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Determination of Logistics Distribution Centers: A Combination of Spatial Analysis and Analytical Hierarchy Process

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ABSTRACT

The strategic siting of logistics distribution centers, particularly within the medical sector, has increasingly emerged as a crucial consideration in optimizing the supply chain. This study focuses on identifying the most advantageous location for a new logistics distribution center in Aceh Province, leveraging the integration of the analytical hierarchy process (AHP) and geographic information systems (GIS) overlay techniques. Parameters were weighted using AHP, and spatial analysis facilitated the classification of zones into three suitability categories: low, moderate, and high. It was determined that the optimal location for the establishment of a new center would be within a high suitability zone. Six potential sites, designated as Locations A through F, were initially identified. Subsequent evaluation, which included considerations of access road availability and the capacity to uniformly service all health-related warehouses, led to the selection of Location C as the most ideal. This selection underscores the importance of comprehensive spatial and hierarchical analysis in the decision-making process for logistics operations, ensuring effective distribution networks within critical sectors such as healthcare.

1. INTRODUCTION

Logistics is crucial to effectively managing supply requirements and competing in the trade industry. Hence, identifying the logistics center is a crucial tactic that must be executed. An essential factor to consider when selecting a logistics center is its ability to facilitate the integration of diverse modes of transportation globally [1-3]. Nevertheless, significant calamities frequently obliterate transportation infrastructure and restrict transportation capacity. This results in the impeding and intricate nature of the logistics distribution process. An alternative is to utilize air transportation, specifically helicopters. Nevertheless, utilizing helicopters in distribution incurs significant costs and involves intricate procedures [4-6]. Hence, identifying the logistics center is an aspect that necessitates additional investigation. An assessment encompassing socio-economic, geographical, and disaster factors must be conducted to determine the optimal placement for a strategic logistics center. In terms of socio-economics, the logistics center should be strategically located to facilitate the efficient transportation of goods between different locations. Additionally, it should have convenient accessibility to minimize distribution costs [7, 8]. The logistics

center must be located in a geographically safe area, free from natural disasters that could harm its infrastructure or the transportation routes connecting it to the distribution area. Natural disasters encompass seismic events such as earthquakes, tidal waves known as tsunamis, mass movements of land called landslides, and other catastrophic occurrences of natural origin [9-13].

Aceh, located in Indonesia, exhibits remarkably elevated seismic activity. This phenomenon results from multiple seismic sources, including subduction zones and faults that traverse the province. The 2004 earthquake in Indonesia was one of the most significant seismic events ever recorded. There was a tsunami that followed it, which caused significant property damage and over 250,000 fatalities. Transportation reached a standstill during this event, causing significant challenges in distributing essential logistics such as medicine and food [14-17]. Distributing medicines is one of the essential steps that must be carried out immediately when a disaster occurs [18, 19]. However, the situation changes if, simultaneously, the logistics center is impacted by a disaster, particularly the medical logistics center. This will result in logistical delays as the distribution of logistics needs to be carried out from distant logistics centers, which inevitably

takes more time [5, 20-27]. An additional instance that can exemplify the significance of the medical logistics distribution process is the COVID-19 pandemic. The urgent priority in this situation is the immediate distribution of medicines and vaccines to all health facilities in response to the virus's rapid transmission [2, 28-30].

Hence, identifying the logistics center will require a comprehensive analysis involving multiple disciplines. To determine the optimal location for a logistics center and ensure its safety from potential natural disasters, it is necessary to conduct comprehensive reviews of various aspects. Multi-disciplinary assessment results are utilized to identify numerous study variables that must be assigned relative importance. Incorporating interdisciplinary research findings into the GIS framework assigns relative importance to numerous study variables identified through multi-disciplinary assessment results [23, 31-36]. The AHP and analytical network process (ANP) methods are two approaches that can be employed for weighting criteria [37]. The two approaches are applicable and can be seamlessly incorporated with GIS principles. Several studies have used the AHP framework to select a site. The AHP assesses and renders decisions involving multiple criteria. This approach offers multiple options based on specific criteria and assigns a relative score to each option. The AHP enables incorporating both subjective and objective elements into the decision-making process, facilitating the identification of the most crucial factors in intricate scenarios [37-46].

2. MATERIALS AND METHODS

2.1 Research location

A case study was conducted in this study to test the results of the AHP analysis. The selected case study location is situated in Aceh Province, Indonesia. Geographically, the research site is located at 20-60 N and 950-980 E. On the northern and eastern sides, Aceh Province is bordered by Malaysia and the Strait of Malacca; on the southern side by North Sumatra Province; and on the western side by the Indian Ocean. Figure 1 displays the map of the case study location.

2.2 Material

The data used in this study consists of secondary data collected from various references. The data consists of shapefiles for each parameter used in the study. Seven parameters were selected for this research, which include four hazard parameters (earthquake, landslide, tsunami, and volcanic activity), as well as land cover type, soil type, and annual rainfall. The first parameter used in this study is the earthquake vulnerability parameter. According to Priambodo et al. [47], the earthquake hazard vulnerability zones are divided into three categories: low, moderate, and high (descriptions for each classification can be seen in Table 1). Based on Priambodo et al. [47], the classification of earthquake hazard vulnerability zones in Aceh Province is divided into two categories: moderate and high (refer to Figure 2a).

The second parameter used in this study is the landslide vulnerability zone. The landslide vulnerability zone is divided into four classifications: very low, low, medium, and high (each classification is explained in Table 1) [48]. In general, the coastal areas of Aceh Province are classified as having very low to low landslide vulnerability zones. This is because the coastal areas have relatively gentle slopes and lower elevations. On the other hand, the central areas with steeper relief and higher elevations are classified as medium- to high-landslide vulnerability zones (Figure 2b).

