an extreme influence over the other, the score was nine (Saha and Roy, 2021). Because the geometric mean is consistent with the judgment and priorities, the judgment values of ten experts were combined into a group judgment (Satty, 1990; Bamrungkhul and Tanaka, 2022). Weights were determined using the arithmetic mean method after normalizing each value by dividing the actual value by the sum of the column values in a pairwise comparison matrix (Satty, 1990; Saha and Roy, 2021). The pairwise comparison matrix was then prepared using geometric mean values. After calculating the weights for each criterion in every AHP-based analysis, it was essential to calculate the consistency ratio (CR) to check the consistency level made by experts. The consistency was checked using the same index developed by Satty (1990), which is as follows (Saha and Roy, 2021):

$$CR = CI \div RI \times 100 \tag{1}$$

CR stands for consistency ratio, CI stands for consistency index ratio, and RI stands for random inconsistency index of randomly derived pairwise comparison matrix of one to ten generated by approximating random indices.

The CR equation derived CI using the following equation (Saha and Roy, 2021).

$$CI = (\lambda - n) \div (n - 1) \tag{2}$$

If the CR value is lower than 0.1 it can be acceptable, and if it is higher than 0.1 assumption/opinion becomes inconsistent. The derived CR value was lower than 0.1, making the criterion weights reasonable and acceptable.

2.3.5 Evaluating elephant habitat suitability and HEC risk

The Arc Map 10.8 (ESRI) spatial analysis extension capabilities make modeling computations simpler and provide an appropriate environment for displaying a variety of factors and variables as raster and vector datasets with spatial controls. Several spatial procedures must be followed to achieve the two goals of finding elephant habitat suitability and predicting the HEC risk in the study area. Initially, the spatial database was created, then all spatial data layers related to habitat suitability and HEC risk mapping were reclassified using the weights and rating scores derived through AHP results. As the intermediate point of HEC risk prediction elephant habitat suitability index was evaluated using the following equation:

$$HSI = \sum_{j=1}^{n} W\ j\ w_{ij} \tag{3}$$

HSI denotes the habitat suitability index and W is the total weight value of the criteria.

The weight value of class I for criterion j from the rating pattern is w, and n is the number of criteria at level three. Using the same equation HEC risk index is also calculated as:

$$HECI = \sum_{j=1}^{n} W\ j\ w_{ij} \tag{4}$$

HECI denotes the HEC risk index and W is the total weight value of the criteria. The weight value of class I for criterion j from the rating pattern is w, and n is the number of criteria at level three.

The Weighted Linear Combination (WLC) method was used to derive the maps of habitat suitability and HEC risk, which multiplied the weight of each criterion map from the AHP with the rating score to evaluate the habitat suitability and HEC. The sum of the multiplied values from each criterion was then used to calculate the habitat suitability and HEC risk indexes. Because this method is commonly used to categorize suitability levels, the Jenks natural breaks classification technique divided the habitat suitability areas into five categories: very high, high, moderate, low, and least suitable (Bamrungkhul et al., 2022). HEC risk was also divided into five categories: least risk, low risk, moderate risk, high risk, and very high risk.

2.3.6 Evaluating human-elephant conflicts

Spatial analysis tools in Arc Map 10.8 were used to identify the spatial patterns and characteristics of HEC point data over space. Thus, each HEC incidence point data was used to identify the spatial pattern of the HEC in the study area. In that way, the distribution and clustering patterns of human and elephant deaths, and property damage (destruction of housing/other constructions) were mapped using kernel density analysis. The area-wide HEC incident density maps were created to identify specific regions with higher concentrations of occurrences as hot spots and to assess whether any natural or artificial qualities in the research area are related to the measured density.

3 Results

3.1 Elephant habitat suitability

Tank distance scored high in relation to environmental factors, while LST had the lowest weight (**Table S1**). Moreover, both rainfall and river distance received low but equal weights. In the case of land, the size of the land scored a high weight (**Table S2**), while land use component was of secondary importance. The slope was the least significant, while elevation contributed as the third importance criterion (**Table S2**). After assigning weights it was possible to observe different suitability levels as per the spatial variations of each criterion (Fig. 3). The results place the northern region and a few eastern GNDs in the least suitable range. Because of their proximity, nearby GNDs to the KPK nature reserve are the best areas when considering the land criterion.

The area is the best habitat for wild elephants since almost 15% (60 km^2) is in very high and 25% in high suitable classes, and 33% (133 km^2) is moderately suitable. In comparison, low and least suitable areas contribute 25% together (**Fig. S4**). Most very high and highly suitable areas are found in forests, nature reserves, and scrub areas. In contrast, moderately suitable areas are found in gardens when analyzing the geographical distribution of suitability classes over land use occupancy. The paddy cultivation areas are the least suited class for habitat suitability. Overall suitability ranking environment and land were equal (**Table S3**) according to the results of expert judgments. Accordingly, the southern and central regions of the DS (Fig. 4) exhibit very high and highly suitable locations for elephants in terms of environmental criteria.

3.2 HEC risk

Five probable risk zones for HEC in the DS were identified at varied spatial extents (Fig. 5). Among three exposure factors, population density received a high weight (**Table S4**). In contrast, habitat suitability received a low weight (0.13929). According to the weights and scores given by experts, distance to forests and elephant occurrences were rated as equally important (**Table S5**) in the HEC risk assessment in the DS. In contrast, cropland distance, and fence distance were rated equally but less important. When determining the probable HEC risk in DS, the proximity factor received a high weight (**Table S6**), while exposure contributed relatively less weight.

However, when taking a more comprehensive look, the study area indeed has a comparatively high probable HEC risk situation (Fig. 6). The very high and high categories cover about 32.2% (127 km^2), whereas a probable low-risk zone only covers 17.8% (60 km^2) of the total area (**Fig S4**). Furthermore, 26.1% (103 km^2) of the land area was identified as moderate risk. While looking at the spatial distribution of the probable HEC risk map, most areas, except for the western and southwestern parts, are at risk for HEC. In particular, most GNDs along the eastern boundary that blend forests and protected areas in the east and southeast are very high-risk locations for HEC. Moreover, the several GNDs in the central part of DS with scrubs are in high and moderate probable risk zones.

3.3 Spatial pattern of HECs

According to the Kernel density estimate results, most HEC incidents, including human and elephant deaths and property damages were

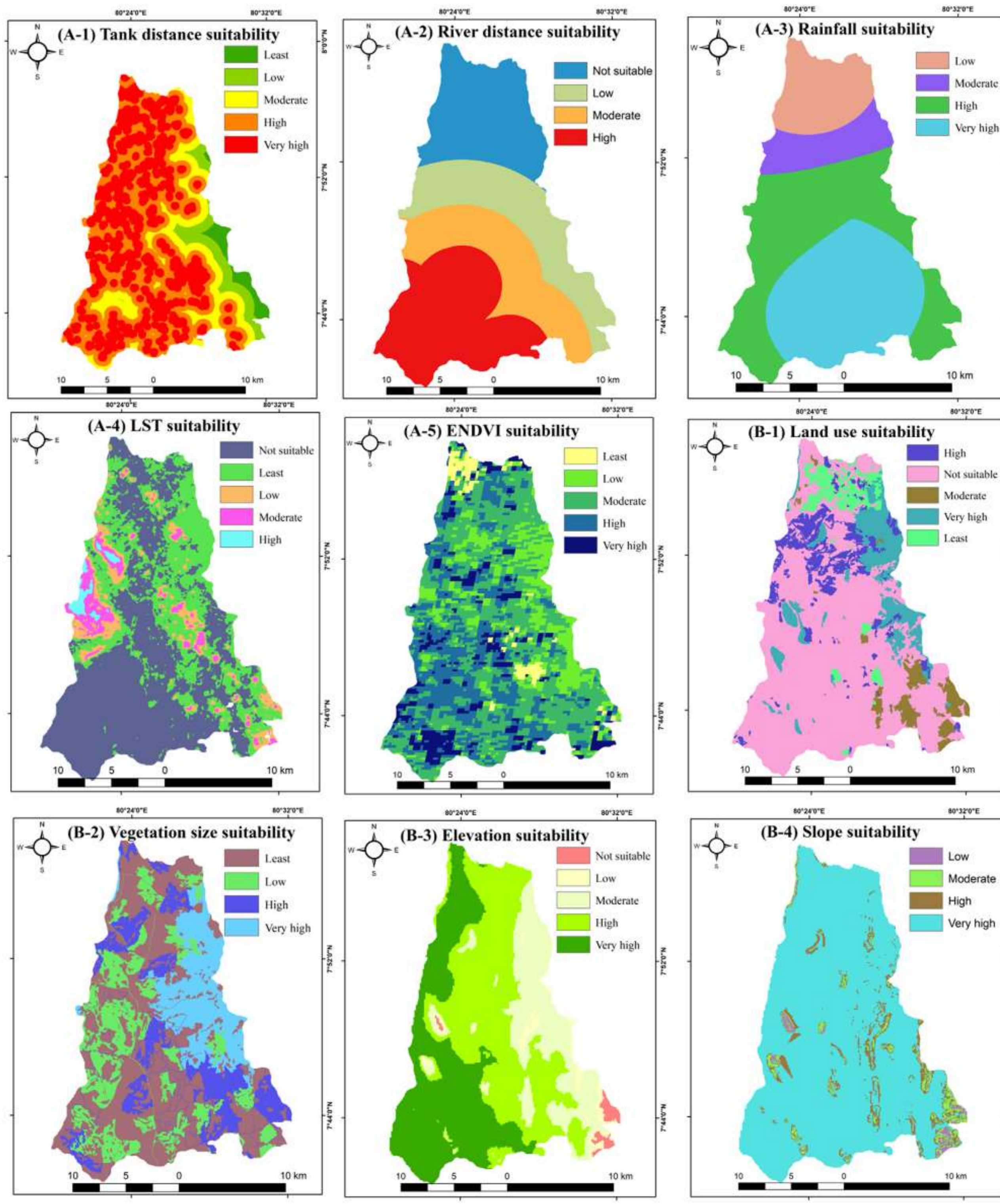

Fig. 3. Elephant habitat suitability based on environmental and land factors.

concentrated in the southeast part of DS (Fig 7). There were 13 human deaths from elephant attacks which showed an HEC hotspot in the GNDs, close to Rambe and Maeliya. Moreover, several GNDs near Madagalla and Pallekele are two hotspots for elephant-caused human fatalities. Regarding the extent of the property damage caused by elephants, a similar spatial concentration pattern was seen in the southeast part of the DS.

There were several places of property damage along the route of the Kahalla-Pallekele elephant corridor from the southeast corner to the northeast region of the DS. The case of the elephant deaths, they are similar to the pattern of human deaths.

4 Discussion

4.1 Suitable habitats for wild elephants

The wild elephant population in Sri Lanka is declining, owing primarily to habitat loss and fragmentation caused by expanding human

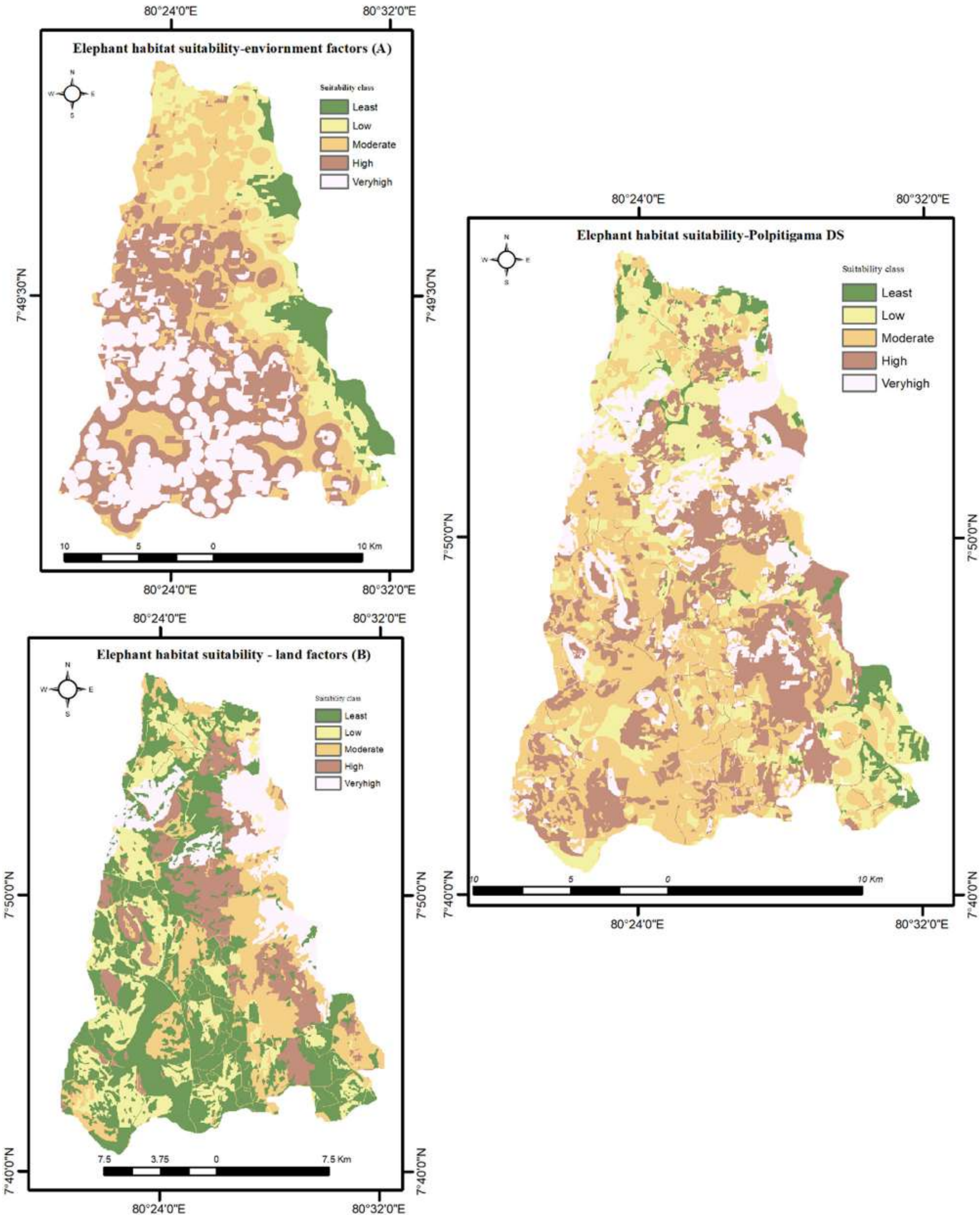

Fig. 4. Elephant habitat suitability in Polpitigama DS.

populations and increased demand for resources (Rathnayake et al., 2022a). Forests and other natural vegetation areas in DS are highly suitable for wild elephants near the KPK sanctuary. A similar study of the Nepal transboundary (Khanal, 2022) also found that 1/3 of the study area was suitable for elephants based on the results of GIS machine learning techniques that integrated eight criteria, including climate, water, vegetation, and topographic factors. Due to encroachments of forests by people (settlements, paddy fields, homesteads, *Chena*) are most preferable for elephants. Similar studies in Asia showed that the forest and non-forest elephant habitat ratio was 50:50, with over-

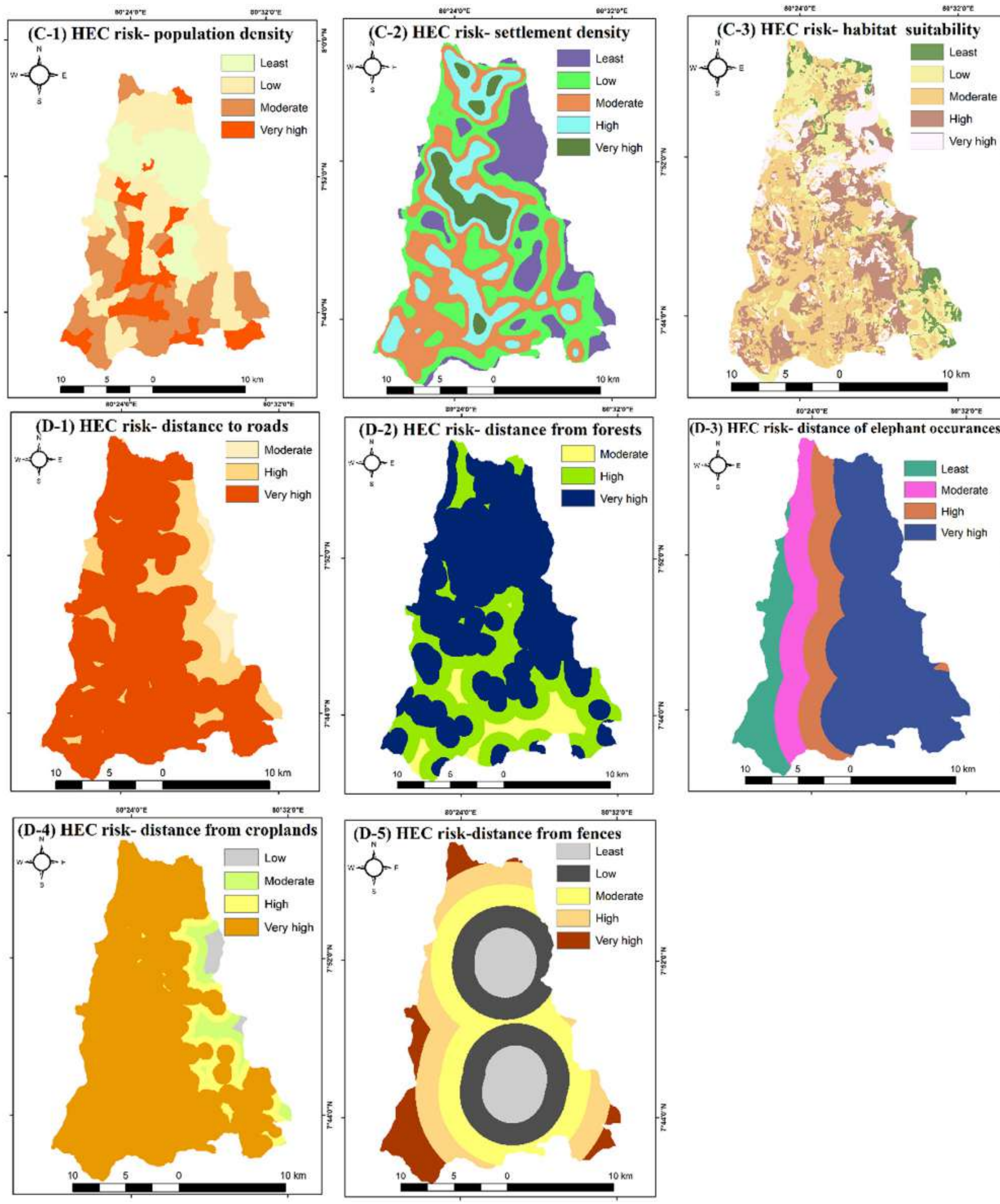

Fig. 5. HEC risk zones for exposure and proximity factors.

lapping land and resource utilization between elephants and humans (Khanal, 2022; de la Torre et al., 2021).

