

Geospatial Modelling of Landfill Suitability Using Geophysical and Remote Sensing Data in a Basement Complex Area

¹Kehinde Anthony Mogaji, ²Soliu Ademola Mudashiru, *³Sodiq Solagbade Oguntade, ⁴Mariam Yetunde Toyib

^{1,2,4}Department of Applied Geophysics, Federal University of Technology Akure, Ondo State, Nigeria

³School of Natural and Built Environment, Queen's University Belfast, Belfast, United Kingdom

Email: soguntade01@qub.ac.uk

Authors ORCID IDs: ¹<https://orcid.org/0000-0001-7069-1319>, ²<https://orcid.org/0009-0003-2305-9646>, ³<https://orcid.org/0000-0002-6247-1284>, ⁴<https://orcid.org/0009-0000-5796-2348>

Abstract

Sustainable waste management solutions, such as optimal landfill siting, are important due to the significant increase in solid waste generation. This research employed a geospatial framework to model seven (7) landfill suitability assessment factors (LSAFs) sourced from geophysical and remote sensing datasets, leveraging on Entropy (En), Analytical Hierarchical Process (AHP) and Grey Relational Analysis (GRA) models within the basement complex area of Nigeria. The seven Landfill Suitability Assessment Factors (LSAFs): slope, lineament density, drainage density, overburden thickness, hydraulic conductivity, depth to basement, and reflection coefficient, were systematically analysed using the aforementioned models to create landfill suitability assessment maps (LSAMs) of the study area employing ArcGIS 10.7 software. The result of the En-LSAM model revealed that 65% (288m²), 32% (153m²), 9% (43m²) while that of AHP modeled LSAM showed that, 35% (169m²), 49% (238m²), 16% (77m²) whereas GRA modelled LSAM showed that 38% (185m²), 47% (228m²), 15% (71m²) of the study area fall into low, moderate and high landfill suitability respectively. The proxy validation technique, employing qualitative validation with the longitudinal conductance data of the study area, demonstrated accuracies of 71%, 64% and 70% for the Entropy, AHP and GRA models, respectively. The accuracies reveal the superiority of the entropy and GRA models, which are data-driven weighted approaches, over the expertly weighted AHP model in dividing the landfill suitability regions within the study area. This research presents an approach of integrating remote sensing and geophysical parameters for landfill suitability modelling in regions falling within the basement geologic settings. The findings from this research not only provide actionable insights for informed decision-making but also contribute to the advancement of geophysical knowledge and sustainable environmental management.

Keywords: Waste management, Landfill, Geophysics, Remote sensing, Geospatial analysis, Entropy

Introduction

The exponential increase in urbanisation and industrial activities has led to a dramatic increase in the generation of municipal solid waste (MSW), creating an urgent need for sustainable waste management solutions (Das et al., 2019; Soni et al., 2022). The inability of the natural environment to decompose and recycle these vast quantities of waste effectively has resulted in significant ecological and public health challenges. Among various strategies, landfill development remains one of the most widely employed waste management approaches, particularly in developing regions (Idowu et al., 2019; Rajoo et al., 2020). A landfill is a system/facility in which solid wastes from municipal and/or industrial sources are disposed of. Since landfills house wastes, improper landfill siting can exacerbate environmental degradation, contaminate water resources, and therefore pose significant risks to human health and the environment at large (Enisan et al., 2024; Milutinović et al., 2016; Nadiruzzaman et al., 2022). Thus, identifying optimal landfill sites employing robust and scientifically driven methodologies is paramount not only for academic analysis but also for practical applications necessary to ensure a sustainable Earth (Bibri, 2021).

Landfill suitability assessment (LSA) is a complex process that involves evaluating multiple environmental, surface and subsurface factors to determine the most appropriate locations for waste disposal (Bilgilioglu et al., 2022; Goulart Coelho et al., 2017). Traditional approaches to LSA, including ad-hoc methods and economic approaches, often fail to capture the interplay of all the factors that impact the suitability of landfills. This is because of their over-reliance on the subjective assessments of experts, which are most of the time inconsistent, biased and less focused on the most important data that can be derived from thorough analysis (Laski, 2020). Recent advancements, including geospatial framework-based multi-criteria decision analysis (MCDA) employing conditioning factors spanning across surface and subsurface, have significantly improved the accuracy and reliability of suitably choosing the best and effective landfills (Alkaradaghi et al., 2019; Roy et al., 2022). This combined approach enables the modelling and the integration of several factors, such as drainage density, lineament density and hydraulic conductivity, which are paramount to assessing landfill suitability.

Several multicriteria decision-making models have been adopted in the realm of modelling LSA. Yazdani et al. (2015) used GIS to assess the suitability of existing landfills, Demesouka et al. (2016) used a GIS framework-based MACBETH for landfill suitability analysis, and Saatsaz et al. (2018) used a GIS-based AHP model for the suitability assessment of an existing old landfill. Similarly, Chabuk et al. (2017) applied GIS-based AHP and SAW for selecting

suitable land for a landfill, and Ali et al. (2021) also applied AHP and FTOPSIS in a GIS environment for choosing a sanitary landfill site. However, there is currently limited research on modelling LSA in the case study of interest, which is a rapidly expanding community that needs efficient management of its wastes. Such efficient management can be realised with appropriate landfill suitability assessment leveraging the computational prowess of widely adopted MCDMs, thereby setting a precedent for further similar research in the study area. In doing so, this study presented the application of three MCDM models: Entropy, Analytical Hierarchy Process (AHP) and Grey Relational Analysis (GRA), to determine the suitability assessment of the study area for landfill development. The rationale for selecting the three MCDM models, which integrate geophysical and remote sensing datasets within a GIS framework, is discussed below.

The entropy model is an objective weighting model (Lam et al., 2021) that gives priority weight to the criteria through the quantification of the amount of useful information each criterion provides, thereby bypassing human bias in the criteria weighting assignment. This data-driven property makes it a model of choice, as the result will show the landfill suitability from the lens of the available data. Conversely, to assess how the landfill suitability would be ranked given the introduction of experts' opinions in the weight assignment process, the AHP model was also selected. In such a scenario in which experts' opinions need to be considered, the AHP model has been widely used in several applications (Buran & Erçek, 2022; Mu & Pereyra-Rojas, 2017), due to its ability to incorporate expert knowledge and judgment in determining the relative importance of each criterion. Since the two previously elaborated models are weighting models, our approach also assessed the suitability of giving equal weight to the considered criteria while selecting an efficient ranking model. The GRA model was chosen not only due to its limited use case as a ranking model in selecting optimal landfill area, but also its ability to assess multiple heterogeneous parameters. In assessing the parameters, GRA brings the heterogeneous criteria on a common scale for effective ranking of the alternatives (Esangbedo et al., 2024; Hsiao et al., 2017), thereby fitting directly into the theme of this current research that involves criteria from two different sources.

Thus, through the lens of different MCDM models, this paper presents the integration of remote sensing and geophysical datasets within a GIS framework for efficient decision-making as related to the assessment of landfill suitability of the selected case region. Ultimately, the findings from this research will serve as a reference for relevant stakeholders within the environmental management domain, and the methodology presented will also be a reference

for research on the suitability assessments of landfills in places falling within a heterogeneous geologic environment similar to the case study region.

Materials and methods

Site description

The study area is located at Ibule Soro, within the Ifedore Local Government Area of Ondo State, Nigeria. It is situated between the latitudes 808400 and 809600N and longitudes 732800 and 733600E. Access to the area is primarily facilitated via the Ilesha-Akure express road, along with several minor roads linking Akure and other nearby settlements (Fig. 1). The terrain in the survey area is characterised as undulating, with elevations ranging from 352 meters at the lowest point to 380 meters at the highest point. The study area lies within the rainforest zone, characterised by dense vegetation comprising evergreen shrubs. The predominant drainage pattern is dendritic, with rivers flowing mainly in the East-West direction. The tropical climate of the region is characterised by a significant amount of rainfall, largely due to the prevailing winds blowing from the Atlantic Ocean toward the Guinea coast. The area experiences a short dry season and a longer wet season, with high rainfall averaging between 25 and 30 mm and relatively high humidity during the wet season, while lower humidity levels characterise the dry season.

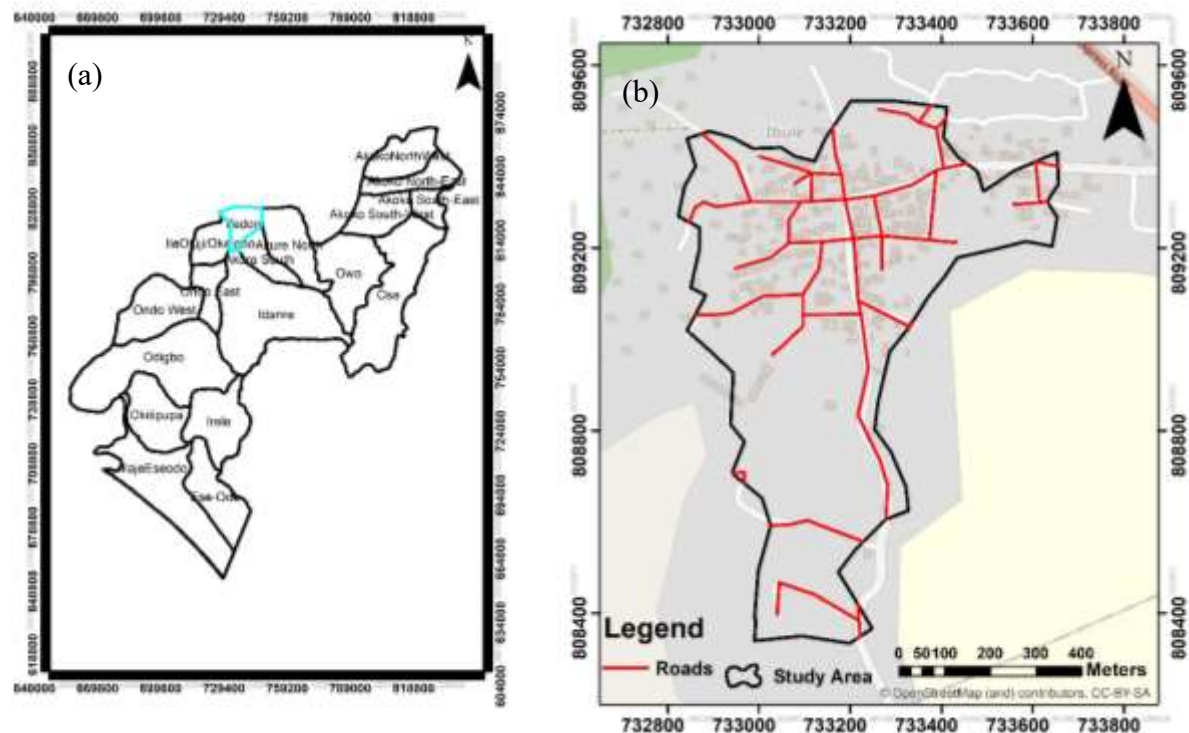


Fig. 1 (a) Ondo State showing the local government of the study area (b) Study area location

Geology of the study area

The study area is underlain by the Nigerian Southwestern Precambrian Basement Complex, with migmatite gneiss as the predominant rock type (Fig. 2). Migmatite Gneiss is a basement complex rock which comprises Biotite, Hornblende Gneiss, Quartzites, Quartzschist and small lenses of calc-silicate rocks. It has ages ranging from Pan-African to Eburnean.

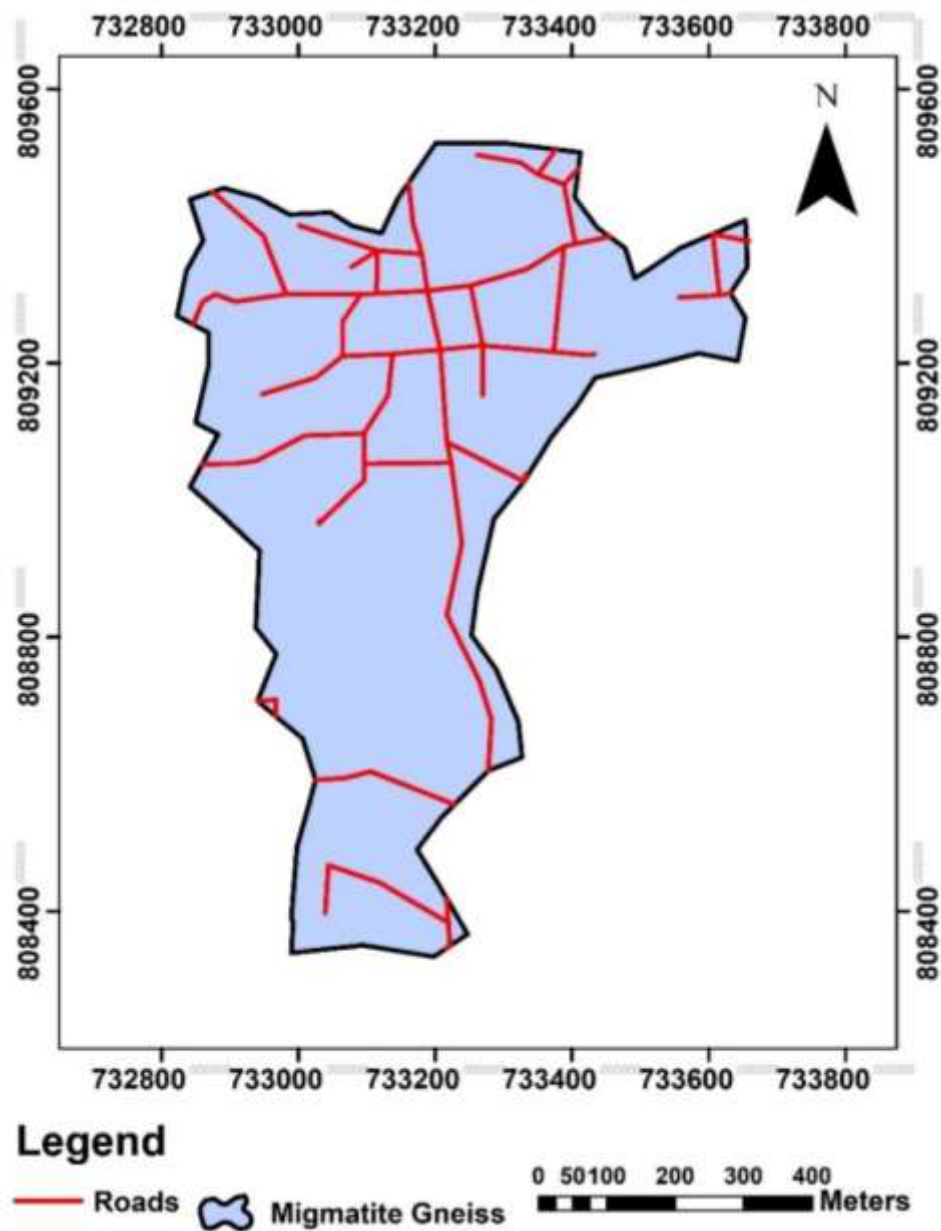


Fig. 2 Geological map of the study area modified after Anthony et al. (2020)

Geoevaluation of landfill suitability of the study area

The geoevaluation of landfill suitability within the study area shows the complex interaction of different surface and subsurface factors inherent in basement complex regions. These regions, characterised by crystalline igneous and metamorphic rocks, exhibit secondary porosity and permeability that stem from the weathering and fracturing of the rocks. These weathering and fracturing are critical determinants in assessing the area's capacity to support landfill siting without compromising the underlying groundwater system, thereby making the landfill conform to key environmental safety protocols (Nkwunonwo et al., 2024). Leachate, the liquid that drains from landfills, contains dissolved and suspended substances like toxic chemicals, heavy metals, and microbial pathogens. Therefore, assessing the suitability of a landfill site must consider the potential environmental safety impacts of these harmful materials (Carević et al., 2021; Mukherjee et al., 2015; Postacchini et al., 2018). These impacts include, but are not limited to, groundwater contamination, surface water pollution, soil degradation and air pollution. Thus, key landfill suitability assessment factors (i.e. overburden thickness, hydraulic conductivity, depth to bedrock, and reflection coefficients), which stem from subsurface evaluation involving geophysical data interpretation, provide necessary insights into the subsurface protective capacity against leachate infiltration. Since the environmental impacts of improper landfill siting are immense, the evaluation of subsurface factors will also need to be complemented with the evaluation of surface factors (i.e., slope, lineament density, and drainage density).

Air pollution, which arises from landfill gas emissions (i.e. methane and carbon dioxide) and surface water contamination, is one of the critical environmental impacts of improper landfill siting, which can be curbed through the assessment and understanding of these surface factors (Kebede et al., 2021; Siddiqua et al., 2022). Understanding the role of slope as a critical surface factor can help optimise landfill design to minimise gas escape and enhance efficient gas collection, whereas insights from drainage density can help identify landfill sites in regions where leachate from the landfill has little to no interaction with surface water (Naveen et al., 2018). In addition, the accumulation of heavy metals and toxins from an improperly sited landfill could also degrade soil quality, thereby negatively impacting the agricultural potential of the soil. Assessing surface factors, especially lineament density, could help site landfills in areas with robust structural integrity and minimal fault lines, thereby mitigating soil infiltration of the harmful substances that could cause ecosystem degradation (Bechrone et al., 2024).

Therefore, considering subsurface (i.e. overburden thickness, hydraulic conductivity, etc.) as well as surface (i.e. slope, drainage density, etc.) factors in landfill suitability assessment helps to create a holistic approach that aims to address

various environmental impacts (i.e. groundwater contamination, air pollution, surface water contamination, etc.) of improper landfill siting, thereby leading to more sustainable and environmentally responsible waste management solutions.

Landfill suitability assessment factors (LSAFs)

As explained in the previous section, it is crucial to conduct a landfill suitability assessment of the study area by considering both surface and subsurface factors. In this study, the surface factors employed are Slope (Sl), Lineament density (Ld), and Drainage density (Dd), whereas the subsurface factors employed are Hydraulic conductivity (K), Reflection coefficient (Rc), Overburden thickness (Ot), and depth to basement (Db). The relevance of each of these factors to landfill suitability assessment is elaborated below:

Slope (Sl)

The slope is crucial in various landscape processes, influencing soil water quality, erosion risk, and surface runoff (Mallick, 2021). Its stability is particularly significant in landfill site design, impacting material weight and construction costs (Mallick, 2021). Steeper slopes can lead to increased excavation expenses, indicating that areas with higher slope values are relatively not preferred when siting a landfill as compared to areas having lower slope values (Wang et al., 2009).