Moving on to the aspect of tsunami hazards, the tsunami hazard vulnerability zones in this study are divided into three categories: low, moderate, and high (descriptions for each classification are explained in Table 1). The map displaying the distribution of tsunami hazard vulnerability zones is shown in Figure 2c [49]. The last hazard parameter examined is the volcanic hazard vulnerability zone. Aceh Province has three active volcanoes, according to data from the Indonesian Meteorology, Climatology, and Geophysics Agency (BMKG): Seulawah Agam, Bur Ni Telong, and Peut Sagoe [50-52]. The volcanic hazard vulnerability zones are divided into six zones: A, B, C, D, E, and F (descriptions for each zone are displayed in Table 1). The first three zone groups, A, C, and E, represent zones of lava flow and lahars, while the other three zone groups, B, D, and F, represent zones of projectile rocks and volcanic ashfall. The distribution maps of the zones for each volcano are shown in Figure 3.
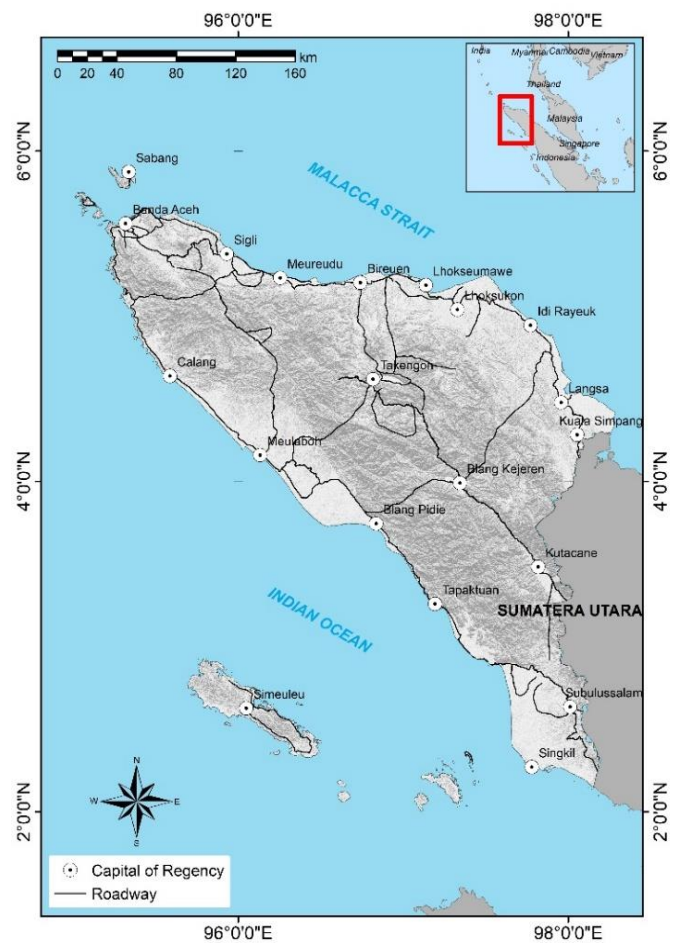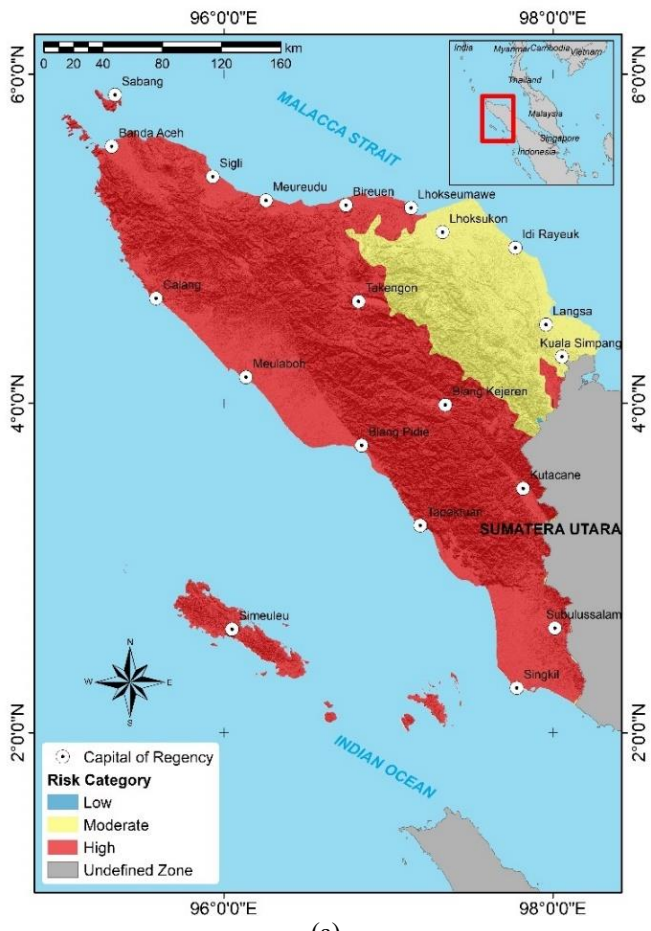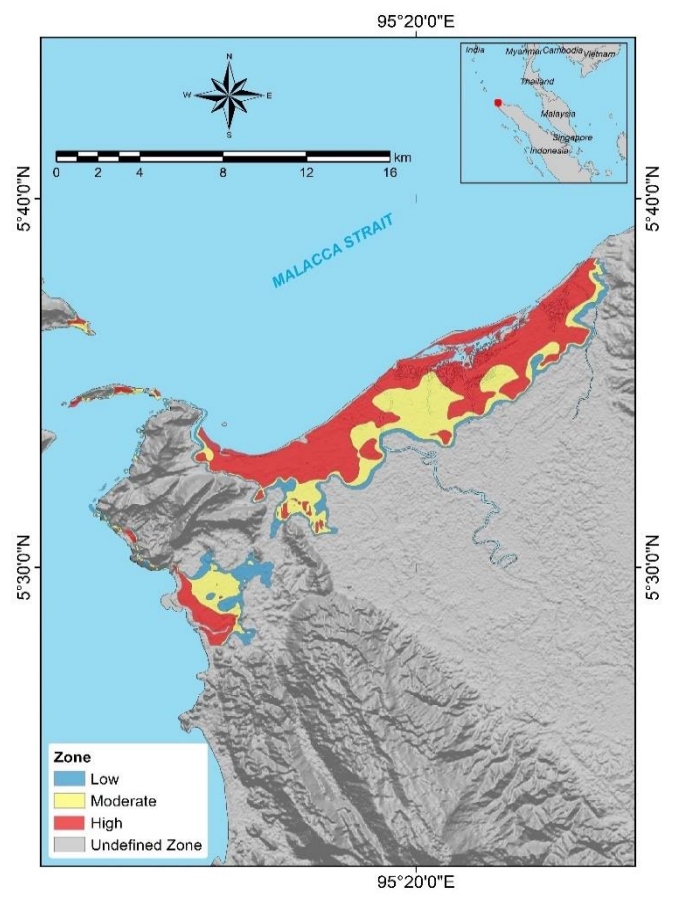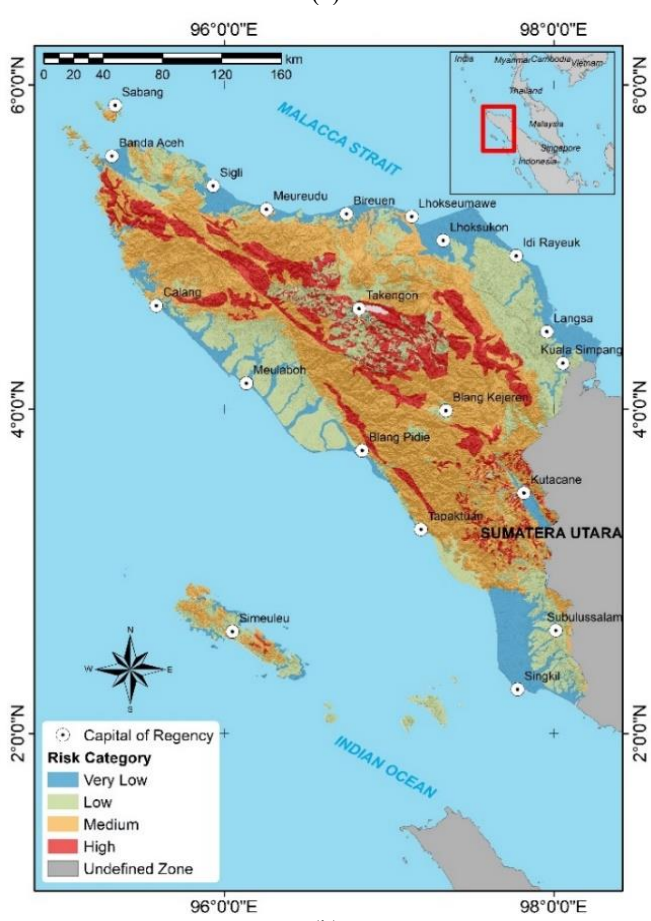

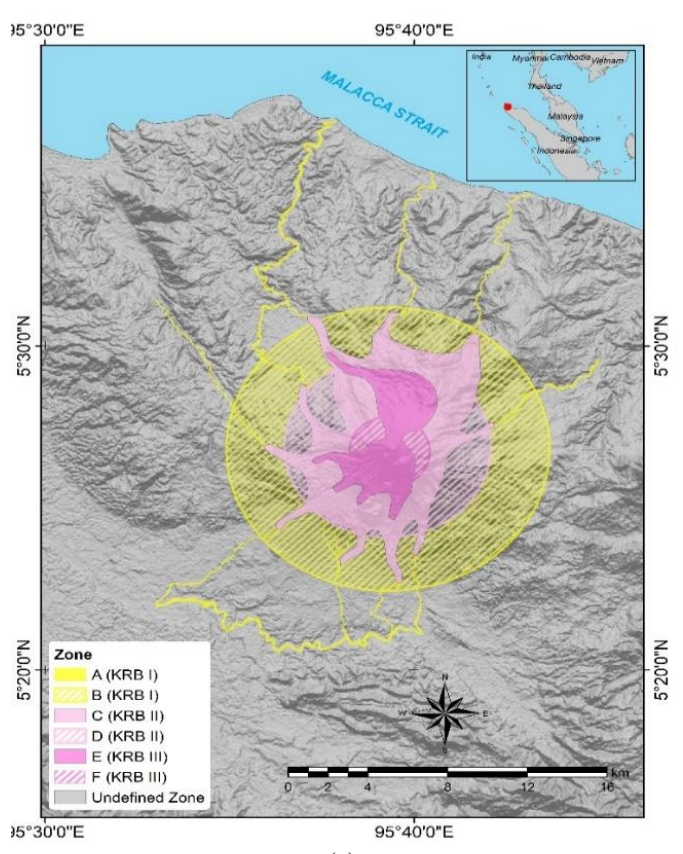**Figure 1.** Research location

(a)