4.2 Factors affecting habitat suitability

Though in overall suitability, elevation, and slope act as less important factors for habitat since the area is comparatively flat. Most of the study area's lands are highly suitable habitats for elephants, except for the mountainous areas in the east and southeast. The slope factor is also advantageous for elephant habitats in the DS due to the slight gradient in most of the lands. In Nepal, Khanal's study found that the rich forest covers at high terrain are highly suitable areas for elephants. Khanal found a correlation between slope and elevation that prevent elephants from rugged terrain and steep slopes. A similar study in peninsular Malaysia (Mohd et al., 2021) found that elephants prefer low-elevation forests with water. In the study, it was shown that most low-elevated areas

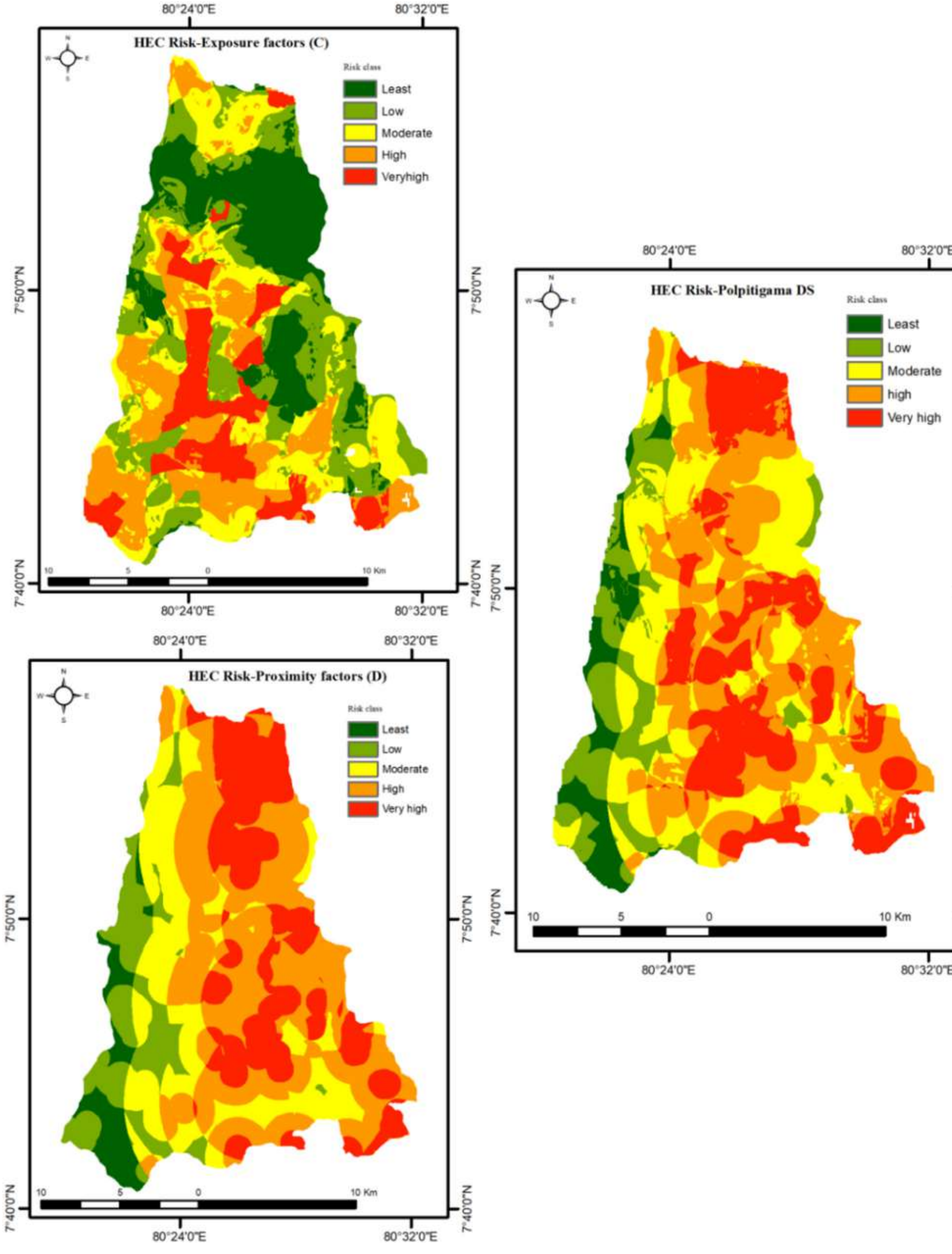

Fig. 6. Probable HEC risk zones of DS.

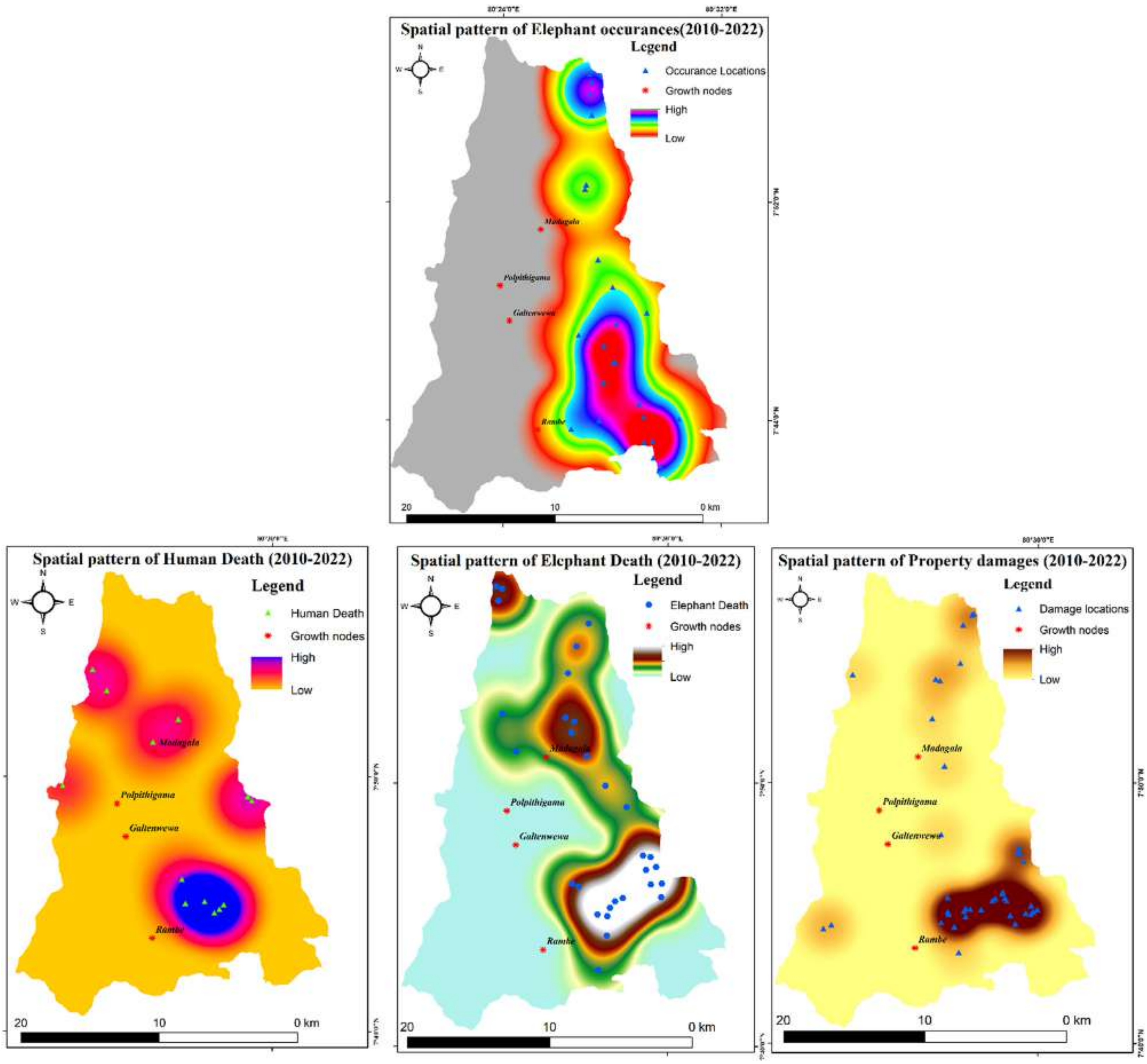

Fig. 7. Spatial pattern of HECs between 2010 and 2022.

with tanks are highly suitable for elephants. Water availability often influences the movement of elephants. Based on tank distance, most of the study region favored elephant habitats. Williams et al. (2008) proved that elephants prefer habitats near water resources linked to general water requirements and thermoregulation. de Knegt et al. (2011) found a similar pattern in African elephant habitats since elephants avoid steep slopes. The results show that areas with high precipitation are most suitable for elephants. The findings are consistent with Li et al. (2019) that confirmed the influence of precipitation on habitat suitability. Regarding environmental criteria, the southern and central regions of the DS are very high and high suitable locations for elephants.

4.3 Determining factors of HEC risk

Human-elephant conflict is a major threat to elephant survival, especially in rural agricultural areas where human populations are growing and encroaching on elephant habitats (Fernando et al., 2011). Accordingly, the results prove that people in DS cause a high risk of HEC. Habitat and HEC risk maps show that most HEC risk areas have very high and high suitable areas for elephant habitats due to increased human interference. Kernel density estimation proved that most HEC incidence occurred in the highly suitable areas for elephants along the boundary of the KPK sanctuary. A similar trend was identified in the Nepal study that showed the high probability of HEC risk between and around protected areas like Baridya NP and Katarniyaghat WS (Khanal, 2022). Because local people depend on nearby forests and tank-based water resources for their farming, cattle grazing, and water intake, it was evident that there is a high HEC risk for the settlements near those areas since elephants also prefer forests and water resources. According to Khanal (2022), crop raiding and physical property damage are more noticeable in Nepal's protected area boundaries. Comparing human deaths, elephant deaths, and property damage to the HEC risk maps, most incidents were in the high-risk zone of the HEC since traditional migratory routes of elephants are negatively affected by human settlements, and croplands as reported in previous studies in Nepal and north Bengal (Khanal, 2022; Naha et al., 2019). As a result, wildlife authorities have taken some measures to minimize HEC risk, especially along the villages of the KPK sanctuary (**Fig. S5**).

4.4 Limitations and future research direction

Due to time constraints and a lack of digital data, the study should have considered the factors related to ranging patterns, elephant population, forage quality, forest canopy, height, and management practices. However, the study indicates the importance of using the GIS-MCDA approach for elephant habitats and HEC risk in human-dominated landscapes. Integrating other factors in future spatial modeling of habitat suitability and HEC risk studies in Sri Lanka will be more helpful in getting a comprehensive spatial-temporal insight into elephant habitat suitability and HEC risk prediction.

5 Conclusions

The study utilized the GIS-MCDA for indexing elephant habitat suitability and HEC risk in a human-dominated landscape, integrating different criteria. About one-third of the study area is highly suitable for elephant habitat, and most of these areas are in forests. Both environmental conditions and land criteria equally contributed to elephant habitat suitability, while proximity factors are most significant factors in HEC risk assessment. Most high HEC risk zones are within suitable areas for elephants, a sign of the high human interference in elephant habitats. As a result, settlements located on traditional elephant migratory routes are more prone to HEC occurrences like property damage and human deaths. Facilitating and maintaining elephant corridors that connect forests and the KPK sanctuary is crucial to achieving positive outcomes for both humans and elephants.

Ethical statement

Ethical approval was not required for this study since human participants were ensured following local legislation and institutional requirements. All proceeds of this research were carried out following the Helsinki Declaration principles of human subject investigation. Participation in this survey was anonymous and voluntary, assuring consent of prospective respondents before participation. Data accumulated for this research was treated confidentially.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.geosus.2023.08.004.

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PLOS ONE

RESEARCH ARTICLE

A quality of life index for the rural periphery of Sri Lanka using GIS multi-criteria decision analysis techniques

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Abstract

Spatial evaluation of the region is associated with the assessment of the Quality of Life (QoL). Despite numerous research endeavoring to define, measure, quantify, and map the quality of life, there exists a consistent fault in Sri Lanka. Hence, the objective of this study was to construct a QoL index and determine the spatial disparities of QoL from the Polpitigma town to its periphery. The assessment was conducted by employing 20 geographical factors that quantify QoL using the Geographic Information Systems (GIS). The evaluation assigned weights to each criterion based on the assessments of both local residents and experts, utilizing the Multi-Criteria Decision Analysis (MCDA) and the Analytical Hierarchy Process (AHP). The findings indicated that cultural factors made a greater contribution compared to the environment,service functions,security and socioeconomic factors. Within the study area, the region with a higher quality of life (HQoL) only covered 4.5% (17.3 km^2), whilst the lower QoL zone encompassed 63.8% (252 km^2). And also, the distance from the town is a crucial factor in determining the spatial variations in QoL. The derived model can serve as a road map for local-level planning, as it has been validated and shown to have an accuracy of 74% through the Receiver operating characteristic (ROC) curve. Considering the lack of previous research in this field, this study offers a crucial contribution in enhancing the QoL for underprivileged communities in the study area by improving employment, income, and accessibility to physical infrastructure, public utility services, and cultural and recreational facilities. Especially the findings of this study can efficiently guide decisions for the distribution of financial resources to enhance the QoL in impoverished rural communities on the rural periphery of DS.

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Introduction

The topics of Quality of Life (QoL) and social well-being have long been the focus of attention. However, in recent decades, there has been a rise in studies exploring these subjects using multi-disciplinary approaches. Researchers in the fields of social science, environmental science, and health science have shown a special interest in topics related to the quality of life [1]. Consequently, numerous definitions of QoL have been published in the international literature [2]. Contrary to the commonly held idea that QoL is mostly linked to health, in actuality QoL is a complex subject that poses difficulties in its definition from a singular standpoint. Various factors were considered when addressing QoL, as indicated (**S1 Fig**) in previous research [3,4]. Thus, it is evident that QoL is centred around enhancing one's overall well-being, as explicitly outlined by the World Health Organization's Quality of Life (WHOQOL)[5]. The World Health Organization (2012) defines quality of life as the subjective evaluation individuals make about their position in life, taking into account their objectives, ambitions, standards, and concerns, within the framework of the culture and value systems of their society. This method encompasses various components like as physical well-being, psychological state, degree of autonomy, social relationships, and personal beliefs, along with their interactions with significant environmental elements [6].The research remains focused on assessing the quality of life, taking into account the physical and social environment, societal expectations, and the changing importance of these needs throughout time. Several recent studies have been conducted to evaluate the QoL on both a local and global scale, and several methodologies have been proposed for these assessments. QoL indices and maps facilitate decision-making for targeted interventions aimed at enhancing QoL within the focused area by effectively displaying the spatial distribution [7–10]. Extensive study has consistently shown that an individual's QoL is closely linked to their residential location. In simpler terms, a favourable living environment is indicative of a favourable life [11–13]. Therefore, when assessing the QoL in a certain area, it is crucial to primarily consider the characteristics that contribute to the overall QoL in that particular place. Prior studies have shown that a diverse set of indicators and criteria, encompassing demographic, socioeconomic, and physical characteristics, can be employed to evaluate the quality of life in different geographical areas. Examining the spatial analysis of the QoL of individuals in different regions is particularly advantageous and essential for decision-makers in local-level governance, as it effectively illustrates the distribution of resources in the area. Thus, much research has been conducted to guide government agencies and policymakers in an international context though it is very rare in Sri Lanka.