Lineament density (Ld)

Lineaments are crucial groundwater controls in any subsurface environment. Due to their permeable nature, they typically act as conduits for the movement or accumulation of groundwater. Consequently, it is essential to avoid locating landfill sites in areas with high lineament density, as this may lead to significant contamination of groundwater supplies through leaching (Todd & Mays, 2004). Also, High lineament density regions tend to support the high groundwater availability (Mogaji et al., 2011), suggesting that landfills should be located in areas with low lineament density.

Drainage density (Dd)

Drainage density represents the total sum of stream (wadi) lengths within a watershed divided by its overall area (Prabu & Baskaran, 2013; Yeh et al., 2016). Regions with elevated drainage density tend to have a reduced infiltration rate, in contrast to low drainage density areas, indicative of heightened infiltration potential (Mogaji et al., 2014).

Therefore, priority is given to areas with low drainage density, and less emphasis is placed on those with high drainage density when selecting suitable landfill sites.

Hydraulic conductivity (K)

Hydraulic conductivity refers to the rate at which water flows through a unit area of an aquifer under a unit hydraulic gradient(Shahbazi et al., 2020). Areas with high hydraulic conductivity will be able to transmit water more easily when subjected to a hydraulic gradient; thus, such areas will leach more contaminants into the groundwater system(Fetter et al., 2017).

Reflection coefficient (Rc)

The reflection coefficient is a geophysical parameter used to determine the degree of weathering or fracturing of the basement rock in a particular location (Vijay Kumar et al., 2015). As the reflection coefficient in a particular location is higher, the weathering is higher, which in turn makes such an area unsuitable for landfill site selection. The weathering will jeopardise the foundation integrity of such bedrock. Thus, a higher reflection coefficient leads to reduced suitability of landfills and vice versa.

Overburden thickness (Ot)

Considering the aquifer layer, overburden thickness refers to the thickness of the layer overlying the aquiferous layer. Areas with thick overburden are most suitable for sitting a landfill, as such thickness acts as a protective layer, reducing the likelihood of contaminants leaching into the aquiferous layer/groundwater system(Adenuga & Popoola, 2020). Furthermore, such thicknesses act as a natural filter, making it unlikely for contaminants to pollute the groundwater system, unlike areas with thin overburden, which filter fewer contaminants.

Depth to basement (Db)

Depth to bedrock refers to the vertical distance measured from the topsoil to the top of the bedrock. To prevent groundwater pollution by the leaking of leachate, landfills should be located in areas with sufficient depth to bedrock(Demesouka et al., 2014; Eskandari et al., 2012). Thus, higher bedrock areas are preferred in landfill siting compared to areas with lower bedrock and vice versa.

Methodology

The methodology employed in this study involves the acquisition, processing, and interpretation of geophysical and remote sensing data and the application of multicriteria decision-making (MCDM) methods to generate suitability maps for the study area. The flowchart (Fig. 3) depicts the step-by-step approach adopted for the research.

Data acquisition

This study integrates information from two primary data sources: remote sensing and the electrical resistivity geophysical method. The remote sensing data employed is the Shuttle Radar Topography Mission (SRTM) 30m resolution digital elevation model (DEM) raster data of the study area, which was accessed from the USGS Earth Explorer website (www.earthexplorer.usgs.gov). This approach is widely accepted as it offers an accurate and reliable method for identifying the necessary surface datasets for landfill suitability assessment, i.e., slopes and lineaments (Olusina & Shyllon, 2014). In terms of the electrical resistivity geophysical method, vertical electrical sounding (VES) data acquisition utilising the Schlumberger electrode configuration was adopted in the study. A total of 40 VES data points were strategically and randomly acquired in the study area (Fig. 4) to gather necessary information on the subsurface for a comprehensive assessment of the landfill suitability in the study area.

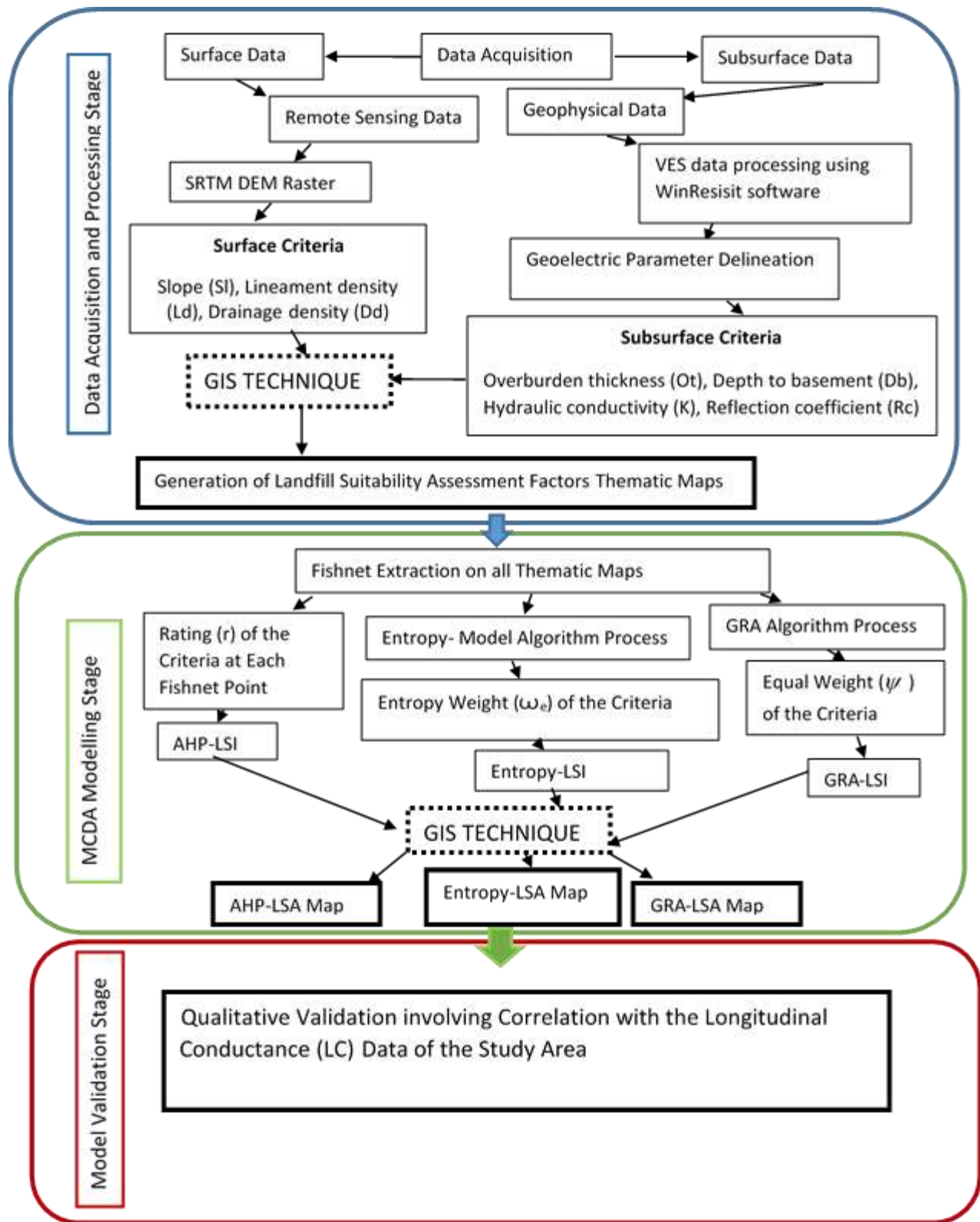


Fig. 3 The methodology flow chart

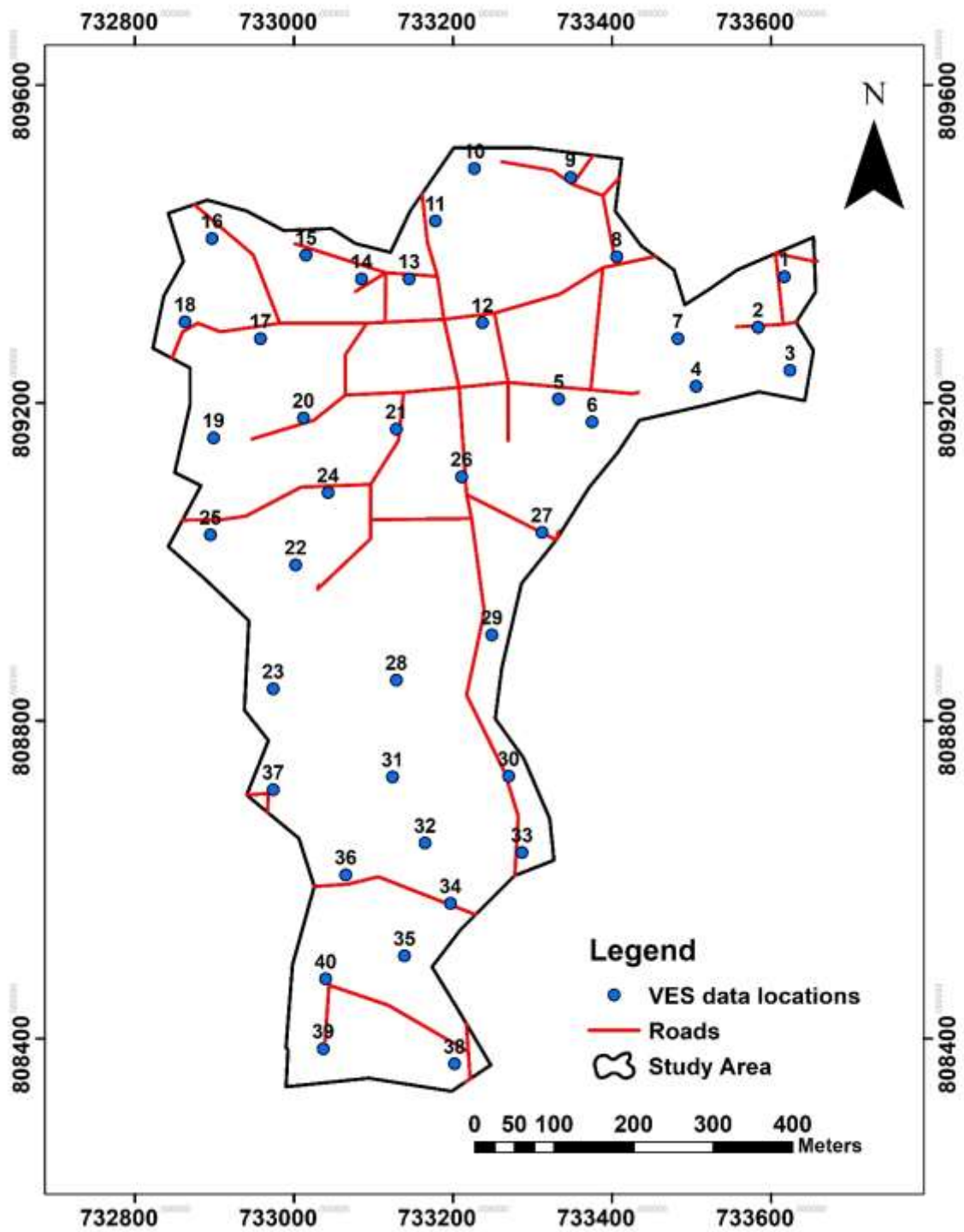


Fig. 4 Data acquisition for the VES

Data processing and interpretation

The DEM data obtained underwent processing using the ArcGIS 10.7 software. This processing involves extracting slope, lineaments, and drainages using the necessary Arc Toolbox (i.e. spatial analyst tool) within the software. Slope was calculated in degrees, lineaments were extracted employing different azimuths and altitudes, and drainages were extracted by performing several hydrological processes within the software. The slope map was then created by masking the surface area boundary from the entire slope. A lineament density map was created by using the line density feature to convert the lineaments, which are line features, into densities, and the same approach was also adopted for the creation of the drainage density map of the study area.

Regarding the VES data processing, partial curve matching was performed on each sounding curve using the master and auxiliary curves (Keller & Frischknecht, 1966). The modelled parameters from the curve matching were then iterated using the WinResist™ 1.0 software (Vander Velpen, 2004) to generate the apparent resistivity and thicknesses of the geoelectric layers at each of the VES locations across the study area. The resistivity and thickness values were then used to determine the relevant geophysical factors, leveraging the corresponding equations (Eqs. 1 to 3).

$$k = 0.0538e^{-0.0072\rho} \quad 1$$

used to calculate the hydraulic conductivity,

$$Rc = \frac{\rho_n - \rho_{n-1}}{\rho_n + \rho_{n-1}} \quad 2$$

used to calculate the reflection coefficient

$$LC = \sum_{i=1}^n \frac{h_i}{p_i} = \frac{h_1}{p_1} + \frac{h_2}{p_2} + \dots + \frac{h_n}{p_n} \quad 3$$

used to calculate the longitudinal conductance

Where;

k is hydraulic conductivity, Rc is reflection coefficient, LC is longitudinal conductance, p is the apparent resistivity, h is the layer thickness, ρ_n is the apparent resistivity of the n th layer, and ρ_{n-1} is the apparent resistivity of the $(n-1)$ th layer.

Multicriteria decision-making analysis (MCDA)

Fishnet Creation

Fishnets are a grid of evenly spaced cells or rectangles generated over a specific geographic area within a Geographic Information System (GIS) software for seamless geospatial analysis (Frye et al., 2018). Thus, sufficient fishnet points were generated across the study area to perform a coordinated multi-criteria decision analysis (MCDA) for the landfill suitability assessment of the study area. Using the data management tools within ArcMap 10.7 software, 83 fishnet points (Fig. 5) were generated across the study area for easy interpolation and modelling of the parameters.

Entropy – landfill suitability assessment (En-LSA) model

To deal with uncertain information, Shannon proposed the concept of the entropy model (Li et al., 2020). Later, researchers (Chodha et al., 2022; Yazdani et al., 2019) adopted the entropy model to determine the objective weight of conditioning criteria in the decision-making process, leveraging dispersion within the value of the criteria. The calculation process of the entropy objective weighting method is presented step-by-step within the supplementary file section (S3).

For the En-LSA model, the weights obtained from the entropy model (Table 1) were used in conjunction with the adopted rating of the LSAFs (Eq. 4) to then compute the LSI based on the entropy model, herein regarded as En-LSI

$$\text{En-LSI} = \text{Sl}_{ew} \times \text{Sl}_r + \text{Ld}_{ew} \times \text{Ld}_r + \text{Dd}_{ew} \times \text{Dd}_r + \text{Ot}_{ew} \times \text{Ot}_r + \text{Db}_{ew} \times \text{Db}_r + \text{K}_{ew} \times \text{K}_r + \text{Rc}_{ew} \times \text{Rc}_r \quad 4$$

The computed En-LSI was later employed to create the En-LSA map of the study area using the interpolation tool in the ArcGIS 10.7 software.

Table 1: The computed entropy weight of the factors

LSAF	Entropy Weight
Sl	0.03608
Ld	0.56607
Dd	0.27598
K	0.05070
Rc	0.00612
Ot	0.05098
Db	0.01407

AHP- landfill suitability assessment (AHP-LSA) model

Generating AHP weights by computing Saaty's 1980 AHP model algorithm (S4) is the first step involved in the AHP-LSA model. This process was followed by performing the expert rating of the alternative fishnet points through correlation with the actual class within the thematic map of the criteria at that particular fishnet (Table 2). The weight generated for each of the factors (Table 3) was now incorporated into the AHP-Landfill Suitability Indices (AHP-LSI), modified after Mogaji and Lim (2017) (Eq. 5). Furthermore, the AHP-LSI was then used to produce the AHP-LSA map of the study area by employing the inverse distance weighting (IDW) interpolation technique within ArcGIS 10.7 software.

$$\text{AHP} - \text{LSI} = \text{Sl}_{\omega} \times \text{Sl}_r + \text{Ld}_{\omega} \times \text{Ld}_r + \text{Dd}_{\omega} \times \text{Dd}_r + \text{Ot}_{\omega} \times \text{Ot}_r + \text{Db}_{\omega} \times \text{Db}_r + \text{K}_{\omega} \times \text{K}_R + \text{Rc}_{\omega} + \text{Rc}_r \quad 5$$

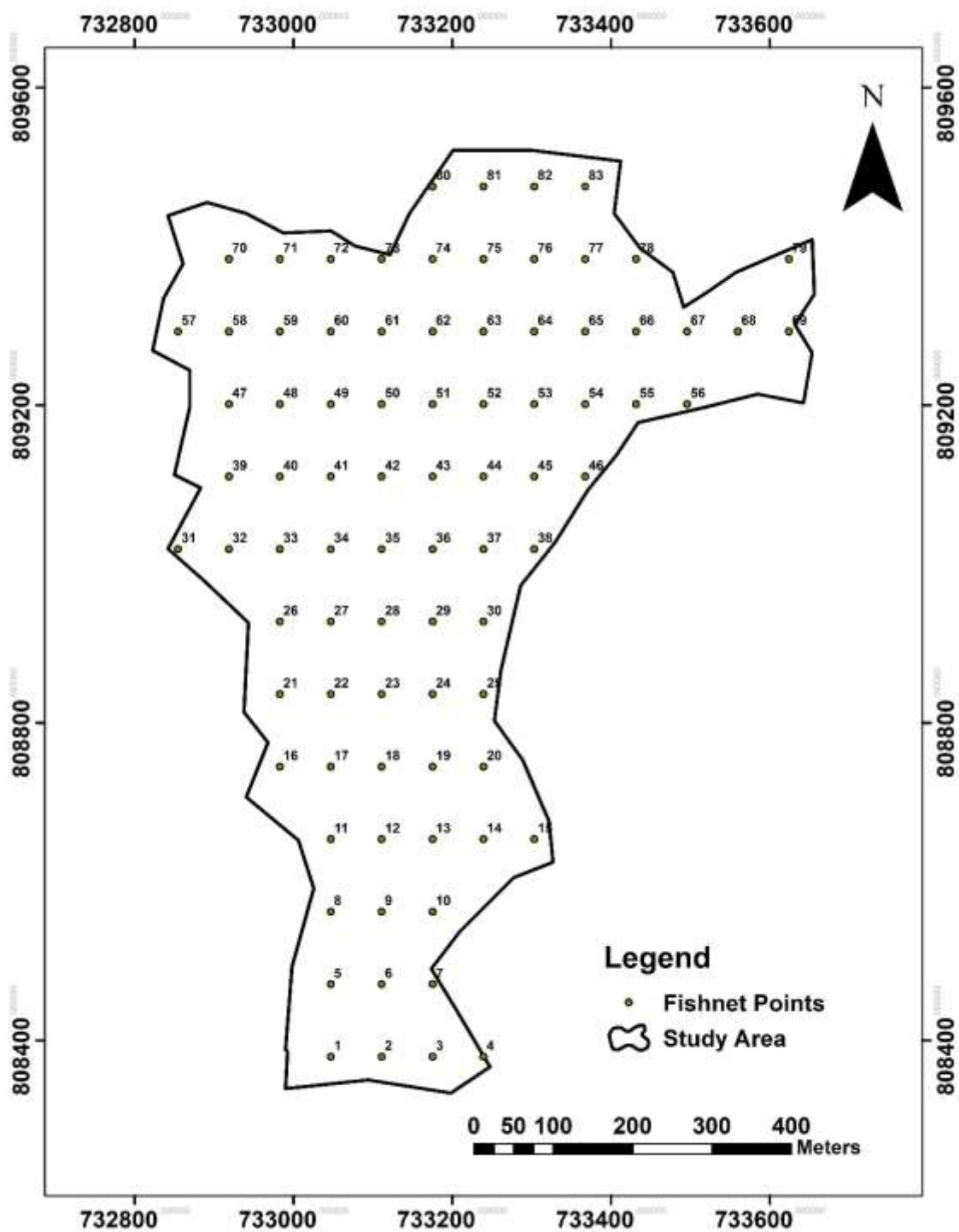


Fig. 5 Fishnet created for the study area

Table 2 The rating of the criteria according to their minimum or maximum value preference