(c)

Figure 2. Hazard Map of Aceh, (a) Earthquake [47], (b) Landslide [48], (c) Tsunami Hazard Map of Banda Aceh City [49]
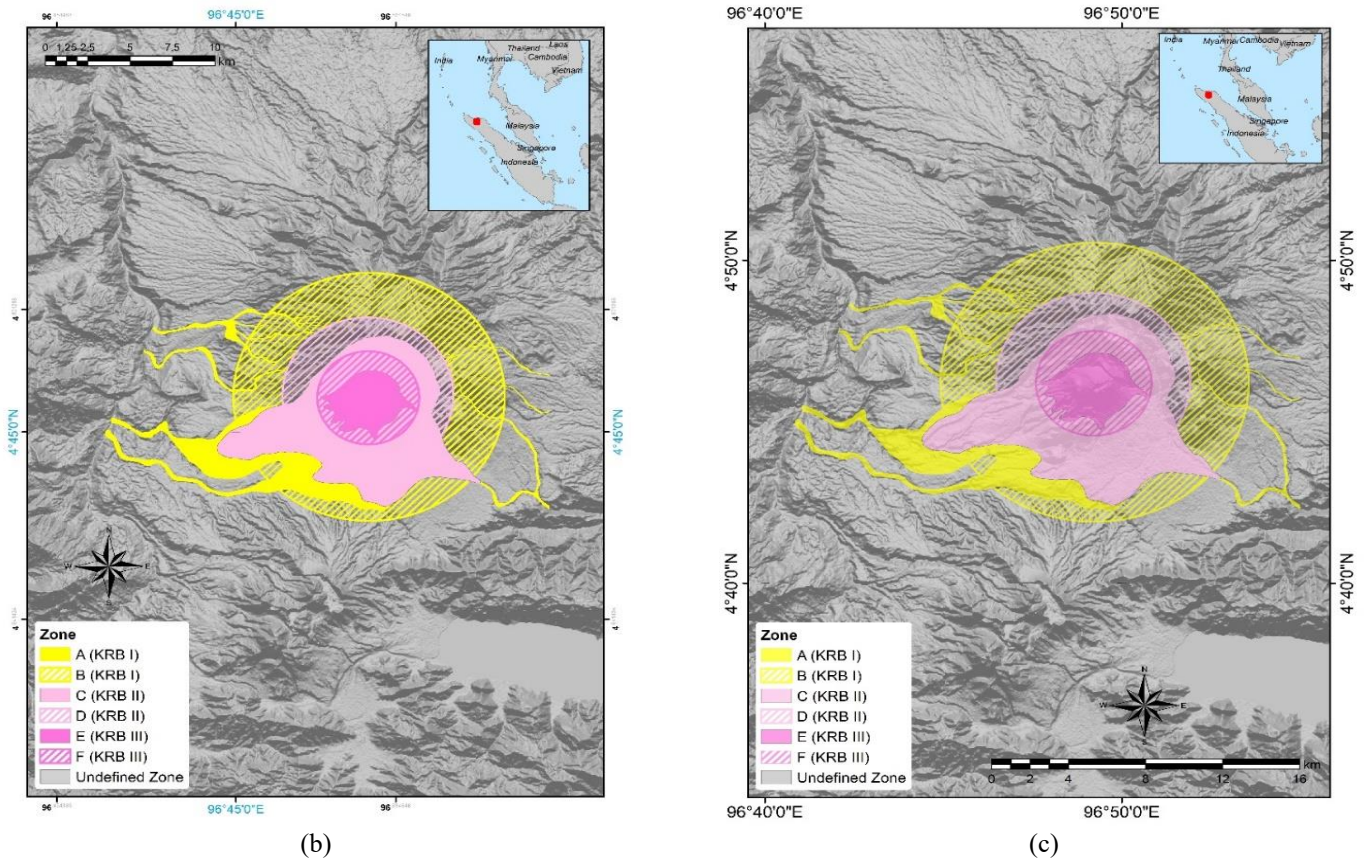

(b)

(a)

(b)

(c)

Figure 3. Volcano Hazard Map of Aceh, (a) Seulawah Agam [51], (b) Bur Ni Telong [52], (c) Peut Sagoe [49, 50]

Table 1. Hazard zone classification

Earthquake Hazard Zone Classification [47]	
Classification Zone	**Description**
Low	The area has the potential to be affected by earthquake shaking with an intensity scale between V-VI MMI (Modified Mercally Intensity)
Moderate	The area has the potential to be hit by an earthquake with an intensity scale between VII-VIII MMI (Modified Mercally Intensity)
High	The area has the potential to be hit by strong earthquake shaking with an intensity scale greater than VIII MMI (Modified Mercally Intensity)
Landslide Zone Classification [48]	
Classification Zone	**Description**
Very Low	The zone has very low susceptibility to landslide evidence. The zone was rarely or never been subjected to landslide. There is no landmark of old or new landslide found in this zone, except on the small area on the river sides. The area is mostly flat to gentle undulating areas with natural slope less than 5-15%, and the slope is not formed by landslide deposits, filling material or plastic and swelling clay
Low	The zone has low susceptibility to landslide evidence. Landslide rarely occur unless the slope is disturbed and old landslide has been stabilized during the past period. Small landslide may occur especially on the river side or gulley. Interval of the natural slope is gentle (5-15%) to steep (30-50%), depending on the physical and engineering properties of rock and soil forming the slope. On the steep slope area, slope is mostly composed of rock with thin soil, and converted by dense vegetation in the form of forest and plantation
Medium	The zone has moderately susceptibility to landslide evidence. Landslide may occure in this zone, especially along the river side, scarp, road cut, of the slope to be disturbed. Old landslide may be activity especially when induced by high rainfall and strong erosion process. Interval of the natural slope is gentle (5-15%) to very steep (>70%), depending on the physical and engineering properties of rock and soil forming the slope. The slope is mostly covered by poor to very poor vegetation
High	The zone has high degree susceptibility to landslide. In this zone, landslide occur very frequently. Old and new landslides still occur induced by high rainfall or strong erosion process. Interval of the natural slope is moderate (30-50%) to very steep (>75%), depending on the physical and engineering properties of rock and soil forming the slope. The slope is mostly very poor coverage vegetation
Tsunami Hazard Zone Classification [49]	
Classification Zone	**Description**
Low	This area has the potential to be hit by a tsunami with an inundation height of less than 1m with a tsunami intensity scale of V or less
Moderate	This area has the potential to be hit by a tsunami with an inundation height of 1-3m with a tsunami intensity scale of V-VI

|	
High	This area has the potential to be hit by a tsunami with an inundation height of >3m with a tsunami intensity scale of VII or more

Classification of Volcanic Hazard Zone [50-52]

Classification Zone	Description
A (KRB I)	Potentially affected by lava flow
B (KRB I)	Potentially affected by ashfall and possible incandescent rockfalls
C (KRB II)	Potential for hot clouds, lava flows, and toxic gases
D (KRB II)	Potential for incandescent rock ejections and heavy ash rains
E (KRB III)	High potential for hot clouds, lava flows, and toxic gases
F (KRB III)	High potential for incandescent rockfalls and heavy ashfalls

The next parameter used in the study is the land cover parameter. This parameter is used to determine the land use in a particular area. By understanding the land use types, we can select a more suitable area for the development of a logistic distribution center (LDC). Based on the Ministry of Environment and Forestry (2019), the land cover classification is divided into 19 categories, which are then modified and simplified into five classifications: industrial zone (including airports, seaports, and mining areas), forest zone (including primary and secondary dryland forests, plantation forests, and scrub zones), swamp zone (including swamp scrub, secondary mangrove forests, and primary and secondary swamp forests), residential zone (including residential areas, open lands, transmigration areas, savannahs, and grasslands), and agricultural zone (including plantations, dryland farming areas, mixed dryland farming areas, and ponds). More detailed explanations can be found in Table 2, while the map showing the distribution of land cover types in Aceh Province is displayed in Figure 4a [53]. Soil type is one of the parameters used in this study. The classification of soil types is based on the classification by the Food and Agriculture Organization of the United Nations (FAO/UNESCO). According to this classification, there are five soil types found in the study area: andosol, ferrasol, fluvisol, luvisol, and rendzina. The description of each soil type is provided in Table 2, while the map showing the distribution of soil types is displayed in Figure 4b [54]. The last parameter used in this study is annual rainfall. Essentially, these two parameters (rainfall and soil type) are closely related to each other. High rainfall can certainly affect the level or precipitation capacity of the soil in a particular location [55]. The classification of annual rainfall in this study is based on Indonesia's agroclimate resources. The average annual rainfall is divided into three classifications: dry, moderate, and wet. The classification and detailed descriptions are explained in Table 2. Furthermore, the map displaying the distribution of average annual rainfall in Aceh Province is shown in Figure 4c [56-58].