According to the expert's perspective, the optimal and suitable conclusions are often achieved through the evaluation of numerous possibilities, a process aided by the application of the AHP. MCDA approaches were created by two schools: American and European operational research schools. While the American School largely concentrate on the functional approach that leverages value, the European school focuses on the relational notion. In this context, the AHP, TOPSIS, and MAUT methodologies are the most often used MCDA approaches created by American schools. ELECTRE, PROMETHEE, and NAIADE are the most prominent MCDA techniques established by European schools. Because AHP can recognize and balance the relevance of complex aspects, researchers regularly utilize it to support decision-making in the process of environmental planning and natural resource management. Over mentioned MCDM methodologies, AHP obtains more attention in suitability analysis due of its flexibility and practical application. Thus, in many prior studies, most researchers have utilized AHP to locate suitable sites in diverse spatial and socioeconomic perspectives. AHP can calculate the ratio values for many criteria by means of pairwise comparison. Subsequently, weights can be allocated to each criterion for assessment [14]. The AHP is a highly effective technique for policy-making that involves generating ratio scales from the collection of judgement [15–19]. During the AHP process, several processes must be undertaken, including establishing objectives, delineating criteria and elements for various levels, and ultimately constructing a hierarchical structure [20–22]. The AHP and MCDA are extensively employed in spatial decision-making research because to their numerous benefits, such as time efficiency and cost-effectiveness. MCDA can be employed as a methodology to minimize cost and time in spatial decision-making. Therefore, it is evident that GIS is a crucial tool for accurately identifying the connections between several criteria [20,23].

A number of studies have been conducted in the context of life quality variance employing GIS technology. Faka et al., [24] used a variety of QoL influencing characteristics to customize and evaluate life quality in Greece. Another study suggests an integrated methodology for analyzing and mapping QoL at a micro-scale in Katerini, Greece [6]. Studies have also been conducted by integrating GIS and location-allocation models with MCDA. El Karim and Awawdeh [25] attempted to assess the QoL in Buraidah City, Saudi Arabia. Zhong et al., [26] used a data-driven analytical strategy to examine living handiness in Kaifeng City, China using multi-sourced urban information and geo-design methods on an individual scale. Merschdorf et al., [27] attempted to customize and analyze the correlation between urban attributes and peoples' discerned quality of city life using statistical analysis and geospatial analysis. Karadimitriou et al., [28] analyzed the spatial distribution of multiple deprivations and established a connection between geographical patterns and the history of urban development access in Athens. Garau and Pavan [29] have demonstrated that the development of qualitative and quantitative descriptors of urban environments can benefit from a system of indicators. By combining census data warehouse analysis with remote sensing-derived characteristics, Rao et al., [30] in their study also evaluated the quality of life in the state of Uttarakhand, India utilizing Geoinformatics. All the studies revealed that life quality mapping is a powerful decision-making tool that identifies the factors to be considered to improve life quality in a particular area. However, due to Sri Lanka's lack of technical advancement, it is difficult to access research that aids decision-makers, particularly in local-level planning. There is only one available research conducted by Dissanayake et al.,[23], which discusses the evaluation of QoL using the GIS technique. This research specifically focuses on the city of Kandy in Sri Lanka. This study focuses on the development of a QoL index. The index is constructed based on 13 criteria and highlights the application of GIS to visually represent spatial variations in QoL.

Galagamuwa, Mahawa, Polpitigama, and Abanpola DS in the Kurunegala district are economically underdeveloped because of the geographical and socioeconomic disparities. Polpitigama is particularly notable due to human-elephant conflicts and droughts as well.Therefore, rural communities in Polpitigama are encountering numerous challenges in their day-to-day living. Hence, it is crucial to implement remedial planning measures at the local level in order to enhance the QoL for the underprivileged segment. Thus, this DS was chosen as the experimental object. Building upon the same limitation observed in earlier research conducted at both national and local levels, this study aimed to derive a QoL index and evaluate the spatial disparities of QoL using spatial techniques within a relatively small geographical area. This approach was chosen to ensure more accurate and reliable results, since it effectively accounts for spatial heterogeneity.Therefore, this study tried to address the current deficiencies in research by incorporating specific QoL factors and indicators that are relevant to the underdeveloped study area.Hence, a QoL variation index was created in Polpitigama DS by incorporating various variables in the GIS environment. Additionally, an attempt was made to quantify the impact of the distance from the city centre on differences in QoL as one moves out from the town center. The reliability of the derived index was ensured by validating the QoL map through field verification. This will serves as a comprehensive road map for local-level planning in the study area, with the goal of improving the QoL.

Materials and methods

Description of the study area

The Polpitigama Divisional Secretariat is situated in the Kurunegala District (Fig 1) of the North Western Province in Sri Lanka. It is positioned between 80˚.20 E to 80˚.32 E' and 7˚.40' N to 7˚.79' N latitude, covering a land area of 389.9 km^2. The research area is delimited by the Divisional Secretariats of Glanewa and Palagala to the north, Galewela and Ibbagamuwa to the east, Ganewathha DS to the south, and Mahawa and Ehetuwewa to the west, based on its relative location. The DS elevation varies from 77m and 506m above mean sea level. The DS exhibits a combination of dry and intermediate climatic characteristics, with an approximate mean annual temperature of 23.4–C. Based on the US Air Quality Index (AQI) value, it is evident that the air quality in the Kurunegala district, including the study region, is within the usual range, typically ranging from 28 to 37. The southern part of the DS generally experiences an annual precipitation of 1750 mm, whereas the northern area normally receives 1500 mm. The study area consisted of 294 villages and 82 Grama Niladhari Divisions, with 93,795 total

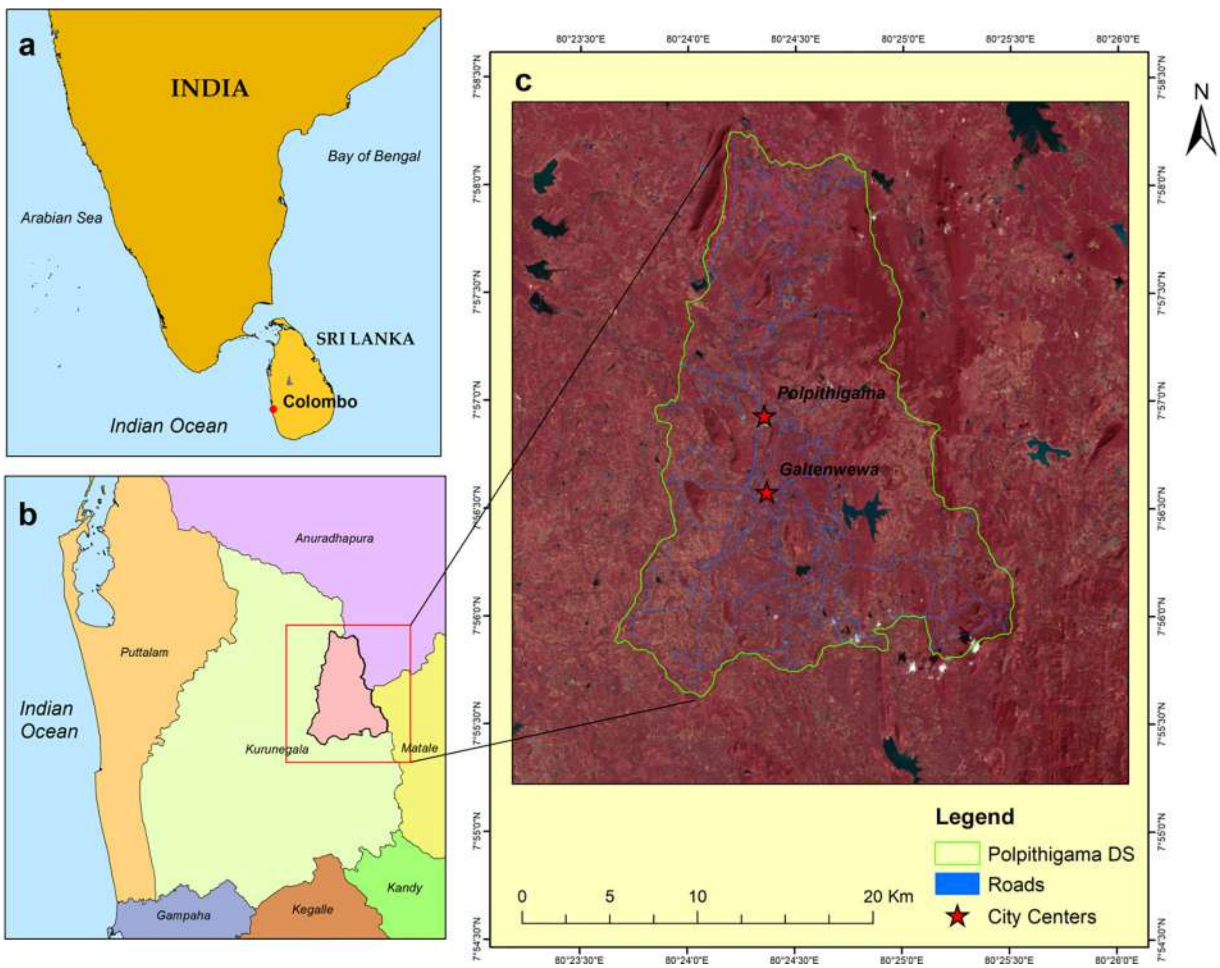

Fig 1. Location maps: **(a)** Sri Lanka in the Indian Ocean.The World topographic map was obtained at ArcGIS and is the property of ESRI, used herein under license [31]. The copyrights belong to ESRI, but according to the terms of use, the copyright holder does not need to apply for permission to use because it is free for academic publications, and can be used freely and commercially under the CC BY 4.0 license.; **(b)** Location of Polpitigama DS.; **(c)** Polpitigama DS in Landsat8 false colour (5,4,3) composite. Map was edited by authors using United States Geological Survey Earth Explorer Landsat images [32].

https://doi.org/10.1371/journal.pone.0308077.g001 population, covering a land area of 38,995 hectares. Among the 22,994 household units, 16,946 (41.2%) are engaged in agricultural activities, while 5,684 individuals work in government sectors and 364 in semi-government sectors. The total number of dwellings is 25,682, consisting of 21,926 permanent residences, 2,999 semi-permanent homes, and 757 temporary residences.

Materials

The study utilized 20 spatial data layers, which used in earlier research on GIS-integrated QoL assessment and formal interviews with randomly selected experts [6–7,23–24]. The spatial data layers were classified into five criteria: environment, service functions, cultural, security, and socioeconomic. Criteria and factors were structured in a hierarchical tree and evaluated using MCDA in conjunction with GIS spatial analysis tools. Geographical phenomena often determine environmental elements, whereas cultural, security, service functions, and socioeconomic factors are influenced by human activities. The attributes of each aspect and their relevance to QoL and the nature of the raw data is illustrated in **S1 Table**. The data were collected from both primary and secondary sources. The Global Positioning System (GPS) was utilized to collect location data of the schools, healthcare facilities, postal services, security, historical sites, libraries, and religious places.

The Land Surface Temperature (LST) spatial data layer was generated by utilizing USGS Landsat8 OLI/TIRS data acquired from the USGS website (https://earthexplorer.usgs.gov/).The risk index of HEC was determined by utilizing both secondary and primary data collected in previous research conducted in the same study area. The statistical data obtained from the DS office was utilized to create density maps for power, telephone, income, sanitary facilities, and drinking water.

Methods

The spatial indexing of QoL was conducted using a methodical flow consisting of four steps: selecting criteria, establishing a decision hierarchy, weights assignment, and deriving the QoL index.

Selecting criteria. The initial analysis stage involved the careful selection of criteria and factors. The study selected five categories of criteria, namely environmental, security, service functions, cultural, and socioeconomic, after assessing the previous literature. Subsequently, a total of 20 factors were integrated in order to analyse the spatial disparities in QoL and establish a spatial index for QoL within the study area.

Constructing the decision hierarchy. To conduct the GIS-MCDA, it is important to organize and integrate the goal, criteria, and factors in a hierarchical framework. Following a thorough review of relevant literature and an examination of the background of the study area, the next phase was constructing an AHP framework. This framework was utilized to facilitate the analysis of spatial data and ultimately provide a QoL index for the area. The criteria and components were organized into a three-level hierarchical structure (**Fig 2**) during the process of creating the QoL index. The research aimed to achieve the goal at the first level of the decision hierarchy, while the second level consisted of five criteria. The third level consists of 20 factors that have been taken into account for the evaluation of QoL.

Weight assignments for criterion and factors should be conducted in a methodical manner. Pair-wise comparison matrices were utilized to ascertain the significance of each criterion and factor. The weights were derived from the expert opinion poll conducted using a semi-structured questionnaire. The experts were chosen based on their expertise in specific professional fields, particularly their research interests. Consequently, a panel of 10 experts specializing in GIS, sociology, geography, public policy, and planning provided their input on the prioritization and ranking of criteria and factors.

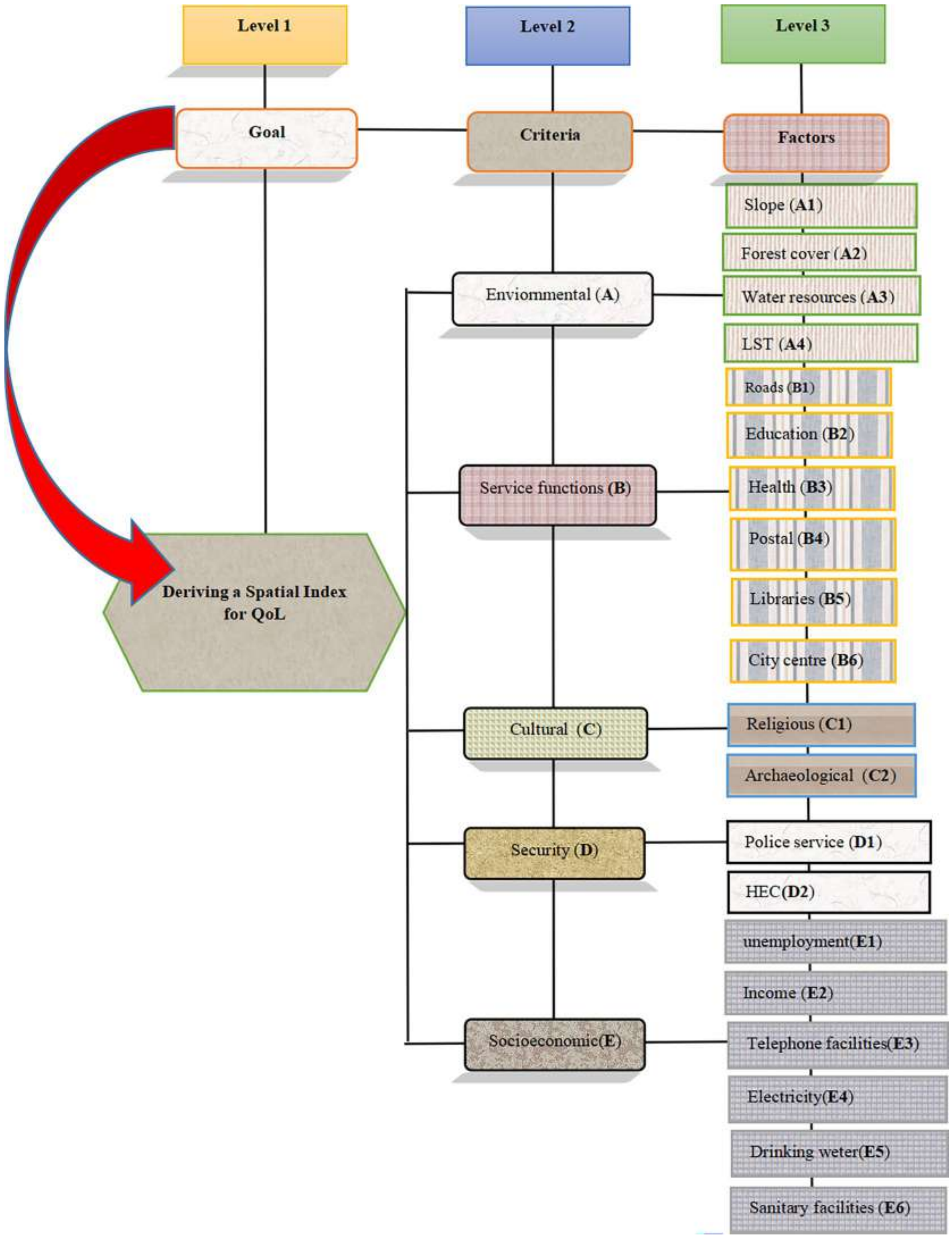

Fig 2. AHP structure of QoL analysis in Polpitigama DS.

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Weights assignment for criteria and factors. The experts were asked to prioritize the criteria and factors for evaluating and categorizing the QoL in the study area using Satty's 1–9 ratio scale. The judgement values of 10 experts were combined into a group judgment using the geometric mean, which is in line with the judgment and priority [14,26]. Following the process of normalizing each value in the pairwise comparison matrix by dividing it by the sum of the column values, weights were determined using the arithmetic mean approach [30]. The geometric mean values were subsequently utilized to construct the pairwise comparison matrix. Calculating the Consistency Ratio (CR) is essential in AHP-based studies to assess the degree of discrepancy in experts' judgment. This is done after finding the weights for each criterion. Utilizing the identical index established by Satty [14], the consistency was computed using the Eq (1);

$$CR = CI \div RI \times 100 \tag{1}$$

In the equation *CR* is the consistency ratio, *CI* is the ratio of consistency index and *RI* is the random inconsistency index. In the equation of consistency ratio (*CR*), *CI* was derived using the Eq (2);

$$CI = (\lambda - n) \div (n - 1) \tag{2}$$

If the *CR* numeral is less than 10% it can be acceptable and if it is higher than 10%,it means that the opinion of the expert is inconsistent. The derived CR value was lower than 10% and which means that the criterion weights are reasonable and acceptable.