Criteria	Min (lower value preferred) or	Class	Rating
	Max (higher value preferred)		
Sl (⁰)	Min	0.55 – 2.77	1
		2.77 – 4.99	2
		4.99 – 7.20	3
Ld (m/m ²)	Min	0 – 12.89	1
		12.89 – 25.78	2
		25.78 – 38.67	3
Dd (m/m ²)	Min	0 – 17.46	1
		17.46 – 34.92	2
		34.92 – 52.38	3
K (m/day)	Min	0.00051 – 0.01195	1
		0.01195 – 0.02188	2
		0.02188 – 0.03890	3
Rc	Min	0.30445 – 0.63231	1
		0.63231 – 0.77211	2
		0.77211 – 0.95255	3
Ot (m)	Max	1 – 4.5	3
		4.5 – 9.6	2
		9.6 – 17.0	1
Db (m)	Max	2.5 – 11.8	3
		11.8 – 17.3	2
		17.3 – 27.7	1

Table 3: The calculated AHP weight of the factors

LSAF	AHP Weight
Sl	0.18540
Ld	0.11626
Dd	0.06696
K	0.34589
Rc	0.18541
Ot	0.05118
Db	0.04890

GRA landfill suitability assessment (GRA-LSA) model

GRA is an alternative ranking model that calculates geometric proximity between discrete sequences. This proximity is described by the grey relational grade, which measures the similarities of discrete data that can be arranged in sequential order (Li et al., 2014). The algorithmic processes of GRA, outlined in steps 1 through 5 (i.e., Eqs. 6 to 13), elaborate on how alternatives can be ranked and prioritised using the computational power of the GRA model. Thus, in the GRA-LSA approach, the decision matrix consists of the fishnet as the alternatives in the rows, while the criteria

are represented along the columns. However, since criteria weights are needed, an equal weighting approach was adopted, leveraging the analysis of several researchers (Kuo et al., 2008; Odu, 2019). The GRA-LSA model map was then produced by utilising the IDW interpolation technique on the computed GRA-LSI using ArcGIS 10.7 software.

Step 1: Generate the referential series of $x_0 = (x_0(1), x_0(2), \dots, x_0(j), \dots, x_0(n))$ with j entities, and x_i is the compared series of $(x_i(1), x_i(2), \dots, x_i(j), \dots, x_i(n))$, where $i = 1, 2, 3, \dots, m$. The compared series x_i can be represented in a matrix form:

$$X_i = \begin{bmatrix} x_i(1) & x_i(2) & \cdots & x_i(n) \\ x_2(1) & x_2(2) & \cdots & x_2(n) \\ \vdots & \vdots & \ddots & \vdots \\ x_n(1) & x_n(2) & \cdots & x_n(n) \end{bmatrix} \quad 6$$

Step 2: Normalise the dataset. Normalisation can be one of three types: maximising, minimising, and nominal..

For maximising criteria,

$$x_i^*(j) = \frac{x_i(j) - \min_j x_i(j)}{\max_j x_i(j) - \min_j x_i(j)} \quad 7$$

For minimising criteria,

$$x_i^*(j) = \frac{\max_j x_i(j) - x_i(j)}{\max_j x_i(j) - \min_j x_i(j)} \quad 8$$

For nominal is the best criteria,

$$x_i^*(j) = \frac{|x_i(j) - x_{ob}(j)|}{\max_j x_i(j) - \min_j x_i(j)} \quad 9$$

Also, the referential series x_0 should be normalised using the suitable normalisation step as given by equations 6 – 7.

Thus, the normalised referential series can be expressed as;

$$X_i^* = \begin{bmatrix} x_1^*(1) & x_1^*(2) & \cdots & x_1^*(n) \\ x_2^*(1) & x_2^*(2) & \cdots & x_2^*(n) \\ \vdots & \vdots & \ddots & \vdots \\ x_n^*(1) & x_n^*(2) & \cdots & x_n^*(n) \end{bmatrix} \quad 10$$

Step 3: Compute the distance, $\Delta_{0j}(j)$, representing the absolute value difference between x_0^* and x_i^* at the j -th point.

The formula is;

$$\Delta_{0i}(j) = |x_0^*(j) - x_i^*(j)| = \begin{bmatrix} \Delta_{01}(1) & \Delta_{01}(2) & \cdots & \Delta_{01}(n) \\ \Delta_{02}(1) & \Delta_{02}(2) & \cdots & \Delta_{02}(n) \\ \vdots & \vdots & \ddots & \vdots \\ \Delta_{0m}(1) & \Delta_{0m}(2) & \cdots & \Delta_{0m}(n) \end{bmatrix} \quad 11$$

Step 4: Apply the grey relational equation to compute the grey relational coefficient $\gamma_{oi}(j)$ using Eq. 12

$$\gamma_{oi}(j) = \frac{\Delta \min + \zeta \Delta \max}{\Delta_{0i}(j) + \zeta \Delta \max} \quad 12$$

Where, $\Delta \max = \max_i \max_j \Delta_{0i}(j)$, $\Delta \min = \min_{ii} \min_j \Delta_{0i}(j)$, and $\zeta \in [0,1]$

Step 5: Compute the degree of grey coefficient Γ_{oi} .

$$\Gamma_{oi} = \sum_j^n [w_i(j) \times r_{oi}(j)] \quad 13$$

w_i is the criteria weight, which can be determined using any different weight generation approach. For the decision-making process, the higher the degree of grey coefficient, the better the rank of such an alternative.

The computational equation of **GRA-LSI** is then given by equation 13 as;

$$\Gamma_{oi} = \sum_j^n [\omega_i(j) \times r_{oi}(j)] \quad 14$$

Where ω_i is the computed mean weight of the criteria (Table 4)

Table 4: The generated mean weight of the criteria

LSAF	Mean Weight
Sl	0.14286
Ld	0.14286
Dd	0.14286
K	0.14286
Rc	0.14286
Ot	0.14286
Db	0.14286

LSAFs thematic maps

In generating the thematic maps using ArcGIS 10.7 software, the processes employed for the thematic maps of remote sensing (i.e. the surface) parameters slightly differ from those employed for the geophysical (i.e. the subsurface) parameters. In making the slope (Sl) map, an extract by mask was used to cut out the study area's slope from the whole slope created for the DEM data. For the drainage density (Dd) and Lineament density (Ld) map, the line density tool

was adopted to convert the drainages and lineaments into densities. For the creation of the geophysical thematic maps, the same approach involves converting the point (i.e. x-y-z) data containing the coordinates as x-y and each of the parameters as the z value into raster format by performing IDW interpolation on the discrete data. IDW interpolation is a widely adopted interpolation technique for creating smooth and accurate raster data from point data, and equally offers simplicity and ease of implementation (Khouni et al., 2021). Fig. 6 illustrates the workflow of generating the raster data (i.e. IDW interpolated map) from the point data (i.e. LSAF data) using ArcGIS 10.7 software.

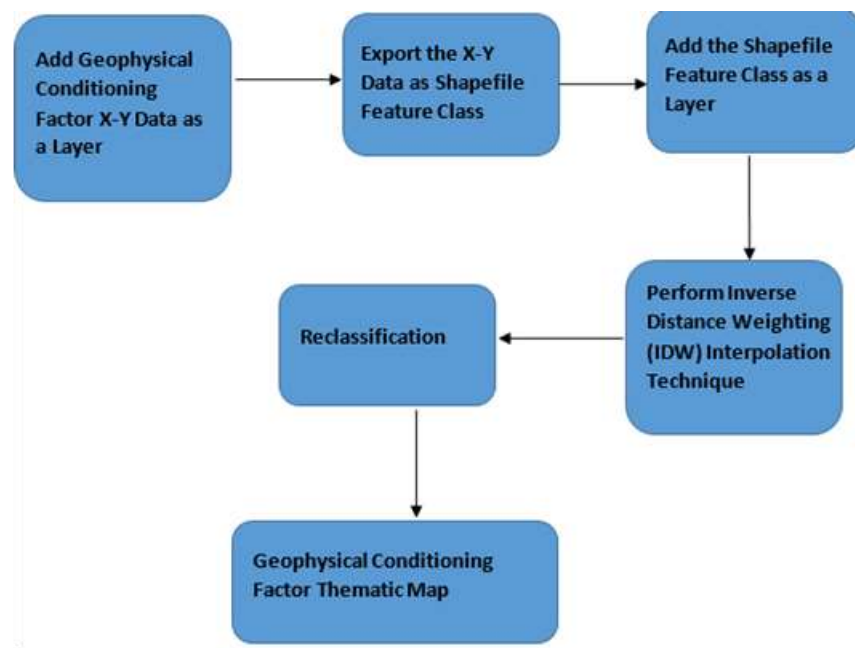


Fig. 6 Workflow of creating the geophysical thematic map in ArcGIS 10.7 software

LSAM maps

The creation of the En-LSA, AHP-LSA, and AHP-GRA LSA map of the study follows a similar approach to creating maps from point data. This approach involves employing the model's index with ArcGIS 10.7 software and utilising a suitable interpolation technique, specifically IDW, to create raster format maps. However, leveraging the research of several researchers (Liu et al., 2022; Vojtek et al., 2021), reclassification was done on the maps employing Jenks Natural Break.

Validation of the LSAM maps

Model validation is as important as model development, as it demonstrates the efficacy of the developed models for decision-making processes (Şimşek & Alp, 2022). To validate the LSAM maps generated for each applied model (i.e.

En-LSA, AHP-LSA and GRA-LSA), qualitative validation involving correlation with longitudinal conductance (LC) data of the study area was utilised. LC gives the protective capacity of a particular location, suggesting the adoption of its values as a benchmark/inference for the developed LSAM models, as if a location will be suitable for landfill, then it will possess a high protective capacity, whereas unsuitable areas will have lower protective capacity (Akintorinwa & Okoro, 2019). In the adopted approach, the extracted fishnet points of LC across the study area served as the actual data, while the LSI from each model served as the predicted data. The models' predicted landfill suitability indices that coincide with the interpreted LC data of that particular fishnet point is regarded as 'agree', while the models' predicted area that do not coincide is regarded as 'not agree'. This data is then used to compute the percentage agreement between the model's prediction and the LC data as given in Eq. 14 below;

$$PA = \frac{NAP}{NOB} \times 100\% \quad 14$$

PA is the percentage agreement, NAP is the number of agreed points, and NOB is the number of observed points (i.e. fishnet points).

Furthermore, this adopted approach was used to assess the performance of the models in predicting low and high suitability regions, since the goal is to either select an area that is suitable for landfill siting or avoid an area that is not suitable. Thus, by way of expert opinions, all the medium classes were converted into low classes in both the landfill suitability indices of each model and the longitudinal conductance data of the study area before the correlation was done, as elaborated above.

Result

Geoelectric results

The geoelectric layers delineated in the study area range from 3 to 5 layers. The topsoil has resistivity value range of 27–400 Ω -m with thickness range of 0.7–4.3 m, the second layer has resistivity value range of 25 – 593 Ω -m with thickness range of 1.1–24.8 m, the third layer has resistivity value range of 51–3454 Ω -m with thickness range of 3.1–20 m, the fourth layer has resistivity value range of 155–8822 Ω -m with thickness 18.3 and the fifth layer has resistivity value of 1727 Ω -m with infinite thickness (Table 2). In addition, as related to the curve type distribution in the study area, H, HA, A, HKH, AA and KH curve types (Fig. 7) were delineated using WinRest software with their occurrence times as follows, H- 5 (i.e. 13%), HA - 13 (i.e. 33%), A- 15 (i.e. 38%), HKH- 1 (i.e. 3%), AA - 3 (i.e. 8%) and KH - 2 (i.e. 5%) (Figs. 8 a and b).

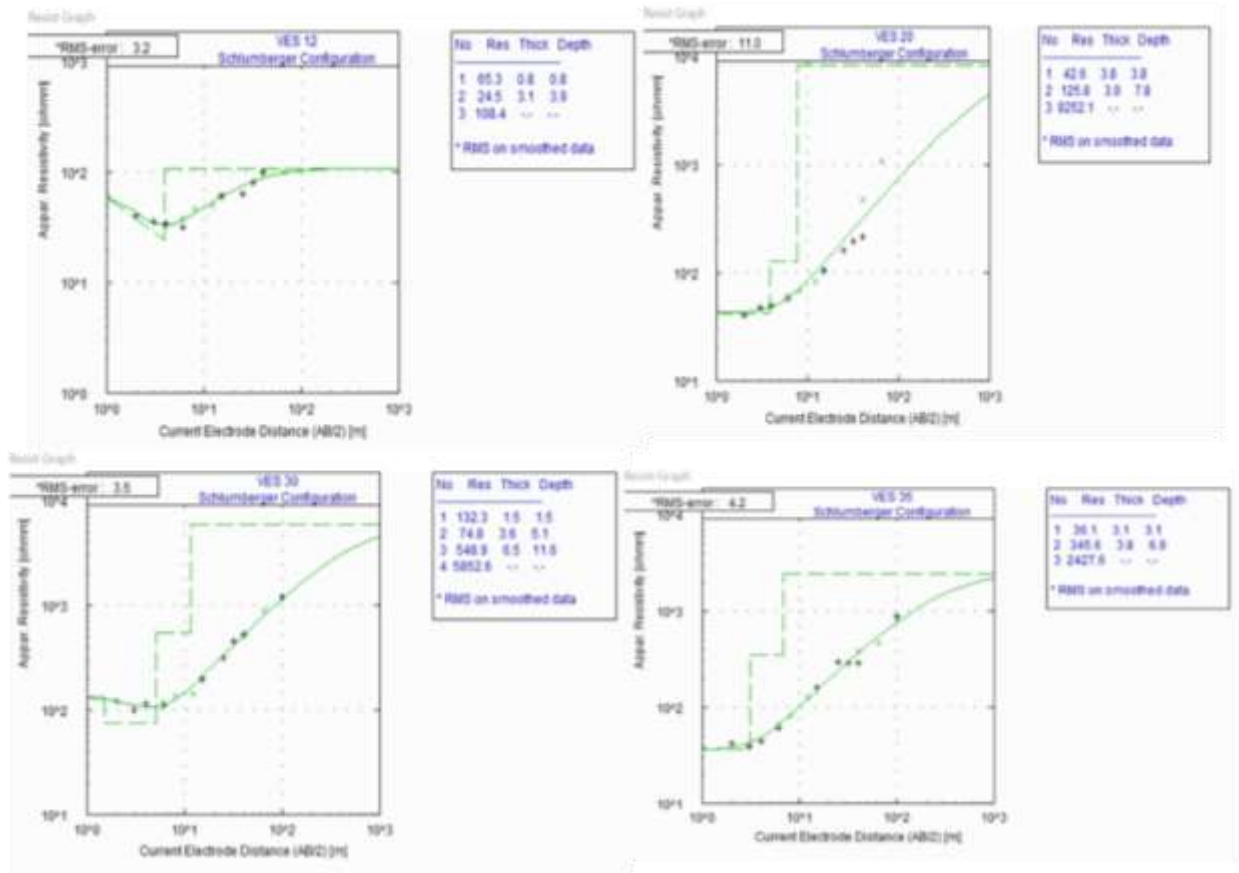


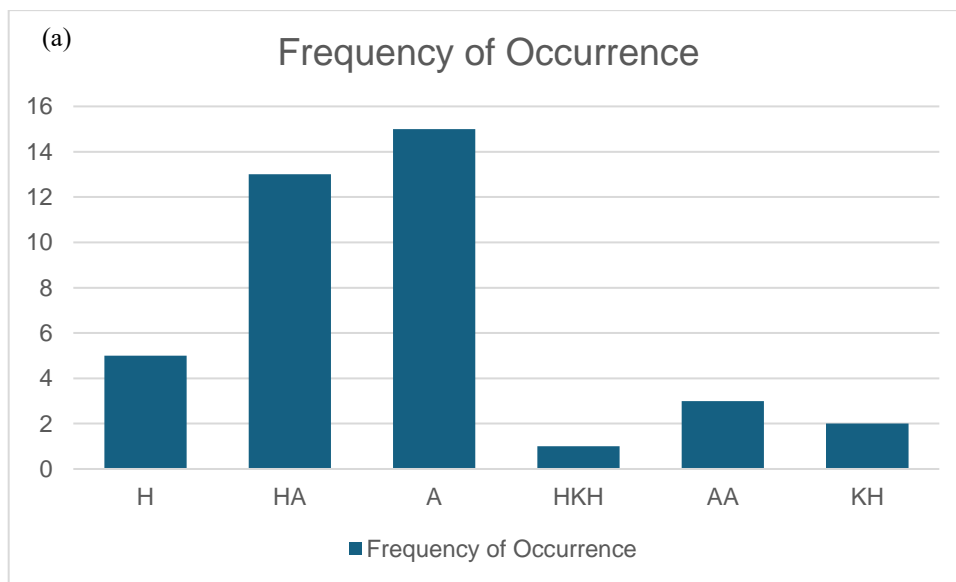
Fig. 7 Typical curve types in the study area

