

Article

GIS-Based Suitability Analysis of LPG Refill Stations Using Boolean and Hybrid Multi-Criteria Approaches: A Case Study of Nairobi, Kenya

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Abstract

Rapid urbanization has increased demand for safe and reliable energy infrastructure, with Liquefied Petroleum Gas (LPG) emerging as an important clean cooking fuel. In Nairobi, Kenya, the siting of LPG refill stations is critical to minimizing safety risks and supporting sustainable urban development. This study applied a GIS-based Multi-Criteria Decision Analysis (MCDA) framework to evaluate LPG station suitability by integrating land use, elevation, slope, geology, soil texture, and regulatory constraints. Two approaches were compared: a Boolean-only overlay model and a hybrid weighted overlay–Boolean model incorporating Analytic Hierarchy Process (AHP)-derived weights. The Boolean model produced an overly restrictive outcome, identifying no feasible locations under the combined exclusion criteria. In contrast, the hybrid model excluded 91.7% of the study area and identified 2779 potential candidate locations distributed across suitability classes. AHP results indicated that land-use compatibility and LPG proximity were the most influential criteria in determining suitability. Comparison with existing LPG stations revealed a spatial mismatch, with most facilities located in less suitable or unsuitable areas. The findings demonstrate that while Boolean approaches strictly enforce all constraints, hybrid GIS–MCDA models provide a more flexible and spatially differentiated basis for LPG infrastructure planning in rapidly growing urban environments.

Keywords: LPG refill stations; suitability analysis; GIS-MCDA; hybrid weighted-Boolean overlay; weighted overlay; Boolean overlay; urban energy planning; Nairobi; Kenya



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1. Introduction

Rapid urbanization has intensified the need for safe, reliable and accessible energy infrastructure, with clean cooking fuels such as Liquefied Petroleum Gas (LPG) becoming increasingly important. The transition from traditional biomass and kerosene fuels to LPG is increasingly recognized as a critical strategy for reducing household air pollution, mitigating environmental degradation, and advancing public health outcomes [1,2]. As a result, the spatial planning and regulation of LPG infrastructure, particularly refill and distribution stations, has become a major urban governance challenge.

Globally, the inappropriate siting of petroleum and gas facilities has been associated with severe safety, environmental, and socio-economic consequences, including explosions, fires, and exposure of vulnerable populations to hazardous risks [3,4]. These risks are often exacerbated in rapidly growing urban areas where land-use competition, informal

development, and weak enforcement of planning regulations result in fuel facilities being located in close proximity to residential areas, schools, hospitals and commercial centers [5]. Furthermore, recurrent fuel-related explosions and persistent regulatory compliance failures as reported in parts of Asia and Africa have raised sustained concerns regarding siting practices and enforcement mechanisms [6–10]. Kenya has experienced comparable challenges, most notably the 2024 Embakasi LPG explosion in Nairobi, which highlighted the risks associated with locating LPG facilities within densely populated residential areas [11]. At the same time, national policy commitments to expand access to clean cooking energy, including Kenya's Vision 2030 and Sustainable Energy for All (SE4All) agenda [2], have intensified the need for safe and strategically planned LPG infrastructure. In Nairobi, the country's primary urban consumption hub, rapid population growth and land-use pressures further complicate the implementation of spatially informed and safety-compliant siting strategies.

In response to these planning and enforcement challenges, spatial decision-support tools, particularly Geographic Information Systems (GIS) integrated with multi-criteria decision analysis (MCDA), have become increasingly central to infrastructure siting worldwide. Within this framework, a substantial body of research has applied GIS–MCDA to a range of infrastructure siting problems, including fuel stations, petroleum hubs, renewable energy facilities and waste management systems [3,4,7,12–14]. These studies commonly integrate biophysical and environmental criteria (e.g., elevation, slope, soil, geology, land use, rivers, wetlands), socio-economic factors, and regulatory and planning constraints into unified decision models. In most applications, MCDA has been operationalized using Analytical Hierarchy Process (AHP)-based weighted overlay techniques [4,13]. Criteria such as land use, proximity to roads, slope, elevation, soil, geology, and distance from sensitive receptors (e.g., schools, hospitals, residential areas) are standardized, weighted and aggregated to generate composite suitability surfaces. For example, AHP and Weighted Linear Combination (WLC) have been applied in gas station site selection studies [12]. Similarly, AHP-based MCDA has been combined with entropy weighting and restriction mapping in landfill siting studies to improve decision reliability [15]. Methodological advancements have further expanded MCDA applications. For instance, hybrid decision frameworks combining AHP–WLC with optimization algorithms such as Genetic Algorithms have been applied in solar photovoltaic [16] and gas station site selection studies [17], to improve spatial optimization. Other studies have incorporated fuzzy AHP approaches [14], as well as hybrid ranking methods such as Fuzzy AHP and VIKOR method combined with weighted overlay and restriction models to address uncertainty and enhance robustness in infrastructure planning [5].

In addition, several studies have compared different GIS–MCDA approaches to evaluate differences in site selection outcomes. Riad et al. [18] applied both Boolean logic and weighted overlay methods for identifying suitable locations for artificial groundwater recharge, demonstrating that Boolean logic is effective for initial screening but can underutilize partially suitable areas, whereas weighted overlay provides more accurate results. Similarly, Aslani and Alesheikh [19] compared Boolean, index overlay, and fuzzy methods for small fuel station siting, demonstrating that fuzzy and weighted approaches capture partial fulfillment of criteria and provide more spatially inclusive suitability maps compared to rigid Boolean rules. Mahdavi and Akhavan [20] applied Boolean, overlay and fuzzy approaches for artificial groundwater recharge, finding that Boolean logic identified only a limited portion of the study area, while overlay and fuzzy MCDA captured varying degrees of suitability across larger areas, highlighting greater flexibility and sensitivity.

Most studies have adopted a single decision-logic framework, such as weighted overlay or hybrid Boolean-weighted overlay models, and treated the resulting suitability surface as the final output. Consequently, relatively few studies have systematically compared how different MCDA decision rules influence spatial suitability outcomes for the same siting problem. In particular, limited attention has been given to how the distinction between non-compensatory Boolean logic and hybrid Weighted-Boolean models affects spatial suitability outcomes in highly constrained urban environments and sector-specific applications such as LPG infrastructure siting. This gap is particularly relevant in rapidly urbanizing African cities, where land scarcity and regulatory enforcement conditions may significantly alter the practical performance of MCDA decision rules.

To address this gap, the present study makes the following contributions. First, it develops an LPG-specific GIS-MCDA suitability framework by adapting established fuel station siting constraints reported in previous studies, such as Zhu et al. [17], for LPG refill station siting. Second, it evaluates how non-compensatory Boolean logic and hybrid Weighted-Boolean decision rules influence spatial suitability outcomes, thereby providing insight into the implications of decision-rule selection for LPG infrastructure planning. Specifically, the analysis compares: (i) a Boolean-only suitability model in which all regulatory, planning, biophysical, and environmental criteria are treated as strict pass-fail conditions, and (ii) a hybrid weighted-Boolean model in which regulatory and planning requirements are enforced through Boolean exclusion masks while biophysical factors (slope, elevation, soil, and geology), land use and LPG proximity distances are standardized and aggregated using an AHP-based weighted overlay approach. Third, it demonstrates the application of these approaches in a high-density African urban context (Nairobi), where land-use competition and spatial constraints significantly influence site availability and suitability patterns.

By contrasting the resulting suitability maps, the study demonstrates how MCDA decision logic influences the spatial distribution of candidate LPG sites. The Boolean-only model produces a highly restrictive outcome, classifying the entire study area as unsuitable and identifying no feasible candidate site. In contrast, the hybrid weighted-Boolean model identifies a broader set of potentially suitable locations across eastern, northern, and western regions of the city. These findings provide practical insights for informed, transparent, and context-sensitive urban energy planning in Nairobi and other rapidly growing urban areas.

2. Materials and Methods

2.1. Study Area

The study was conducted in Nairobi City County, Kenya, the country's capital and a major economic hub (Figure 1). The County covers an area of 696.1 km² and is located between longitudes 36°45' East and latitudes 1°18' South. It is bordered by Kiambu, Kajiado, and Machakos counties and lies at an average elevation of 1798 m above sea level [21]. The terrain is characterized by predominantly gentle to moderately steep slopes.

Nairobi City County exhibits a heterogeneous land-use structure comprising residential, commercial, industrial, government and institutional areas, transport and communication infrastructure, hospitality and tourism facilities, informal settlements, and peri-urban agriculture [21]. Rapid urbanization has increased demand for infrastructure and services, including the growing need for Liquefied Petroleum Gas (LPG) distribution networks as the adoption of clean cooking fuels expands [22] (pp. 40–60) and [23]. The city's mix of dense urban cores and lower-density outskirts [24], provides a suitable context for evaluating the

spatial suitability of LPG refill stations while considering environmental, regulatory, and planning factors relevant to safety.