**Table 2.** Land cover, soil type, and rainfall classification

Land Cover Zone Classification [53]	
Classification Zone	**Description**
Industrial	Airports, ports and mining zones fall under this zone. These zones are grouped by land use as areas that have been utilized and cannot be changed as new zones
Forest	Primary and secondary dryland forest, plantation forest and scrub zones belong to this zone. These zones are not recommended for use as they are mostly protected forest areas
Swamp	Swamp scrub, secondary mangrove forest, primary and secondary swamp forest belong to this zone. This zone is not recommended for use because it takes time to develop the area and also in terms of inadequate access
Residential	Residential, open land, transmigration, savannah and grassland zones fall under this zone. This zone is highly recommended for use as it already has access points and is easy to develop
Agricultural	Plantation, dryland farming, mixed dryland farming and ponds are classified in this zone. This zone is recommended for use as it already has access points and is easy to develop

Soil Type Classification [54]		
Soil Type	**Contents**	**Description**
Andosol	Volcanic eject	Andosols are highly porous, dark-coloured soils developed from parent material of volcanic origin, such as volcanic ash, tuff, and pumice
Fluvisol	Alluvial lowlands	Fluvisols are found typically on level topography that is flooded periodically by surface waters or rising groundwater, as in river floodplains and deltas and in coastal lowlands
Luvisol	Clay accumulation; distinct seasons	The mixed mineralogy, high nutrient content, and good drainage of these soils make them suitable for a wide range of agriculture, from grains to orchards to vineyards
Ferralsol	Deeply weathered, red or yellow soils of the humid tropics	Clay assemblage dominated by low activity clays (mainly kaolinite) and a high content of sesquioxides
Acrisol	Acidic soils with a layer of clay accumulation; seasonally dry, humid tropics	Clays with low cation exchange capacity
Rendzina	Humus-rich; shallow soils	Carbonates or occasionally sulfate-rich

Rainfall Zone Classification [57, 58]	
Classification Zone	**Description**
Wet	The area that has an annual rainfall of >2,500mm/year
Moderate	The area that has an annual rainfall of 1,500-2,500mm/year
Dry	The area that has an annual rainfall <1,500mm/year

(a)

(b)

(c)
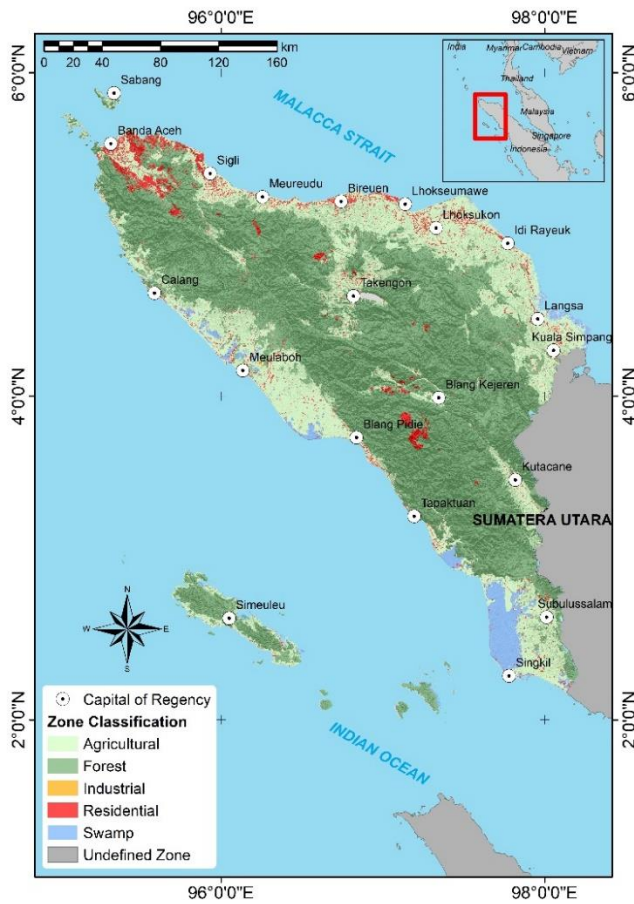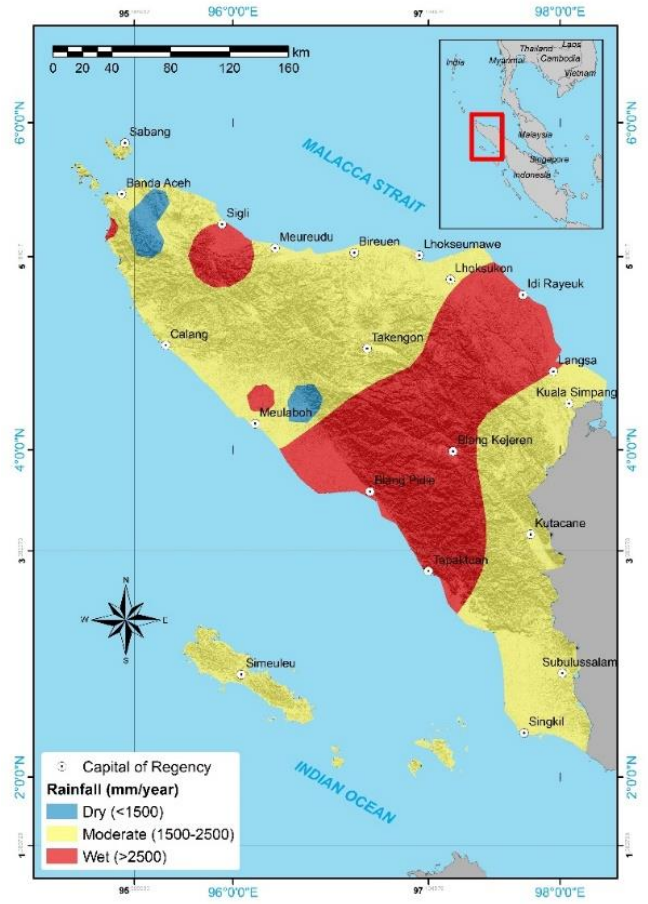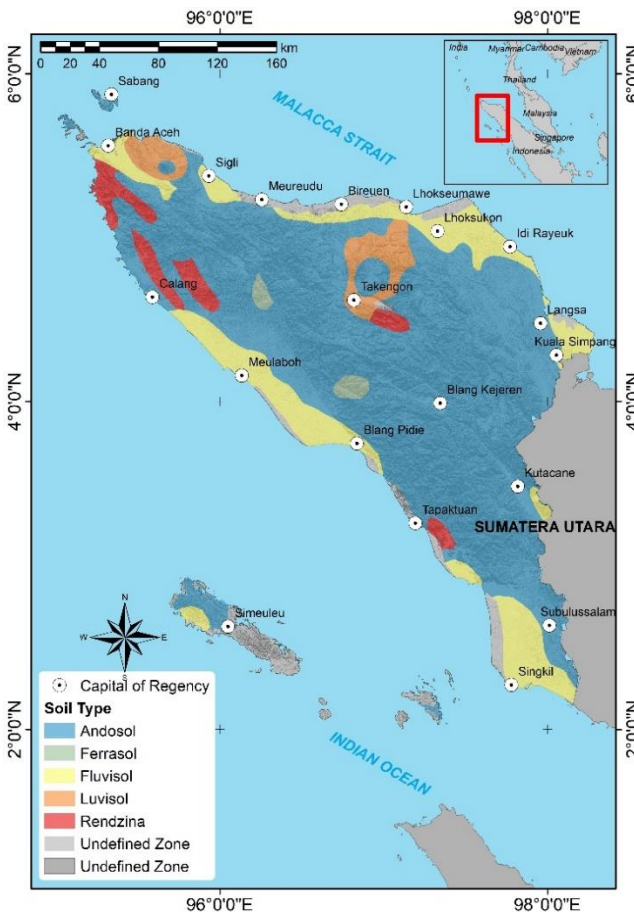
Figure 4. (a) Landcover Map [53], (b) Soil Map [54], (c) Annual Rainfall Map [56]