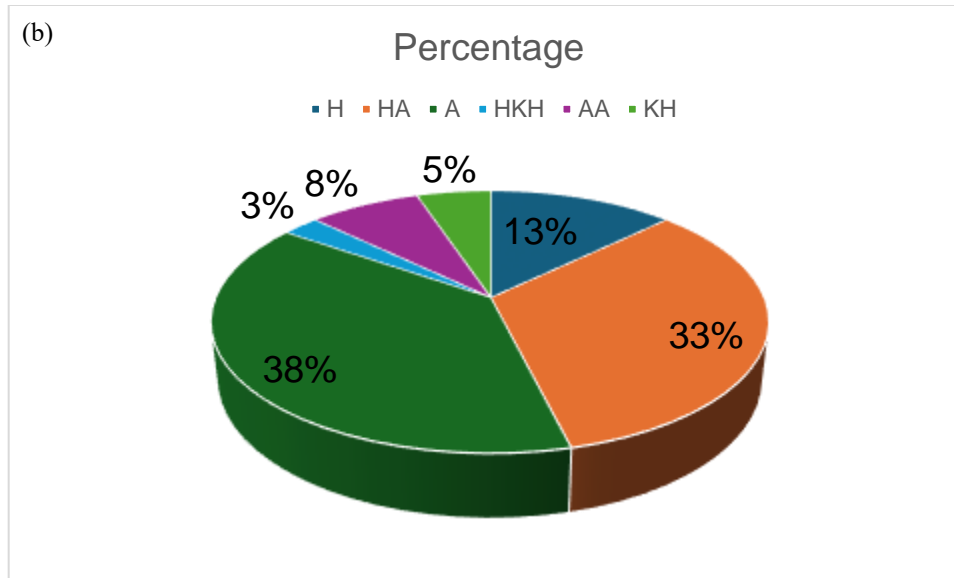
Table 2 Summary of interpreted geoelectric results in the study area

VES No	Easting	Northing	Layer Resistivity (Ohm-m)	Layer Thickness (m)	Curve Type	Inferred Layers	Geoelectric
			$\rho_1/\rho_2/\rho_3/\rho_4/\rho_5$	$h_1/h_2/h_3/h_4$			
1	733617	809359	205/55/775	1.4/8.5	H	Topsoil/Clay/Basement	
2	733584	809295	400/88/575/1984	2/5/7.5	HA	Topsoil/Clay/Weathered layer/Fresh basement	
3	733624	809241	61/593/4331	2.3/2.5	A	Topsoil/Weathered layer/Fresh basement	
4	733506	809221	377/69/1793	1.6/8.5	H	Topsoil/clay/fresh basement	

5	733333	809205	275/66/515/1295	1.5/1.1/10	HA	Topsoil/clay/partially weathered layer/Fresh basement
*39	733037	808387	130/302/649/7362	1/4.5/8.5	HA	Topsoil/Weathered layer/Partially weathered layer/Fresh basement
40	733040	808475	117/402/2827	1.5/6.3	A	Topsoil/Partially weathered layer/Fresh basement

*the remaining interpreted geoelectric results in the supplementary file (Table S5)





Figs. 8 (a) Bar chart showing curve type frequency of occurrence (b) Pie chart showing pie chart frequency of occurrence

LSAFs thematic maps

Slope (SI) map

The slope of the study area ranges from 0.55 to 7.2 degrees and is classified into low, medium, and high slope (Fig. 9). The higher the slope of an area, the lower the landfill suitability (Mogaji et al., 2011). Therefore, the pockets of the high slope, e.g., VES locations 33, 14, etc., will be less suitable, while the low slope area, extending from the northern part of the study area to the central part at VES locations 9, 33, etc., falls within this low region and is more suitable. Most of the study area, such as VES locations 35, 10, etc., falls within the moderate suitability category, indicating that most of the study area will be of moderate landfill suitability, based on the slope distributions.

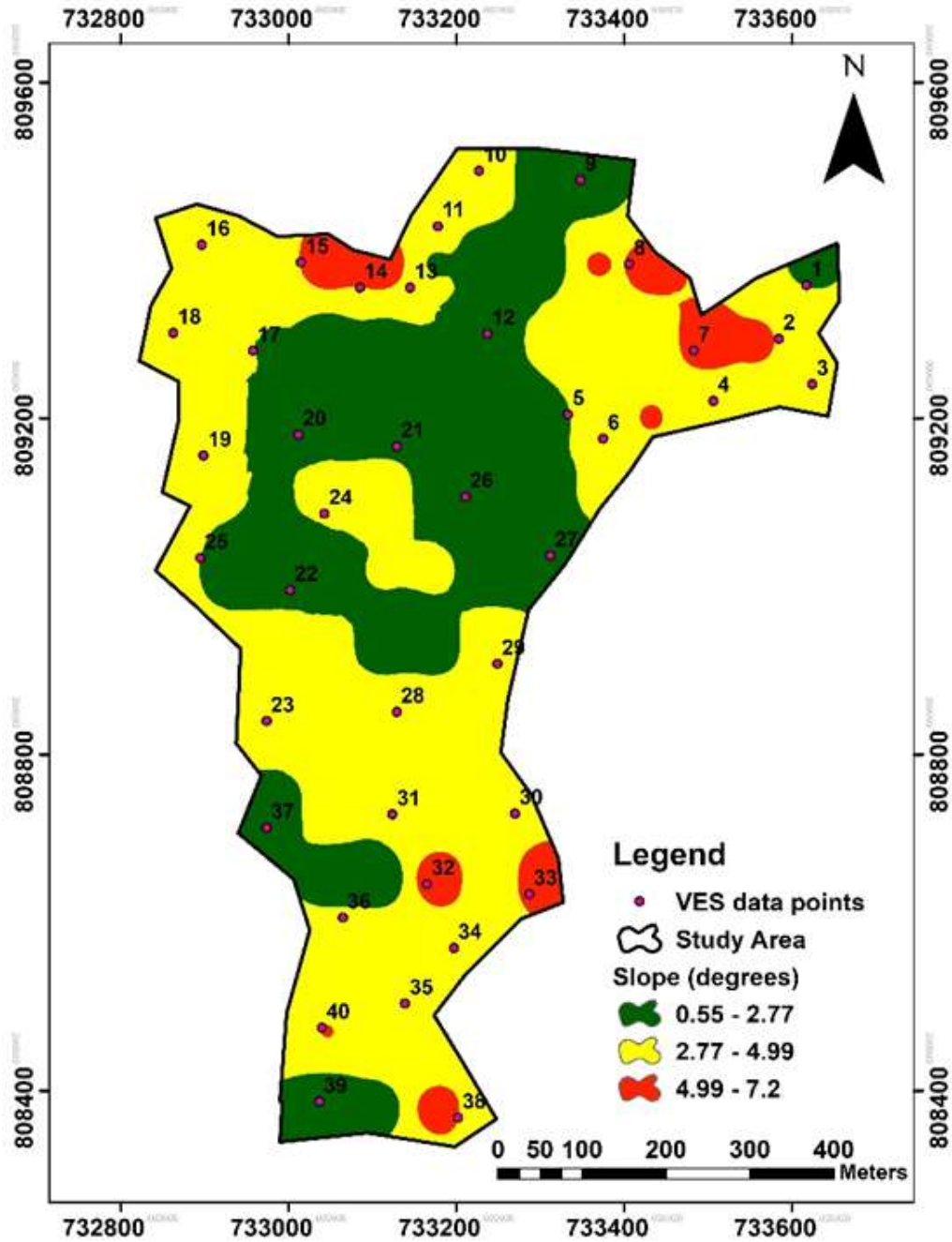


Fig. 9 Slope map of the study area

Lineament density (Ld) map

The lineament density map of the study area displays the distribution of lineaments and is classified into three categories: low, medium and high. The lineament density ranges from 0 to 38.67 m/m², with most of the study area falling within the low lineament density areas (Fig. 10). Higher lineament density reduces the landfill suitability, while lower lineament density leads to higher suitability (Mogaji et al., 2011). Since most of the study area, e.g VES locations

7, 39, etc., falls within low lineament density, most of the area will be suitable for landfill. The medium and higher lineament density areas occur as pockets and are mainly concentrated within the central part of the study area, indicating moderate to low suitability.

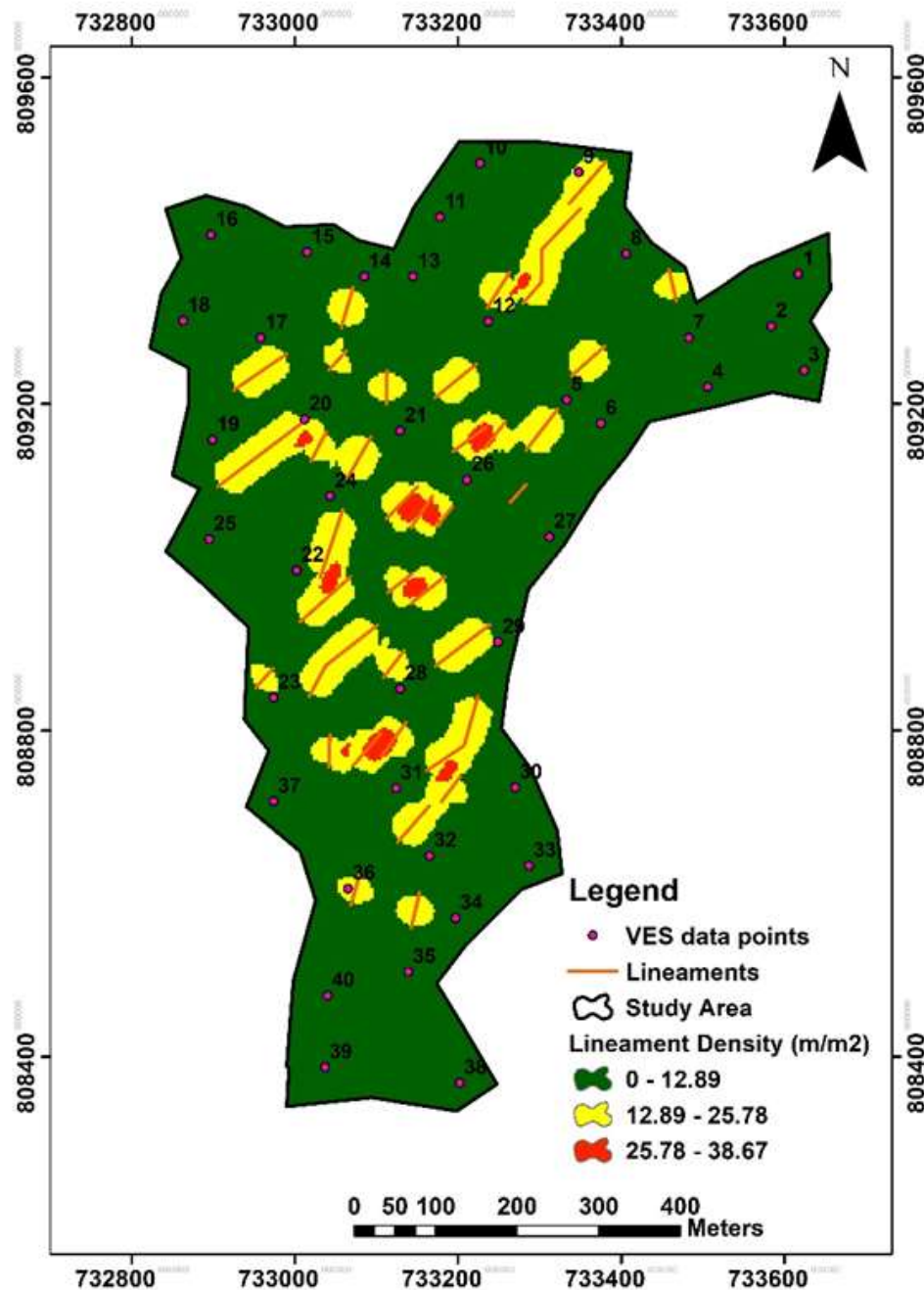


Fig. 10 Lineament density map of the study area

Drainage density (Dd) map

The spatial variation of the drainages in the study area is classified into three categories: low, moderate, and high. The drainage density ranges from 0 to 52.38 m/m² (Fig. 11), and most of the study area, with typical VES locations such as 17 and 29, falls within the low drainage density region. The lower the drainage density, the more the suitability for landfill siting and vice versa (Yeh et al., 2016). This implies that most of the study area, which falls within low drainage density regions, will be suitable for landfill siting, whereas the high drainage density regions, which occur as pockets within the study area, will be less suitable. In addition, the medium drainage density areas, which can be observed in the central part of the study area, with typical VES locations 20, 8, etc., falling within them, will be of moderate suitability.

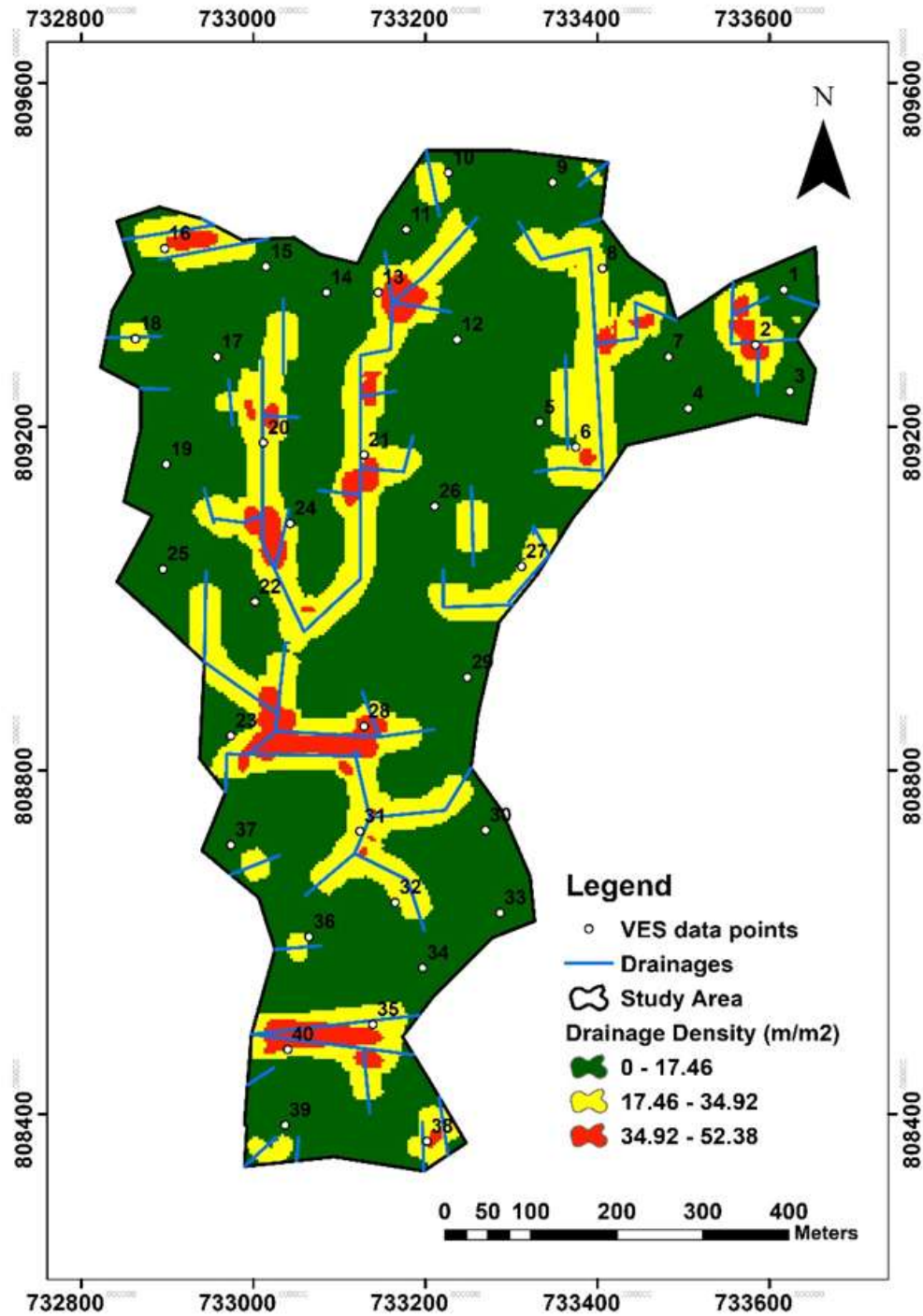


Fig. 11 Drainage density map of the study area

Overburden thickness (Ot) map

The overburden thickness (Ot) map of the study area gives the spatial range of the thickness of all the layers overlying the delineated aquiferous layer. The Ot of the study area ranges from 1-17 m (Fig. 12). The Ot map is classified into

three classes: low, moderate and high, with most of the study area falling within the low class. There is a high overburden thickness at the extreme north-western part of the study area, with VES locations 15 and 16 falling within this high zone. From the spatial distribution of Ot, most of the study area might be unsuitable for landfill siting; low overburden thickness is attributed to lower landfill suitability(Adenuga & Popoola, 2020).