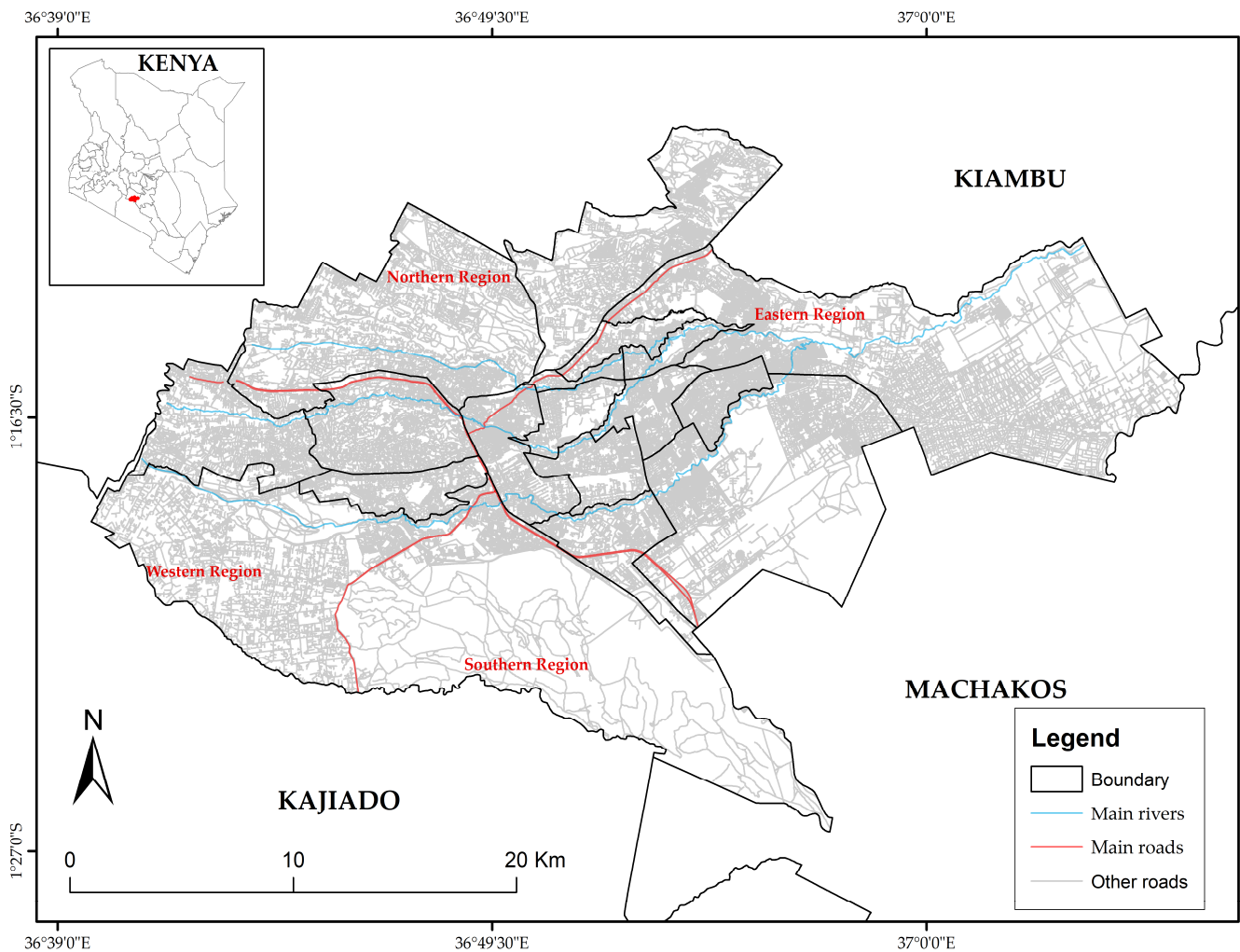


Figure 1. Study area map showing the sub-county boundaries of Nairobi County and the neighboring counties of Kiambu, Kajiado, and Machakos. Map projection: WGS 84/UTM Zone 37S (EPSG:32737). The area is divided into Northern, Eastern, Southern and Western regions, delineated by major roads (red). Source: Adapted from Hellen et al. [25], based on boundaries from the Independent Electoral and Boundaries Commission, Kenya.

2.2. Data Sources and Preprocessing

Data used in this study were grouped into two main categories: (i) thematic datasets (Table 1), representing continuous spatial variables and discrete spatial classes, and (ii) buffered datasets (Table 2), representing features whose suitability was determined by using regulatory and planning-based distance thresholds. These datasets were derived from different years but were selected as the most recent, authoritative, and publicly available sources at the time of analysis. Supporting datasets used for study area delineation and candidate filtering are described in Section 2.2.3.

Table 1. Thematic datasets used in the suitability analysis.

Dataset	Source	Year	Variable Derived	Purpose
ALOS PALSAR DEM (12.5 m)	Alaska Satellite Facility (ASF) https://search.asf.alaska.edu (accessed on 11 July 2025)	2007	Elevation, Slope	Identify flood-prone lowlands and avoid steep terrain
Soil Grids (250 m; 30–60 cm depth)	ISRIC—World Soil Information https://data.isric.org/ (accessed on 7 June 2025)	2017	Soil texture	Evaluate foundation stability and risk of differential settlement
Land use/Land cover (LULC) (10 m)	Esri Global Land Cover https://livingatlas.arcgis.com/landcoverexplorer/ (accessed on 9 June 2026)	2025	Land use categories	Identify compatible land uses for LPG stations
Geological map	Guth & Wood (2013) (accessed via GSA Digital Maps: https://www.geosociety.org/maps/2014-DMCH016/ on 6 June 2025)	2014	Volcanic rocks	Assess ground stability

Table 2. Buffered datasets used in the suitability analysis.

Category	Dataset	Year	Buffer Distances (m)	Source	Purpose
Environmental Constraints	Main rivers	2016 (Afrikt); 2025 (OSM)	30	Digitized from Afrikt map (2016) [26], supplemented with OSM(2025) [27].	Maintain safe separation from environmentally sensitive areas and comply with planning guidelines.
	Tributaries, Streams	2025	30	OpenStreetMap (OSM) [27]	
	Reservoirs	2025	30	OpenStreetMap [27]	
	Boreholes/Wells	2022 (MoWSI); 2024 (UNESCO-OSM); 2025 (OSM)	10	Ministry of Water, Sanitation and Irrigation (MoWSI) (2022); OpenStreetMap(2025) [27] OSM processed by UNESCO (2024) [28].	
	Wetlands	2017	200	World Resources Institute via Land Portal [29].	

Table 2. Cont.

Category	Dataset	Year	Buffer Distances (m)	Source	Purpose
Environmental Constraints	Forests	2022	20	Kenya Forest Service via RCMRD [30].	Reduce fire risk
	National parks	2017	5000	World Resources Institute via Land Portal [29].	Reduce external pressures
	Dumpsites	2025	10	Digitized by Author	Ensure safe separation from environmentally sensitive area.
Physical Infrastructure	Power plants, Substations, Power lines, Distribution Transformers	2020; 2023	Power Plant (2020)-2000; Power lines (2020) 5–30; Substations (2020)-50; Transformers (2023)-15 m	Kenya Power and Lighting Company published via EnergyData.info [31].	Minimize ignition hazards
	Water Treatment and wastewater treatment plants	2025	Water treatment-300; wastewater-1000	Digitized, supplemented with OpenStreetMap [27].	Protect water infrastructure and ensure public health
	Drinking water and Water towers	2025	Drinking Water-10; and Water towers-60	OpenStreetMap [27].	Ensure safety protection and comply with planning guidelines.
	Road Intersections, Parking, Railways, Airports	2025	Intersections & parking-100; Railways 60.96–70; Airports 75	OpenStreetMap [27].	Ensure safety protection.
	Roads	2023	15–110 (by class)	Kenya Roads Board via EnergyData.info [32].	Protect road reserves and prevent encroachment
	Oil Pipeline	2018	30	Kenya Pipeline via EnergyData.info [31].	Prevent hazardous encroachment

Table 2. Cont.

Category	Dataset	Year	Buffer Distances (m)	Source	Purpose
Social Infrastructure	Schools	2025	75	Ministry of Education via EnergyData.info [31].	Ensure public safety and comply with regulations.
	Hospitals	2018	75	Kenya Open Data Portal via EnergyData.info [31].	
	Market, Libraries, police stations, courthouses, hotel, prison, Military, Religious sites, Community Centers, stadiums, Theaters, Auditoriums, Sports grounds, parks	2025	75	OpenStreetMap [27].	
	Residential buildings	2023	50	Google Open Buildings [33].	
Hot works	Recycling metal, glass, paper	2025	10	OpenStreetMap [27].	Prevent ignition risks
Existing LPG stations	Existing LPG stations	2025	500	personal communication	prevent service overlap

2.2.1. Thematic Datasets

The study used five thematic datasets (Table 1), namely elevation, slope, geology, soil, and land use. Land use data are presented in Figure 2, whereas elevation, slope, geology, and soil are shown in Figure 3. Elevation and slope surfaces were derived from the Advanced Land Observing Satellite Phased Array L-band Synthetic Aperture Radar (ALOS PALSAR) Digital Elevation Model (12.5 m resolution) [34]. Elevation data were used to identify low-lying areas prone to flooding, while slope data were used to exclude steep terrain [10,17]. Geological data from the Southern Kenya Rift map [35], were used to assess ground stability and mitigate risks associated with landslides, subsidence, and seismic activity [17]. Soil texture dataset was obtained from Africa SoilGrids (250 m, 30–60 cm depth) [36], developed and documented by Hengl et al. [37], to evaluate foundation stability and prevent differential settlement in line with KS 1938-3:2020 [38]. Land use data were obtained from the ESRI Land Cover dataset (10 m resolution) [39], which provides high-resolution land cover classification and was used to represent land-use types within the study area.

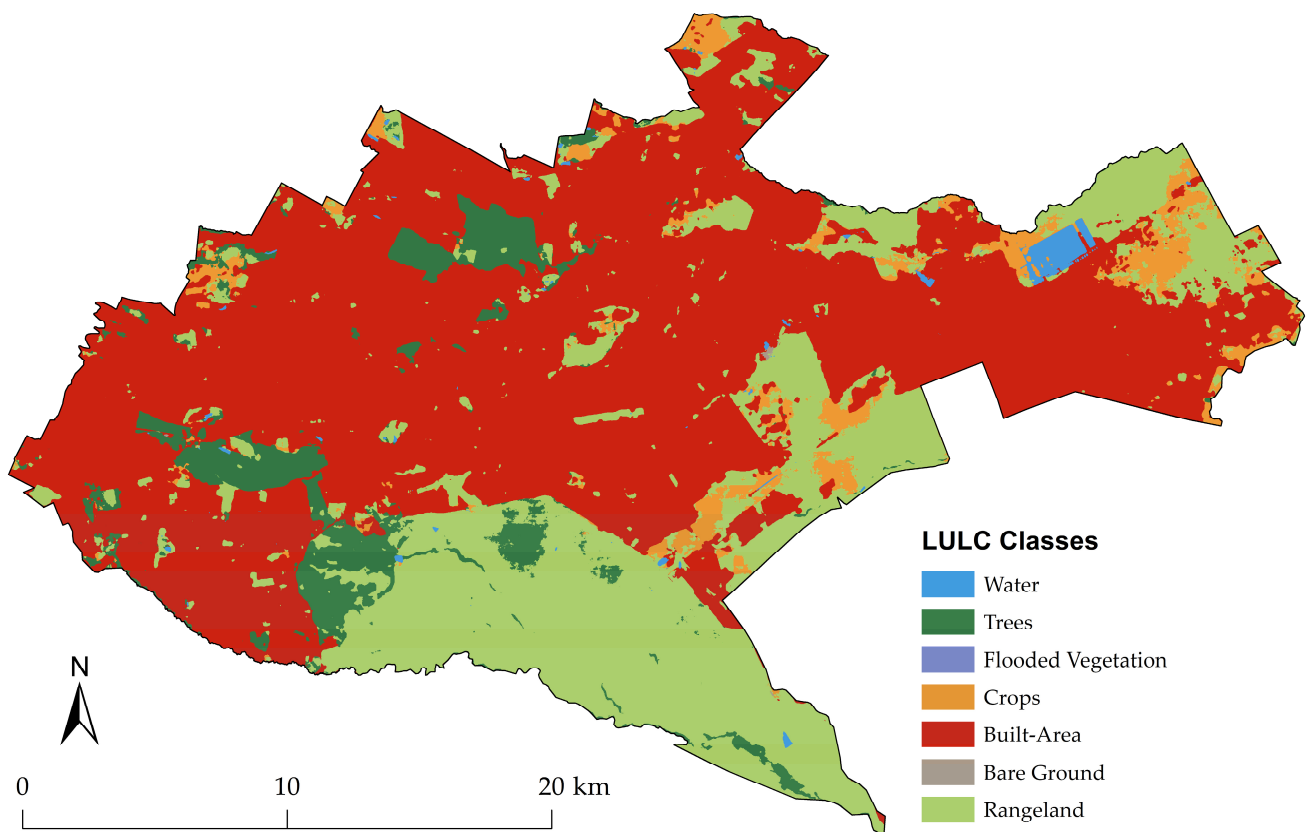


Figure 2. Land-use/land-cover (LULC) map used in the site-suitability analysis.