2.3 Method

2.3.1 AHP

The method used in this research is AHP combined with the concept of GIS overlay. The study begins with the collection of shapefile data for each parameter, which is then classified based on specific references. The 7 parameters are analyzed, and weightings are calculated based on their level of importance. The higher the level of importance, the greater the assigned value. AHP is one of the methods classified under the multi-criteria decision-making (MCDM) approach. AHP is a popular method for decision-making compared to other methods because it can determine criteria that have significant importance compared to other parameters [59, 60]. Basically, the AHP method consists of three stages: creating a hierarchy tree based on importance levels, determining weights through pairwise comparison, and estimating the consistency level of the weighting [60, 61]. In other words, the weights assigned to indicators in AHP indicate the dominance and significance of each element compared to other indicators. Consistency between evaluations and weights is a critical aspect of AHP for factor weighting. The Consistency Index (CI) is used to ensure this consistency, which is defined as follows:

$$CI = \frac{\lambda_{max} - n}{n - 1} \qquad (1)$$

where, n represents the order of a matrix, and λmax indicates the principal eigenvalue of a pairwise comparison matrix.

Finally, the consistency ratio (CR) can be calculated using the following equation:

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

where, RI represents the random consistency index, which can be seen in Table 3. For simplicity, Figure 5 displays a detailed flowchart of the AHP analysis. The results of the AHP calculations for the 7 parameters, along with their respective sub-criteria, can be seen in Table 4.

2.3.2 GIS analysis

After the AHP weight calculations are completed, the next step is to input the calculated weights into each parameter's respective shapefile. In this study, GIS analysis is conducted using ArcGIS software. Some map shapefiles are obtained directly from secondary data, while there are also parameter map shapefiles obtained through interpolating secondary data, such as rainfall data. The average rainfall map is obtained by interpolating data from several rainfall observation stations owned by BMKG. Table 5 displays the interpolated rainfall data using the IDW tool in ArcGIS, resulting in a rainfall map as shown in Figure 4c.

Once each parameter map is prepared, the next step is to add the AHP weighting data field to each parameter. The data entered includes the weight factor of the main parameter and the pairwise weight factor for each parameter. These two values are then multiplied to obtain the weight value for each parameter. After all the parameters are weighted according to

the AHP calculations, the next step is to apply the overlay technique to the seven weighted parameter maps. The overlay technique used is union, where all the parameters are combined into a new shapefile [62]. Next, the result of the overlay (union) is assigned a new attribute or field that is filled with values calculated using the mathematical model obtained from the AHP calculations. The calculation result with the mathematical model yields the AHP calculation values, which are then filtered based on predefined range classes. This filtering is useful for classifying zones that have the best potential to be selected as the location for the LDC. A detailed flowchart of the GIS analysis can be seen in Figure 6. In simpler terms, the overall analysis process can be seen in the research diagram displayed in Figure 7.

Table 3. Random consistency index (RI)

n	RI
1	0
2	0
3	0.58
4	0.90
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.49
11	1.52
12	1.54
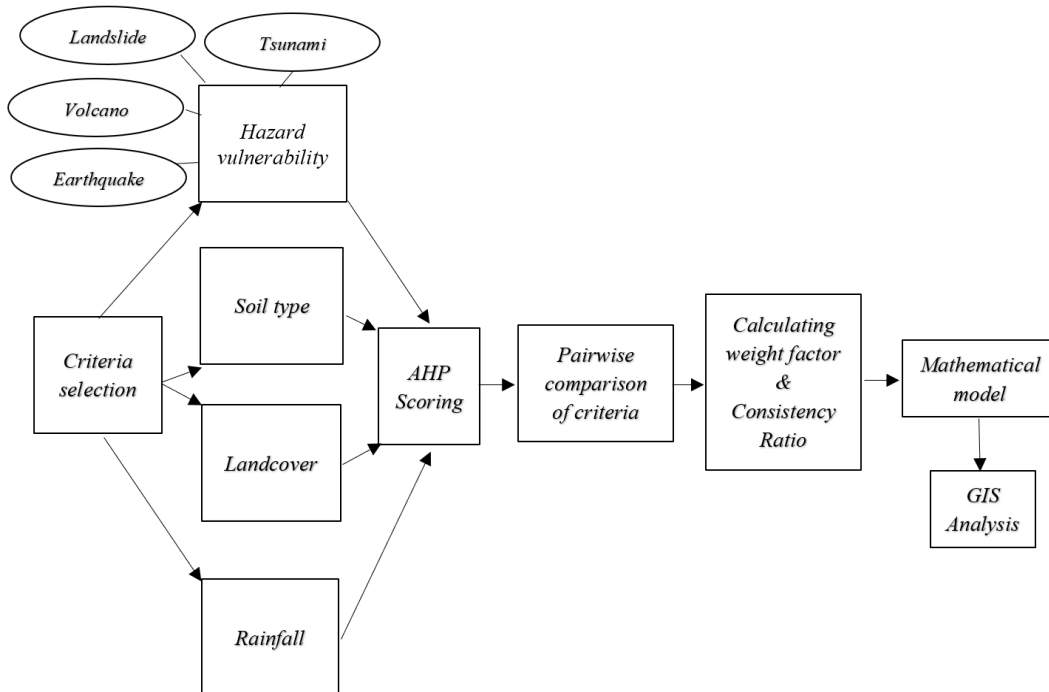
Figure 5. AHP flowchart

Table 4. AHP calculation

			AHP Pairwise Comparison Matrix (PCM) Calculation							
	Soil Type	Land Cover	Earthquake Zone	Tsunami Zone	Landslide Zone	Volcano Eruption	Rainfall	Priorities (P)	Principal Eigen Value (PEV)	Eigen Vector
Soil Type	1.000	0.333	0.111	0.111	0.111	0.111	4.000	0.027	0.208	7.812
Land Cover	3.000	1.000	0.111	0.111	0.111	0.111	5.000	0.038	0.303	8.053

Earthquake	9.000	9.000	1.000	1.000	1.000	1.000	9.000	0.230	1.647	7.166
Tsunami	9.000	9.000	1.000	1.000	1.000	1.000	9.000	0.230	1.647	7.166
Landslide	9.000	9.000	1.000	1.000	1.000	1.000	9.000	0.230	1.647	7.166
Volcano	9.000	9.000	1.000	1.000	1.000	1.000	9.000	0.230	1.647	7.166
Rainfall	0.250	0.200	0.111	0.111	0.111	0.111	1.000	0.015	0.133	7.988

Earthquake Vulnerability Zone Pairwise Comparison Matrix (PCM) Calculation

Earthquake Zone	Low	Moderate	High	Priorities (P)	PEV	Eigen Vector
Low	1.000	3.000	9.000	0.655	2.019	3.080
Moderate	0.333	1.000	7.000	0.290	0.892	3.080
High	0.111	0.143	1.000	0.055	0.169	3.080

Landslide Vulnerability Zone Pairwise Comparison Matrix (PCM) Calculation

Landslide Zone	Very Slow	Low	Medium	High	Priorities (P)	PEV	Eigen Vector
Very Slow	1.000	2.000	2.000	9.000	0.432	1.805	4.176
Low	0.500	1.000	3.000	9.000	0.338	1.446	4.275
Medium	0.500	0.333	1.000	9.000	0.195	0.830	4.249
High	0.111	0.111	0.111	1.000	0.034	0.141	4.160