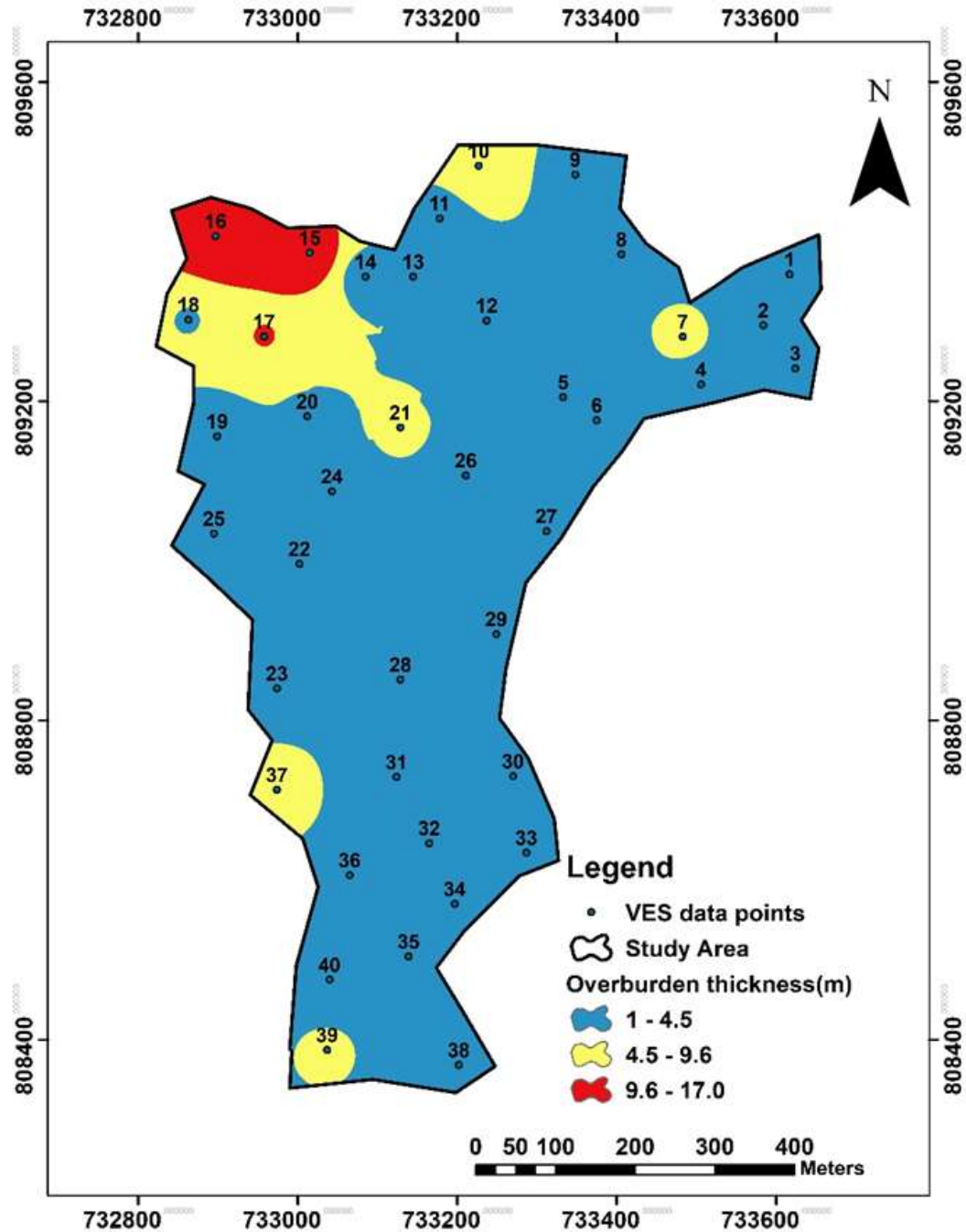


Fig. 12 Overburden thickness map of the study area

Depth to basement (Db) map

The depth to basement (Db) map of the study area provides the spatial variation of the depth to the top of the basement throughout the entire study area, and it is classified into three classes: low, moderate and high. Areas with high Db are of high suitability for landfill and vice versa (Demesouka et al., 2014). The Db of the study area ranges from 2.5 – 27.7 m (Fig. 13), with most of the study area falling within the moderate zones. The low Db areas are mainly located within the southern part of the study area, with some pockets of occurrence scattered across the study area (VES locations 1, 17, 40, etc.). The high Db areas occur as pockets and are observed at the study area's northern, western, and southern parts (VES locations 9, 10, 19, etc.).

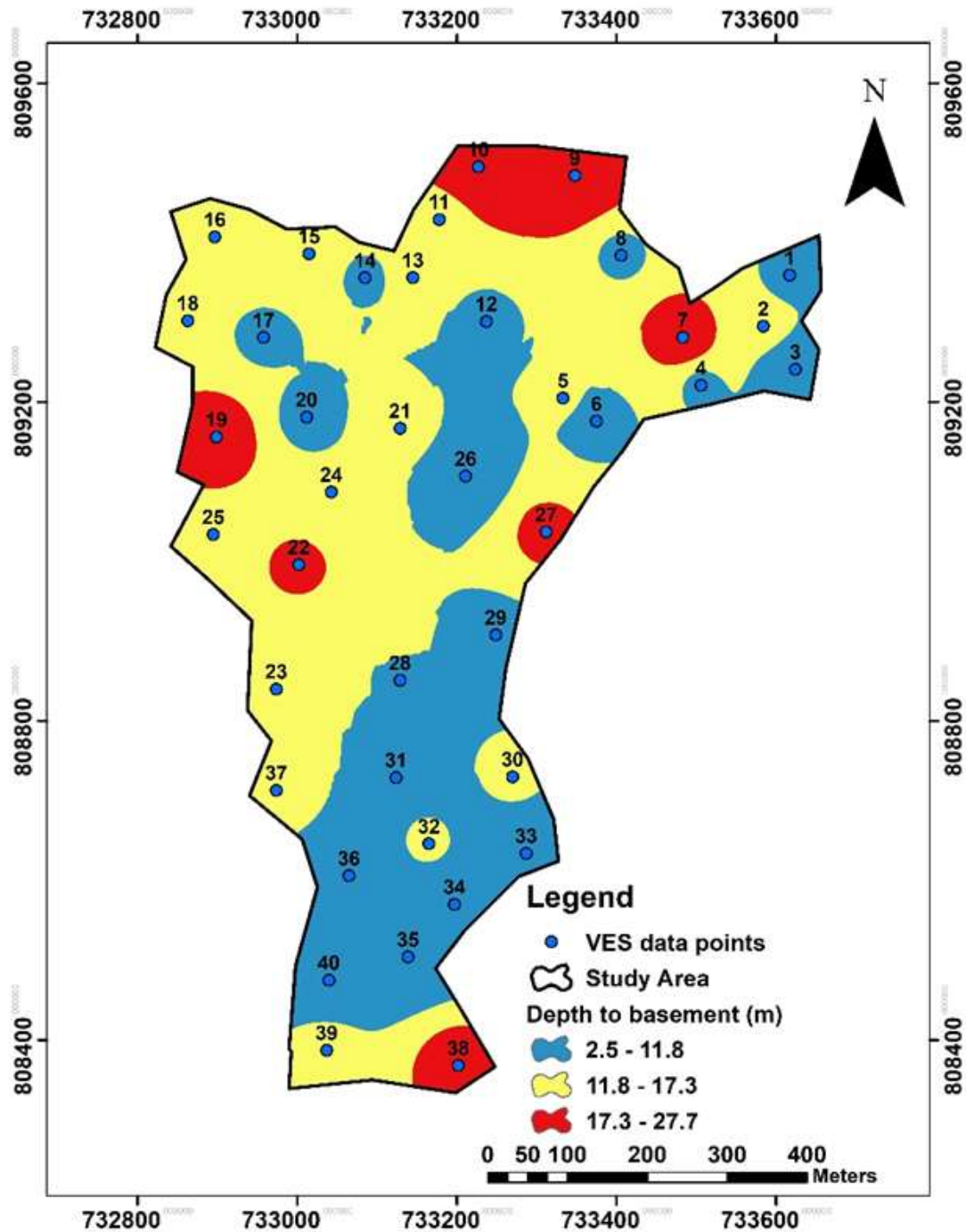


Fig. 13 Depth to basement map of the study area

Hydraulic conductivity (K) map

The hydraulic conductivity map of the study area shows the spatial distribution of hydraulic conductivity values, which have been classified into three categories: low, moderate, and high. The K values of the study area range from 0.00051–0.03890m/day (Fig. 14), with most of the study area falling within the moderate K values at VES locations

24, 27, 10, etc. A predominant occurrence of high K values is observed in the north-western part of the study area, with some pockets of these high occurrences also noted at various locations, notably VES locations such as 31, 18, and 2. Furthermore, the low K areas are predominant in the southern part of the study area, and there are also pockets of these low areas at several locations, including VES locations 25, 39, 9, etc. Based on the findings of Fetter et al. (2017), the spatial variation of these K values showed that most central part of the study area will fall within the moderate suitability region since it falls within moderate K values, while the north-western part of the study area, showing the high K values, should be avoided for landfill siting. In contrast, the focus should be on the southern part of the study area, which falls within the low K regions.

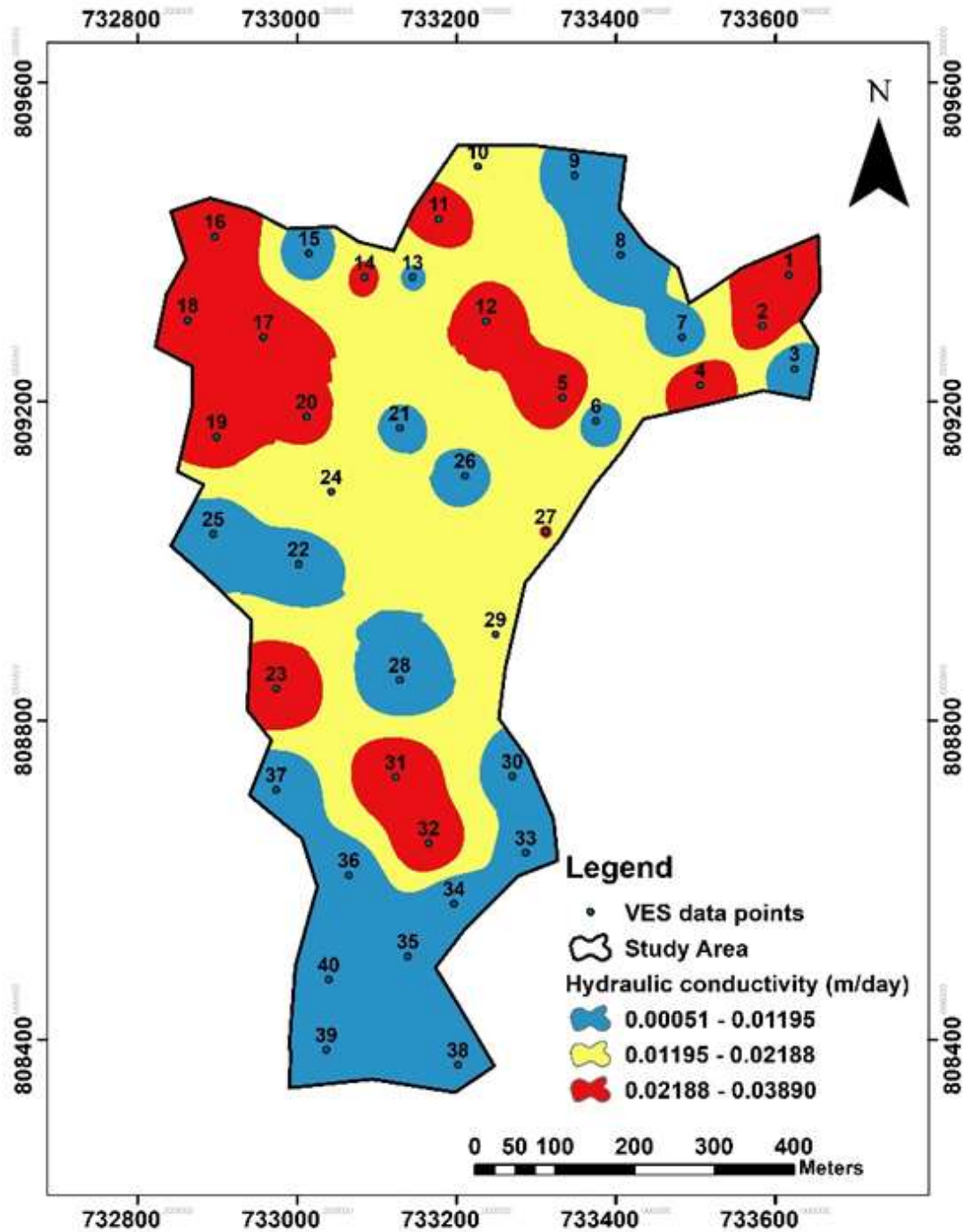


Fig. 14 Hydraulic conductivity map of the study area

Reflection coefficient (Rc) map

The reflection coefficient (Rc) map of the study area shows the spatial distribution of the reflection coefficient across the area and is categorised into low, moderate, and high categories. The Rc of the study area ranges from 0.30445–0.95255 (Fig. 15), mainly falling within the high Rc regions such as VES locations 1, 16, 33, and 39. The low Rc

regions are predominant in the northern part of the study area (VES locations 23, 38, 14, 13, etc.). In contrast, the moderate R_c regions can be observed in the northern and southern parts with VES locations 40, 22, 6, etc. According to Khan and Samadder (2015), lower R_c values lead to higher landfill suitability, implying that areas with lower R_c values will be highly suitable for landfill siting, while those with higher R_c values will be of lower suitability for landfill siting. In addition, the medium R_c areas in both the northern and southern parts of the study area will be of medium suitability.

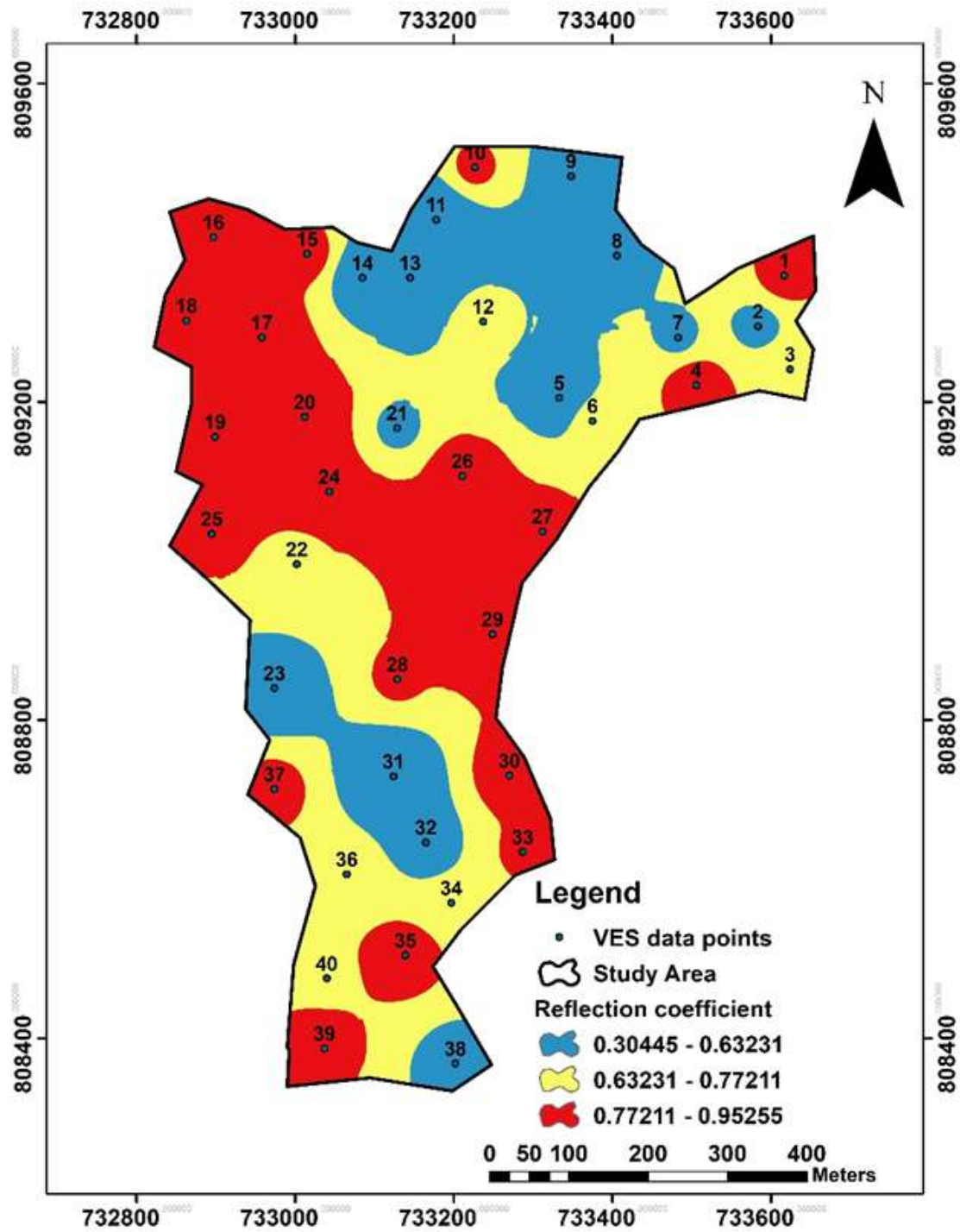
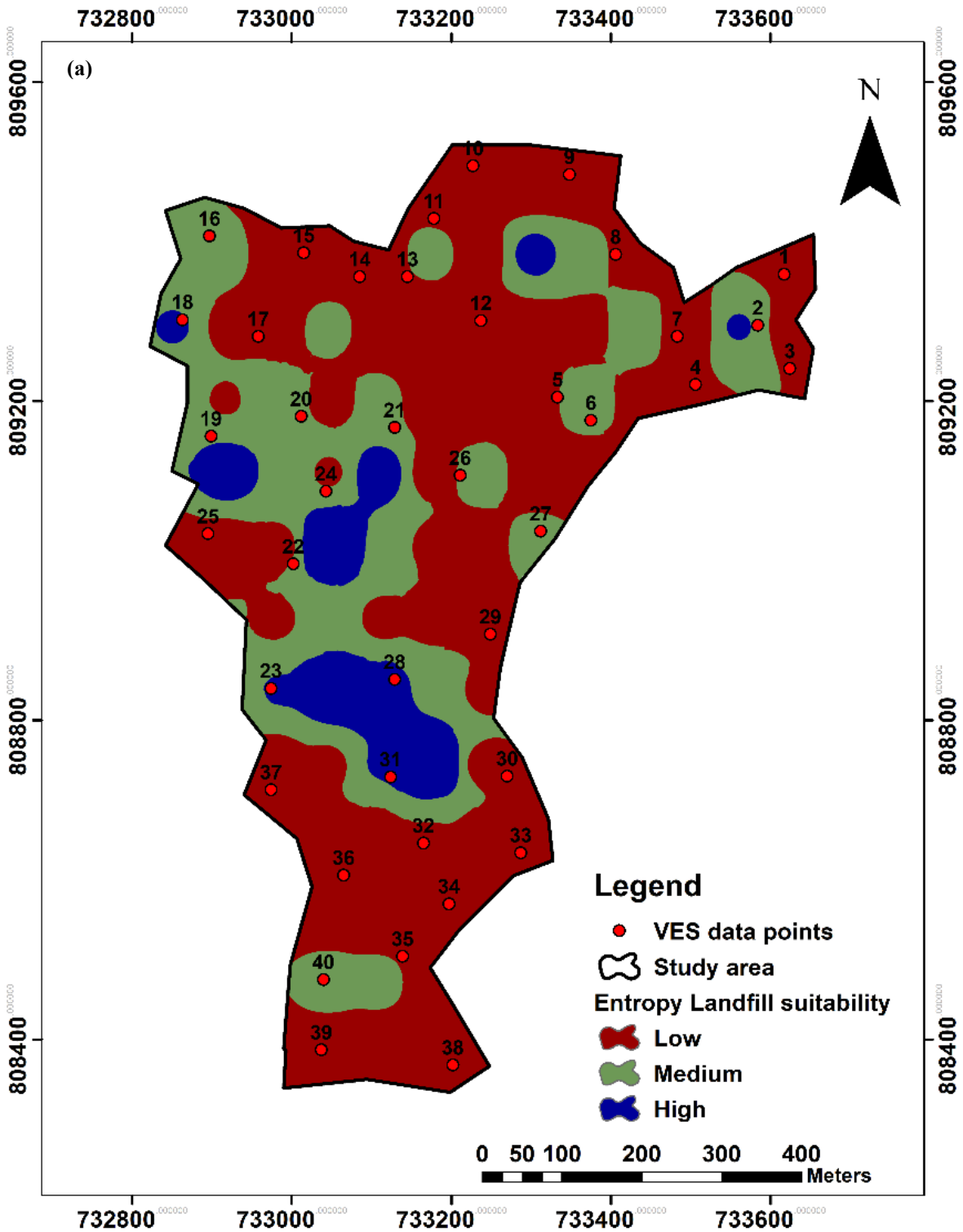