2.2.2. Buffered Datasets

Buffered datasets included: (i) environmental constraints (protected areas, water resources), (ii) physical infrastructure (power infrastructure, utilities, and transport networks), (iii) social infrastructure (public institutions/installations such as schools and hospitals, places of assembly, and residential areas) and (iv) hazardous facilities. This category also included existing LPG stations, which were used to enforce minimum distance constraints and were further classified into distance thresholds for the weighted overlay analysis. Buffer distances, sources, and rationale are summarized in Table 2.

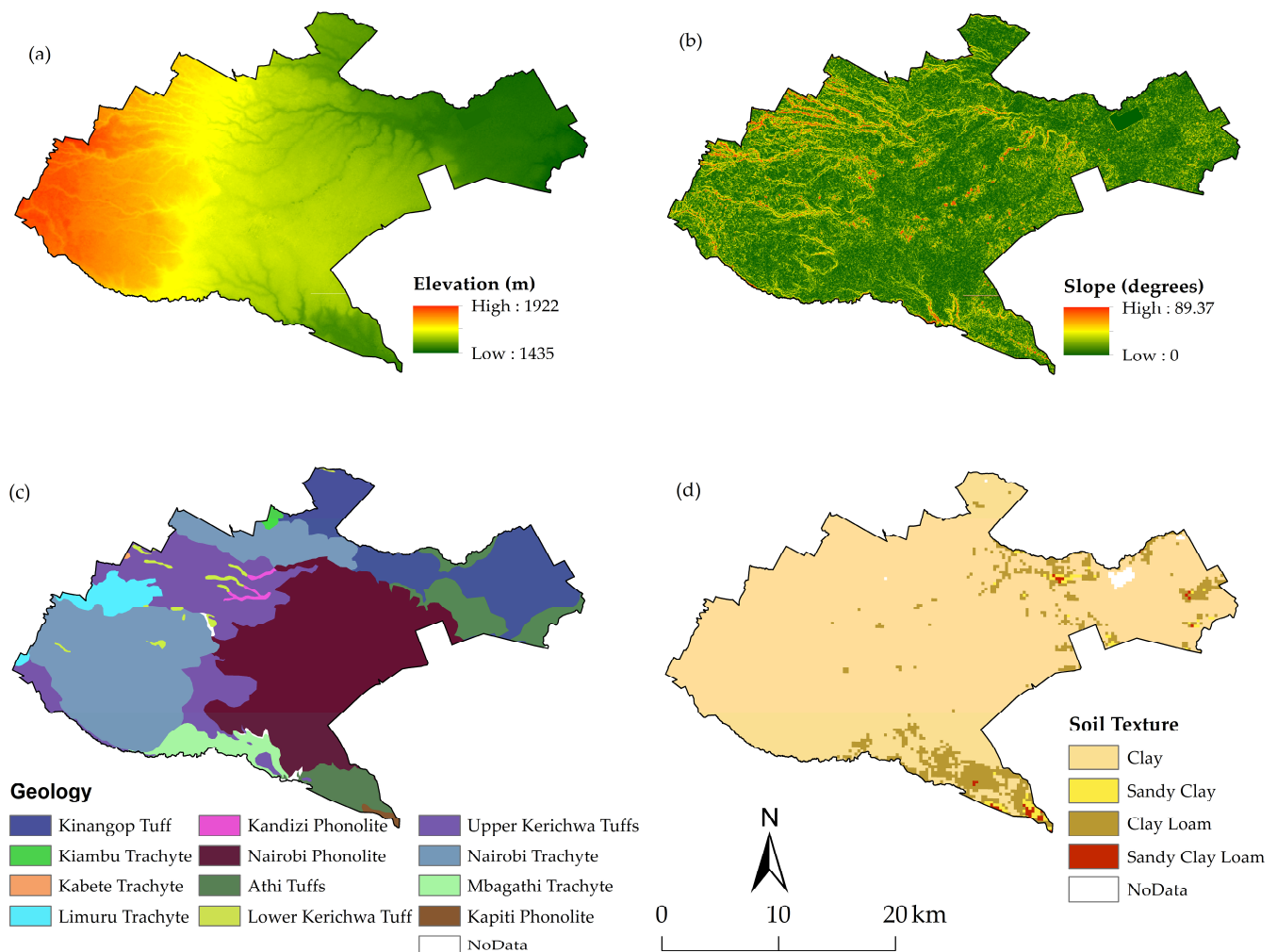


Figure 3. Elevation (a), slope (b), geology (c), and soil (d) thematic layers used in the site-suitability analysis.

2.2.3. Supporting Datasets

Supporting datasets included GADM Level 2 administrative boundaries (https://gadm.org/download_country.html, version 4.1; accessed on 15 April 2025), which were used in the preparation of the study area map and to represent the administrative divisions within Nairobi County. Building footprints from Google Open Buildings (<https://sites.research.google/gr/open-buildings/>, accessed on 10 July 2025) were employed to filter candidate sites using a minimum 9.5 m distance to building boundaries and to identify residential buildings for buffer-based exclusion analysis. The Nairobi County boundary from Overpass Turbo (<https://overpass-turbo.eu/>, accessed on 15 April 2025) was used to define the study area extent.

2.2.4. Preprocessing

All datasets were reprojected to WGS 84/UTM Zone 37S (EPSG:32737) and clipped to the Nairobi County boundary. Buffer zones were generated in Python (Jupyter Notebook 7.2.2) using thresholds derived from national planning guidelines [40], safety regulations [38], and prior fuel siting studies [10,17].

Residential buildings were prepared following a similar approach to Huang et al. [41], by refining Google Open Buildings footprints. Non-residential areas were removed using OSM land-use polygons, including commercial, industrial, institutional, recreational, and other non-residential categories. To improve classification accuracy, empirical size

thresholds were applied: footprints smaller than 10 m² were excluded as likely noise or non-habitable structures, while those larger than 2500 m² were excluded as they predominantly represent commercial, institutional, or industrial buildings. These thresholds were derived through visual inspection of sample buildings using high-resolution satellite imagery in Google Earth. The resulting residential building layer was used for buffer-based exclusion analysis. Parking areas from OSM polygons and points were merged into a consolidated dataset and buffered; however, point-based buffers produced circular zones that do not always reflect actual spatial extents. Main rivers were digitized from a georeferenced Afrikt map [26] and supplemented with OSM waterways. Boreholes, wastewater plants, and water treatment plants were consolidated from multiple sources, while the main dumpsite was digitized in ArcMap. Existing Liquefied Petroleum Gas (LPG) station locations were extracted by filtering petrol stations offering retail LPG services.

All final layers, including thematic and buffered datasets, were rasterized or resampled to a common 12.5 m resolution using the ALOS PALSAR DEM as the reference grid. Categorical datasets, including soil, geology, and land use, were resampled using nearest-neighbor interpolation. This resolution was chosen to preserve fine-scale spatial details and adequately represent localized constraints, including small-distance features such as regulatory buffer zones, within Nairobi's heterogeneous urban setting. The overall workflow summarizing methodological steps is illustrated in Figure 4.

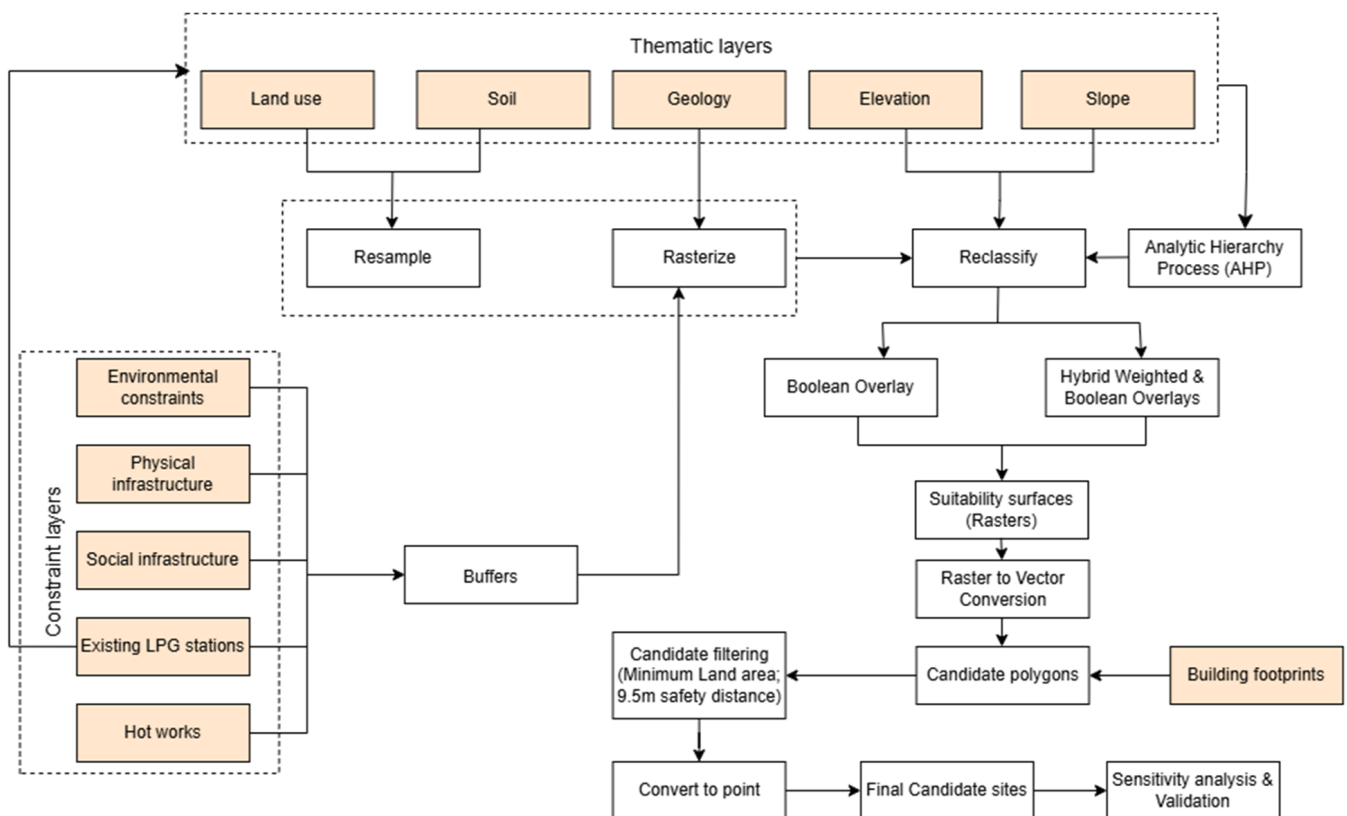


Figure 4. Study methodology workflow (Arrows indicate the workflow sequence). Light orange boxes represent datasets, while white boxes represent processing steps.