Tsunami Vulnerability Zone Pairwise Comparison Matrix (PCM) Calculation

Tsunami Zone	Low	Moderate	High	Priorities (P)	PEV	Eigen Vector
Low	1.000	4.000	9.000	0.701	2.178	3.108
Moderate	0.250	1.000	6.000	0.243	0.755	3.108
High	0.111	0.167	1.000	0.056	0.175	3.108

Vulcanic Vulnerability Zone Pairwise Comparison Matrix (PCM) Calculation

Volcano Eruption	A	B	C	D	E	F	Priorities (P)	PEV	Eigen Vector
A	1.000	2.000	2.000	3.000	4.000	9.000	0.329	2.074	6.311
B	0.500	1.000	2.000	2.000	3.000	9.000	0.232	1.479	6.365
C	0.500	0.500	1.000	2.000	9.000	9.000	0.222	1.564	7.059
D	0.333	0.500	0.500	1.000	2.000	9.000	0.128	0.778	6.080
E	0.250	0.333	0.111	0.500	1.000	9.000	0.070	0.491	6.976
F	0.111	0.111	0.111	0.111	0.111	1.000	0.019	0.128	6.689

Landcover Zone Classification Pairwise Comparison Matrix (PCM) Calculation

Land Cover	Industrial	Forest	Swamp	Residential	Agricultural	Priorities (P)	PEV	Eigen Vector
Industrial	1.000	2.000	0.500	0.111	0.125	0.050	0.269	5.366
Forest	0.500	1.000	0.500	0.111	0.250	0.044	0.232	5.323
Swamp	2.000	2.000	1.000	0.111	0.167	0.070	0.364	5.207
Residential	9.000	9.000	9.000	1.000	4.000	0.581	3.076	5.295
Agricultural	8.000	4.000	6.000	0.250	1.000	0.255	1.396	5.463

Soil Type Pairwise Comparison Matrix (PCM) Calculation

Soil Type	Andosol	Fluvisol	Luvisol	Ferrasol	Acrisol	Rendzina	Priorities (P)	PEV	Eigen Vector
Andosol	1.000	9.000	9.000	4.000	5.000	9.000	0.575	3.625	6.310
Fluvisol	0.111	1.000	2.000	2.000	2.000	0.500	0.102	0.705	6.947
Luvisol	0.111	0.500	1.000	1.000	2.000	1.000	0.081	0.518	6.423
Ferrasol	0.250	0.500	1.000	1.000	1.000	2.000	0.092	0.590	6.396
Acrisol	0.200	0.500	0.500	1.000	1.000	2.000	0.079	0.521	6.579
Rendzina	0.111	2.000	1.000	0.500	0.500	1.000	0.072	0.505	7.034

Rainfall Pairwise Comparison Matrix (PCM) Calculation

Rainfall	Wet	Moderate	Dry	Priorities (P)	PEV	Eigen Vector
Wet	1.000	0.500	1.000	0.250	0.750	3.000
Moderate	2.000	1.000	2.000	0.500	1.500	3.000
Dry	1.000	0.500	1.000	0.250	0.750	3.000

Table 5. Annual rainfall data [56]

| X	Y	Station	Rainfall (mm/year)
96.42702	4.257144	Krueng Seunagan	617.5
95.56333	5.37025	Desa Seuneubok	2138.8
95.36989	5.536033	Desa Cot Irie	1707.43
96.58098	4.0512	Gunung Kong	4456.5
95.45833	5.422558	Desa Kp. Lheue	1059.1
95.49589	5.363611	Desa Siron Blang	127
97.95225	4.164472	Peunaron	2288.11
95.2391	5.359892	Pulau Tiga	2854.68
96.20003	4.311306	Sarah Mane	2647.8
95.85882	5.220469	Sawang Teubee	3272.45
97.6803	4.634925	U. Gadeng	2748.97
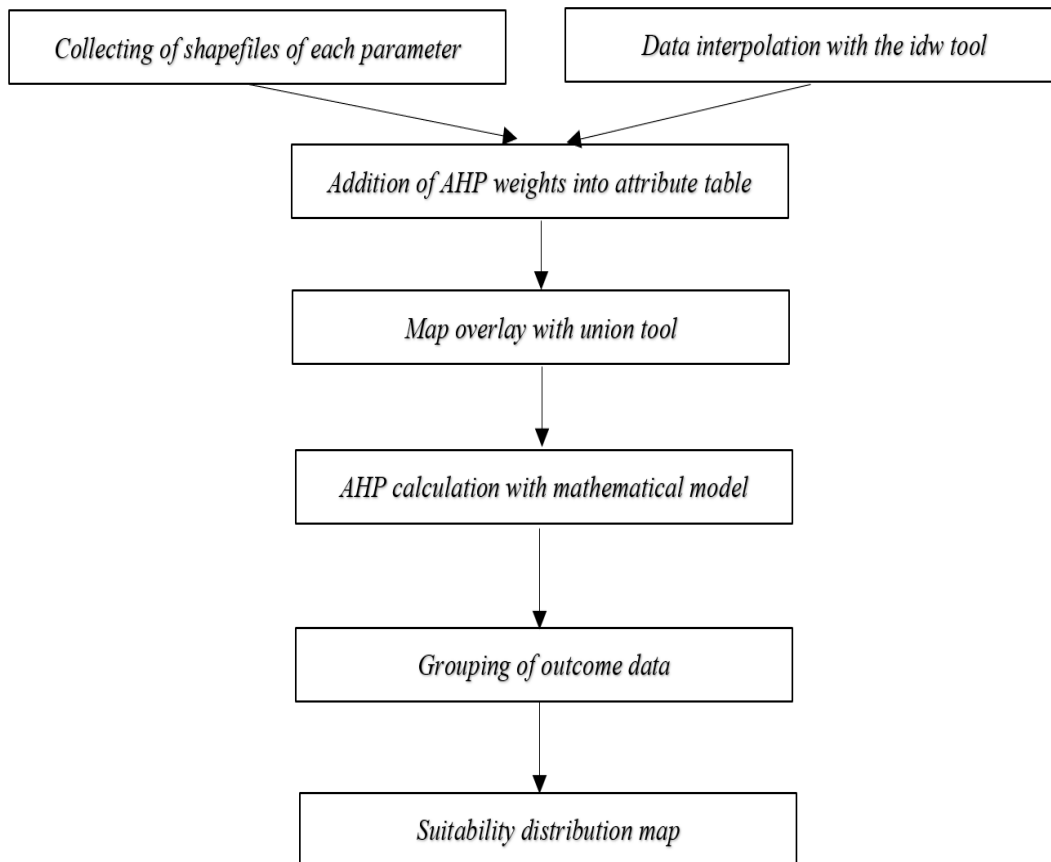
Figure 6. GIS analysis flowchart
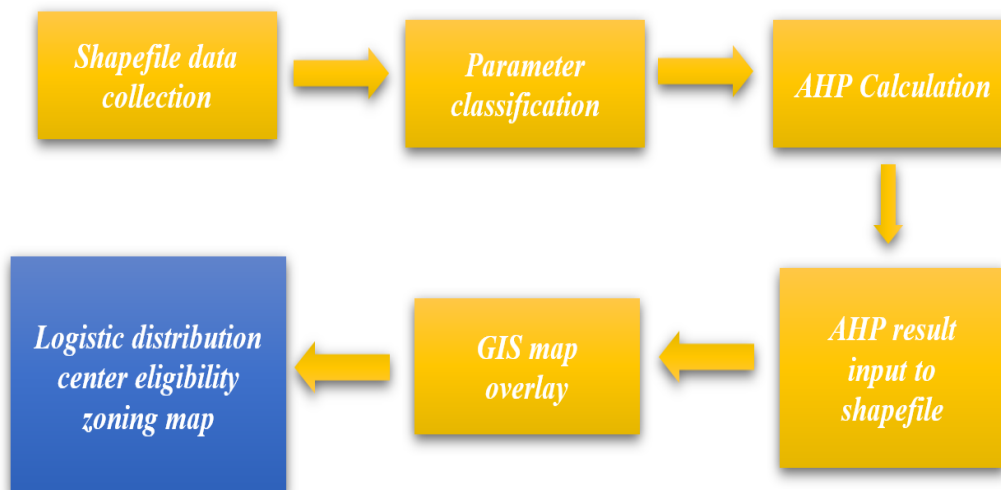
Figure 7. Research flow chart

3. RESULTS AND DISSCUSSION

3.1 Results

3.1.1 Weight factor and mathematical model

The results of the weight calculations for AHP are presented in Table 6. The AHP calculations are based on weighting according to the level of importance of each parameter. The AHP weights are calculated for both the main criteria and sub-criteria. Based on the AHP calculations, a mathematical model can be derived that can be used in GIS analysis. The model equation is as follows:

$$LDC = 0.23(E + Ls + Ts + V) + 0.038Lc + 0.027St + 0.017R$$

where, LDC represents the logistic distribution center, E represents the weight of the earthquake parameter, Ls represents the weight of the landslide parameter, Ts represents the weight of the tsunami parameter, V represents the weight of the volcano parameter, Lc represents the weight of the landcover parameter, St represents the weight of the soil type parameter, and R represents the weight of the rainfall parameter. Furthermore, the results of the CR testing are displayed in Table 7. In addition to the CR testing, sensitivity

analysis is also conducted, and the results are presented in Table 8.