The AHP method computed the consistency index and ratio for the 5×5 matrix of the main criteria to be 0.0487 and 0.0434, respectively. The consistency ratio was 0.0561, whereas the consistency index for the 5×5 matrix of socioeconomic factors was 0.0695. The 0.0985 consistency index and 0.0794 consistency ratio were reported for 5×5 service factors matrix. The consistency index and consistency ratio for a 4×4 matrix of environmental factors were 0.0654 and 0.0726, respectively. 1×1 security and cultural service matrices both returned consistency scores of negative infinity and zero.

Deriving the QoL index. The spatial analysis extension capabilities of Arc Map10.8 streamline modelling calculations provide a convenient environment for displaying different criteria and factors as raster and vector data sets. The purpose of the study was achieved by following a series of steps. The establishment of a spatial database marked the first phase. Subsequently, the weights and rating scores generated by the AHP and the findings of the questionnaire survey were utilized to reclassify all spatial data layers pertaining to the QoL. To calculate the QoL, the index weights that obtained were multiplied by their respective variables, and all the elements were then aggregated into a single layer. The QoL index was calculated using the Eq (3) [23];

$$QoLI = \sum_{i=1}^{n=20} x_i w_i \tag{3}$$

Here *QoLI* is the quality of life index, *xi* is factor *i*, and *wi* is the weight of factor *i*.

The QoL index is determined by dividing the area into four zones based on specific threshold values for factors as shown in **S2 Table**. These zones range from high QoL (HQoL) to the least QoL (LEQoL). The location that most effectively fulfil all requirements is the one with the highest quality of life. Upon meeting each requirement, the other two intermediate zones were also classified as Moderate Quality of Life (MQoL) and Low Quality of Life (LQoL).

Results

Criteria weight and consistency

The AHP analysis indicated that the socioeconomic criteria had a greater weight, specifically 0.3721 (**Table 1**). The pairwise comparison matrix for the main criteria and factors is presented in **S3–S8 Tables**, while the normalization of the main criteria and factors is provided in **S9–S14 Tables**. In the study area, service function rated as the third most important criterion,

Table 1. Weight assignment to criteria for QoL indexing.

Criteria	weight	Factor	weight
Environmental	0.0930	Slope	0.2725
		Forest cover	0.1274
		Water resource	0.5333
		LST	0.0666
Service function	0.2182	Roads	0.1414
		Education	0.3341
		Health	0.3341
		Postal	0.0479
		Libraries	0.0497
		City centre	0.0925
Cultural	0.0490	Religious	0.7509
		Archaeological	0.2490
Security	0.2673	Police service	0.1666
		HEC	0.8333
Socio economic	0.3721	unemployment	0.1829
		Income	0.2397
		Telephone	0.0481
		Electricity	0.0833
		Drinking water	0.3075
		Sanitary facilities	0.1383

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with a weight of 0.2182. On the other hand, security criterion dropped to second place, with a weight of 0.2673. Environmental and cultural factors were assigned minimal importance in the AHP computation.

The socioeconomic criteria assigned the maximum weight (0.3075) to the availability of clean drinking water, while the percentage of fixed telephone usage received a lower weight (0.0481). The security criteria were computed by assigning a high weight of 0.8333 to the probability of human-elephant conflicts, while a weight of 0.1666 was allocated to the proximity to police stations. The religious places in closest proximity obtained the highest weight (0.7509), whereas cultural facilities, specifically archaeological sites, were assigned a weight of 0.2490 during the evaluation process. The service functions assigned the highest weight, 0.3341, to both schools and healthcare institutions. Libraries and post offices, on the other hand, were given weights of 0.0479 and 0.0497, respectively. The environmental criteria assigned the highest weight (0.5333) to the proximity to surface water resources, while the lowest weight (0.0666) was given to the LST.

Spatial variations of QoL factors

The spatial variations of QoL in the DS for each of the 20 factors were illustrated in **Fig 3**. Due to the flat topography of the study area, with heights ranging from 77m to 506m above mean sea level, except for the southeastern portion which features mountains, the QoL is greater. Eastern border is home to the majority of its natural forests and protected areas. Consequently, these localities exhibit a higher standard of living compared to the western half.

Therefore, when near dense natural forests, most locations in the western part are classified as LEQoL. Several tanks are distributed throughout the western region of the study area, serving as surface water resources for agricultural and domestic purposes. This portion has a greater QoL index compared to the eastern section, which has a least and low QoL. The study

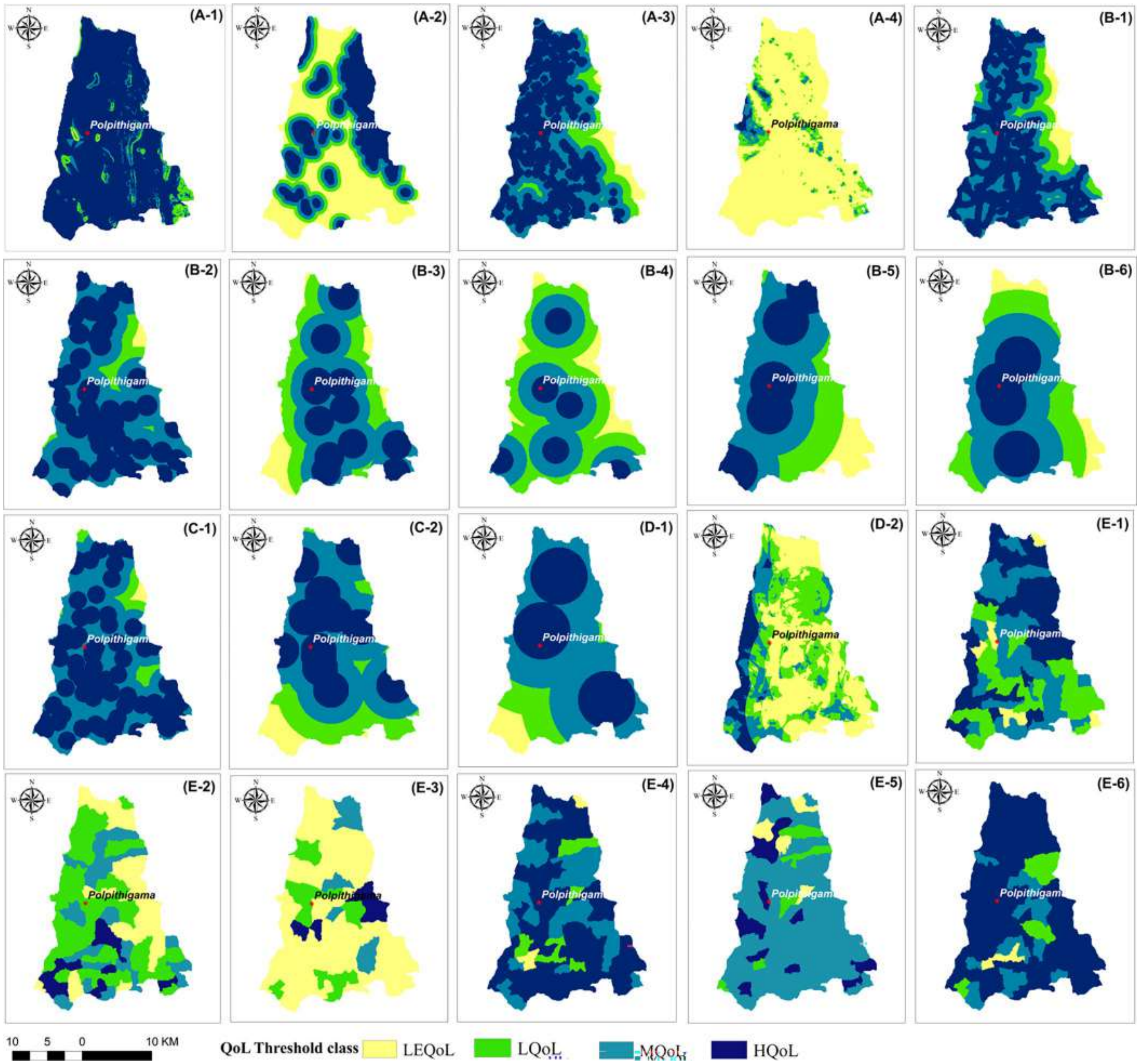

Fig 3. QoL threshold class maps: **(A-1)** Slope; **(A-2)** Proximity to forest; **(A-3)** Proximity to tanks; **(A-4)** LST; **(B-1)** Proximity to roads; **(B-2)** Proximity to schools; **(B-3)** Proximity to hospitals; **(B-4)** Proximity to postal facilities; **(B-5)** Proximity to library;**(B-6)** Proximity to growth centers; **(C-1)** Proximity to religious places; **(C-2)** Proximity to archaeological sites; **(D-1)** Proximity to police stations; **(D-2)** Human Elephant conflict risk; **(E-1)** Unemployment %; **(E-2)** Household income; **(E-3)** Fixed telephone facilities; **(E-4)** Electricity facilities; **(E-5)** Drinking wells; **(E-6)** Sanitary facilities. Maps were edited by authors using United States Geological Survey Earth Explorer Landsat images [32].

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area is often located in the dry part of the Kurunegala district, adjacent to the Anuradhapura district. Consequently, the QoL is typically rated as being in the low and least categories, based on the LST. The presence of forest areas has resulted in the LEQoL classes in areas close to roads. However, the dense road network in the western and southern parts of DS has significantly contributed to high QoL. These regions cover 61% (245 km^2) of the total area and just

11% (44 km^2) falls within the least QoL class. As a result of the limited number of government schools in the eastern region, the QoL in terms of school proximity is generally rated as very poor, covering an area of 164 km^2 (41%). In contrast, only 36 km^2 (9%) in the southern and central portions of the DS are classified as having HQoL in this regard.

Exception of Polpitigama Town, the health facilities classify Galtanwewa in the centre and Rambe in the south as areas with low and the least QoL respectively. The majority of the study area is devoid of postal services, with the exception of Polpitigama Town, Madagalla, Galtanwewa, and Rambe Junction. Approximately 70% of regions fall into the LQoL category due to inadequate library facilities. Almost 75% of localities fall into the high QoL category based on their closeness to cultural amenities. The majority of the DS is within the LEQoL category upon the proximity to police stations.

The eastern side of DS poses the highest danger of Human-Elephant Conflict due to its connection to the Kahalla-Pallekele (KPK) elephant corridor. Therefore, the areas with LQoL and the LEQoL encompassed a bigger portion of 221 km^2 (56%). Considering the HEC risk, only small areas in the western and southwestern parts fall inside the HQoL zone, which spans an area of 21km^2. The majority of GNDs have the HQoL when socioeconomic variables are taken into account. Nonetheless, most of the areas are in the zone with the LEQoL in terms of monthly income and fixed telephone connectivity. For instance, upon fixed telephone connection facility the LEQoL zone contributed 70% (282 km^2) while the HQoL zone accounted for 6% (25 km^2). Given the significant proportion of households with a monthly income of less than Rs.10000, the majority of the GNDs fall into the least and low QoL category, with the exception of four GNDs located in the southern part.

Quality of life index for Polpitigama DS

The QoL index was derived in the DS by integrating AHP and MCDA, through the overlay of five criteria. Fig 4 revealed varying levels of QoL for different criteria ranging from high to low.

In addition, Arc Map 10.8 software calculated descriptive data for the area coverage in both km^2 and the percentage contribution of each QoL class as Table 2. The cultural facility, which covered an area of 148 km^2, accounted for 36.9% of the HQoL zone. It had the greatest percentage among all the criteria in this class. The areas with the LEQoL in terms of cultural facilities are limited to small patches in the northeast and northern areas. The minimum area coverage for the HQoL class was determined to be 0.7% (2.5 km^2) based on security factors. Most communities, excluding the western section, have a LEQoL mostly because of the presence of the DS in the HEC risk area. The security criterion accounted for the biggest percentage (54.7%) of the LEQoL among the five criteria, covering an area of 216 km^2. On the other hand, the environment criteria had the lowest contribution (1.4%) to the LEQoL. Furthermore, there are no areas that fall into the least quality of life category based on socioeconomic criteria, and most of the GNDs are situated in the moderate quality of life zone, accounting for 76.6%.

The areas of Polpitigama, Madagalla, and Galtanwewa have become highly desirable locations due to the abundance of service facilities, resulting in a good quality of life. However, by amalgamating each criterion, these separate conclusions were distinguished. The results revealed that a mere 4.5% (17.3 km^2) of the total area of 394 km^2 met the criteria for high quality of life. In contrast, the majority of the area, accounting for 63.8% (252 km^2), fell into the low quality of life category (Fig 5). The zone with moderate quality of life accounted for 17.8%, while the zone with the least quality of life accounted for 13.9%.

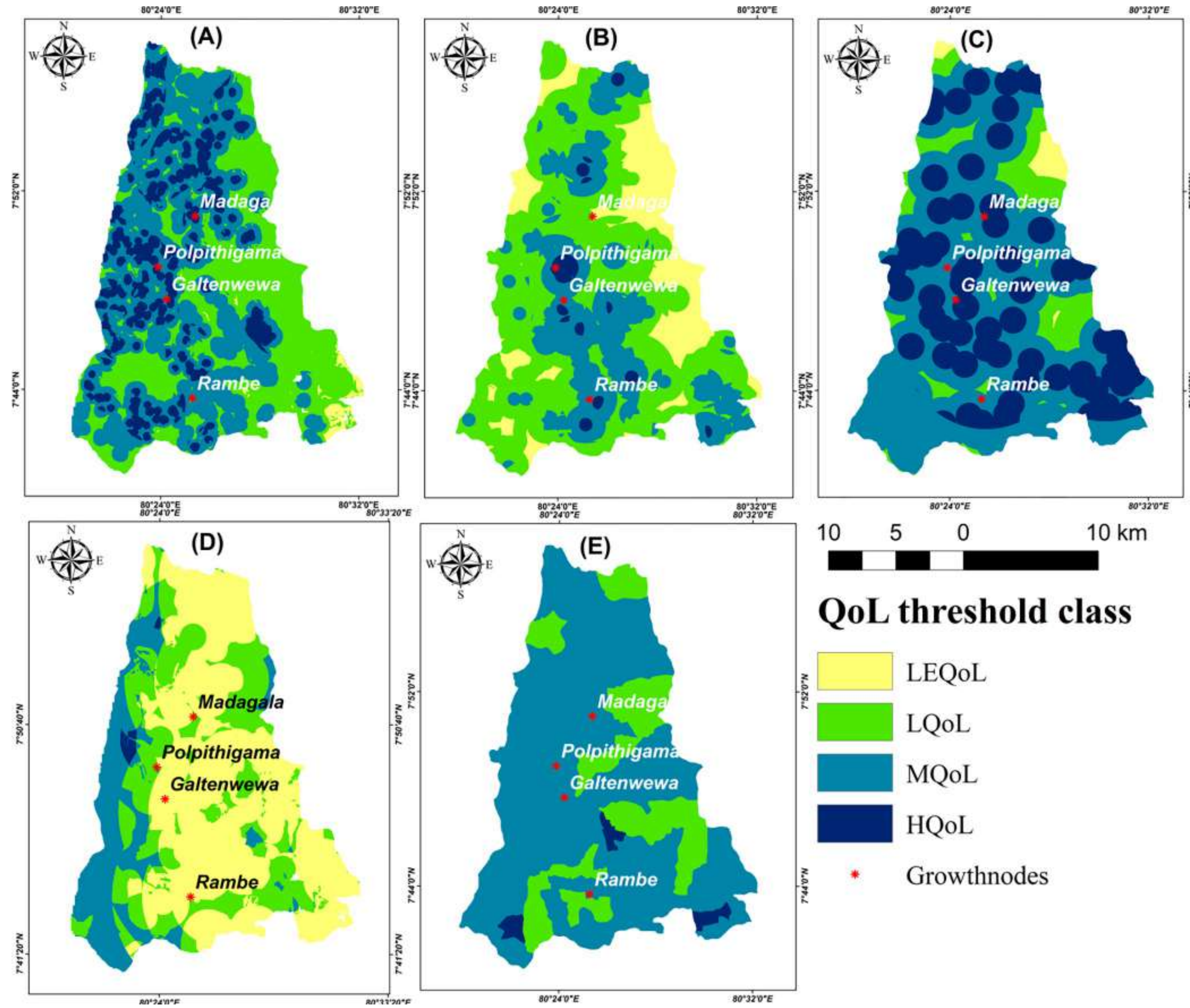

Fig 4. Spatial variations maps of QoL: Environment **(A)**; service functions **(B)**; cultural facilities **(C)**; Security **(D)**; socioeconomic factors **(E)**. Maps were edited by authors using United States Geological Survey Earth Explorer Landsat images [32].

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Discussion

Effect of town distance on QoL

The agglomeration effect leads to the concentration of service functions and infrastructure facilities in towns and cities. Hence, a distance-based gradient analysis was conducted to investigate whether the town centre had any influence on the QoL. In order to examine the influence of distance from Polpitigama Town on spatial variations in QoL, ten gradient zones were created with intervals of 0.5 km (Fig 6A). The 5 km gradient zone has an area of 90 km^2. Based on the coverage of each QoL class, the MQoL zone covers 48.5 km^2, the HQoL zone covers 10.5 km^2, and the low and least QoL zones cover 28.3 km^2 and 2.9 km^2 correspondingly.