2.3. Suitability Analysis

2.3.1. Criteria Standardization and Threshold Determination

Threshold values for suitability classification were derived using a combination of data-driven segmentation, literature review, regulatory guidance, engineering principles, and expert consultation. Elevation thresholds were derived using the Natural Breaks (Jenks) method to ensure that class boundaries reflect natural groupings within the observed elevation distribution. The resulting classes were interpreted in relation to topographic conditions relevant to infrastructure siting, where lower elevation areas were assigned lower suitability due to their potential susceptibility to flooding [17,42]. Slope classes were guided by national physical planning recommendations for industrial development in Kenya [40].

Soil texture suitability was classified based on geotechnical performance indicators relevant to foundation stability, bearing capacity, and volumetric change potential. This classification was informed by fuel facility siting literature [17], geotechnical engineering recommendations provided by Bowles [43], and KEBS [38], which emphasize construction stability and the minimization of differential settlement. Sandy clay loam was designated as highly suitable due to its balanced composition, which provides favorable shear strength, drainage, and bearing capacity for heavy infrastructure. In contrast, clay-rich soils were assigned lower suitability due to high plasticity and shrink–swell behavior, which are associated with reduced bearing capacity and increased risk of differential settlement in foundation systems. Land use suitability classes were adopted and interpreted from [5] and classified according to their compatibility with LPG refill station development. Proximity thresholds to existing LPG stations were adopted from fuel station siting literature [13] where minimum separation distances are used to avoid excessive clustering and overlap between fuel service facilities. Geological suitability was interpreted based on the lithological strength and hydrogeological characteristics of Nairobi’s volcanic formations, drawing on the Geological Map of the Nairobi Region report [35] and the hydrogeological characterization of the area by Kirui et al. [44]. Tuffaceous formations were assigned lower suitability due to their relatively higher permeability and structural variability, which may increase groundwater vulnerability and reduce ground stability. Trachytic formations were classified as suitable owing to their intermediate engineering properties, while phonolitic units were considered highly suitable due to their greater structural competence and lower permeability.

2.3.2. Criteria Weight Determination Using AHP

Criteria weights were derived using the Analytic Hierarchy Process (AHP), which was selected due to its suitability for incorporating expert judgment into multi-criteria spatial decision-making problems [45]. A total of seven subject-matter experts participated in the pairwise comparison process, comprising two experts in urban and physical planning and one expert each in energy and LPG regulation, GIS and spatial analysis, engineering and infrastructure development, environmental management, and fire and safety management. Pairwise comparisons were conducted using Saaty’s 1–9 fundamental scale [45]. The resulting individual matrices were aggregated using the geometric mean method to obtain the group consensus pairwise comparison matrix presented in Table 3. The consistency of expert judgments was evaluated using the Consistency Ratio (CR), where a CR value of less than 0.1 indicates acceptable consistency. The normalized eigenvector values were used as the final criteria weights in the weighted overlay analysis.

Table 3. Group Pairwise Comparison Matrix.

Criterion	Elevation	Slope	Land Use	Geology	Distance from Existing LPG	Soil Texture
Elevation	1	0.53	0.15	1.60	0.23	1.37
Slope	1.87	1	0.18	2.54	0.29	3.47
Land use	6.83	4.83	1	5.84	2.19	8.08
Geology	0.62	0.39	0.17	1	0.21	1.17
Distance from existing LPG	4.42	3.47	0.46	4.80	1	6.28
Soil texture	0.73	0.29	0.12	0.85	0.16	1

2.3.3. Data Reclassification

To support both Boolean and hybrid analyses, all input datasets were reclassified into standardized suitability formats following established GIS procedures [46,47]. For the Boolean overlay, buffered and thematic datasets were converted into binary classes (0 = unsuitable; 1 = suitable), adopting a strict compliance approach. Thematic factors, including LPG proximity, classified as not suitable or less suitable (scores 1–2) were assigned a value of 0, while those classified as moderately suitable to highly suitable (scores 3–5) were assigned a value of 1. LPG proximity thresholds in the Boolean model were defined as a methodological design choice rather than regulatory limits. Under this non-compensatory decision rule, failure to satisfy any single criterion resulted in exclusion. Accordingly, areas falling within defined threshold distances were classified as unsuitable.

In contrast, thematic factors and LPG proximity distances were reclassified using a graded five-class ordinal scheme (1 = not suitable to 5 = highly suitable) for the weighted overlay analysis. This broader scale captures gradations in relative suitability and allows compensatory trade-offs among thematic criteria within the multi-criteria decision analysis framework. Buffered regulatory and planning constraints were retained as Boolean exclusion masks. Both approaches used identical input datasets, thereby ensuring methodological comparability. The reclassification schemes for both thematic datasets and LPG proximity are summarized in Table 4.

Table 4. Reclassification of Thematic Layers and LPG proximity distances.

Criterion	Class Description	Suitability Category	Weighted Overlay Score (1–5)	Boolean Reclassification (0 = Unsuitable, 1 = Suitable)
Elevation (m)	1435–1539	Not suitable	1	0
	1539–1619	Less suitable	2	0
	1619–1697	Moderately suitable	3	1
	1697–1791	Suitable	4	1
	1791–1922	Highly Suitable	5	1
Slope (degrees)	0–2.9	Highly Suitable	5	1
	3.0–5.7	Moderately Suitable	3	1
	5.8–6.8	Less suitable	2	0
	>6.8	Not suitable	1	0
Soil Texture	Clay	Less suitable	2	0
	Sandy Clay	Moderately suitable	3	1
	Clay loam	Moderately suitable	3	1
	Sandy Clay loam	Highly Suitable	5	1

Table 4. Cont.

Criterion	Class Description	Suitability Category	Weighted Overlay Score (1–5)	Boolean Reclassification (0 = Unsuitable, 1 = Suitable)
Land use	Water, Trees, Flooded vegetation	Not suitable	1	0
	Built-up	Less suitable	2	0
	Crops	Moderately suitable	3	1
	Rangeland	Suitable	4	1
	Bare ground	Highly suitable	5	1
Geology	Athi Tuffs, Kinangop Tuff, Upper Kerichwa Tuffs, Lower Kerichwa Tuff	Less suitable	2	0
	Nairobi Trachyte, Limuru Trachyte, Mbagathi Trachyte, Kabete Trachyte, Kiambu Trachyte	Suitable	4	1
	Kapiti Phonolite, Nairobi Phonolite, Kandizi Phonolite	Highly Suitable	5	1
Distance from existing LPG Station	0–500 m	Not Suitable	1	0
	500–600 m	Less Suitable	2	0
	>600 m	Moderately Suitable	3	1

2.3.4. Boolean Overlay Analysis

A binary exclusion mask was generated by combining all buffered constraint and thematic rasters using a Boolean AND operation, following the procedure described by Eastman [46], and subsequent siting studies such as Mohamed et al. [15]. The resulting Boolean raster identified suitable and unsuitable areas, with cells excluded during processing (NoData) subsequently reclassified as unsuitable for visualization and analysis. Suitable areas were converted into polygons and filtered using a minimum area threshold of 0.0725 ha and a 9.5 m clearance buffer from buildings. Candidate polygons intersecting building footprints were excluded to ensure compliance with the specified building setback requirements.

2.3.5. Weighted Overlay Analysis with Exclusion Mask

Weighted overlay analysis was performed by combining reclassified thematic layers and distances from existing LPG refill stations using the Weighted Linear Combination (WLC) method [16]. At each location, the composite suitability score $S(x, y)$ was calculated as:

$$S(x, y) = \sum_{i=1}^n w_i \cdot r_i(x, y) \quad (1)$$

where $r_i(x, y)$ is the reclassified suitability score of layer i and w_i is the normalized weight derived through AHP. A Boolean exclusion mask was then applied to enforce regulatory and safety constraints, producing a final suitability layer showing both suitability classes and excluded areas [48,49]. NoData cells were reclassified as unsuitable for visualization and area calculations. The output was converted to vector format and filtered using criteria described in Section 2.3.4.

2.4. Sensitivity Analysis

To evaluate the robustness of the weighted overlay model, a sensitivity analysis was conducted by systematically adjusting the weights assigned to each criterion. The weight of each criterion was increased and decreased by 10%, while the remaining weights were proportionally adjusted to maintain a total weight of 100%. For each scenario, the suitability model was recalculated, and the resulting maps were compared with the baseline output to assess the influence of individual criteria on the spatial distribution of suitable areas [50].

Boolean layers representing regulatory exclusions (e.g., minimum safety distances from buildings) were treated as fixed constraints and were therefore excluded from the sensitivity analysis. Thematic layers such as slope, soil type, elevation, and land use were initially evaluated as hard constraints in the Boolean analysis but were later incorporated as weighted criteria. Sensitivity testing was therefore conducted only on the weighted criteria, as Boolean constraints remained binary and fixed throughout the analysis.

2.5. Validation

To evaluate the site-suitability results of the hybrid model, a total of 3147 feasible polygons (2779 potential candidate polygons and 368 unsuitable polygons) were identified after applying the minimum area threshold and the 9.5 m safety buffer. From this population, a stratified random sample of 343 sites (suitable candidates = 303, unsuitable = 40) was drawn to ensure representation of both suitability classes. The sample size was calculated using Cochran's formula for finite populations with a 95% confidence level and a 5% margin of error [51], as shown in Equation (2):

$$n = \frac{Z^2 p(1-p)}{e^2 + \frac{Z^2 p(1-p)}{N}} \quad (2)$$

where n is the required sample size, N is the population size (total number of feasible polygons), $Z = 1.96$ (standard normal deviate for 95% confidence), p is the expected proportion of suitable sites (0.5 was used to represent maximum variability) and $e = 0.05$ is the desired margin of error.