Table 6. AHP Weight factor scale result

Parameter	AHP Weight Factor Scale
Earthquake	0.23
Landslide	0.23
Tsunami	0.23
Volcano	0.23
Landcover	0.038
Soil Type	0.027
Rainfall	0.015

AHP Pairwise Calculation

Parameter	AHP Pairwise Weight Factor	AHP Weight Factor
Earthquake Hazard		
Low	0.655	
Moderate	0.29	0.23
High	0.055	
Landslide Hazard		
Very Low	0.432	
Low	0.338	
Medium	0.195	0.23
High	0.034	
Tsunami Hazard		
Low	0.701	
Moderate	0.243	0.23
High	0.056	
Volcanic Hazard		
A (KRB I)	0.329	
B (KRB I)	0.232	
C (KRB II)	0.222	
D (KRB II)	0.128	0.23
E (KRB III)	0.07	
F (KRB III)	0.019	
Landcover		
Industrial	0.05	
Forest	0.044	
Swamp	0.07	
Residential	0.581	0.038
Agricultural	0.255	
Soil Type		
Andosol	0.575	
Fluvisol	0.102	
Luvisol	0.081	
Ferralsol	0.092	0.027
Acrisol	0.079	
Rendzina	0.072	
Rainfall		
Wet	0.25	
Moderate	0.5	0.017
Dry	0.25	

Table 7. Consistency ratio testing

Parameter	Eigen Value	CI	n	RI	CR
Main criteria	7.503	0.084	7.000	1.320	0.063
Soil type	6.615	0.123	6.000	1.240	0.099
Land cover	5.331	0.083	5.000	1.120	0.074
Earthquake	3.080	0.040	3.000	0.580	0.069
Tsunami	3.108	0.054	3.000	0.580	0.093
Landslide	4.215	0.072	4.000	0.900	0.080
Volcano	6.580	0.116	6.000	1.240	0.094
Rainfall	3.000	0.000	3.000	0.580	0.000

Table 8. Sensitivity analysis

Criterion	Trial 1	Trial 2	Main Result
Soil Type	2.56	3.19	2.66
Land Cover	3.12	4.46	3.76
Earthquake Zone	23.05	22.6	22.98
Tsunami Zone	23.05	22.6	22.98
Landslide Zone	23.05	22.6	22.98
Volcano Eruption	23.05	22.6	22.98
Rainfall	2.1	1.94	1.66

3.1.2 GIS analysis

The GIS analysis was conducted using the ArcGIS software. A case study was developed using the obtained mathematical model, and the study location was Aceh Province, Indonesia. The weights obtained from the AHP analysis for each parameter were incorporated into shapefiles or polygons representing each parameter in the case study. The map overlay was performed using the ArcGIS software, specifically utilizing the union tool (as explained in Section 3.2.2). The calculation of the LDC in the Aceh region was carried out using the equation mentioned in Section 4.1.1. Subsequently, grouping was performed based on predetermined ranges, resulting in a map illustrating the distribution of suitability zones for the construction of a LDC in Aceh Province, as shown in Figure 8.
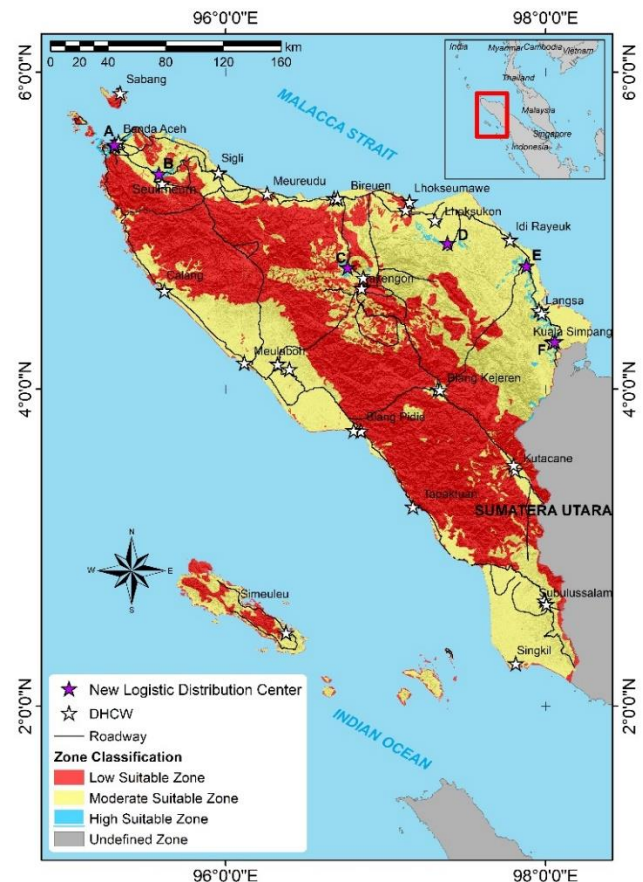

Figure 8. The recommendation of logistic distribution center location based on AHP and GIS analysis

3.2 Discussion

3.2.1 Weight factor

The process of analysis or weighting using the AHP method can be seen more concisely in Figure 7. As explained earlier,

disaster parameters are given higher priority than other parameters, resulting in a weight value of 0.23 for the disaster parameter. As for the alternatives or sub-criteria within each disaster parameter, zones with the lowest risk receive the highest weight values compared to other zones. This is done with the aim of identifying strategic and safe locations for potential natural disasters. The parameters that are considered to be represented by the earthquake vulnerability parameter are the earthquake source zone parameters (subduction zones and faults) and the distribution of earthquake acceleration levels. Both parameters serve the purpose of identifying areas that would experience greater impacts during an earthquake event and determining the areas closest to the earthquake source. However, these two parameters are adequately represented since the analysis or determination of earthquake vulnerability zones already incorporates them [14, 63, 64]. The second parameter chosen is the landslide vulnerability parameter. The landslide vulnerability parameter is considered to represent three other parameters: elevation, terrain morphology, and slope. This is because in the analysis of vulnerability zones, these three parameters are inherently included in the analysis process [65, 66]. This parameter is primarily used with the aim of minimizing the possibility of soil movement at the future distribution center location.

Another selected disaster parameter is tsunami hazard vulnerability. This aspect is considered to be one of the crucial parameters in this study. The classification of tsunami hazard vulnerability zones is primarily conducted in coastal areas, which are the areas that receive the most severe impacts.

The volcanic eruption hazard The volcanic eruption hazard parameter is the last selected disaster parameter. This parameter is used to avoid areas that are prone to disaster if a volcano erupts.

One of the limitations of this study is the lack of socio-economic parameters included in the analysis. Socio-economic parameters that could be important to incorporate include land ownership data for each area. This information would be useful in determining whether a location has the rights or permits to construct buildings or if the location has the appropriate purchasing power when it is selected as a LDC area.

Residential zones are selected as sub-criteria with the highest weight. This is due to the accessibility criterion, as residential areas generally have open and easily accessible roads. Similarly, agricultural zones are chosen with the assumption that their access is guaranteed since they are usually located near residential areas. However, the weight of these zones is not equivalent to that of residential zones due to factors such as land conversion. Generally, access to agricultural zones is not as good as that of residential zones, so if agricultural zones are converted into LDC locations, the effectiveness of the logistic distribution may be reduced due to their potentially more remote locations compared to residential areas.