The gradient analysis indicates that the high quality of life zone's influence is decreasing as one moves out from the center of the town (Fig 6b). The zone with a least quality of life is

Table 2. Descriptive statistics of the QoL index.

a. Area (km ^{2}) by criteria

QoL class	Overall QoL	EnviQoL	Service QoL	Cultural QoL	Security QoL	SocEco QoL
LEQoL	54.9	5.3	68.6	7.9	216	none
LQoL	252	132	216	42.9	107.9	85
MQoL	70	186.3	107.9	201.9	68.4	301.6
HQoL	17.3	70.5	8.5	148.3	2.5	8.5
Total	394.2	394.1	394.1	394.1	394.8	394.1

b.Area (%) by criteria

QoL class	Overall QoL	Envi QoL	Service QoL	Cultural QoL	Security QoL	SocEco QoL
LEQoL	13.9	1.4	17.1	1.9	54.7	none
LQoL	63.8	33.6	53.8	10.7	27.3	21.2
MQoL	17.8	47.2	26.9	50.5	17.3	76.6
HQoL	4.5	17.8	2.2	36.9	0.7	2.2
Total	100	100	100	100	100	100

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progressively growing in size. The areas with the lowest quality of life within the study region have fluctuations, but generally show an upward trend. Approximately 70% of the areas with moderate and high quality of life were located within a 2 km radius from the town center. However, this number declined by approximately 40% while moving 5 km away from the town.

Validating the QoL index

Validating the QoL index was essential for the reliability of the derived results [33–35]. The receiver operating characteristic (ROC) curve is the most generally used strategy that illustrates the correlation between false positive values (Y-axis) and false negative values (X-axis) as used in the investigation also (**Fig 7**) [33–37].

The prediction accuracy of the ROC curve is demonstrated by the area under the curve (AUC) that describes the absence and presence of the events [33–35,38]. For validation 40 random points were collected from the current QoL zones and compared with the generated QoL map (**S2 Fig**). Out of 40 sample points 32 locations perfectly fit with the obtained QoL classes (**S15 Table**). The ROC curve obtained shows high AUC values: 0.95 for LEQoL areas, 0.93 for MQoL, 0.86 for HQoL, and 0.77 for LQoL. This indicates an overall prediction accuracy of 87.7%. In summary, resulted AUC value suggests that the AHP-based QoL analysis is better than random chance. In the absence of prior research the resulted index is credible and may be applied as a road map for the livelihood improvement of poor households in the study area.

Equitable resource allocation to improve QoL

The findings indicate that the majority of the areas in Polpithigama are characterized by low and moderate QoL. Socioeconomic factors exert a greater influence than environmental, cultural, and safety factors. The results align with the findings made by Dissanayake et al. [23] in the city of Kandy, Sri Lanka. The data indicated that socioeconomic factors had a significant impact on the quality of life in the majority of the region. Therefore, policymakers should prioritize the provision of employment opportunities, electricity, drinking water, housing, and sanitary facilities for the marginalized people, particularly those residing in rural areas. However, whereas transportation was identified as a significant component in the study conducted by Dissanayake et al. [23], the current data indicate that schools and healthcare facilities have a

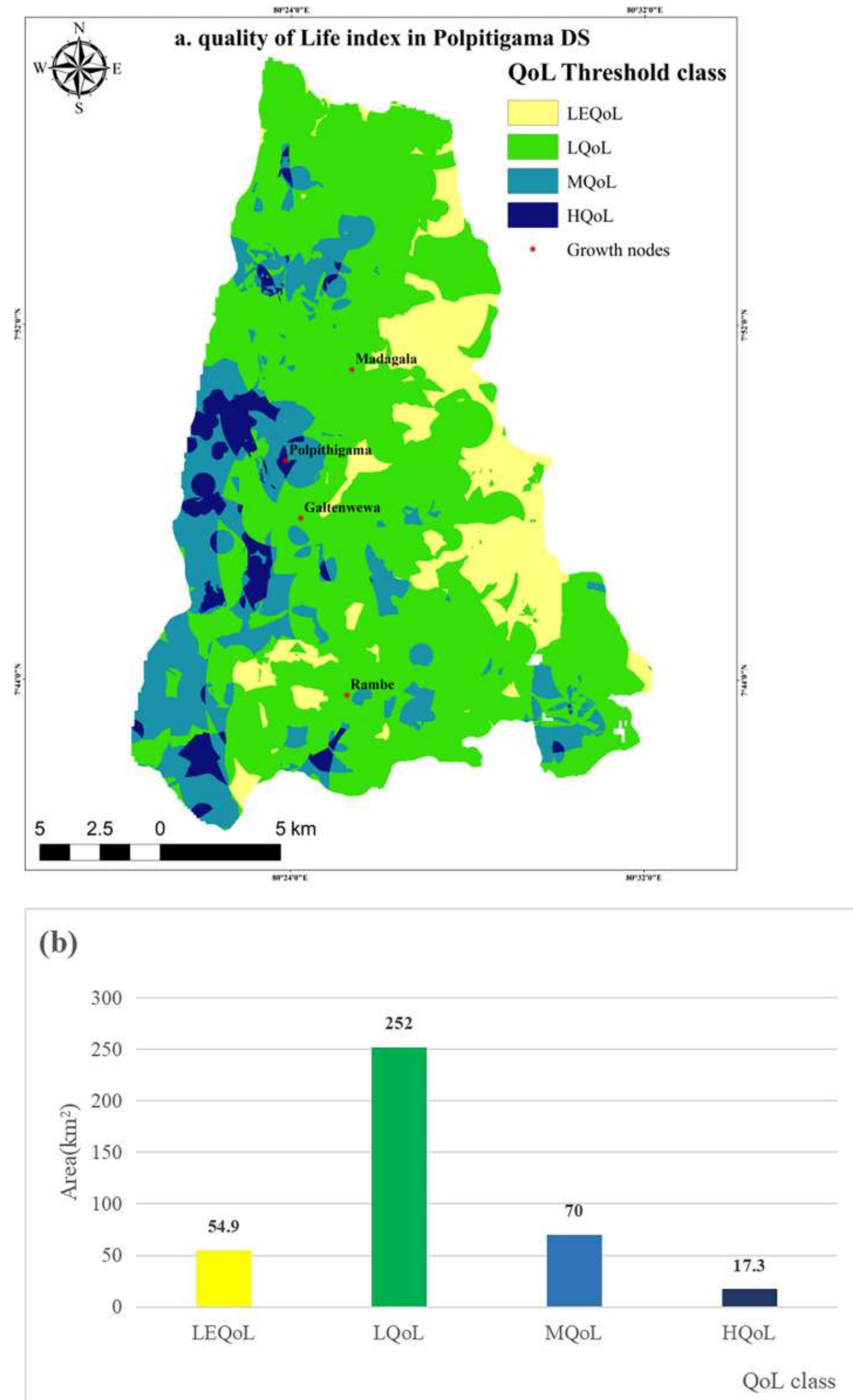

Fig 5. Quality of Life index: **(a)** QoL index map in Polptigama DS; **(b)** Descriptive statistics of QoL index. Map was edited by authors using United States Geological Survey Earth Explorer Landsat images [32].

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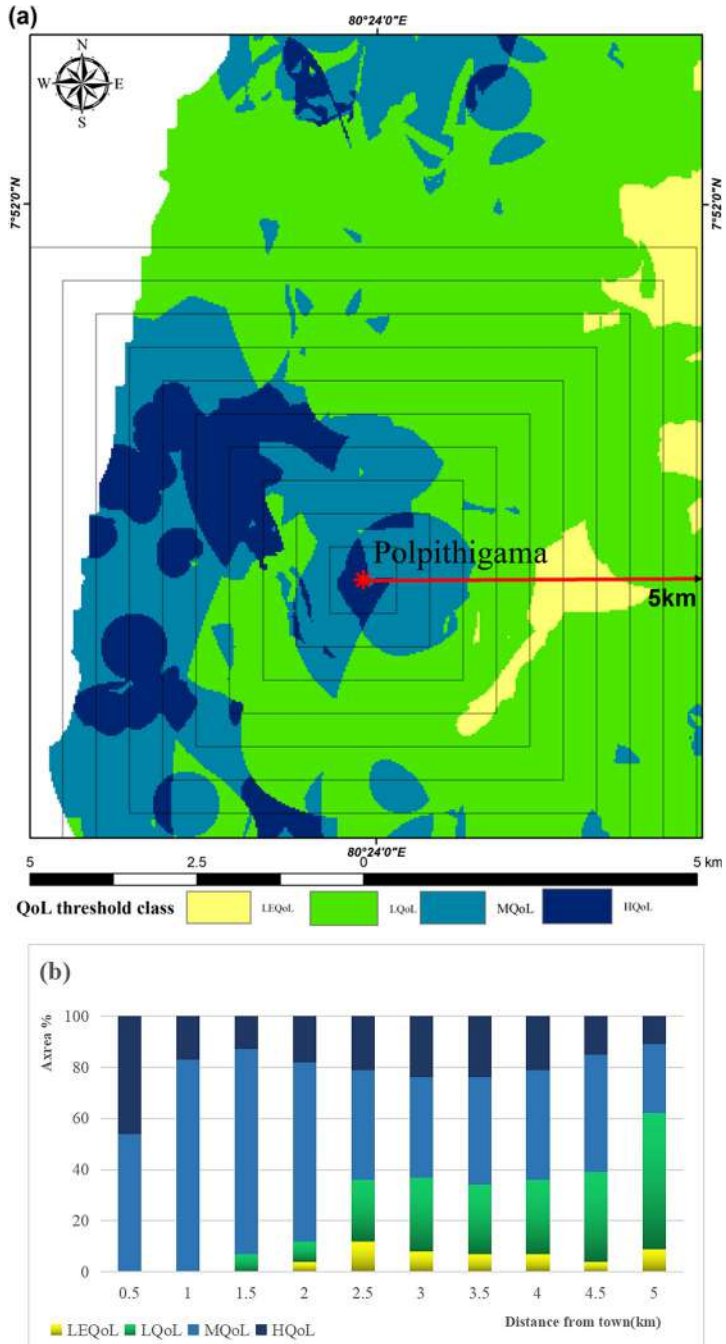

Fig 6. Distance effect for QoL: **(a)** Variations of Quality of Life (QoL) from the town center to the periphery; **(b)** Percentage contribution of QoL gradient zones. Map was edited by authors using United States Geological Survey Earth Explorer Landsat images [32].

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greater impact on QoL. The study conducted in the municipality of Katerini, Greece [8] also discovered that service factors play a vital role in determining the QoL. The town significantly influences the study area's quality of life. The proximity of the town is a significant factor affecting the levels of life quality. This aligns with the findings of Dissanayake et al. [23], which indicate that as the distance between settlements and the town increases to approximately

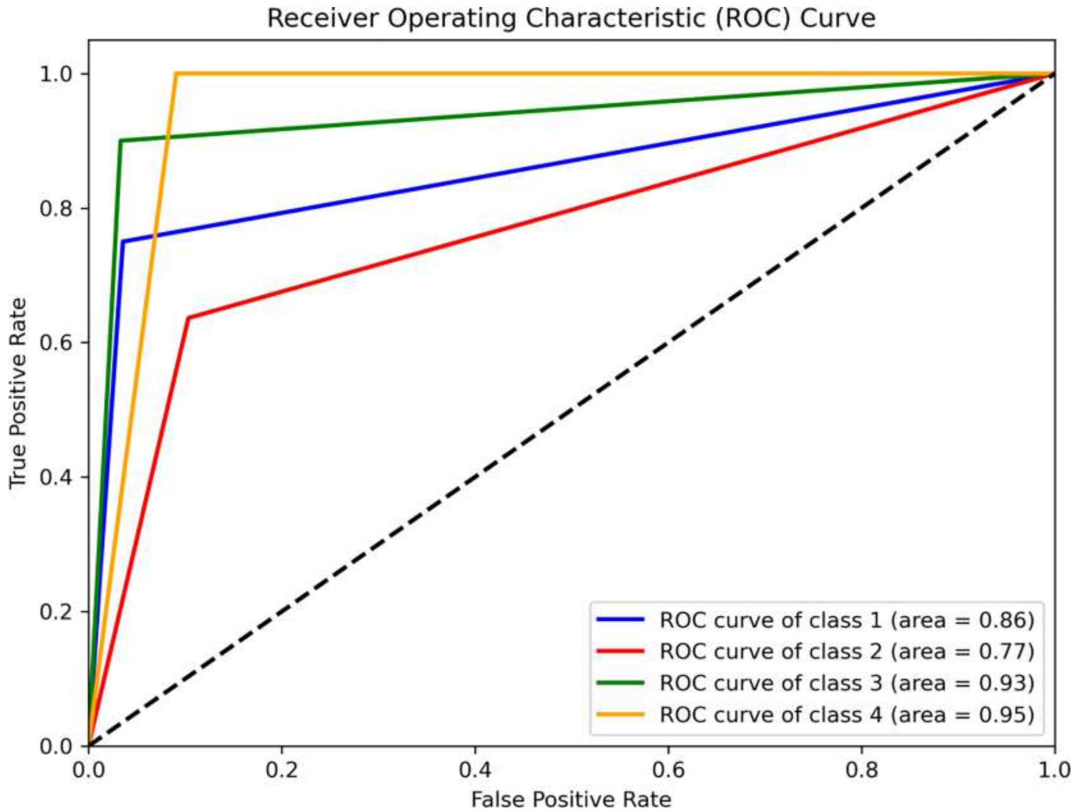

Fig 7. Receiver operating characteristic (ROC) curve of the model validation.

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5km, the life quality also decreases. Faka et al., [24], found comparable results in Athens city, suggesting that the urban center provides more advantages than the rural outskirts due to the strategic location of service facilities. Rural residents face hindered prosperity as a result of inadequate provision of essential amenities and services, including easily accessible schools, healthcare facilities and retail establishments. In many impoverished rural areas, the absence of adequate housing, transportation, and access to safe and sufficient drinking water poses significant challenges in meeting basic needs. Planners and rural societies can employ adaptable strategies to engage economically disadvantaged and fatigued individuals who face barriers to participation, are typically not involved in government procedures, or are disproportionately affected by development initiatives. Given that the HEC risk is the most significant factor in determining safety standards, decision-makers should prioritize minimizing HEC risk and developing more effective methods to safeguard both elephants and humans.

Limitations and future research direction

The research only undertook 20 criteria into account based on earlier scholars [8,23,24]. Other factors were not included in this due to time and data limitations.Therefore, the study was limited to a small area due to limitations in time and resources. Identifying the QoL is a crucial matter due to its significant influence on underdeveloped regions within the district. Therefore, it is necessary to conduct more extensive research in the future to explore the quality of life in remote areas with limited socioeconomic and service infrastructure by consolidating intricate criteria and factors. Conducting comparative studies with other established MCDA methodologies, such as TOPSIS and DELPHI, will yield more realistic results in the future, in addition to model validation.

Conclusions

This research was conducted to derive a QoL index for a Divisional Secretariat located in a rural periphery of Sri Lanka using GIS integrated MCDA techniques. Spatial variables allows for the mapping of factors and criteria, facilitating the identification of spatial patterns associated with low or high QoL. Socioeconomic and service factors were shown to have greater significance than environmental and cultural variables. Based on the gradient zone analysis, the area surrounding the town of Polpitigama exhibits the highest QoL. Furthermore, the distance from the town has a notable influence on the quality of life. The results indicate that improving socio-economic infrastructure and service functions, such as hospitals and schools, can enhance the quality of life in rural areas. Model validation was more useful in maintaining the scientific reliability of the resulting index through ROC curve and it has shown a good consistency of the derived model with real world scenario. Furthermore, policymakers should prioritize the implementation of initiatives to minimize the adverse effects of HEC in their local land use planning. Although, not all criteria are applicable, the same approach remains adaptable. Consequently, this approach can be utilized to assess the QoL in most rural areas in Sri Lanka.

Supporting information

S1 Fig. Common factors/aspects of QoL.
(TIF)

S2 Fig. Field verification samples used for model validation.
(TIF)

S1 Table. Factors used for the spatial analysis of QOL and their relevance, type, and sources.
(DOCX)

S2 Table. Factor threshold and QoL classes.
(DOCX)

S3 Table. Pairwise comparison matrix for main criteria.
(DOCX)

S4 Table. Pairwise comparison matrix for environment factors.
(DOCX)

S5 Table. Pairwise comparison matrix for service facilities.
(DOCX)

S6 Table. Pairwise comparison matrix for cultural facilities.
(DOCX)

S7 Table. Pairwise comparison matrix for security facilities.
(DOCX)

S8 Table. Pairwise comparison matrix for socioeconomic facilities.
(DOCX)

S9 Table. Main criteria normalization.
(DOCX)

S10 Table. Environment factors normalization.
(DOCX)

S11 Table. Service factors normalization.
(DOCX)

S12 Table. Cultural factors normalization.
(DOCX)

S13 Table. Security factors normalization.
(DOCX)

S14 Table. Socioeconomic factors normalization.
(DOCX)

S15 Table. Information of field data and pixel correlation with suitability map.
(DOCX)

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water

Article

Application of GIS, Multi-Criteria Decision-Making Techniques for Mapping Groundwater Potential Zones: A Case Study of Thalawa Division, Sri Lanka

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Abstract: Groundwater resources are depleting due to phenomena such as significant climate change and overexploitation. Therefore, it is essential to estimate water production and identify potential groundwater zones. An integrated conceptual framework comprising GIS and the analytical hierarchy process (AHP) has been applied for the present study to identify groundwater potential areas in the Thalawa division of Sri Lanka. The criteria, including rainfall, soil types, slope, stream density, lineament density, geology, geomorphology, and land use, were taken into account as the most contributing factors when identifying the groundwater zones. Weights were allocated proportionally to the eight thematic layers according to their importance. Hierarchical ranking and final normalized weighting of these determinants were performed using the pairwise comparison matrix (PCM) available in AHP. Based on the results obtained, the groundwater potential zone (GWPZ) was classified into three regions: low potentiality (33.4%), moderate potentiality (55.8%), and high potentiality (10.6%). Finally, the zoning map was compared to find consistency with field data on groundwater discharge and depth taken from 18 wells in the division. The results revealed that the GIS-multi-criteria decision-making (MCDM) approach brings about noticeably better results, which can support groundwater resource planning and sustainable use in the research area.