Each sampled site was visually inspected using high-resolution satellite imagery in QGIS to assess whether the observed land conditions were consistent with the suitability classification. The verification considered visible characteristics such as land occupancy, surrounding development, and road accessibility. Statistical validation was not performed because no ground-truth dataset of verified suitable and unsuitable LPG refill station locations was available for the study area. Validation was conducted only for the hybrid suitability model, while the Boolean model was excluded from the validation procedure due to the nature of its suitability outputs. Consequently, the assessment focused on evaluating the reliability of the hybrid model through visual interpretation of high-resolution imagery at sampled locations.

2.6. Software and Tools

The analysis combined GIS platforms with Python-based automation. QGIS 3.28.11 was used for initial boundary processing, clipping of the building footprint layer, and manual validation of candidate sites against high-resolution satellite imagery. ArcMap 10.8.1 was used for the preparation of final maps for reporting. Python 3.12.9 (Jupyter Notebook 7.2.2) served as the primary analytical environment, where most preprocessing, reclassification, overlay analyses, and suitability statistics were conducted. Key Python libraries included geopandas, shapely, and rasterio for spatial operations; numpy and pandas for data processing; and rasterstats for zonal statistics.

3. Results

3.1. Reclassification Results

Reclassification outputs of thematic and constraint layers under the Boolean and weighted overlay frameworks are presented in Figure 5. The Boolean reclassification (Figure 5a–c) categorized the land use, geology, and soil layers into binary suitability classes, whereas the weighted reclassification (Figure 5d–f) transformed the same layers into multi-class suitability maps (1–5). These examples illustrate the reclassification procedure applied consistently across all buffered and thematic layers used in the analysis. The Boolean reclassification produced more restrictive spatial patterns due to its strict pass–fail structure, whereas the weighted approach exhibited greater spatial variability across the study area.

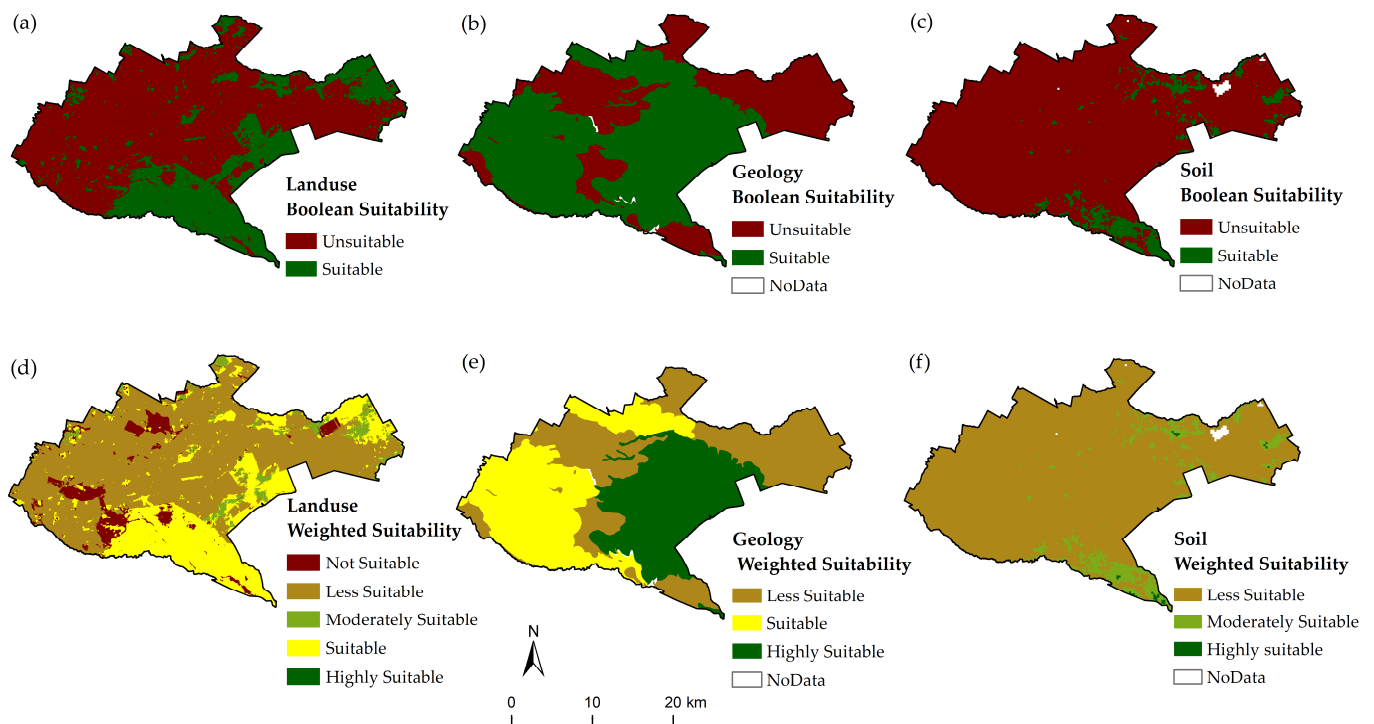


Figure 5. Examples of reclassification outputs for the thematic layers. (a–c) Boolean reclassification of land use, geology, and soil layers into binary suitability classes. (d–f) Weighted reclassification of the same layers into five suitability classes (1–5).

3.2. Criteria Weighting Results

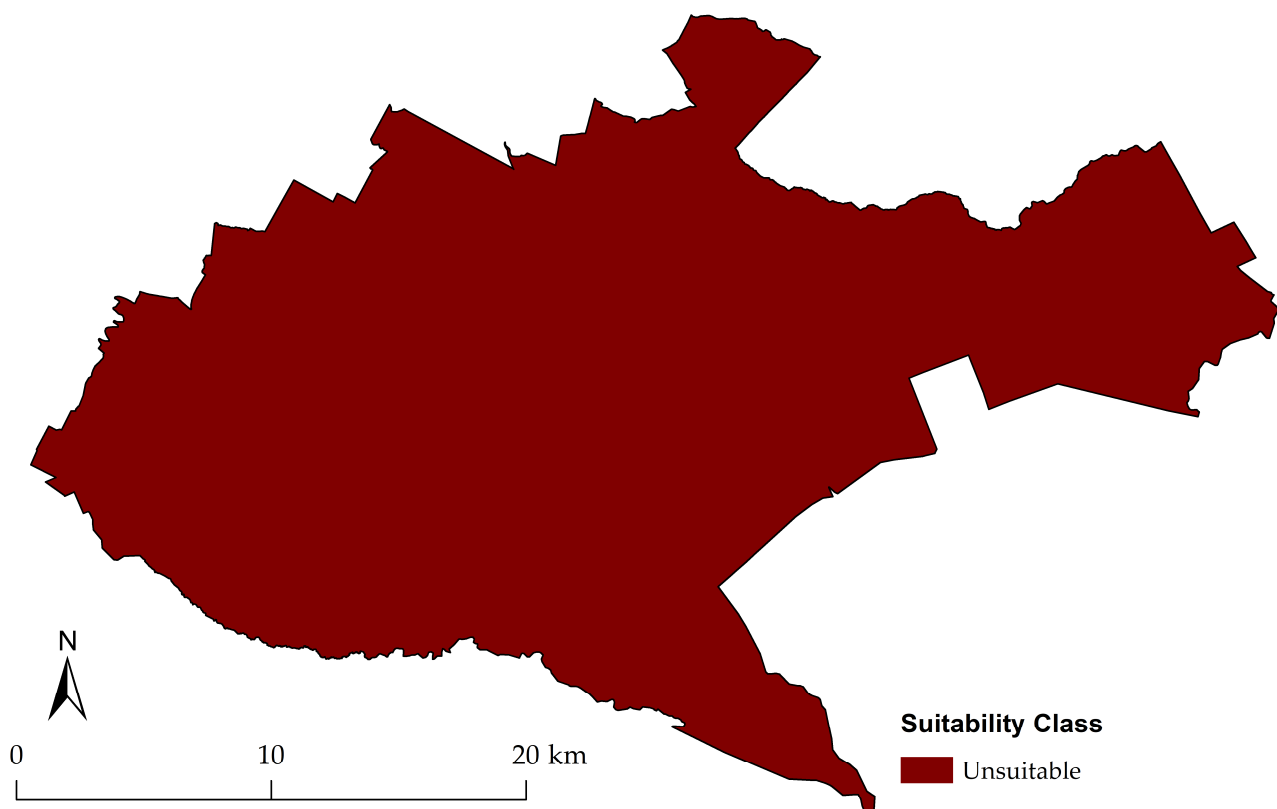
The normalized pairwise comparison matrix and the corresponding eigenvector weights used in the weighted overlay model are presented in Table 5. The calculated Consistency Ratio ($CR = 0.015$) was below the acceptable threshold of 0.1, indicating that the expert judgments were sufficiently consistent. Among the evaluated criteria, land use received the highest weight (0.441), followed by distance from existing LPG stations (0.277) and slope (0.115), indicating their greater influence in determining LPG refill station suitability.

Table 5. Normalized pairwise comparison matrix and criteria weights.

Criterion	Elevation	Slope	Land Use	Geology	Distance from Existing LPG	Soil Texture	Normalized Weight	Percentage Weight
Elevation	0.065	0.051	0.070	0.096	0.056	0.064	0.067	6.7%
Slope	0.121	0.095	0.087	0.152	0.071	0.162	0.115	11.5%
Land use	0.441	0.460	0.482	0.352	0.537	0.378	0.441	44.1%
Geology	0.040	0.037	0.082	0.060	0.051	0.055	0.055	5.5%
Distance from existing LPG	0.286	0.330	0.219	0.289	0.246	0.294	0.277	27.7%
Soil texture	0.047	0.027	0.060	0.051	0.039	0.047	0.045	4.5%
	1.000	1.000	1.000	1.000	1.000	1.000	1.000	100%

3.3. Boolean Overlay Results

The Boolean overlay produced a highly restrictive suitability outcome, classifying the entire study area as unsuitable. No candidate sites were identified following the integration of all criteria, as no spatial locations simultaneously satisfied the combined regulatory and thematic requirements. Consequently, the Boolean suitability map (Figure 6) indicates complete spatial exclusion of potentially suitable areas under the applied decision rules.