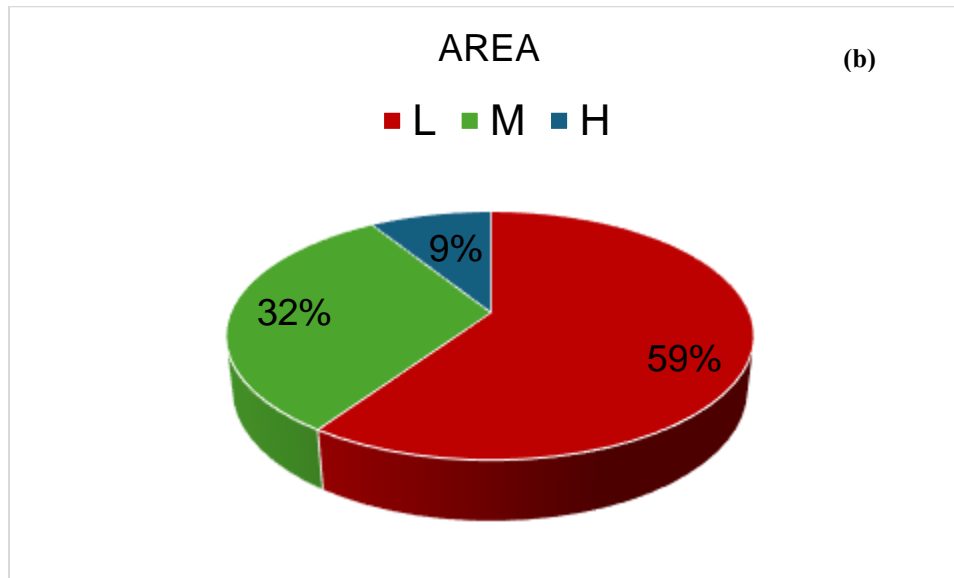
Fig. 15 Reflection coefficient map of the study area

LSAM maps

En-LSAM map

The fishnet distribution points of the En-LSI (Table S1) were employed to create the suitability aggregation map of the study area based on entropy model (Fig. 16a). Employing three classifications, further analysis on the map involving the creation of pie chart (Fig. 16b) showed that, 12%, 56% and 32% of the study area falls within low, medium and high suitability respectively. Most of the Southern and Northern parts of the study area, with notable VES 9, 10, 38 and 39, fall into this low category. While the medium suitability is distributed within the study area, notable occurrences can be noted within the Western parts, while a pocket of occurrence with VES 40 can also be observed within the Southern part. The high suitability areas occur mostly as pockets within the central, North-eastern, and North-western parts, with VES 18, 23 and 28 typically falling within this high region. The aggregation of the extent of each of the classes is given in Table 3





Figs. 16 (a) Landfill suitability map based on AHP model (b) Pie chart showing the percentage area classification

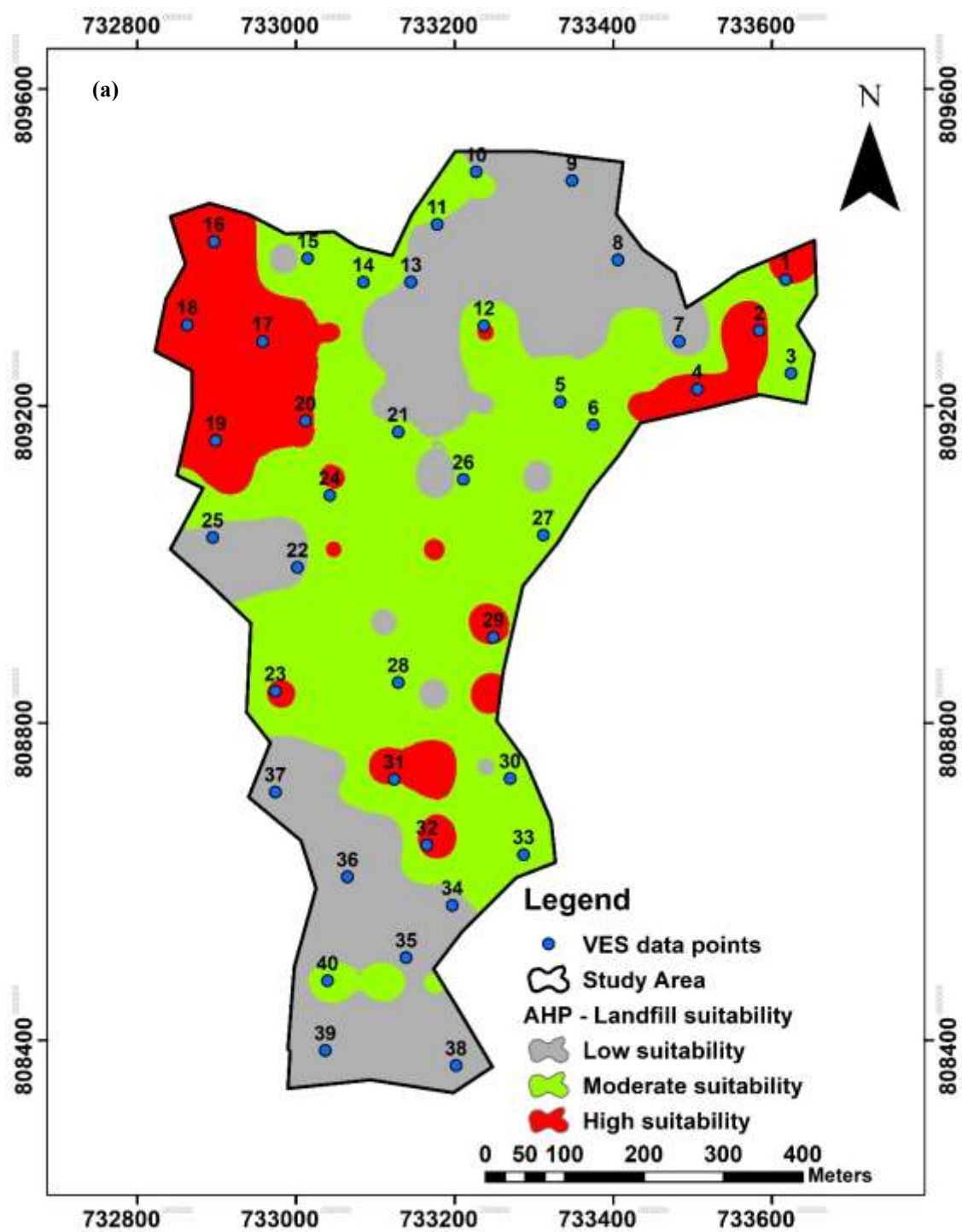
Table 3 Percentage and area extent of each of the suitability classes based on the Entropy model

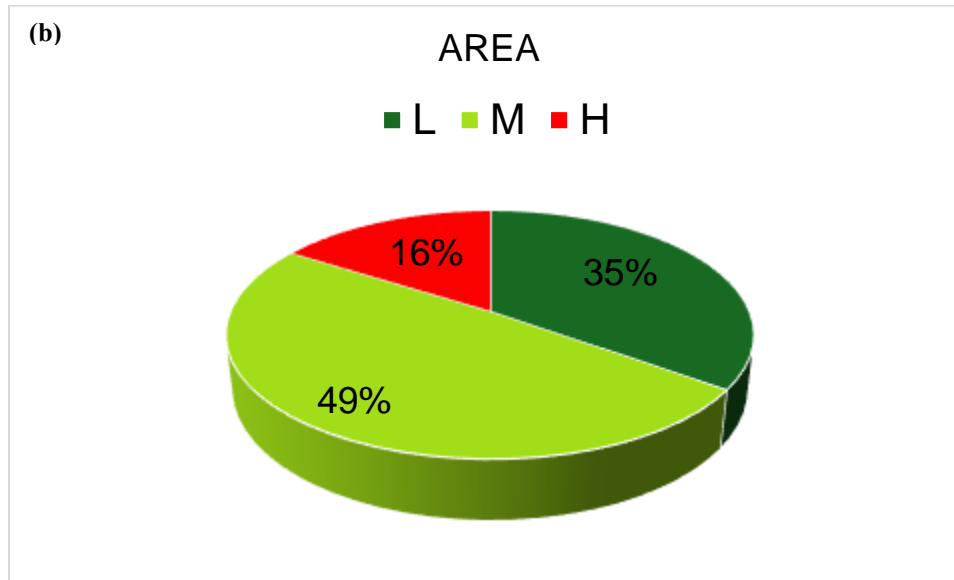
Class	Percentage	Area Extent
Low	59%	288m ²
Moderate	32%	153m ²
High	9%	43m ²

AHP-LSAM map

The spatial distribution of the AHP-LSI (Table S1) was used in the creation of the AHP-LSAM map. The AHP-LSAM map classified the study area into three classes: low, moderate and high landfill suitability (Fig. 17a). Further analysis involving a pie chart shows the percentage occurrence of each class and the area extent (Fig. 17b). The percentage and area extent of each of the suitability classes are presented in Table 3. It can be observed from the map that most of the study area falls within the moderate landfill suitability regions, with VES locations 26, 3, 15, etc. falling within these moderate suitability regions. Also, the high suitability region can be observed predominantly in the north-western part of the study area, and some pockets of the high suitability region can also be noticed in the north-eastern as well as the southern part of the study area. VES locations such as 16, 1, and 32 are some of the VES locations that fall within

the high landfill suitability region. Furthermore, the low landfill suitability regions are prominently observed in the study area's southern and northern parts, with a few pockets of low suitability occurring in the central and western parts of the study area. VES locations 38, 22, 7, etc., are some of the VES locations that fall within this low landfill suitability assessment region.





Figs. 17 (a) Landfill suitability map based on AHP model (b) Pie chart showing the percentage area classification of each of the suitability classes

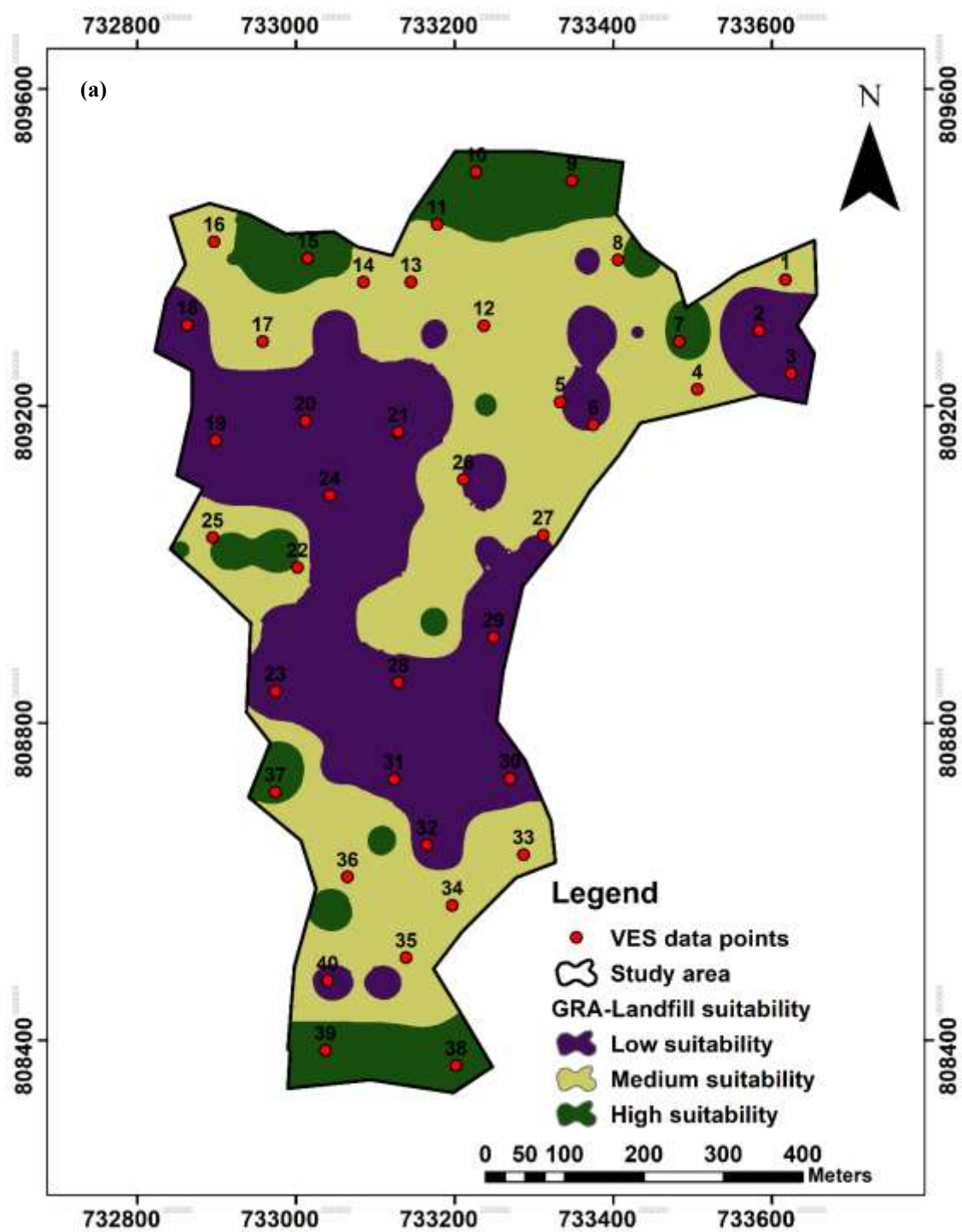
Table 3 Percentage and area extent of each of the suitability classes

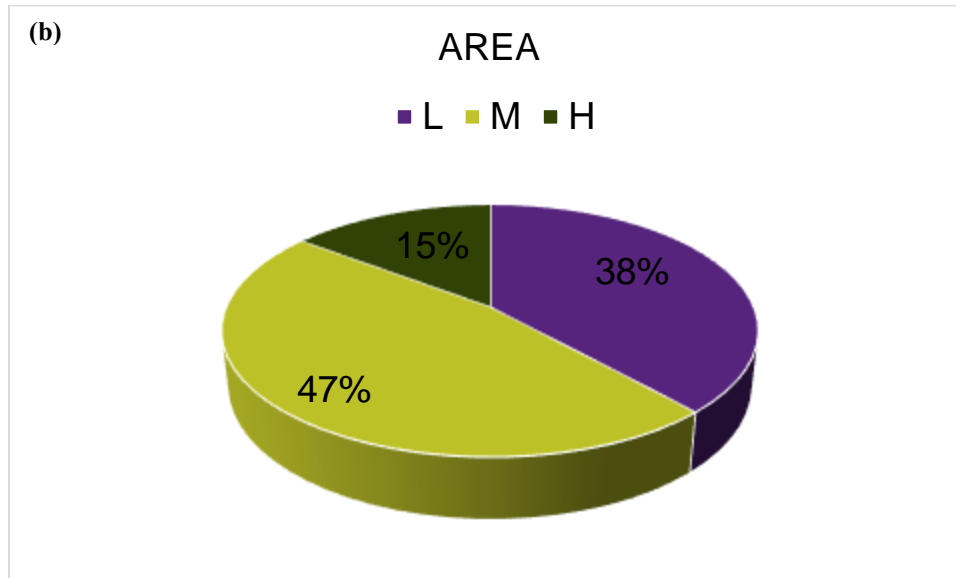
Class	Percentage	Area Extent
Low	35%	169m ²
Moderate	49%	238m ²
High	16%	77m ²

GRA-LSAM map

The GRA-LSAM map was also created using the fishnet data of GRA-LSI (Table S1), employing the approaches discussed in the methodology section. The GRA-LSAM map distributed the study area into three classes: low, moderate and high landfill suitability (Fig. 18a). Also, further analysis involving a pie chart shows the percentage occurrence of each class and the area extent (Fig. 18b). The percentage and area extent of each suitability class are shown in Table 4. From the map, most of the study area falls within the low landfill suitability regions. In addition, the low suitability regions can be observed predominantly within the central, northwestern, and northeastern parts of the study area. VES locations 19, 23, 32, etc., are in this low suitability region. The high suitability region is

predominantly located in the southern part of the study area, with some pockets of high suitability also noticeable in the northern and north-eastern parts of the study area. VES locations 38, 39, 37, etc., fall within the high suitability region. The moderate region falls predominantly within the northern and near southern parts of the study area. VES locations 9, 25, 40, etc., fall within this moderate suitability region.





Figs. 18 (a) Landfill suitability map based on the GRA model (b) Pie chart showing the percentage area classification of each of the suitability classes

Table 4 Percentage and area extent of each of the suitability classes

Class	Percentage	Area Extent
Low	38%	185m ²
Moderate	47%	228m ²
High	15%	71m ²

Validation of the suitability models maps

Longitudinal conductance map

Qualitative validation involving correlation with the longitudinal conductance data was adopted for the models. The longitudinal conductance map shows the spatial distribution of the longitudinal conductance values across the study area. It ranges from 0.00233 to 0.14985 mhos (Fig. 19). Most of the study area, with typical VES locations 5, 38, etc., fall within the low longitudinal conductance region. According to Eze et al. (2022), the higher the longitudinal

conductance of the layer overlying the aquifer, the greater their protective capacity, and hence, the higher the suitability for landfill siting. Conversely, lower longitudinal conductance will lead to reduced landfill suitability. This implies that, most of the study area falling within the low longitudinal conductance regions noticeable in the southern as well as at the north-eastern part of the study area with VES locations 1, 16, 40 etc. will not be suitable for landfill siting whereas, the high longitudinal conductance regions prominently occurring within the central and eastern parts of the study area will be of high suitability. VES locations 16, 20, 33, etc., are among the locations that fall within the high longitudinal conductance region. Also, the moderate longitudinal conductance region with VES locations 18, 19, 35, etc., can be observed at the central and northern parts of the study area.