Industrial zones have a lower weight because they typically serve as ports or mining areas, which are less strategic if located in inland areas (in the case of mining areas). Ports and airports are already considered separate strategic areas, making them unsuitable for selection as LDC locations. Wetland zones also have a lower weight due to cost-effectiveness considerations. It would require extra costs to reclaim wetland areas, making them less recommended as LDC locations. Additionally, these zones have limited accessibility. Forest zones are strongly discouraged as they not only lack accessibility but are also often protected forest areas, making them highly unsuitable as LDC locations.

Regarding soil types, weighting is based on the soil content, where materials with higher precipitation levels receive higher weight values compared to those with lower precipitation levels. As for the rainfall parameter, moderate rainfall has a higher weight than wet and dry rainfall. This is because excessive rainfall increases the likelihood of soil movement in areas with high relief and slope, while low rainfall increases the possibility of limited or difficult access to water. The results of the consistency level testing can be seen in Table 7. The CR obtained from the AHP analysis with 7 parameters is 0.063 < 0.1. Similarly, for all criteria, the CR is also <0.1. Therefore, it can be concluded that the degree of inconsistency is considered satisfactory [37]. The CR refers to how consistent or stable the pairwise comparisons that have been established are. Calculating the CR is important to ensure that the final results of the AHP analysis are more reliable and valid. When the CR value approaches zero, it indicates that the pairwise comparisons are highly consistent (an example of such a result is the calculation of the sub-criteria rainfall (CR = 0.000)). However, if the CR value is too high, it indicates that the calculations are inconsistent and a recalculation is necessary [67-69]. Fundamentally, the AHP method has advantages in terms of its usage. It can be easily scaled and adjusted according to its level of importance. The method is highly compatible with GIS analysis due to its simple weighting system. However, a different scenario arises when there are excessive alternative variations and expert opinions, which can lead to an extensive workflow due to differing results. Inconsistency can also be experienced with this method when there are too many variations in decision-making. However, this can be minimized by conducting CR testing [70, 71]. One of the other MCDM methods that can be used as a benchmark with the AHP method is the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE). This method has the advantage of providing rankings for alternatives, either partially or as a whole. However, it does not explain in detail the method for determining the importance level of each parameter [70, 72]. Therefore, in research that involves determining criteria based on their importance level and does not involve too many alternatives, the AHP method is highly recommended for use. This is because it can easily be combined with GIS, making it a suitable choice for such studies.

3.2.2 Sensitivity analysis

Sensitivity analysis is conducted with the aim of determining the parameters that have the greatest impact on determining the location of LDCs. Sensitivity testing is performed through two trials: trial 1 involves changing the importance values of alternatives (sub-criteria), while trial 2 involves changing the importance values of main criteria (this reweighting process is done by seeking opinions from two different experts). The results of the sensitivity analysis are presented in Table 8.

In trial 1, the altered alternatives or sub-criteria are related to parameters such as landslides, tsunamis, earthquakes, and landcover. In trial 2, the importance values of the main criteria are changed, specifically for non-hazard parameters such as rainfall, soil type, and landcover. Based on Table 8, it can be observed that there is an increase in priority for hazard-related parameters in trial 1, while non-hazard parameters experience a decrease. Similarly, in trial 2, there is an increase in priority

for hazard-related parameters, while non-hazard parameters experience a decrease. Based on these results, it can be concluded that hazard-related parameters (including earthquakes, tsunamis, landslides, and volcanoes) have the greatest impact in the AHP analysis for determining LDC locations.

3.2.3 Case study

The province of Aceh was chosen as the case study location based on the results of the AHP analysis and modeling in this study. The selection of parameters and their respective weights is fundamentally based on the existing conditions in the Indonesian region, particularly Aceh. Indonesia is an area that is highly prone to disasters [73]. Therefore, disaster-related parameters become crucial factors to include in the AHP analysis for determining the location of LDCs. Earthquakes are one of the significant parameters in this study, considering their frequent occurrence in the province of Aceh. One of the largest earthquakes ever recorded in Aceh was the 9.1 Mw earthquake in 2004, accompanied by a devastating tsunami that caused infrastructure damage and the loss of lives. Building upon this event, the earthquake parameter becomes an essential component to be considered in this study. The high occurrence of earthquakes in Aceh can be attributed to various factors, including the presence of seismic sources such as subduction zones and the Sumatra fault passing through the region [74-76]. In addition to earthquakes and tsunamis, the presence of active volcanoes also underlies the reason why disaster-related parameters are prioritized over others. Furthermore, the occurrence of landslides in highland areas, such as the Tangse region, is another strong reason for prioritizing disaster-related parameters. Therefore, the prioritization of disaster-related parameters, including earthquakes, tsunamis, active volcanoes, and landslides, is justified based on their significant impact and occurrence in the study area. [77, 78]. Using ArcGIS software (with the "Union" tool), a map overlay was performed on the seven parameter maps generated (Figures 2-4). The result of the map overlay is presented in Figure 8. Based on the overlay of the seven parameter maps, which were assigned AHP weight values, calculation values ranging from 0.0017 to 0.3000 were obtained. These values were then divided into three equally sized ranges: 0-0.1 (low suitable zone) with a total area of 29,033.58 km², 0.1-0.2 (moderate suitable zone) with a total area of 28,663.028 km², and 0.2-0.3 (high suitable zone) with a total area of 117.76 km². This division is based on the weighting of each parameter class, where classes with higher importance criteria have higher weights than those with less important criteria (using the benefit criteria concept). Therefore, locations with higher AHP values are chosen as highly suitable locations compared to locations with lower AHP values [79-81]. Figure 8 displays the overlay of the map, including the locations of health warehouses in each district within Aceh Province (indicated by white star symbols) and the recommended locations for the new LDC based on the analysis (indicated by purple star symbols). The new recommended locations are chosen within the high-suitable zone, which fulfills specific criteria such as easy road access, strategic positions (close to city centers), and the ability to reach the health warehouses in each district. Based on these criteria, location C can be selected as the LDC for Aceh Province. This decision is influenced by the central position of location C within Aceh Province, allowing for evenly distributed travel distances to the health warehouses in each

district, whether they are located in the northern or southern parts of the province. On the other hand, locations A, B, D, E, and F can still be considered as potential LDC locations due to their accessibility via national roads. However, their positions, being either too far north or too far south in the province, make them less prioritized as the central LDC. Furthermore, no suitable zones for selecting a LDC were found in the western part of Aceh Province based on the AHP analysis mentioned above.

4. CONCLUSIONS

The AHP method has proven to be a useful approach for weighting parameters based on their level of importance. In determining the location of LDCs, seven parameters were considered. These parameters include four disaster-related factors (earthquake hazard, landslide hazard, tsunami hazard, and volcanic eruption hazard), land cover, soil type, and rainfall. The selection of each parameter was carefully considered to adapt to the environmental conditions and obtain the most ideal results. However, there are several limitations that need to be considered when using the AHP approach for weighting. One prominent limitation is the significant level of bias that can arise if expert opinions vary greatly. This can make it challenging to prioritize parameters with higher importance. One way to minimize bias or errors is by conducting a CR test and sensitivity analysis. These tests can help assess the validity of the AHP analysis results and identify parameters that have the most significant impact.

Based on the applied case study, the results yielded a high level of accuracy and alignment with expectations. The suitability zones were distributed according to the weighted importance levels, and the high suitable zone was only found in specific areas that truly met the ideal criteria based on the weighting of each parameter. However, it is worth noting that this research has limitations, such as the absence of socio-economic parameters in the AHP analysis to determine LDCs. It is hoped that future studies will address this limitation by incorporating more complex parameters to achieve more ideal and accurate results. Additionally, the inclusion of additional weighting methods could provide further comparative insights.

AUTHOR CONTRIBUTIONS

Hizir Sofyan, as the corresponding author, has contributed to overseeing all the authors in preparing the manuscript. Y. Rimadeni has prepared the manuscript and collected shapefile data from various references. S. Rahman has conducted the AHP weighting. S. Pramana has participated in interpreting the AHP results and manuscript preparation. Juellyan has prepared all the maps and figures, as well as interpreted the results.

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