**Figure 6.** Boolean overlay suitability map for LPG refill station siting in Nairobi County.

To better understand the factors contributing to this outcome, the thematic and exclusion criteria were evaluated separately. The combined exclusion constraints retained approximately 8.16% of Nairobi County (363,497 pixels), representing areas not excluded by regulatory constraints and therefore potentially available for suitability assessment, whereas the intersection of all thematic criteria retained only 0.19% (8410 pixels). These results indicate that the thematic criteria were more restrictive than the regulatory exclusion constraints. Among the thematic factors, soil emerged as the most restrictive criterion. As shown in Figure 5c, clay soils are widespread across much of Nairobi and were classified

as unsuitable based on the adopted suitability criteria. Soil suitability alone retained only 7.98% of the study area, making it the most limiting thematic factor. When combined with the remaining thematic and regulatory constraints, the extensive distribution of clay soils substantially reduced the extent of land capable of meeting all criteria simultaneously under the Boolean framework.

Analysis of individual exclusion constraints further showed that residential land-use buffers were the dominant regulatory constraint, excluding 57.65% of the study area, followed by Nairobi National Park (30.52%) and existing LPG facilities (13.67%). In contrast, most other constraints individually excluded less than 2% of the study area, indicating a highly uneven distribution of spatial influence across constraint layers. Overall, the scarcity of suitable locations was primarily associated with restrictive soil conditions and a small number of dominant exclusion constraints. Because the Boolean analysis yielded no suitable candidate sites, subsequent post-processing procedures, including the application of a minimum site area threshold and the 9.5 m safety buffer from buildings, were not undertaken.

3.4. Weighted Overlay Results

3.4.1. Suitability and Candidate Filtering

The weighted overlay produced a four-class suitability surface for Nairobi (Figure 7a). Unsuitable areas (Class 1) accounted for 8.33%, while less suitable areas (Class 2) dominated with 65.68%. Moderately suitable areas (Class 3) comprised 25.98%, whereas suitable areas (Class 4) were extremely limited, occupying only 0.01% of the study area.

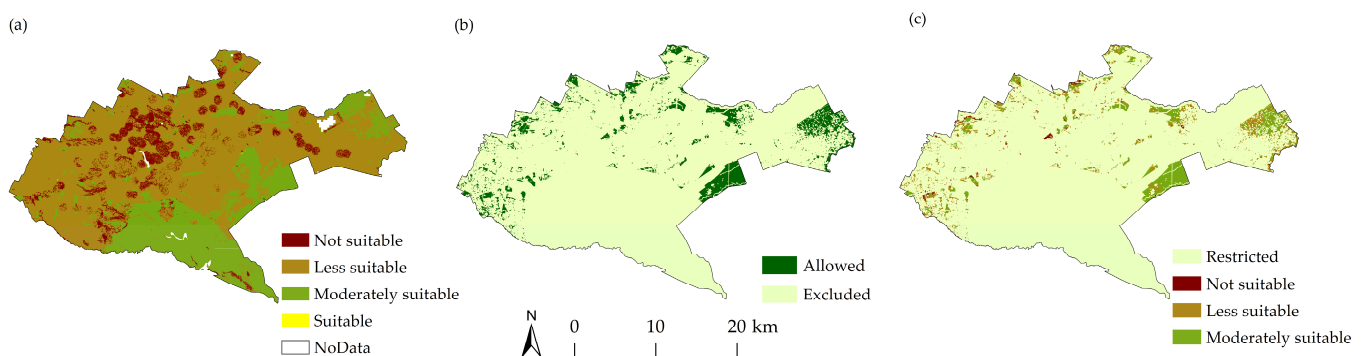


Figure 7. Weighted suitability and exclusion maps for LPG refill station siting in Nairobi County: (a) Weighted overlay surface showing suitability classes, (b) Boolean exclusion mask highlighting areas restricted by regulatory and physical constraints, (c) Combined weighted suitability and exclusion map.

Spatially, Class 2 dominated much of the study area and was widely distributed across central, northern, and western Nairobi. Class 3 formed relatively continuous patches, particularly in the southern and southeastern parts of the county, with smaller occurrences elsewhere. In contrast, Class 4 appeared only as very small, isolated patches, while Class 1 was distributed in scattered clusters mainly in central and western Nairobi.

The Boolean exclusion map (Figure 7b) removed 630.3 km² (91.2%) of the study area, substantially reducing the available land for LPG station siting. The combined weighted suitability and exclusion map (Figure 7c) shows the distribution of suitability classes across the remaining surface. Following the application of the exclusion map, the suitable class (Class 4) was completely removed, leaving only classes 1–3. The remaining area comprised 0.5% unsuitable, 4.0% less suitable, and 4.3% moderately suitable zones. Overall, this indicates that 91.7% of the study area falls within restricted or unsuitable categories.

The resulting suitability raster was converted into vector polygons to delineate candidate areas, with adjacent grid cells of the same suitability class merged to produce spatially continuous polygons. This process generated 7815 candidate polygons across Classes 2 and 3 (Figure 8a). Application of a minimum area threshold and a 9.5 m safety buffer reduced this to 2779 potential candidate areas (Figure 8b), which were subsequently converted into points (Figure 8c). Among these, Class 2 (less suitable) dominated with 1997 sites (71.9%), while Class 3 (moderately suitable) accounted for 782 sites (28.1%). These represent preliminary candidate locations requiring further field verification and planning assessment.

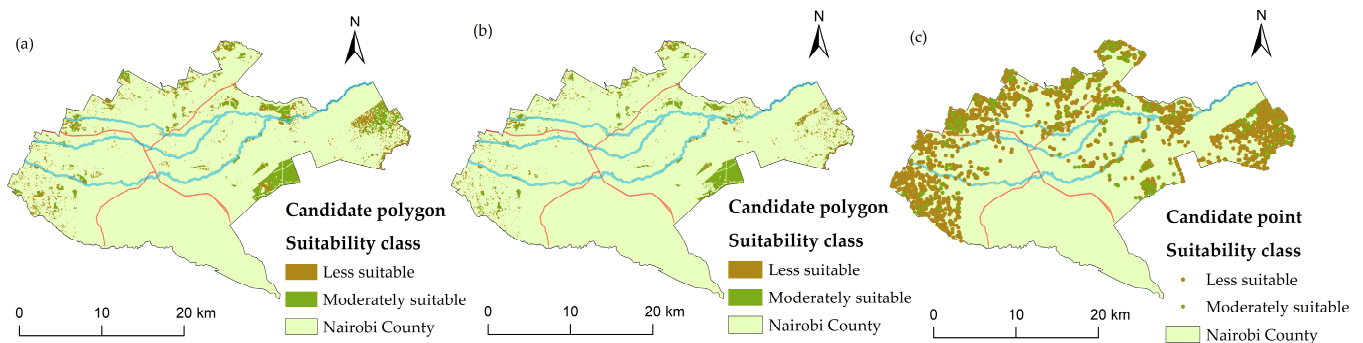


Figure 8. Candidate sites identified using the weighted overlay model. (a) Initial candidate polygons within suitability Classes 2–3 ($n = 7815$), (b) Potential candidate polygons after applying the minimum area threshold and 9.5 m building-clearance buffer ($n = 2779$), (c) Centroid points generated from the filtered candidate polygons. (Red lines represent the major roads used to delineate the Northern, Eastern, Southern, and Western regions of Nairobi County, while blue lines represent the major rivers).

3.4.2. Spatial Distribution of Candidate Sites by Region

The final candidate sites exhibited a distinct spatial concentration in the peri-urban areas of Nairobi rather than within the densely developed urban core (Figure 8c). The eastern region contained the highest proportion of candidate sites, accounting for 1306 locations (47.0%), followed by the northern region with 915 sites (32.9%). The western region contributed 557 sites (20.1%), while the southern region contained no candidate sites, largely due to the Nairobi National Park exclusion buffer. Overall, candidate sites were concentrated in areas where land remained available following the application of regulatory exclusion zones and suitability filtering criteria.