Keywords: analytical hierarchy process (AHP); dry zone; geographic information system (GIS); groundwater potential zones; multi-criteria decision making (MCDM); SDG-6

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1. Introduction

Water is an essential resource for every organism to maintain its life. Water that stays below the earth's surface is called groundwater. Also, the term refers to all water found beneath the surface of the ground as groundwater [1,2]. The total volume of water resources and water on earth is estimated at 1386 trillion liters, of which 97% is saltwater, 3% is freshwater, and only 0.6% is available as groundwater [3]. It is crucial for ecology, food security, and human health [4]. Due to the scarcity of surface water, the significance of subsurface water reduction is highlighted, notably in dry areas [5]. With climate change and increased use of groundwater, many groundwater sources are experiencing water depletion. Groundwater availability depends on several factors, such as porousness, permeability, storage capacity, and transmissivity. The term “Groundwater potential” can be defined as the potential for groundwater to exist in an area [6,7].

The main indicator of groundwater storage reduction is the decrease in groundwater heads in wells. Groundwater in the Sri Lankan dry zone is mainly fed by rainfall. It should also be mentioned that, due to changes in rainfall patterns and excess water withdrawal for domestic and agricultural activities, the amount of water that reaches the ground is gradually decreasing. It is proven that 72% of Sri Lanka’s rural population and 22% of its urban residents use groundwater for drinking and domestic purposes [7]. The importance of a proper assessment of groundwater potential is indicated by studies on water scarcity and drought [8–11]. The potential for groundwater in Sri Lanka is lower compared to surface water resources [12]. According to the hydrogeological conditions, about 90% of the land area of the country consists of hard rocks with low potential for groundwater, and the rest of the land consists of sedimentary rocks with high groundwater potential [13]. Sedimentary rock is limited to the north, northwest, and northeast regions of Sri Lanka [13]. There is a significant need to use groundwater in a sustainable manner in the dry zone due to reduced rainfall and an increased population [14,15]. Thalawa is one of the most important agricultural regions in the dry zone that belongs to irrigated farming. In the study area, groundwater is currently obtained from shallow and very deep wells. Sustainable development of groundwater resources as the best option to support dry zone people can contribute to improving their well-being by increasing agricultural productivity without depleting groundwater resources.

We must make decisions in our daily lives; some may be complex, while others are simple. Multi-criteria decision analysis (MCDA) ranks potential actions or alternatives in order of priority. To make the best choice feasible, MCDA is used to assess and contrast several factors, which are frequently at odds with one another [16]. Multi-criteria approaches are referred to in the academic community in a variety of ways, including multiple-criteria decision aiding (MCDA), multi-criteria decision making (MCDM), multi-objective decision making (MODM), and multi-attribute decision making (MADM) [16–18]. Different MCDA techniques are available, including the analytical hierarchy process (AHP), TOPSIS, PROMETHEE, ELECTRE, SWARA, WASPAS, etc. However, the AHP, TOPSIS, and VIKOR approaches were the most popular techniques that have been used in previous research works during the last four decades [16,19]. The spatial dimension of the assessment criteria, decision substitutes, and geographic data models are all factors that MCDA takes into account while assessing the criteria [20,21]. Researchers frequently use AHP to support decision making in the processes of environmental planning and natural resource management because of its capacity to recognize and balance the significance of complex aspects [22–25]. Different approaches have been used in recent years to delineate groundwater potential zones globally. Many researchers have found in their studies that AHP and MCDA methods are effective tools for identifying groundwater potential. In the case of Sri Lanka, only a limited set of studies have been carried out to identify groundwater potential areas based on the geographic information system (GIS) [3,12,14,26,27]. Groundwater research has reached a turning point with the use of remote sensing (RS) and GIS in resource discovery, which has significantly aided in groundwater resource analysis, monitoring, and protection [28,29]. Abijita et al. [30] attempted to delineate potential groundwater zones in the Ponnaniyar Basin, Tamil Nadu, using AHP and the multi-influence factor (MIF). Detection of potential groundwater zones through an appropriate modeling approach was essential in solving water problems in the drought-prone Kilinochchi district [12,14]. Kumar et al. [31] have tried to identify groundwater potential zones in the Chennai river basin using GIS and AHP in their study. Rajasekhar et al. [32] identified groundwater potential areas in the Jiledubanderu River catchment, India, using GIS, AHP, and combined fuzzy-AHP techniques. A study was undertaken by Doke et al. [33] using a systematic and scientific GIS-based AHP to prepare a groundwater potential map for the Ulhas Basin, India. The concept of using the latest techniques, such as RS and GIS, for groundwater management research is relatively new [34–37]. As time- and cost-effective methods, combined GIS and AHP demonstrate it is a useful method for defining probable groundwater zones [38–41]. Hence, based on the literature, the GIS-MCDA integrated method has been used for the present study.

In the Anuradhapura district, there is not sufficient water to meet the required volume, and the potential of groundwater needs to be explored. No related studies have been carried out in this area previously. Therefore, the study has been conducted to fill the existing research gap in the study area. The resulting groundwater potential map will provide better insights into sustainable water resource management. The current study is primarily focused on using GIS MCDA methodologies to map the potential groundwater zones using eight different criteria. The research was structured into the five sections listed below. Section 1 is devoted to explaining the research background and previous literature, and Section 2 describes the study area, materials, and methods. The results are thoroughly explained in Section 3, along with the model validation. In the Section 4, the similarities and differences of the key findings are compared with other similar research works. Section 5 gives the conclusions.

2. Materials and Methods

2.1. Study Area

This study was carried out in the Thalawa Divisional Secretariat Division (DSD), located in the Anuradhapura district of the North Central Province of Sri Lanka, covering a 218.45 km^2 area and having 39 Grama Niladhari Divisions (GNDs). It lies between 8^0 10″ 63″ N and 80^0 36″ 72″ E (Figure 1). The study area belongs to the dry zone; the average annual rainfall in the study area is around 1300 mm, with a mean annual temperature of 21 to 32 °C. There is 3182 ha of agricultural land in the Thalawa DSD under the agrarian service division of Thalawa, Eppawala, and Katiyawa [42]. The primary source of income in the study region is agriculture, with paddy being the predominant crop [43]. The area is part of the Mahaweli H zone, where irrigation water is used to support agriculture. All agricultural zones in the region are covered by the irrigation canal system. The northeast monsoon, which lasts from December to February, contributes significantly to the region's annual rainfall. Based on the annual rainfall pattern, agriculture is carried out in two seasons: '*Yala*' from March to September and '*Maha*' from October to February. The tank cascades spread over the area are linked to agriculture; a substantial portion of the entire area's topography is made up of very flat terrain with heights of less than 150 feet. The area has unique climatic characteristics, and except for a few months of the year, the other months are dry. There are a variety of plants adapted to dry climates. Reddish-brown earth soils, which are commonly found in the dry zone, are also available in the Talawa area. The lithological formation in the region is an important factor in the groundwater composition, quality, and formation of aquifers.

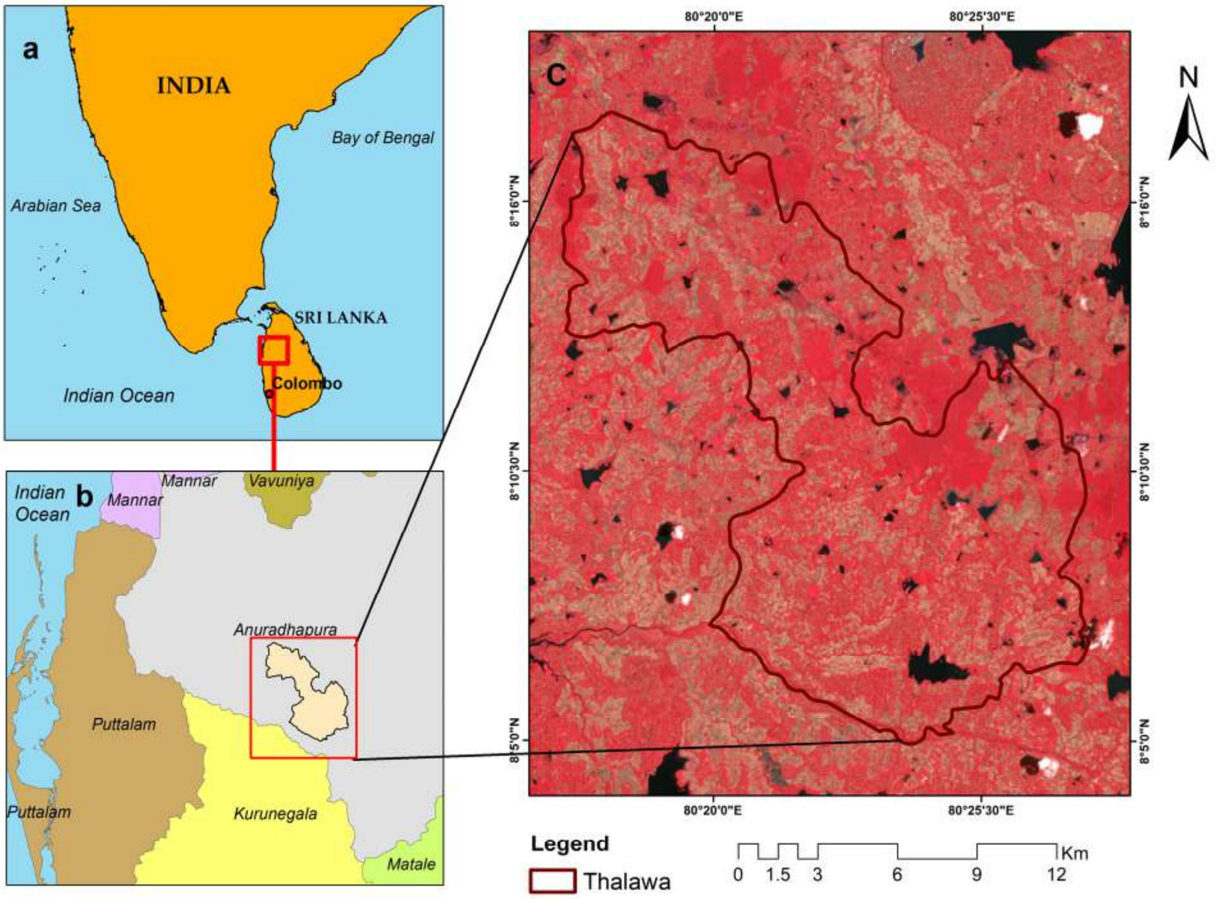

Figure 1. Geographical location of the study area: (**a**) Location of Sri Lanka in the Indian Ocean; (**b**) Location of Thalawa DSD; (**c**) Thalawa DSD in Landsat 8 false color (5,4,3) composite.

2.2. Selecting Criteria and Data Preparation

The selection of criteria for ranking is an important step in the suitability assessment process in any area for potential groundwater zones. Table 1 illustrates the criteria considered in earlier research when analyzing suitability for potential groundwater zones. Necessary data were obtained from various institutes, and then the steps required for ground-water potential zoning were followed by GIS MCDA [44].

Table 1. Criteria used in previous studies to determine the potentiality of groundwater**.**

References	RF	GM	GL	SL	SP	LU	DS	LD	AS	GL	TWI
Ibrahim-Bathis and Ahmed [1]	×	×			×	×	×	×			
Pathmanandakumar et al. [12]	×	×	×	×	×	×	×	×			
Aslan & Celik [39]	×	×	×	×	×	×	×	×			
Kumar et al. [31]	×	×	×	×	×	×	×	×	×	×	
Sarwar et al. [44]	×	×	×	×	×	×	×	×			
Pal et al. [45]	×		×		×	×				×	×
Verma & Patel [46]	×	×	×	×	×	×	×	×			
Senthilkumar et al. [47]			×		×	×	×			×	
Arulbalaji et al. [48]	×	×	×	×	×	×	×	×			×
Arefin [49]	×	×	×	×		×	×				
Yıldırım [50]	×	×	×	×	×	×	×	×			×
Jhariya et al. [51]	×	×	×	×	×	×	×	×			

Benjmel et al. [52]			×			×	×	×			×
Singh et al. [53]			×	×	×	×	×				
Tiwari et al. [54]	×	×	×	×	×	×	×	×			
Pradhan et al. [55]	×				×	×	×				×

Notes: RF: Rainfall, GM: Geomorphology, GL: Geology, SL: Soil, SP: Slope, LU: Land Use, DS: Drainage Density, LD: Lineament Density, AS: Aspect, GL: Groundwater Level, TWI: Topographic Wetness Index (TWI).

The preparation of thematic layers (criteria) included RS data extraction, digitization of existing maps, and the collection of institutional data. Using preliminary investigation as a basis, the eight thematic layers were developed as follows: rainfall, geology, geomorphology, land use, soil type, stream density, lineament density, and slope [12,14,16,23,36]. Thematic layers were created once all the data were prepared, and these layers were then converted into raster datasets [35]. Finally, utilizing GIS-MCDA-integrated approaches, potential groundwater zones have been identified. The summary of the data sources is described in Table 2.

Table 2. Data sources used for mapping groundwater potential mapping**.**

Variables	Data	Resolution	Source Locations
Rainfall	Rainfall Data		Department of Meteorology [56]
Geology	Geological map	1:100,000	Geological Survey and Mines Bureau [57,58]
Geomorphology	Geomorphological map	1:100,000	Shuttle Radar Topography Mission [58]
Soil type	Soil map	1:100,000	Irrigation Department [59]
Land use	Land use Data		Survey Department of Sri Lanka [60]
Slope	Shuttle Radar Topography Mission (SRTM)	30 m	United States Geological Survey [61]
Stream Density	Shuttle Radar Topography Mission (SRTM)	30 m	United States Geological Survey [61]
Lineament Density	Shuttle Radar Topography Mission (SRTM)	30 m	United States Geological Survey [61]

The methodological flowchart for the groundwater potential zones is illustrated in Figure 2. To map groundwater potentiality, the control factors for groundwater movement, storage, and occurrence may be investigated [62,63]. A rainfall map was produced using the inverse distance weighted (IDW) interpolation technique using point data sources employing Arc GIS 10.8 software. GNU Octave 7.3 software was used to calculate the criteria and factors for AHP weight using an algorithm developed by Mathew, 2020 (https://mathewmanoj.wordpress.com/mul (20 July 2023). Because the point data were scattered and sparse, IDW methods were selected instead of distance thresholding. The dependable IDW model is utilized in this work to interpolate geographical information based on the idea of weighting distance [12]. The geological and geomorphological layers of the study area were prepared using an existing map of the geological survey and mines bureau (GSMB) under the scale of 1:100,000. The soil map was created by digitizing the resource map with the help of the Irrigation Department. Shuttle radar topography mission (SRTM)—digital elevation model (DEM) was used to create the slope, stream, and lineament density layers of the area. Land use information was collected from the Survey Department of Sri Lanka. Finally, these thematic layers underwent raster data conversion and weighted overlay analysis in the Arc GIS environment.