Validated results of the models

The correlation at each of the fishnet points (Table S2) was done leveraging the analysis presented in the methodology section. Employing the last column within the table, which shows agree (*)/not agree (**) points to calculate the percentage agreement, the accuracy of the models was assessed. The accuracy of each of the models is presented as follows;

For the En-LSA model:

Number of agreed points = 59, Total observed points = 83

$$\text{Thus, Accuracy} = \frac{59}{83} \times 100\% = 71\%$$

For the AHP-LSA model:

Number of agreed points = 53, Total observed fishnet points = 83

$$\text{Thus, Accuracy} = \frac{53}{83} \times 100\% = 64\%$$

For the GRA-LSA model:

$$\text{Accuracy} = \frac{58}{83} \times 100\% = 70\%$$

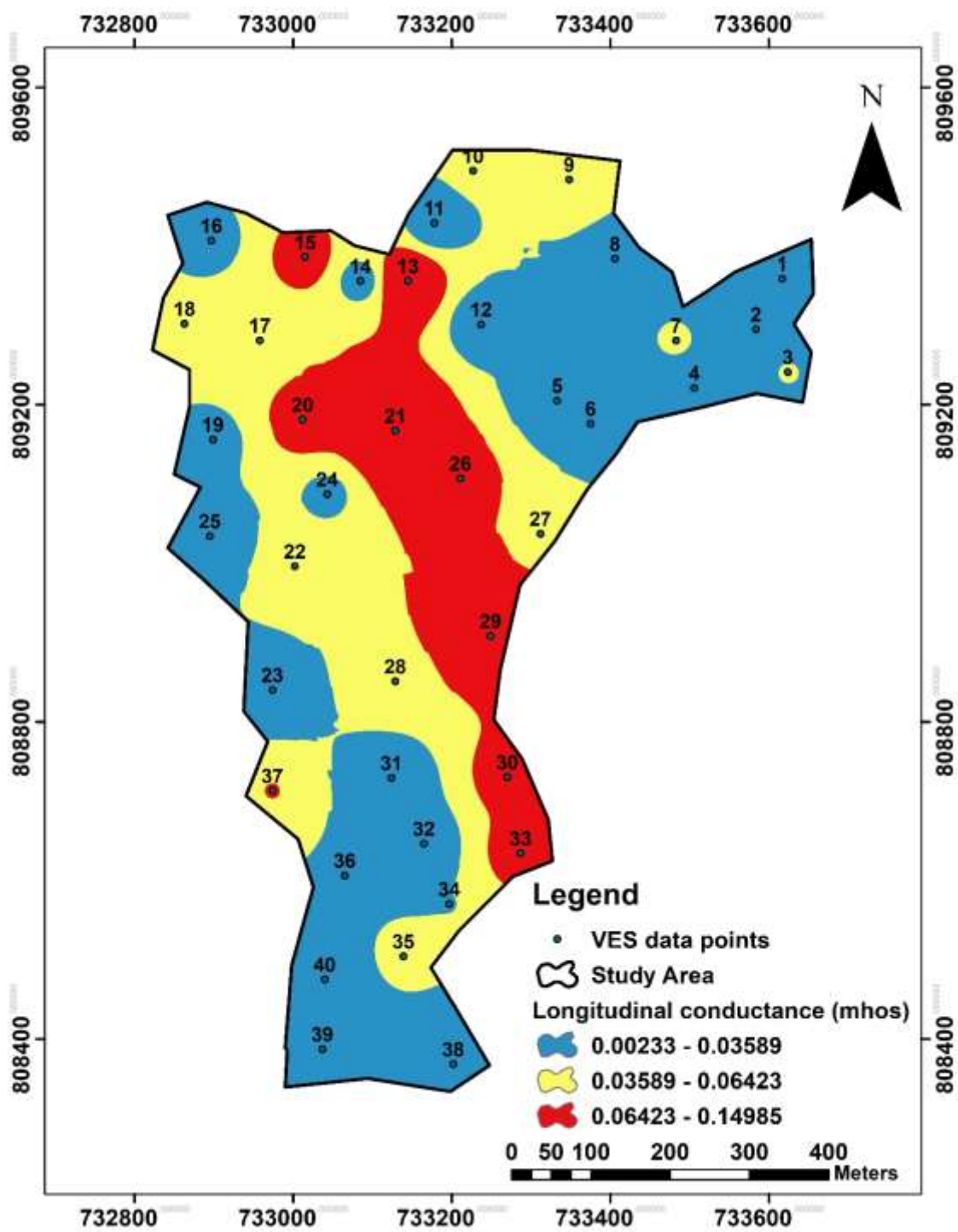


Fig. 19 Longitudinal conductance map of the study area

Discussion

Sustainable waste management in rapidly urbanising environments faces a critical challenge: the effective selection of landfill sites. The surge in waste generation, driven by the expansion of communities and cities, makes the identification of optimal landfill locations not only an urgent environmental concern but also a pressing public health priority (Ali et al., 2021; Wang et al., 2018). Poorly selected landfill sites can pose significant risks to groundwater resources, air quality, and nearby human settlements. Addressing these risks requires scientifically informed decision-making, which is essential for sustainable land-use planning (Wang et al., 2021).

In the case of the study area, which is Ibule Soro, Akure, Southwestern Nigeria, landfill suitability modelling requires a thorough analysis of the geologic settings due to it being underlain by the Precambrian basement complex. Such subsurface geology, according to the study of several researchers (Akanabi & Olukowade, 2018; Obini & Omietimi, 2020; Olorunfemi et al., 2020), is characterised by high variability in geologic characteristics, including but not limited to overburden thickness, hydraulic conductivity, as well as lineament and drainage occurrence. This variability influences leachate migration, infiltration rates, and potential contamination pathways (Adabanija, 2023). Modelling landfill suitability in such an area demands a strategy that is geospatially aware, data-driven, and capable of harmonising several considerations or factors of geological interest.

This study applied three modelling frameworks: Entropy, Analytical Hierarchy Process (AHP), and Grey Relational Analysis (GRA) to support landfill selection in the study area, leveraging remote sensing and geophysical datasets within a GIS environment. Although researchers have worked on landfill site selection (Rahmat et al., 2017; Rezaeisabzevar et al., 2020), in the study area, there is currently limited research on the applicability of geophysical methods integrated with remote sensing for landfill site selection. To set a precedence for such an approach, these models were selected not only based on their widely used cases in other areas of application; Wang et al. (2022) combined the entropy model with the CoCoSo model to select alternative optimal transport systems; Çolak and Kaya (2017) used a fuzzy approach to optimise the AHP and TOPSIS models for prioritisation of renewable energy alternatives; Banik et al. (2023) compared the GRA and MEREC models for the agricultural MCDGM problem, but also their methodological strengths. While the entropy model is grounded in information theory and calculates objective weights by analysing the divergence in the dataset, thereby providing an unbiased estimate of factor significance, the AHP model incorporates expert judgment to create a structured hierarchy of preferences. While these

two models assign relative weights to the criteria, the GRA model was selected to assess the ability of the ranking model, given a simplistic weight assignment approach.

The application of the three models independently allowed for a comparative evaluation of their outputs and performance. Since the scope of the present study is to show the applicability of geologically tied factors in determining landfill site selection, factors such as population density, as well as distance from sensitive sites, were not considered. Despite this, the considered factors, viz. slope, lineament density, drainage density, overburden thickness, hydraulic conductivity, depth to basement, and reflection coefficient, were carefully selected to reflect the hydrogeological characteristics essential for landfill site evaluation. As a result of the difference in methodological applications of the adopted models, each of them assigned different weights to these factors. While the entropy model assigned a higher weight value to lineament density, AHP placed more emphasis on hydraulic conductivity, whereas the GRA model assumed equal importance for the factors. Therefore, the GRA model served as a baseline to understand how uniform factor contributions perform in the context of the suitability assessment.

Model validation is an equally important aspect of decision-making. Researchers (Eisenmann et al., 2021; Lopez et al., 2023) have highlighted that issues with limited data availability, as well as the selection of an appropriate validation technique, always pose a challenge in predictive modelling. This study faces such a challenge: the actual location of the waste disposal site within the study area, which could provide a proper validation approach, is sparsely distributed and thus cannot offer spatially correct suitability validation. Therefore, proxy validation data was utilised, judging from the ability of the chosen data to show true protective capacity (Alao et al., 2022; Ekanem et al., 2021). Although several validation metrics, including percentage agreement, Kappa Index, and AUC-ROC, have been adopted by researchers (Carrington et al., 2023; Marlas et al., 2022; Mogaji & Atenidegbe, 2024), the adoption of percentage agreement as the validation approach was based on its ability to reflect the actual match between predicted zones and the reference data, which is meaningful in applied geospatial contexts (Feizizadeh et al., 2022). The validation approach showed that entropy, AHP, and GRA models have predictive abilities of 71%, 64%, and 70%, respectively, showing that objective weighting approaches offered slightly higher predictive abilities compared to the expertly weighted approach.

This study has presented a unique approach to landfill suitability assessment. However, there were some limitations. Firstly, non-adaptation of socio-economic factors during the modelling phase posed a challenge to the economic

applicability of the adopted approaches. Secondly, the warping of the medium classes into low classes during the validation step is also a perceived limitation. However, since the study area has a relatively small spatial reference, this approach showed the diversity of reference points and the spatial variation; nevertheless, it could have oversimplified the result and therefore exaggerated the validation metric (Ho et al., 2020).

We recommend that future research consider integrating temporal datasets to simulate how landfill suitability may evolve under different environmental scenarios. In addition, several validation metrics could be explored to assess the predictive abilities of models for efficient decision making. Also, stakeholder engagement and participatory GIS could further align the technical outcomes by integrating the practical realities of policy and implementation.

Conclusion

This research highlights the importance of integrating geophysical datasets, remote sensing, and multicriteria decision models within a GIS environment to identify suitable landfill sites. Through this approach, a comprehensive landfill suitability assessment was developed, aiming to streamline decision-making processes and enhance subsurface characterisation accurately. The practical application of these methodologies was demonstrated through a case study within the basement complex area of Nigeria.

The research findings contribute to the advancement of geophysical knowledge, offering a valuable framework for future studies and practical applications in foundational engineering projects. The methodologies provided a systematic framework for evaluating landfill suitability based on seven critical factors: slope, lineament density, drainage density, overburden thickness, hydraulic conductivity, depth to basement, and reflection coefficient. Thematic maps of all these factors showed the spatial distribution within the study area, thereby revealing the landfill suitability trend based on each factor. In addition, the adopted modelling approaches to assess suitability provided a robust view, as they demonstrate the area's suitability for landfill siting from three different modelling perspectives. While the entropy weight computed the weight using a data-driven approach, the AHP approach calculated the relative weights of the factors from experts' perspectives, and the GRA model assigned equal importance to the factors before ranking the alternative fishnet points. The results from these models thus revealed areas with varying degrees of suitability, highlighting zones optimal for landfill establishment and others where landfill should not be sited.

Validation of the models was performed through correlation with longitudinal conductance, which served as a proxy for landfill siting, as it gives the protective capacity of a particular location, with the models achieving slightly different

percentage accuracies. This research thus demonstrates the applicability of modelling landfill suitability given remote sensing and geophysical datasets integrated within a GIS framework. With this applicability, it is expected that the current study will contribute effectively to sustainable waste disposal strategies in the study area and areas with similar geologic settings.

Author contributions

All authors contributed substantially to the success of this study. Author one (KAM) contributed to data provision and supervised the study. Author two (SAM) contributed to data analysis, visualisation and wrote the first manuscript draft. Author three (SSO) contributed to the data analysis and rewrote the entire manuscript. Author four (MYT) contributed to resources and data analysis.

Funding information

This research was self-funded by the authors.

Data availability

Data will be made available upon reasonable request to the corresponding author.

Declarations

Ethics approval All authors have read, understood, and have complied as applicable with the statement on “Ethical responsibilities of Authors” as found in the Instructions for Authors section.

Competing interests The authors declare no competing interests.

References

- Adabanija, M. A. (2023). Spatio-temporal monitoring of leachates dispersion beneath a solid wastes dump in basement complex of southwestern Nigeria. *Journal of Applied Geophysics*, 210, 104953. <https://doi.org/https://doi.org/10.1016/j.jappgeo.2023.104953>
- Adenuga, O. A., & Popoola, O. I. (2020). Subsurface characterization using electrical resistivity and MASW techniques for suitable municipal solid waste disposal site. *SN Applied Sciences*, 2(9), 1549. <https://doi.org/10.1007/s42452-020-03320-x>
- Akanabi, O. A., & Olukowade, O. J. (2018). Lithologic characterisation of the Basement Aquifers of Awe and Akinmorin areas, southwestern Nigeria. *Global journal of geological sciences*, 16, 1–11. <https://doi.org/https://doi.org/10.4314/gjgs.v16i1.1>
- Akintorinwa, O. J., & Okoro, O. V. (2019). Combine electrical resistivity method and multi-criteria GIS-based modeling for landfill site selection in the Southwestern Nigeria. *Environmental Earth Sciences*, 78(5), 162. <https://doi.org/10.1007/s12665-019-8153-z>
- Alao, J., Ahmad, M., Danjumo, T., Ango, A., & Emmanuel, J. (2022). Assessment of aquifer protective capacity, against the surface contamination. A case study of kaduna industrial village, Nigeria. *Phys. Sci. Int. J*, 26(1), 43–51. <https://doi.org/10.9734/PSIJ/2022/v26i130306>
- Ali, S. A., Parvin, F., Al-Ansari, N., Pham, Q. B., Ahmad, A., Raj, M. S., Anh, D. T., Ba, L. H., & Thai, V. N. (2021). Sanitary landfill site selection by integrating AHP and FTOPSIS with GIS: a case study of Memari Municipality, India. *Environmental Science and Pollution Research*, 28(6), 7528–7550. <https://doi.org/10.1007/s11356-020-11004-7>

- Alkaradaghi, K., Ali, S. S., Al-Ansari, N., Laue, J., & Chabuk, A. (2019). Landfill site selection using MCDM methods and GIS in the Sulaimaniyah Governorate, Iraq. *Sustainability*, 11(17), 4530. <https://doi.org/https://doi.org/10.3390/su11174530>
- Anthony, A. A., Esther, O. C., Chris, D. O., & Oni, B. A. (2020). Assessment of clay materials for suitability in drilling mud formulation from part of Ondo State, South-West Nigeria. *Journal of Petroleum Exploration and Production Technology*, 10(7), 2815–2828. <https://doi.org/10.1007/s13202-020-00947-9>
- Banik, B., Alam, S., & Chakraborty, A. (2023). Comparative study between GRA and MEREC technique on an agricultural-based MCGDM problem in pentagonal neutrosophic environment. *International Journal of Environmental Science and Technology*, 20(12), 13091–13106. <https://doi.org/10.1007/s13762-023-04768-1>
- Bechrone, W., Kherrou, L., Belaid, L., & Goumrassa, A. (2024). GIS-MCDM integrated approach for suitable landfill site selection: a case study of the southwestern part of Bejaia Province, Algeria. *Environmental Monitoring and Assessment*, 196(12), 1262. <https://doi.org/10.1007/s10661-024-13381-9>
- Bibri, S. E. (2021). Data-driven smart sustainable cities of the future: An evidence synthesis approach to a comprehensive state-of-the-art literature review. *Sustainable Futures*, 3, 100047. <https://doi.org/https://doi.org/10.1016/j.sfr.2021.100047>
- Bilgilioglu, S. S., Gezgin, C., Orhan, O., & Karakus, P. (2022). A GIS-based multi-criteria decision-making method for the selection of potential municipal solid waste disposal sites in Mersin, Turkey. *Environmental Science and Pollution Research*, 29(4), 5313–5329. <https://doi.org/10.1007/s11356-021-15859-2>
- Buran, B., & Erçek, M. (2022). Public transportation business model evaluation with Spherical and Intuitionistic Fuzzy AHP and sensitivity analysis. *Expert Systems with Applications*, 204, 117519. <https://doi.org/https://doi.org/10.1016/j.eswa.2022.117519>
- Carević, I., Sibinović, M., Manojlović, S., Batočanin, N., Petrović, A. S., & Srejić, T. (2021). Geological Approach for Landfill Site Selection: A Case Study of Vršac Municipality, Serbia. *Sustainability*, 13(14). <https://doi.org/10.3390/su13147810>
- Carrington, A. M., Manuel, D. G., Fieguth, P. W., Ramsay, T., Osmani, V., Wernly, B., Bennett, C., Hawken, S., Magwood, O., Sheikh, Y., McInnes, M., & Holzinger, A. (2023). Deep ROC Analysis and AUC as Balanced Average Accuracy, for Improved Classifier Selection, Audit and Explanation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 45(1), 329–341. <https://doi.org/10.1109/TPAMI.2022.3145392>
- Chabuk, A. J., Al-Ansari, N., Hussain, H. M., Knutsson, S., & Pusch, R. (2017). GIS-based assessment of combined AHP and SAW methods for selecting suitable sites for landfill in Al-Musayyab Qadhaa, Babylon, Iraq. *Environmental Earth Sciences*, 76(5), 209. <https://doi.org/10.1007/s12665-017-6524-x>
- Chodha, V., Dubey, R., Kumar, R., Singh, S., & Kaur, S. (2022). Selection of industrial arc welding robot with TOPSIS and Entropy MCDM techniques. *Materials Today: Proceedings*, 50, 709–715. <https://doi.org/https://doi.org/10.1016/j.matpr.2021.04.487>
- Çolak, M., & Kaya, İ. (2017). Prioritization of renewable energy alternatives by using an integrated fuzzy MCDM model: A real case application for Turkey. *Renewable and Sustainable Energy Reviews*, 80, 840–853. <https://doi.org/https://doi.org/10.1016/j.rser.2017.05.194>
- Das, S., Lee, S. H., Kumar, P., Kim, K.-H., Lee, S. S., & Bhattacharya, S. S. (2019). Solid waste management: Scope and the challenge of sustainability. *Journal of Cleaner Production*, 228, 658–678. <https://doi.org/https://doi.org/10.1016/j.jclepro.2019.04.323>
- Demesouka, O., Vavatsikos, A., & Anagnostopoulos, K. (2014). GIS-based multicriteria municipal solid waste landfill suitability analysis: A review of the methodologies performed and criteria implemented. *Waste Management & Research*, 32(4), 270–296. <https://doi.org/10.1177/0734242X14526632>
- Demesouka, O. E., Vavatsikos, A. P., & Anagnostopoulos, K. P. (2016). Using MACBETH Multicriteria Technique for GIS-Based Landfill Suitability Analysis. *Journal of Environmental Engineering*, 142(10), 04016042. [https://doi.org/10.1061/\(ASCE\)EE.1943-7870.0001109](https://doi.org/10.1061/(ASCE)EE.1943-7870.0001109)
- Eisenmann, M., Grauberger, P., Üreten, S., Krause, D., & Matthiesen, S. (2021). Design method validation – an investigation of the current practice in design research. *Journal of Engineering Design*, 32(11), 621–645. <https://doi.org/10.1080/09544828.2021.1950655>
- Ekanem, A. M., Akpan, A. E., George, N. J., & Thomas, J. E. (2021). Appraisal of protectivity and corrosivity of surficial hydrogeological units via geo-sounding measurements. *Environmental Monitoring and Assessment*, 193(11), 718. <https://doi.org/10.1007/s10661-021-09518-9>
- Enisan, O., Akinrogunde, O., Oginni, O., & Akinola, O. (2024). The socio-environmental implications of solid landfill on residential development in Igando, Lagos. *ISRG Journal of Arts, Humanities & Social Sciences (ISRGJAHSS)*, II(IV), 130–142. <https://doi.org/https://zenodo.org/records/12744029>