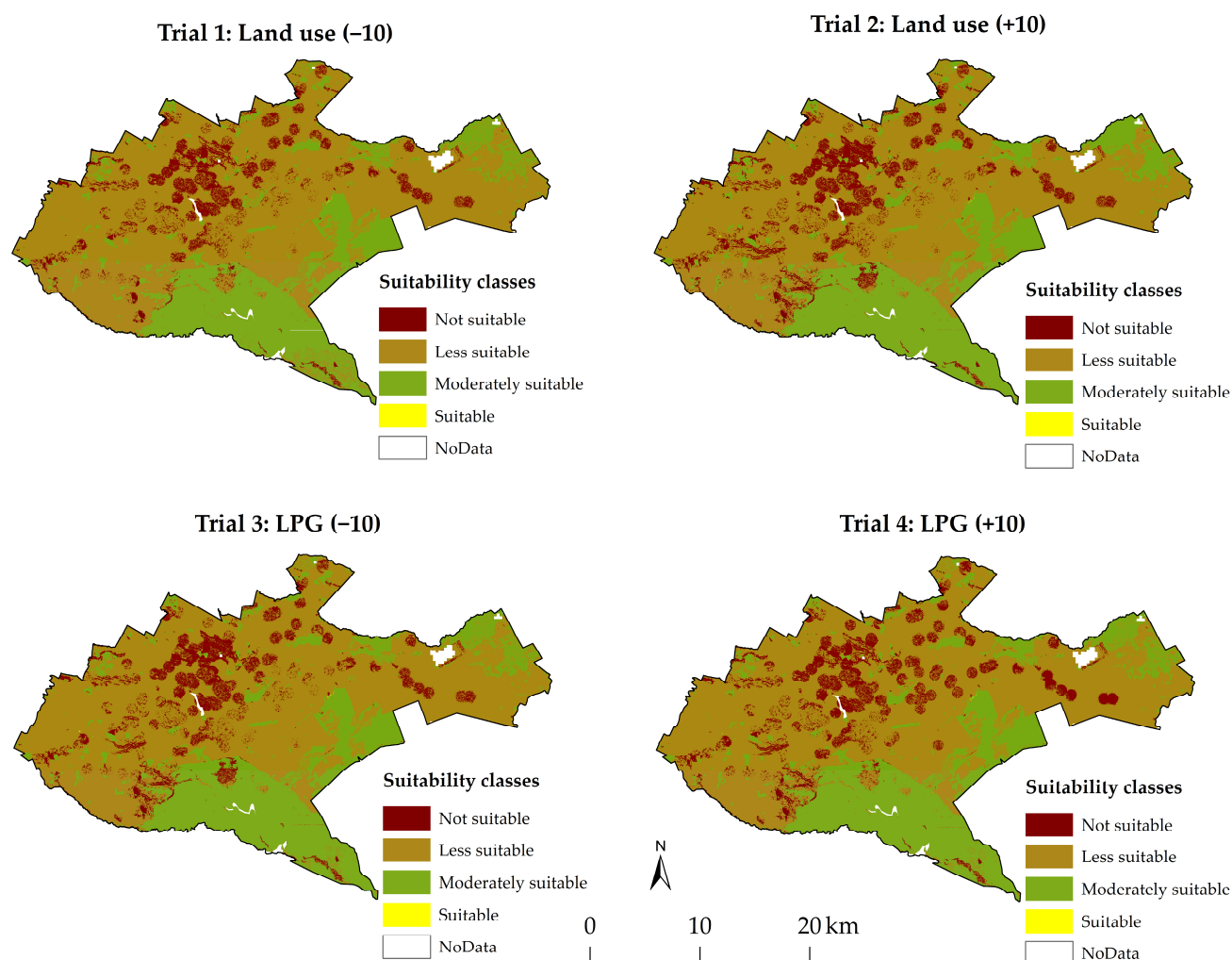
3.5. Sensitivity Analysis Results

The sensitivity analysis results indicated that the weighted overlay model is generally stable under $\pm 10\%$ variations in criterion weights. The maximum and minimum differences between the baseline suitability scores and the sensitivity scenarios are presented in Table 6. Among the evaluated criteria, land use exhibited the greatest influence on the suitability scores, with maximum changes of 0.067 when its weight was increased by 10% and 0.069 when reduced by 10%. LPG proximity also showed notable variations, with maximum score differences reaching 0.064. Slope exhibited moderate sensitivity, with variation ranging between 0.033 and 0.038. In contrast, elevation, geology, and soil exhibited low sensitivity, with maximum variations not exceeding 0.024, 0.020, and 0.014, respectively. These results indicate that the model is more sensitive to changes in land use and LPG proximity weights than to variations in topographic, geological and soil-related criteria.

Table 6. Maximum and Minimum Changes in Suitability Scores under $\pm 10\%$ Weight Variations.

Criterion	+10% Max Change	+10% Min Change	−10% Max Change	−10% Min Change
Land use	0.067	−0.063	0.069	−0.073
LPG proximity	0.036	−0.061	0.064	−0.038
Slope	0.038	−0.032	0.033	−0.039
Elevation	0.024	−0.019	0.019	−0.024
Geology	0.020	−0.010	0.010	−0.020
Soil	0.014	−0.010	0.010	−0.015

Figure 9 presents representative sensitivity maps generated from the $\pm 10\%$ weight adjustments, while the remaining scenarios are provided in Figures A1 and A2. The spatial distribution of suitability classes remained largely consistent with the baseline model, with only minor local variations observed. Importantly, all sensitivity scenarios retained the same four suitability classes (Classes 1–4) as the original weighted overlay output, indicating that the weight adjustments did not alter the overall classification structure of the suitability model.

**Figure 9.** Sensitivity analysis maps for LPG refill station suitability in Nairobi, depicting the effects of $\pm 10\%$ weight variations on the spatial distribution of suitability classes.

3.6. Site-Level Validation

The hybrid suitability model was evaluated through visual interpretation of a stratified random sample of 343 sites using high-resolution satellite imagery in QGIS. The assessment compared model-predicted suitability with observable land surface conditions. Out of the sampled sites, 253 (73.8%) locations were consistently identified as suitable by both the model and visual interpretation of satellite imagery, while 39 (11.4%) locations were consistently classified as unsuitable. These cases indicate general agreement between the model outputs and observed spatial conditions. However, 50 (14.6%) sampled sites were classified as suitable by the model but appeared unsuitable based on visual interpretation, indicating instances of overestimation in highly urbanized or transitional areas. In contrast, only one site (0.3%) was classified as suitable based on visual interpretation but was excluded by the model. Overall, the results indicate a reasonable correspondence between the hybrid model outputs and observed landscape conditions, particularly in correctly identifying unsuitable areas. The observed overestimation suggests that fine-scale urban heterogeneity may not be fully captured by the input thematic datasets. Figures 10 and 11 illustrate the representative validation examples of predicted suitable sites, with Figure 10 showing correctly predicted locations and Figure 11 incorrectly predicted locations. Site-level validation was not performed for the Boolean model because the application of all constraints resulted in complete spatial exclusion and no candidate sites were available for validation against high-resolution satellite imagery.

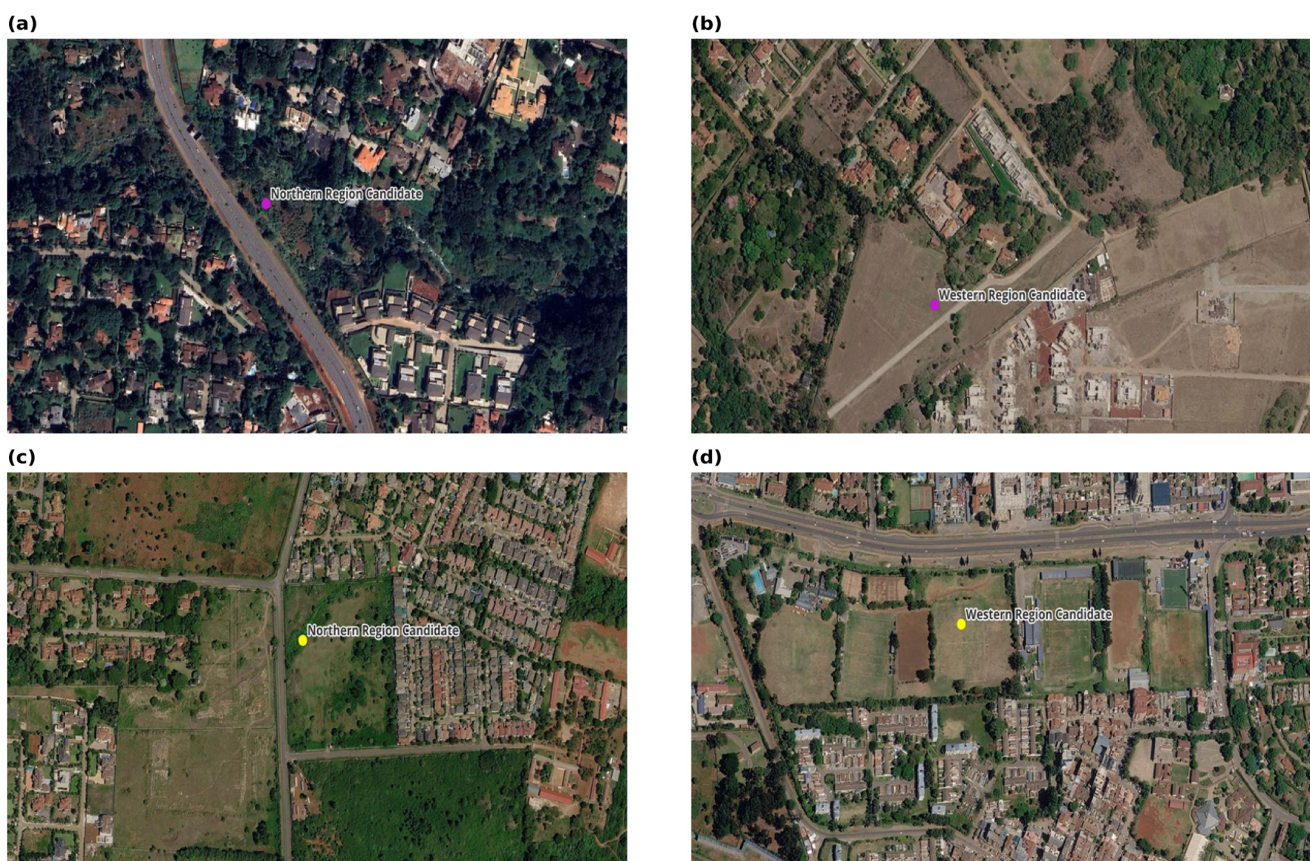


Figure 10. Examples of correctly predicted candidate sites identified by the hybrid suitability model and confirmed through visual interpretation of satellite imagery. (a,b) represent Class 2 (less suitable) sites, whereas (c,d) represent Class 3 (moderately suitable) sites.

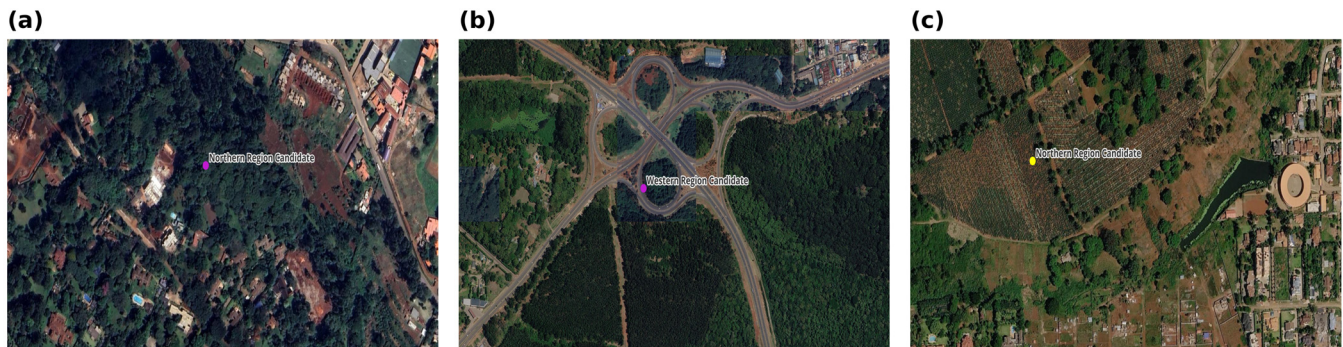


Figure 11. Examples of incorrectly predicted candidate sites identified by the hybrid suitability model and assessed through visual interpretation of satellite imagery. (a,b) represent Class 2 (less suitable) locations, while (c) represents a Class 3 (moderately suitable) location.

3.7. Spatial Comparison of Proposed and Existing LPG Stations

The spatial relationship between existing LPG stations and the weighted suitability model, prior to application of the Boolean exclusion mask, reveals a systematic divergence between current infrastructure distribution and model-derived suitability patterns. Out of 178 existing LPG stations analyzed, 58 (32.6%) were located in areas classified as unsuitable (Class 1), while 120 (67.4%) occurred in less suitable zones (Class 2). No existing stations were located in moderately suitable (Class 3) or suitable (Class 4) areas. This indicates that existing LPG infrastructure in Nairobi is predominantly situated within low-suitability environments under the proposed multi-criteria framework.

In contrast, the weighted overlay results show the presence of moderately suitable and suitable areas, particularly in peri-urban zones. This demonstrates a spatial mismatch between existing infrastructure and modelled suitability patterns. This pattern is illustrated in Figure 12, which shows the spatial distribution of existing LPG stations relative to the weighted suitability map.