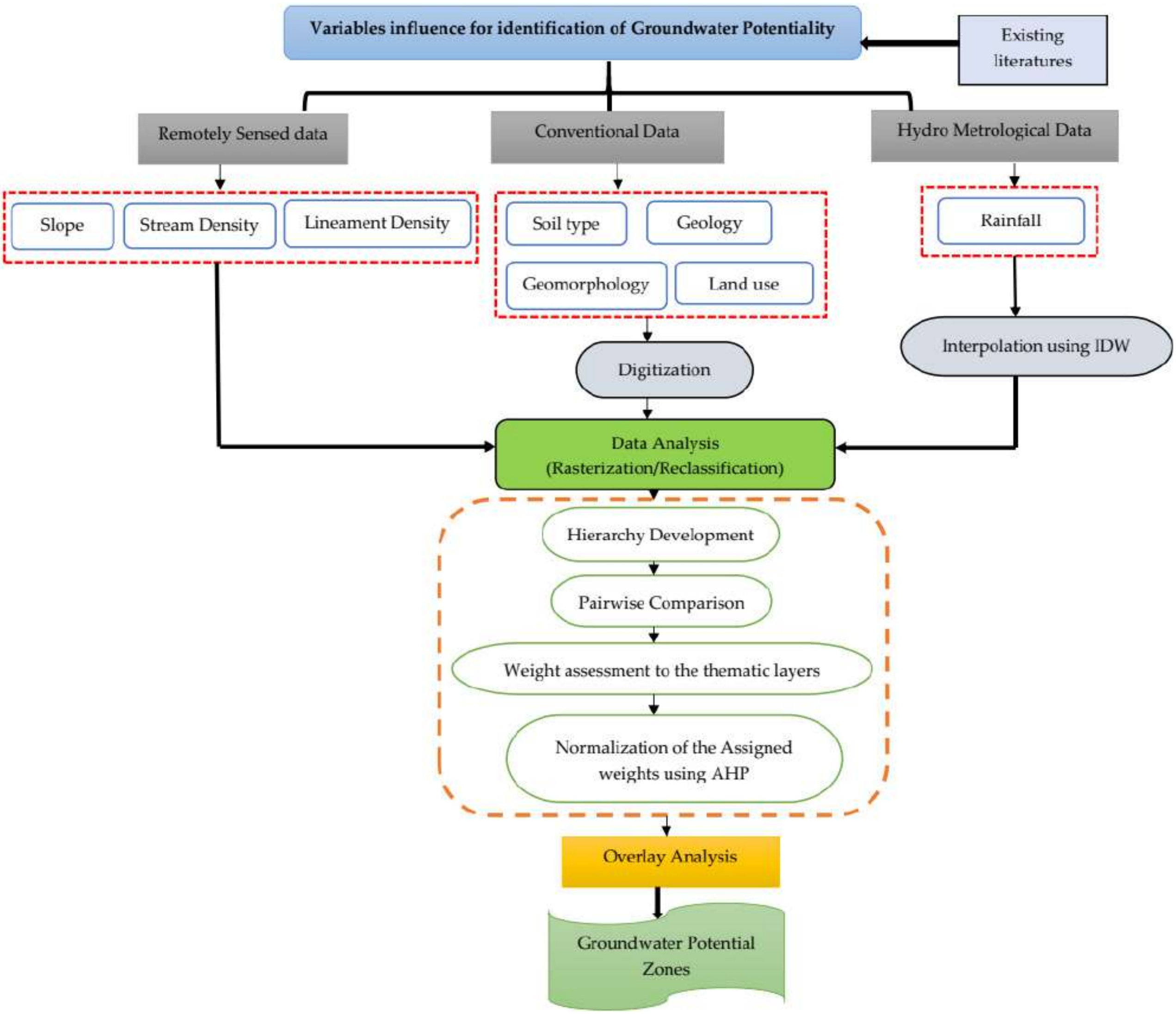

Figure 2. Methodological flowchart for delineating groundwater potential zones.

2.3. Assignment of Weights and Criteria Normalization

In integrated analysis, the weight assignment of each feature class is most important since the weight assignment depends on the output. The AHP proposed by Saaty [63,64] was applied to allocate weight to each of the criteria used in the study. The AHP is a multi-criteria decision-making technique widely used in the field of groundwater studies as well as in environmental and other geospatial contexts [57]. Multi-criteria decision analysis can be identified as a commonly accepted and important technique for solving complicated problems [12]. Saaty's scale was used in allocating standard weights [65]. Establishing weights for each criterion was the next stage. The weight computation determined the relative weights of the various criteria [66]. The AHP has the benefit of reducing pairwise comparisons of complicated judgments and aiding in determining the weight of the criterion [67,68].

For the chosen theme levels, a pairwise comparison matrix (PCM) was initially created to assess the scale weight of the relevant layers in relation to their contribution to groundwater potentiality. After that, a pairwise comparison matrix (M) was prepared, as in Equation (1). If n is the number of criteria, the size of M is $n \times n$ [61].

$$M = \begin{bmatrix} 1 & p & q \\ 1/p & 1 & r \\ 1/q & 1/r & 1 \end{bmatrix} \quad (1)$$

Here, each component of M uses a number ranging from 1 to 9 (Table 3) to represent the relative weight of the two criteria [69]. Typically, the ratings range from 1 (equal importance) to 9 (extreme importance).

Table 3. AHP Scale.

Scale	1	2	3	4	5	6	7	8	9
Importance	Equally	Weak	Moderately	Moderate Plus	Strong	Strong plus	Very Strong	Very very Strong	Extreme

Based on earlier research and expert opinions obtained by referring a semi-structured questionnaire to six experts from different fields, the Saaty scale was used to assign weights to the selected criteria and determine their relationship with characteristics and influence on groundwater potential. Three GIS experts (University academics), one hydrologist, one geologist, and a land use planning director participated in the semi-structured questionnaire survey within their busy schedules and the limited pool of GIS and hydrology experts in the Sri Lankan context. The proportion of influence of the thematic layers and the categorization of the constraints were computed using the PCM, the relative weight matrix, and the normalized primary eigenvalue (Table 4).

Table 4. Normalized pairwise comparison matrix analysis for the AHP Process.

Criteria	Slope	Rainfall	Geomorphology	Soil	Geology	Stream Density	Land Use	Lineament Density
Slope	**1.00**	0.333	0.2	0.333	0.2	3.00	3.00	3.00
Rainfall	3.00	**1.00**	5.00	3.00	5.00	5.00	3.00	5.00
Geomorphology	5.00	0.2	**1.00**	5.00	3.00	5.00	5.00	5.00
Soil	3.00	0.333	0.2	**1.00**	0.2	5.00	5.00	5.00
Geology	5.00	0.2	0.333	5.00	**1.00**	5.00	3.00	5.00
Stream Density	0.333	0.2	0.2	0.2	0.2	**1.00**	3.00	1.00
Land use	0.333	0.333	0.2	0.2	0.333	0.333	**1.00**	5.00
Lineament Density	0.333	0.2	0.2	0.2	0.2	1.00	0.2	**1.00**

The order of layer incentive on groundwater potential is expressed by the eigenvector [70]. The criteria of high groundwater potential are given more weight, whereas the criteria of low groundwater potential are given less weight. The column elements should be divided by the sum of the elements of the same column to normalize M and determine the weight of each criterion. The necessary relative test weights are provided by averaging the rows of the new matrix. Hence, all data are prepared as thematic layers and weighted overlay analysis using spatial analyst tools.

2.4. Normalized Weights and Identification Groundwater Potentiality

The relationship between the layers and their relative importance for the generation of the 8 × 8 pairwise matrix and the groundwater potential preparation determine how the eight thematic layers were integrated. They are displayed as, slope (SP), rainfall (RF), geomorphology (GM), soil (SL), geology (GL), stream density (SD), land use (LU), and lineament density (LD). Consequently, the result is a continuous mapping of suitability to produce a composite suitability map. The overlay tool creates raster layers using a common measurement range and weights each one based on its significance, which gives the final layer values ranges of 1–5 [12,34,71]. The last step was to prepare the composite map for groundwater potential. Weighted criteria are integrated to produce the potential map. This combination was performed by the weighted linear combination (WLC) method. The ability to achieve the relationship between the eight thematic maps using AHP with different classes is remarkable. Based on the PCM, the relative weight matrix and normalized weights were assigned to estimate the importance of the thematic layers on groundwater potential (Table 5).

Table 5. Normalized pairwise comparison matrix and weights were obtained for each criterion.

Criteria	SP	RF	GM	SL	GL	SD	LU	LD	Normalized Weight	%
Slope (SP)	0.06	0.12	0.03	0.02	0.02	0.12	0.13	0.10	0.0732	7.33%
Rainfall (RF)	0.17	0.36	0.68	0.20	0.49	0.20	0.13	0.17	0.3109	31.09%
Geomorphology (GM)	0.28	0.07	0.14	0.33	0.30	0.20	0.22	0.17	0.2231	22.31%
Soil (SL)	0.17	0.12	0.03	0.07	0.02	0.20	0.22	0.17	0.1061	10.61%
Geology (GL)	0.28	0.07	0.05	0.33	0.10	0.20	0.13	0.17	0.1650	16.51%
Stream Density (SD)	0.02	0.07	0.03	0.01	0.02	0.04	0.13	0.03	0.0495	4.9%
Land use (LU)	0.02	0.12	0.03	0.01	0.03	0.01	0.04	0.17	0.0352	3.53%
Lineament Density (LD)	0.02	0.07	0.03	0.01	0.02	0.04	0.01	0.03	0.0369	3.7%

The groundwater potential map was created by superimposing all of the criterion maps and utilizing the WLC technique with Arc GIS software 10.8 [71]. To calculate the groundwater potential index (GWPI), groundwater potential areas were produced using eight layers inserted into the GIS. The following formula describes the WLC process [72–74].

$$\text{GWPI} = \sum_{w=1}^{m} \sum_{1}^{n} (W_j \times X_i) \tag{2}$$

Here, GWPI is the groundwater potential index, Wj is the normalized weight of the j-th thematic layer, X_i refers to the weight of the I class of the criteria, m represents the number of criteria, and n denotes the total number of classes. Table 6 illustrates the weights and ranks for each of the eight impact factors.

Table 6. Weight and ranking for different criteria.

Criteria	Weight	Feature	Rank (r_i)	Potentiality Level
Slope (Degrees)	7	0.018–1.5	5	Very High
		1.6–3.9	4	High
		4–8.3	3	Moderate
		8.4–15	2	Low
		16–22	1	Very Low
Rainfall (mm per month)	31	88.9–94.4	2	Low
		94.5–99.9	2	Low
		100–105	3	Moderate

		106–111	4	High
		112–116	5	Very High
Geomorphology	22	Lower Levels of Intermediate Plantation Surfaces	4	High
		Lower Plant Surfaces, Insel-bergs, and thin Soil (Dry zone)	3	Moderate
Soil Types	10	Alluvial Soils	5	Very High
		Low Humic Gley Soils	4	High
		Red-Yellow Podzoilc Soils	3	Moderate
		Redish-Brown Earth Soils	2	Low
Geology	16	Biotite Gneiss/Hornblende	1	Very Low
		Calciphyre/Minor Marble	4	High
		Carbonatite	1	Very Low
		Charnockitic Gneiss	2	Low
		Granitic Gneiss with Pinkish Microcline	3	Moderate
		Quartzite/Quartz Schist	2	Low
Stream Density (km^2)	4	0–0.735	5	Very High
		0.736–1.47	4	High
		1.48–2.21	3	Moderate
		2.22–2.94	2	Low
		2.95–3.68	1	Very Low
Lineament Density (km^2)	3	0–0.386	1	Very Low
		0.387–0.772	2	Low
		0.773–1.16	3	Moderate
		1.17–1.54	4	High
		1.55–1.93	5	Very High
Land use	3	Paddy	3	Moderate
		Homestead	3	Moderate
		Water Bodies	4	High
		Forest	3	High
		Road Network	1	Very Low
		Scrubs	2	Low

The relative weight (Wi) of the slope is 0.0732, and the ranking was fifth among all criteria. As the Thalawa area is on a flat surface belonging to the dry zone, very high rough, slope (deep) features cannot be identified. Rainfall became the most important criterion, gaining a high relative weight of 0.3109. Geomorphology was the second most important criterion in groundwater potential zoning, derived at 0.2231 relative weight. According to its significance, the soil criterion gained 0.1061 relative weight and became the fourth important factor. Geology was the third most important factor in groundwater potential zoning and derived 0.1650 relative weight from AHP. The land use criterion is the least important among all others according to the relative weight assigned by AHP derived from 0.0352. Stream density gained 0.0495 relative weight (sixth most important criterion) according to the AHP results. Lineament density gained a 0.0369 relative weight and was reported as the seventh most important factor in groundwater potential zoning. To perform GIS overlay analysis, each criterion was assigned a ranking order that ranges from 1–5 (1—very low, 2—low, 3—moderate, 4—high, 5—very high). These ranks were allocated based on the ranking orders collected from experts' opinions using the questionnaire survey.

3. Results

3.1. Groundwater Potentiality for Major Criteria

The outputs of the AHP estimation of eight criteria and sub-criteria used in the research and standardized rating values (r_i) are shown in Tables 5 and 6. As well as the thematic layers that are produced through the reclassification of main criteria using r_i values are shown in Figure 3. Details of all these criteria and their spatial distribution are described below.

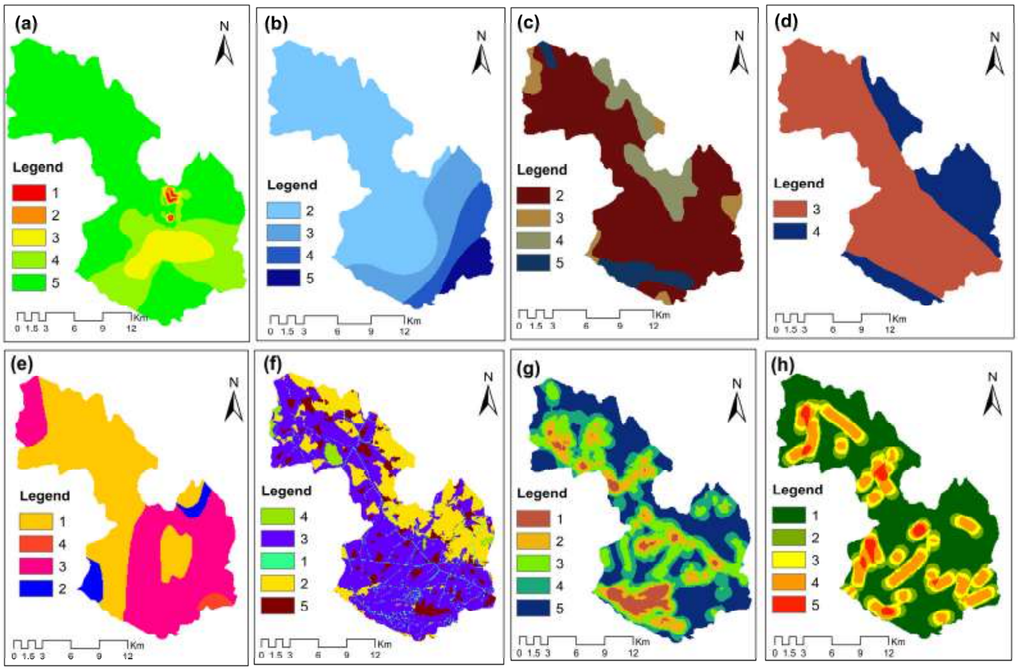

Figure 3. Distribution of rating values for eight criteria in groundwater potential zones in Thalawa: (**a**) Slope; (**b**) Rainfall; (**c**) Soil; (**d**) Geomorphology; (**e**) Geology; (**f**) Land use; (**g**) Stream density; (**h**) Lineament density.

3.1.1. Slope

The flat terrain (Figure 3a) of the study area may reveal the possibility of high groundwater potential. The slope of the area was categorized into five groups very high (0.018–1.5), high (1.6–3.9), moderate (4–8.3), low (8.4–15), and very low (16–22). Towards the center of the area, there is a slightly steeper slope. Due to the flat terrain and high infiltration rate, the research area with a slope of 0.018–1.5 is classified as having "very high" groundwater storage. The slope gradient between 16 and 22 has considered the groundwater storage as 'very low'. While the very high-potential areas comprised 69% the high-potential areas were covered by 19.4%. Moderate, low, and very low were covered by 0.20%, 0.28%, and 7.9%, respectively.

3.1.2. Rainfall

Rainfall has a dominant effect on the hydrological cycle of the area and is directly related to the groundwater capacity. As a result of the dry climate of the study area, there are constant variations in the groundwater potential. The area receives rainfall with the activation of the northeast monsoon from September to December. The annual rainfall of the area has been classified into five classes (Figure 3b). The maximum and minimum rainfall in the area are 116 mm and 88 mm, respectively. Compared with the northern portion of the area, a higher trend of rainfall intensity can be detected in the southeast quarter. Rainfall distribution and slope gradient greatly influence surface water runoff, which also contributes to the determination of groundwater potential. As per the reclassification results, 67.6% of the area is of low potential, while moderate, high, and very high potential areas are covered by 18%, 9.5, and 4.7%, respectively.

3.1.3. Geomorphology

In the study area, two prominent landforms, namely, lower intermediate plantation surfaces and lower plant surfaces, have been observed. Conspicuous landforms were reclassified into two classes (Figure 3c). Porous and permeable zones are well explained in geomorphology and can be considered an essential phenomenon in groundwater recharge. High weight was allocated to the lower intermediate plantation surfaces, and low weight was assigned to the low plantation surfaces geomorphological unit that has moderate groundwater potential zones. 71.3% of the total area is in the moderate potential zone, while 28.7% is in the high potential zone.

3.1.4. Soil Types

Analysis of soil types revealed that the study area is mainly covered by four major soil types. Namely, alluvial, low-humic gley, red-yellow podzolic, and reddish-brown earth. This reddish-brown soil, which is typical of the dry zone, is spread over a large area. The brown texture and drainage of this soil are also widespread. The majority of the study area consists of reddish-brown earth soils (165 km^2). Alluvial soils are covered in the south and northwest areas, and low-humic gley soils can be identified towards the center of the area. Red-yellow podzolic soils are spread over an area of 11.5 km^2. In determining the influence of soil types on the occurrence of groundwater potential in the area, it can be identified that alluvial soils and low-humic gley soil contribute to being considered "very high" and "high", respectively. Red-yellow podzolic soil was assigned a moderate weight because it was generally more conducive to stabilizing groundwater potential than reddish-brown soil. In depicting the groundwater potential, reddish-brown soil was assigned low weight due to its fine surface nature. When 74.1% of the area is in a low potential zone, high, very high, and moderate potential zones are covered at 13.7%, 6.7%, and 5.2%, respectively.