- Esangbedo, M. O., Xue, J., Bai, S., & Esangbedo, C. O. (2024). Relaxed Rank Order Centroid Weighting MCDM Method With Improved Grey Relational Analysis for Subcontractor Selection: Photothermal Power Station Construction. *IEEE Transactions on Engineering Management*, 71, 3044–3061. <https://doi.org/10.1109/TEM.2022.3204629>
- Eskandari, M., Homaei, M., & Mahmodi, S. (2012). An integrated multi criteria approach for landfill siting in a conflicting environmental, economical and socio-cultural area. *Waste Management*, 32(8), 1528–1538. <https://doi.org/https://doi.org/10.1016/j.wasman.2012.03.014>
- Eze, S. U., Orji, O. M., Onoriode, A. E., Saleh, S. A., & Abolarin, M. O. (2022). Integrated geoelectrical resistivity method for environmental assessment of landfill leachate pollution and aquifer vulnerability studies. *Journal of Geoscience and Environment Protection*, 10(9), 1–26. <https://doi.org/https://doi.org/10.4236/gep.2022.109001>
- Feizizadeh, B., Darabi, S., Blaschke, T., & Lakes, T. (2022). QADI as a New Method and Alternative to Kappa for Accuracy Assessment of Remote Sensing-Based Image Classification. *Sensors*, 22(12), 4506. <https://doi.org/https://doi.org/10.3390/s22124506>
- Fetter, C. W., Boving, T., & Kremer, D. (2017). *Contaminant hydrogeology*. Waveland Press.
- Frye, C., Wright, D. J., Nordstrand, E., Terborgh, C., & Foust, J. (2018). Using classified and unclassified land cover data to estimate the footprint of human settlement. *Data Science Journal*, 17, 20–20. <https://doi.org/https://orcid.org/0000-0002-2997-7611>
- Goulart Coelho, L. M., Lange, L. C., & Coelho, H. M. G. (2017). Multi-criteria decision making to support waste management: A critical review of current practices and methods. *Waste Management & Research*, 35(1), 3–28. <https://doi.org/10.1177/0734242X16664024>
- Ho, S. Y., Wong, L., & Goh, W. W. B. (2020). Avoid oversimplifications in machine learning: going beyond the class-prediction accuracy. *Patterns*, 1(2). <https://doi.org/https://doi.org/10.1016/j.patter.2020.100025>
- Hsiao, S.-W., Lin, H.-H., & Ko, Y.-C. (2017). Application of grey relational analysis to decision-making during product development. *Eurasia Journal of Mathematics, Science and Technology Education*, 13(6), 2581–2600. <https://doi.org/https://doi.org/10.12973/eurasia.2017.01242a>
- Idowu, I. A., Atherton, W., Hashim, K., Kot, P., Alkhaddar, R., Alo, B. I., & Shaw, A. (2019). An analyses of the status of landfill classification systems in developing countries: Sub Saharan Africa landfill experiences. *Waste Management*, 87, 761–771. <https://doi.org/https://doi.org/10.1016/j.wasman.2019.03.011>
- Kebede, Y. S., Alene, M. M., & Endalemaw, N. T. (2021). Urban landfill investigation for managing the negative impact of solid waste on environment using geospatial technique. A case study of Assosa town, Ethiopia. *Environmental Challenges*, 4, 100103. <https://doi.org/https://doi.org/10.1016/j.envc.2021.100103>
- Keller, G. V., & Frischknecht, F. C. (1966). Electrical methods in geophysical prospecting.
- Khan, D., & Samadder, S. R. (2015). A simplified multi-criteria evaluation model for landfill site ranking and selection based on AHP and GIS. *Journal of Environmental Engineering and Landscape Management*, 23(4), 267–278. <https://doi.org/https://doi.org/10.3846/16486897.2015.1056741>
- Khouni, I., Louhichi, G., & Ghrabi, A. (2021). Use of GIS based Inverse Distance Weighted interpolation to assess surface water quality: Case of Wadi El Bey, Tunisia. *Environmental Technology & Innovation*, 24, 101892. <https://doi.org/https://doi.org/10.1016/j.eti.2021.101892>
- Kuo, Y., Yang, T., & Huang, G.-W. (2008). The use of grey relational analysis in solving multiple attribute decision-making problems. *Computers & Industrial Engineering*, 55(1), 80–93. <https://doi.org/https://doi.org/10.1016/j.cie.2007.12.002>
- Lam, W. S., Lam, W. H., & Jaaman, S. H. (2021). Portfolio Optimization with a Mean–Absolute Deviation–Entropy Multi-Objective Model. *Entropy*, 23(10), 1266. <https://doi.org/https://doi.org/10.3390/e23101266>
- Laski, H. J. (2020). The Limitations of the Expert. *Society*, 57(4), 371–377. <https://doi.org/10.1007/s12115-020-00498-z>
- Li, X., Li, G., & Zhang, Y. (2014). Identifying Major Factors Affecting Groundwater Change in the North China Plain with Grey Relational Analysis. *Water*, 6(6), 1581–1600. <https://doi.org/https://doi.org/10.3390/w6061581>
- Lopez, E., Etxebarria-Elezgarai, J., Amigo, J. M., & Seifert, A. (2023). The importance of choosing a proper validation strategy in predictive models. A tutorial with real examples. *Analytica Chimica Acta*, 1275, 341532. <https://doi.org/https://doi.org/10.1016/j.aca.2023.341532>
- Mallick, J. (2021). Municipal Solid Waste Landfill Site Selection Based on Fuzzy-AHP and Geoinformation Techniques in Asir Region Saudi Arabia. *Sustainability*, 13(3). <https://doi.org/https://doi.org/10.3390/su13031538>

- Marlas, M., Bost, C., Dorcet, G., Delourme, A., Biotti, D., Ciron, J., Renaudineau, Y., & Puissant-Lubrano, B. (2022). Kappa-index: Real-life evaluation of a new tool for multiple sclerosis diagnosis. *Clinical Immunology*, 241, 109066. <https://doi.org/https://doi.org/10.1016/j.clim.2022.109066>
- Milutinović, B., Stefanović, G., Milutinović, S., & Čojbašić, Ž. (2016). Application of fuzzy logic for evaluation of the level of social acceptance of waste treatment. *Clean Technologies and Environmental Policy*, 18(6), 1863–1875. <https://doi.org/10.1007/s10098-016-1211-2>
- Mogaji, K., Aboyeji, O., & Omosuyi, G. (2011). Mapping of lineaments for groundwater targeting in the basement complex region of Ondo State, Nigeria, using remote sensing and geographic information system (GIS) techniques. *International Journal of water resources and environmental engineering*, 3(7), 150–160. <https://doi.org/https://doi.org/10.5897/IJWREE.9000035>
- Mogaji, K. A., & Atenidegbe, O. F. (2024). Development of PROMETHEE-Entropy data mining model for groundwater potentiality modeling: a case study of multifaceted geologic settings in south-western Nigeria. *Acta Geophysica*, 72(3), 1957–1984. <https://doi.org/10.1007/s11600-023-01095-4>
- Mogaji, K. A., & Lim, H. S. (2017). Groundwater potentiality mapping using geoelectrical-based aquifer hydraulic parameters: A GIS-based multi-criteria decision analysis modeling approach. *Terr. Atmos. Ocean. Sci*, 28, 479–500. <https://doi.org/10.3319/TAO.2016.11.01.02>
- Mogaji, K. A., Lim, H. S., & Abdullah, K. (2014). Modeling groundwater vulnerability prediction using geographic information system (GIS)-based ordered weighted average (OWA) method and DRASTIC model theory hybrid approach. *Arabian Journal of Geosciences*, 7(12), 5409–5429. <https://doi.org/10.1007/s12517-013-1163-3>
- Mu, E., & Pereyra-Rojas, M. (2017). Understanding the Analytic Hierarchy Process. In E. Mu & M. Pereyra-Rojas (Eds.), *Practical Decision Making: An Introduction to the Analytic Hierarchy Process (AHP) Using Super Decisions V2* (pp. 7–22). Springer International Publishing. https://doi.org/10.1007/978-3-319-33861-3_2
- Mukherjee, S., Soumyadeep, M., Ali, H. M., & Sen Gupta, B. (2015). Contemporary Environmental Issues of Landfill Leachate: Assessment and Remedies. *Critical Reviews in Environmental Science and Technology*, 45(5), 472–590. <https://doi.org/10.1080/10643389.2013.876524>
- Nadiruzzaman, M., Shewly, H. J., & Esha, A. A. (2022). Dhaka Sitting on a Plastic Bomb: Issues and Concerns around Waste Governance, Water Quality, and Public Health. *Earth*, 3(1), 18–30. <https://doi.org/10.3390/earth3010002>
- Naveen, B. P., Sumalatha, J., & Malik, R. K. (2018). A study on contamination of ground and surface water bodies by leachate leakage from a landfill in Bangalore, India. *International Journal of Geo-Engineering*, 9(1), 27. <https://doi.org/10.1186/s40703-018-0095-x>
- Nkwunonwo, U. C., Oyem, M. N., Tobore, A. O., Asano, N. O., & Ebinne, E. S. (2024). Geospatial Analysis and Physicochemical Assessment of Groundwater Quality Vulnerability to Municipal Solid Waste from Landfills. *Air, Soil and Water Research*, 17, 11786221241266039. <https://doi.org/10.1177/11786221241266039>
- Obini, N., & Omietimi, E. (2020). Geological Mapping, Petrographic and Structural Attributes of Basement Rocks at Eiyenkorin Area, Southwestern Nigeria. *International Journal of Scientific and research publications*, 187–194. <https://doi.org/http://dx.doi.org/10.29322/IJSRP.10.05.2020.p10122>
- Odu, G. (2019). Weighting methods for multi-criteria decision making technique. *Journal of Applied Sciences and Environmental Management*, 23(8), 1449–1457. <https://doi.org/https://doi.org/10.4314/jasem.v23i8.7>
- Olorunfemi, M. O., Oni, A. G., Bamidele, O. E., Fadare, T. K., & Aniko, O. O. (2020). Combined geophysical investigations of the characteristics of a regional fault zone for groundwater development in a basement complex terrain of South-west Nigeria. *SN Applied Sciences*, 2(6), 1033. <https://doi.org/10.1007/s42452-020-2363-6>
- Olusina, J. O., & Shyllon, D. (2014). Suitability analysis in determining optimal landfill location using multi-criteria evaluation (mce), gis & remote sensing. *Int J Comput Eng Res*, 4(6), 7–20.
- Postacchini, L., Ciarapica, F. E., & Bevilacqua, M. (2018). Environmental assessment of a landfill leachate treatment plant: Impacts and research for more sustainable chemical alternatives. *Journal of Cleaner Production*, 183, 1021–1033. <https://doi.org/https://doi.org/10.1016/j.jclepro.2018.02.219>
- Prabu, P., & Baskaran, R. (2013). Drainage Morphometry of Upper Vaigai River Sub-basin, Western Ghats, South India Using Remote Sensing and GIS. *Journal of the Geological Society of India*, 82(5), 519–528. <https://doi.org/10.1007/s12594-013-0183-7>
- Rahmat, Z. G., Niri, M. V., Alavi, N., Goudarzi, G., Babaei, A. A., Baboli, Z., & Hosseinzadeh, M. (2017). Landfill site selection using GIS and AHP: a case study: Behbahan, Iran. *KSCE Journal of Civil Engineering*, 21(1), 111–118. <https://doi.org/https://doi.org/10.1007/s12205-016-0296-9>

- Rajoo, K. S., Karam, D. S., Ismail, A., & Arifin, A. (2020). Evaluating the leachate contamination impact of landfills and open dumpsites from developing countries using the proposed Leachate Pollution Index for Developing Countries (LPIDC). *Environmental Nanotechnology, Monitoring & Management*, 14, 100372. <https://doi.org/https://doi.org/10.1016/j.enmm.2020.100372>
- Rezaeisabzevar, Y., Bazargan, A., & Zohourian, B. (2020). Landfill site selection using multi criteria decision making: Influential factors for comparing locations. *Journal of Environmental Sciences*, 93, 170–184. <https://doi.org/https://doi.org/10.1016/j.jes.2020.02.030>
- Roy, D., Das, S., Paul, S., & Paul, S. (2022). An assessment of suitable landfill site selection for municipal solid waste management by GIS-based MCDA technique in Siliguri municipal corporation planning area, West Bengal, India. *Computational Urban Science*, 2(18). <https://doi.org/https://doi.org/10.1007/s43762-022-00038-x>
- Saatsaz, M., Monsef, I., Rahmani, M., & Ghods, A. (2018). Site suitability evaluation of an old operating landfill using AHP and GIS techniques and integrated hydrogeological and geophysical surveys. *Environmental Monitoring and Assessment*, 190(3), 144. <https://doi.org/10.1007/s10661-018-6505-x>
- Shahbazi, A., Saeidi, A., & Chesnaux, R. (2020). A review of existing methods used to evaluate the hydraulic conductivity of a fractured rock mass. *Engineering Geology*, 265, 105438. <https://doi.org/https://doi.org/10.1016/j.enggeo.2019.105438>
- Siddiqua, A., Hahladakis, J. N., & Al-Attiya, W. A. K. A. (2022). An overview of the environmental pollution and health effects associated with waste landfilling and open dumping. *Environmental Science and Pollution Research*, 29(39), 58514–58536. <https://doi.org/10.1007/s11356-022-21578-z>
- Şimşek, K., & Alp, S. (2022). Evaluation of Landfill Site Selection by Combining Fuzzy Tools in GIS-Based Multi-Criteria Decision Analysis: A Case Study in Diyarbakır, Turkey. *Sustainability*, 14(16), 9810. <https://doi.org/https://doi.org/10.3390/su14169810>
- Soni, A., Das, P. K., Hashmi, A. W., Yusuf, M., Kamyab, H., & Chelliapan, S. (2022). Challenges and opportunities of utilizing municipal solid waste as alternative building materials for sustainable development goals: A review. *Sustainable Chemistry and Pharmacy*, 27, 100706. <https://doi.org/https://doi.org/10.1016/j.scp.2022.100706>
- Todd, D. K., & Mays, L. W. (2004). *Groundwater hydrology*. John Wiley & Sons.
- Vander Velpen, B. (2004). WinRESIST version 1.0 resistivity depth sounding interpretation software. *M. Sc Research Project, ITC, Delft Netherland*.
- Vijay Kumar, D., Ramadass, G., & Jagadish, S. (2015). Delineation of Groundwater Potential Zones through Electrical Resistivity Parameters in hard rock terrain, Osmania University Campus, Hyderabad, Telangana State, India. *IOSR Journal of Applied Geology and Geophysics*, 3(6), 1–10. <https://doi.org/10.9790/0990-03620110>
- Wang, C.-N., Le, T. Q., Chang, K.-H., & Dang, T.-T. (2022). Measuring Road Transport Sustainability Using MCDM-Based Entropy Objective Weighting Method. *Symmetry*, 14(5). <https://doi.org/https://doi.org/10.3390/sym14051033>
- Wang, F., Song, K., He, X., Peng, Y., Liu, D., & Liu, J. (2021). Identification of Groundwater Pollution Characteristics and Health Risk Assessment of a Landfill in a Low Permeability Area. *International Journal of Environmental Research and Public Health*, 18(14), 7690. <https://doi.org/https://doi.org/10.3390/ijerph18147690>
- Wang, G., Qin, L., Li, G., & Chen, L. (2009). Landfill site selection using spatial information technologies and AHP: A case study in Beijing, China. *Journal of Environmental Management*, 90(8), 2414–2421. <https://doi.org/https://doi.org/10.1016/j.jenvman.2008.12.008>
- Wang, Y., Li, J., An, D., Xi, B., Tang, J., Wang, Y., & Yang, Y. (2018). Site selection for municipal solid waste landfill considering environmental health risks. *Resources, Conservation and Recycling*, 138, 40–46. <https://doi.org/https://doi.org/10.1016/j.resconrec.2018.07.008>
- Yazdani, M., Monavari, S. M., Omrani, G. A., Shariat, M., & Hosseini, S. M. (2015). Landfill site suitability assessment by means of geographic information system analysis. *Solid Earth*, 6(3), 945–956. <https://doi.org/10.5194/se-6-945-2015>
- Yazdani, M., Zarate, P., Kazimieras Zavadskas, E., & Turskis, Z. (2019). A combined compromise solution (CoCoSo) method for multi-criteria decision-making problems. *Management decision*, 57(9), 2501–2519. <https://doi.org/10.1108/MD-05-2017-0458>
- Yeh, H.-F., Cheng, Y.-S., Lin, H.-I., & Lee, C.-H. (2016). Mapping groundwater recharge potential zone using a GIS approach in Hualian River, Taiwan. *Sustainable Environment Research*, 26(1), 33–43. <https://doi.org/https://doi.org/10.1016/j.serj.2015.09.005>