3.1.5. Geology

In the study area, the geological features are formed in relation to three types of rocks, and the determination of groundwater potential varies according to the geological types. Biotite Gneiss/Hornblende, Calciphyre/Minor Marble, Carbonatite, Charnockitic Gneiss, Granitic Gneiss with Pinkish Microcline, and Quartzite/Quartz Schist are the seven geological forms found in the area of study. Biotite Gneiss/Hornblende represents 47.5% and covers mainly the Northern and southwest parts, while other formations such as Granitic Gneiss with Pinkish Microcline, Quartz Schist, Carbonatite, and Calciphyre/Minor Marble are mostly identified in the Eastern portion of the area. Charnockitic Gneiss also represents 2.3% of the study area. The geology of the area indicates that the possible high groundwater holding formation is only Calciphyre/Minor Marble. Also, Calciphyre/Minor Marble is formed under the metamorphic rocks, which greatly influence the consistent groundwater capacity of the area. Calciphyre/minor marble is assigned high weights, while biotite gneiss/hornblende, carbonatite, charnokitic gneiss, and quartzite are given low weights, respectively. Granitic gneiss with pinkish Microcline, the second most widespread geological type in the area, has been found to have moderate suitability for groundwater potential. According to the thematic rating map (Figure 3e), only 1.4% of the area is in the high potential zone, while 42.9% and 51.6% are in the moderate and very low potential zones, respectively.

3.1.6. Land Use

Prominent land use/land covers include, paddy, homesteads, water bodies, forests, roads, and scrubs. Around 40% of the total area is rice paddy land. There is a tendency for water to infiltrate more in the vicinity of agricultural lands and forest areas. This is because a vegetated area has the ability to retain water and also allows for proper drainage. In the study, the water bodies and the forest cover have been identified as land covers that have a high groundwater potential. As the drainage system of the area is mainly connected with tanks and canals, water percolation occurs regularly. Therefore, it has been suggested in the study to give a higher weight to those land uses. Both homestead and paddy land uses have moderate suitability for groundwater potential (Figure 3f). The road network and scrubs are categorized as very low and low, respectively, for groundwater potential. After the rating assignment, 58.6% of the area was identified as having moderate potential, while 8.9% represented very high potential. Low and very low potential areas represented 26.4% and 4.1%, respectively.

3.1.7. Stream Density

The stream density has been categorized into five categories, and it varies in the range of <0.7 to >3.68 km^2. A higher weight is given to regions with low stream density, and a lower weight is given to areas with very high stream density. In the study area, it is not possible to identify many regions with significantly high stream densities, and the stream density is more concentrated in the Southern part of the research area. Areas with low stream density have high levels of infiltration from rainfall. Hence, permeability works inversely and plays an important role in stream density for flow distribution and infiltration rates. Accordingly, 36.8% of the area (Figure 3g) is in the very high potential zone, while 22.9% is in the high potential zone. 5.2% and 12.1% of the area are in the very low and low potential zones, while the moderate potential zone is covered by 22.8%.

3.1.8. Lineament Density

The lineament map of the study area was derived from SRTM DEM using USGS. The lineament density of the study area varies from 0.7 km^2 to 3.6 km^2. In the study area, there is no specific place where the density of lines is high and the lines are distributed in a spreading manner. The linear features were classified into five groups, namely: 0–0.7 km^2, 0.7–1.4 km^2, 1.4–2.2 km^2, 2.2–2.9 km^2, and 2.9–3.6 km^2. Based on the rating assignment for the thematic layer, 56.9% of the area was covered by a very low potential zone, while very high and high potential zones covered 17% together (Figure 3h).

3.2. Distribution of the Groundwater Potential Zones in Thlawa

In the study, every main criterion was individually rated and multiplied by AHP weights. Knowledge-based rating and weighting of various classes for each thematic layer have been assigned through the weighted overlay analysis process based on experts' judgment. The weighted linear combination (WLC) output map displays three distinct groups, including low, moderate, and high potential for groundwater (Figure 4). High (23.34 km^2), moderate (122.04 km^2), and low (73.07 km^2) groundwater potential zones cover about 10.6%, 55.8%, and 33.4% of the area, respectively. The factors of rainfall and geology have directly contributed to the presence of high groundwater potential conditions in the east, southeast, and south regions.

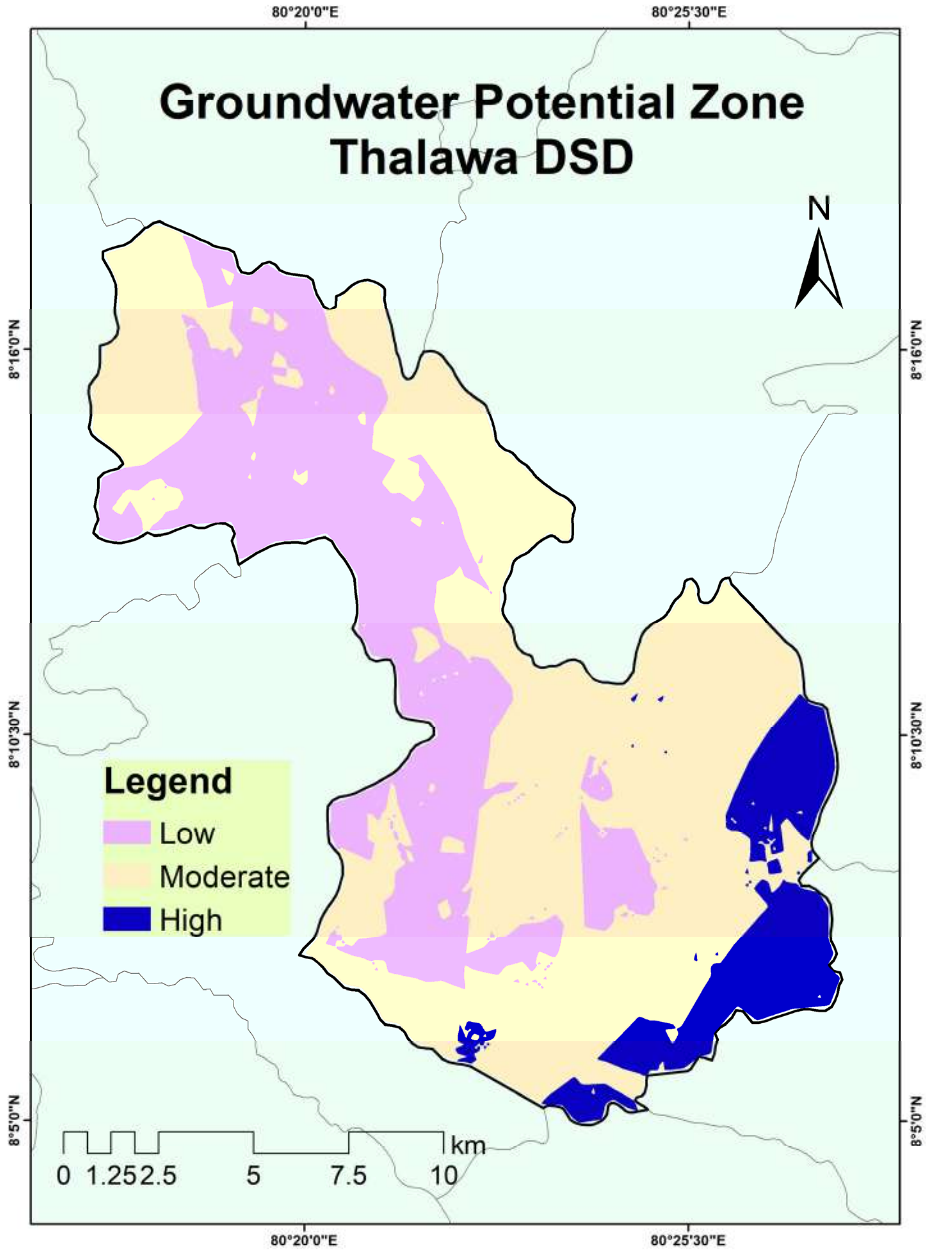

Figure 4. Groundwater potential zones of the study area.

3.3. Validation of Groundwater Potential Zones in Thalawa

Any suitability assessment must be cross-checked with actual ground-truth information to maintain the reliability of the results. The delineated groundwater potential zone map was validated using secondary data and well-discharge statistics gathered during the field survey. To validate the resulting groundwater potential zone map, water discharge and depth data were integrated. Below-ground level (bgl) data were collected from the water resource board and Mahaweli Authority, Sri Lanka. Accordingly, the data was collected from 18 groundwater wells in three different potential zones (Table 7). Water discharge from ground wells ranges from 0.9 Ls^{-1} to 92 Ls^{-1}. Also, the depth of the water level is between 0– 77 m.

Table 7. The data of verified sample wells in the Thalawa division**.**

ID of Well	X and Y Coordinates (WGS 84)		Depth of GW (m bgl)	Water Discharge (Ls^{-1})	GW Potential Zone
	X	Y			
GW1	**324,502**	**164,541**	4.2	74.4	High
GW2	323,444	164,224	2.8	92	High
GW3	322,809	162,213	1.6	43.6	High
GW4	321,327	160,831	0.7	12	High
GW5	323,126	157,345	28.5	64.2	Moderate
GW6	324,396	159,885	24.6	73	Moderate
GW7	325,349	161,895	29	58.3	Moderate
GW8	328,841	163,800	21	34	Moderate
GW9	330,217	164,435	19	54.7	Moderate
GW10	331,381	164,012	0.7	28.6	Moderate
GW11	331,910	162,530	16	14	Moderate
GW12	338,366	155,969	14.3	29.5	Moderate
GW13	340,012	147,185	4.8	36.2	Moderate
GW14	329,370	155,228	72.8	48.6	Low
GW15	331,805	154,805	64.5	77	Low
GW16	331,180	153,958	77	64.5	Low
GW17	335,297	152,900	37	37	Low
GW18	335,297	150,571	46	54.6	Low

According to the validation results, four groundwater wells are located in the high potential area, while nine and five wells are located in moderate and low groundwater potential zones, respectively. The water discharge of the wells in the high potential zones is between 12 Ls^{-1} and 92 Ls^{-1} with a mean of 26 Ls^{-1} and the depth of groundwater ranges from 0.7 m to 4.2 m with a mean of 2.1 m. The mean water discharge of the wells in moderate potential zones is 44, with 14 Ls^{-1} minimum and 73 Ls^{-1} maximum. The mean groundwater depth of the wells in moderate zones is 21.2 m (min: 0.7 m max: 32 m). The water discharge of the wells in low potential zones ranges from 0.7 Ls^{-1} to 0.3 Ls^{-1} with a 0.92 Ls^{-1} mean. The mean water depth is 68 m (min: 37 m, and max: 77 m). The groundwater potential zone produced from the AHP approach demonstrated satisfactory levels of results when predicting the groundwater potential zone in Thalawa DS, Anuradhapura district, according to the verification results. The outcomes further demonstrated that groundwater potential zones might be identified using the methods presented here. Since the research area is essentially an agricultural-dominant DS, this will be more beneficial as a time-cost-efficient approach to choosing and finding groundswells for agricultural uses. This will reduce overexploitation and help conserve the area's scarce groundwater resources. But for this purpose, spatial data at a finer spatial scale may increase the accuracy of the results. The study has limitations since we did not analyze the relationship between groundwater potential and well yield data.

4. Discussion

4.1. The Potentiality of Groundwater, Water Depth, and Discharge

The study area was divided into three distinct groundwater potential zones, namely high, moderate, and low. These zones encompassed 10.6%, 55.8%, and 33.4% of the total area, respectively. The Southern portion of the division is predominantly occupied by high-potential areas, while moderate-potential areas are scattered along the Eastern portion. Low-potential areas, on the other hand, are found in the Western and Northern parts of the division, as depicted in Figure 4. The acceptability of the derived groundwater potential map, generated using GIS-MCDA, was determined based on the groundwater depth and discharge data obtained from a set of representative ground wells. These data were utilized for validation. The existing body of research indicates a considerable correlation between groundwater potential zones and the discharge and water yield seen in the wells within the study locations [75–77].

4.2. The Impact of Slope, Rainfall, and Elevation on Groundwater Potential

The slope is a significant topographic element that influences the process of surface runoff. The impact of slope on groundwater recharge in aquifers is significant [78]. The relationship between slope gradient and surface water percolation is a significant factor in the delineation of groundwater potential zones [79,80]. Previous research has also indicated that flat terrain exhibits significant potential for groundwater accumulation as a result of the extended duration required for water to percolate [75,81–83].

The precipitation patterns exert a significant influence on the hydrological processes within the region and exhibit a direct correlation with the groundwater storage capacity [67,78]. The study area exhibits a maximum rainfall of 116 mm and a minimum rainfall of 88 mm. Several previous studies have demonstrated a strong positive association between rainfall and groundwater [75,84,85]. A study conducted on the Beshilo River watershed in Ethiopia revealed that precipitation had a positive impact on groundwater storage capacity. However, it was observed that the soil structure exhibited variations throughout the catchment area. In regions characterized by the presence of clay deposits, reduced rates of infiltration were found to correspond with decreased groundwater potential. In the context of sandy loam soil, it is observed that regions exhibit rapid absorption and subsequent contribution to the groundwater reservoir. In contrast to higher elevations, lower altitudes exhibited a higher likelihood of groundwater occurrence [86].

4.3. Effect of Geological Factors on Groundwater Potentiality

The utilization of geomorphology as a factor in various studies pertaining to the assessment of groundwater potentiality is of great significance. This is due to its ability to depict the landform and topography of a specific geographical region. Drought, classified as a natural calamity, manifests in regions characterized by arid climatic conditions, leading to the proliferation of vegetation patterns that have evolved to withstand such environmental constraints. The study area is characterized by low plantation surfaces, inselbergs, and a thin soil cover. The eroded relics observed in this context are identified as the oldest plain composed of Vijayan gneiss and quartzite [12]. The moderate and high potentiality of the bulk of the area can be attributed to the high permeability of water on low-level and intermediate plantation surfaces. Prior research has also demonstrated that areas characterized by rocks and sediments exhibiting a high degree of permeability experience rapid infiltration of water into the underlying soil [75,87].

Approximately 40% of the overall land surface consists of rice paddy fields, characterized by a higher degree of porosity that facilitates enhanced water percolation. Consequently, a significant portion of the land falls within the high and moderate potential classifications. Previous research has indicated a positive correlation between arable and agricultural land with moderate and high groundwater potential [75,88,89].

The stream density in a particular area governs the permeability and the percolation rate of precipitation. In the study area, the identification of locations with notably high stream densities that have had a discernible positive impact on water infiltration and movement, particularly in the Southern portion of the research area, is not feasible. Prior research has demonstrated that areas with low stream densities exhibit elevated groundwater potentials [75,90,91]. The hydrological processes of runoff and groundwater penetration in the area are significantly influenced by the presence of linear and curved structural elements [72,79,81]. Water movements have greater intensity in regions characterized by a higher density of lineaments. Previous investigations have also documented similar findings, indicating a favorable correlation between groundwater output and lineament features [75,92,93].

The spatial arrangement of groundwater within a given area is contingent upon the geological attributes of that region, which in turn impact the processes of infiltration and percolation [32,94,95]. Unconsolidated sediments, such as alluvium, exhibit a deficiency in the partitioning process, resulting in a significant proportion (55%) of the region being classified as zones with low and very low groundwater potential. Granitic gneiss, which ranks as the second most prevalent geological formation within the region under study, has been determined to possess a moderate level of appropriateness in terms of its potential for groundwater resources. Other studies utilizing GIS and multi-criteria MCDA have yielded comparable results in the mapping of groundwater potential zones [75,95]. The study area exhibits a limited extent of high water infiltration soil types, namely red-yellow podzolic soils and alluvial soils, which are found in very high and high potential zones, accounting for only 19% of the total area. In contrast, a significant portion of the study area, covering 165 km^2, is characterized by reddish-brown earth with low infiltration capabilities, contributing to 74% of the area classified as having low potential for water infiltration.

5. Conclusions

The current study tries to delineate groundwater potential zones in the Thalawa division using GIS and AHP-MCDA techniques. Weights were assigned to eight potential criteria using AHP. A final groundwater potential map was generated by zoning the area into three classes: high, moderate, and low, using overlay analysis by the WLC method. The final map revealed that 10.6% of the study area has high groundwater potential, 55.08% has moderate potential, and 33.4% has low groundwater potential. Finally, the derived potential zone map was compared with the water discharge and depth data taken from representative groundwater wells in the study area. The mean discharge and mean depth of the groundwater wells in high-potential zones are 26 Ls^{-1} and 2.1 m. In the moderate zone, the mean discharge was 44 Ls^{-1} and the mean depth was 21.2 m, while ground wells in the low potential zone reported 0.92 Ls^{-1} mean discharge and 68 m mean depth. Thus, it revealed that the GIS-AHP integrated zoning map is acceptable and accurate. High groundwater potential areas are located in the Southern portion of the division and moderate potential zones are distributed over the Eastern and Southeastern portions. Low-potential areas are mainly distributed along the Western portion. Due to a lack of data, the relationship between groundwater potential and water yield was not used to validate the result. Incorporating those bivariate analyses into future research will be more helpful in deriving accurate and reliable results. This information will essentially support groundwater management planning decisions. The zoning map will provide policy guidelines for local planning authorities, especially for their agricultural water management. The study will pave the way for more advanced research that incorporates more criteria in national and international contexts.

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