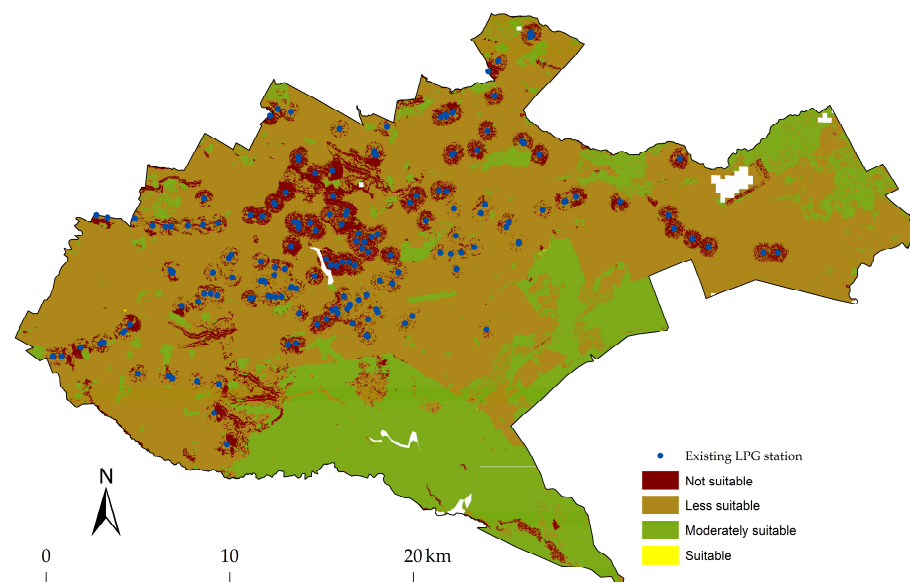


Figure 12. Spatial comparison between existing LPG refill stations and the weighted suitability map.

4. Discussion

The results demonstrate that the choice of spatial decision-making framework has a substantial influence on the identification and interpretation of suitable locations for LPG refill stations. The contrast observed between the Boolean and hybrid weighted MCDA

approaches reveals fundamental differences in how spatial suitability is conceptualized and operationalized in urban infrastructure planning.

The Boolean overlay approach, which operates as a strictly non-compensatory decision rule, requires simultaneous satisfaction of all defined criteria. Under this framework, any violation of a single constraint results in exclusion regardless of performance in other factors. In the present study, this approach led to complete spatial exclusion prior to post-processing, with no feasible candidate locations identified. This outcome reflects a well-established limitation of Boolean logic in spatial modelling, where the progressive intersection of multiple binary constraints can substantially reduce the feasible solution space, particularly when spatially extensive restrictions are present [52]. Similar findings have been reported by Mahdavi and Akhavan [20], who observed significant reductions in suitable land when Boolean logic was applied in complex spatial settings. In this study, the widespread occurrence of unsuitable soil conditions, together with the influence of dominant exclusion constraints such as residential buffers and Nairobi National Park, contributed to this highly restrictive outcome.

In contrast, the weighted overlay approach represents a compensatory decision-making framework in which criteria contribute differentially to overall suitability according to their relative importance. This allows lower performance in one criterion to be offset by higher performance in others, producing a continuous suitability surface rather than a binary classification. Such compensatory MCDA structures are widely recognized in spatial decision-support literature as being more appropriate for complex spatial decision problems where trade-offs among criteria are inevitable [46,53]. Similar observations were reported by Aslani and Alesheikh [19], who found that hybrid weighted overlay and fuzzy-based approaches produced more practical site-selection outcomes than Boolean exclusion methods alone. Their findings support the view that compensatory frameworks are better able to accommodate the complexity of real-world planning problems, where multiple criteria interact and strict compliance with all conditions may be difficult to achieve simultaneously.

The hybrid GIS-MCDA framework adopted in this study integrates both approaches by combining strict exclusion rules with weighted suitability evaluation. This ensures compliance with non-negotiable regulatory and safety constraints while still enabling differentiation among remaining feasible locations. Similar hybrid GIS-MCDA frameworks have been applied in infrastructure siting studies, including electric vehicle charging infrastructure planning, where constraint mapping is integrated with weighted suitability evaluation to support the identification and prioritization of feasible locations [54]. The results therefore suggest that hybrid MCDA approaches provide a more balanced and operationally relevant basis for urban LPG infrastructure planning than either Boolean or compensatory models alone.

Spatial analysis of suitability classes reveals a non-uniform distribution strongly influenced by urban land-use structure and overlapping exclusion constraints. Highly constrained conditions dominate the urban core, where residential density, infrastructure intensity, and regulatory buffers collectively restrict available land. This pattern is consistent with findings by Qonono and Lunga [55], who report that fuel stations in dense urban areas often cluster within urban cores, resulting in overlapping safety buffer zones around residential and institutional land uses and increasing spatial vulnerability. Among individual constraints, residential areas and LPG proximity buffers exert the strongest influence on spatial restriction, leading to fragmented and limited suitability in central zones. In contrast, peri-urban areas exhibit comparatively moderate suitability due to lower land-use intensity and greater spatial continuity, which reduces overlap among exclusion zones and increases spatial flexibility for infrastructure siting.

A comparison between existing LPG stations and modelled suitability surfaces reveals a clear spatial divergence. Most existing stations are located in less suitable areas, while none fall within the highest suitability classes. Similar findings have been reported in previous GIS-based fuel station suitability studies, where a significant number of existing facilities were also found to be located in less suitable or non-suitable zones when evaluated against environmental and safety-based criteria [3]. This pattern reflects the difference between empirically evolved infrastructure distribution and multi-criteria suitability modelling outcomes. In practice, infrastructure location is often shaped by historical development patterns, land availability, and market accessibility rather than spatial decision-support or formalized planning processes. Importantly, lower suitability classification does not imply operational failure but rather indicates potential exposure to higher spatial constraints and environmental pressures.

The weighting structure derived through AHP reflects an expert-driven prioritization of criteria relevant to urban LPG infrastructure planning. Land-use compatibility emerges as the dominant factor (0.441), followed by LPG proximity, while physical terrain variables play a comparatively smaller role. This hierarchy reflects the regulatory nature of urban land-use planning, where zoning compliance and safety considerations often override physical suitability factors, which can frequently be mitigated through engineering solutions.

The validation results provide an indication of the reliability of the hybrid model in capturing general spatial suitability patterns. The observed agreement between model outputs and high-resolution satellite imagery suggests consistency in identifying both suitable and unsuitable areas at a broad spatial scale. However, discrepancies reflect limitations associated with raster-based modelling, particularly the use of secondary datasets that do not fully represent fine-scale urban heterogeneity. In this context, the validation results should be interpreted as an assessment of spatial consistency rather than precise predictive accuracy, given the absence of field-verified ground truth data.

From a planning perspective, the findings of this study provide spatial guidance for urban energy infrastructure planning in Nairobi, with broader relevance for rapidly growing and spatially constrained urban environments. The results indicate that future LPG facilities should be prioritized outside the highly congested urban core, where land-use intensity and regulatory constraints significantly limit available space and increase exposure to conflicting land uses. Peri-urban areas emerge as the most favourable locations for potential expansion due to lower land-use conflict intensity, greater spatial continuity, and reduced proximity to sensitive receptors such as dense residential developments. These conditions offer more flexible opportunities for the siting of hazardous energy infrastructure while maintaining compliance with urban safety requirements. The results further demonstrate the value of integrating regulatory constraints with multi-criteria suitability assessment in urban energy planning, enabling the identification of feasible development opportunities that may not be apparent under purely exclusion-based approaches. Overall, the approach provides a transferable spatial decision-support framework that can be adapted to other rapidly urbanizing cities facing similar energy infrastructure siting challenges.

At a conceptual level, the proposed GIS-MCDA framework consists of both universal and context-specific components. The universal components include the overall modelling structure, the Boolean constraint logic, and the AHP-based weighted overlay procedure, which are transferable across different urban contexts. In contrast, contextual components such as dataset selection, classification thresholds, buffer distances, and regulatory constraints are location-specific and vary depending on local planning conditions and data availability.

While the results provide useful spatial planning insights, several limitations should be acknowledged. First, the reliability of the suitability assessment is influenced by the spatial representation of some input datasets. Although the datasets used provided adequate coverage for city-scale analysis, certain thematic layers, particularly the soil dataset, may not fully capture local-scale variations in environmental conditions. In addition, some exclusion constraints were implemented using simplified spatial proxies, including river buffers derived from centerlines rather than full floodplain extents and sensitive facilities such as schools and hospitals represented as point-based buffers rather than building footprints. These simplifications may affect the precision of exclusion zones and consequently influence the spatial extent of suitable areas. Second, accessibility was evaluated using Euclidean distance measures, which do not account for road network structure, connectivity, travel time, or traffic conditions. While suitable for large-scale screening, this approach provides an approximation of accessibility rather than real-world travel behaviour. Furthermore, the model does not incorporate demand-side variables such as population distribution, household energy consumption patterns, or socio-economic characteristics, meaning that the results represent spatial suitability rather than actual service demand.

Future research could extend this work in several directions. The integration of network-based accessibility measures would improve the realism of spatial interaction modelling, while the use of higher-resolution datasets such as InSAR-derived DEMs could enhance the representation of local environmental conditions. The incorporation of multi-temporal remote sensing data would further enable the assessment of urban growth dynamics and changing land-use conditions over time, thereby improving the temporal robustness of suitability analysis. In addition, risk-based GIS-MCDA frameworks incorporating hazard, exposure, and vulnerability components could be developed to explicitly address Transport Risk Analysis. This would allow for a comprehensive assessment of the transport of dangerous goods in urban areas, including associated environmental impacts such as air pollution dispersion and noise exposure around LPG facilities, thereby supporting urban planning for sustainable future. Data-driven approaches such as machine learning or deep learning may further complement MCDA by capturing complex non-linear relationships between spatial variables and infrastructure distribution. Moreover, alternative decision-support methods, specifically the integration of Data Envelopment Analysis (DEA) for evacuation planning, could be explored to provide a non-compensatory benchmarking perspective. By evaluating the relative efficiency of candidate sites or evacuation routes without predefined weights, DEA enables endogenous handling of trade-offs between criteria. Finally, multi-area application and benchmarking of the framework across different urban contexts would allow systematic evaluation of its transferability and robustness under varying regulatory and morphological conditions.

5. Conclusions

This study developed and applied Boolean-only and hybrid weighted overlay–Boolean GIS-MCDA frameworks to evaluate the spatial suitability of LPG refill station locations in Nairobi. The results show that the Boolean overlay approach yields no feasible locations under the applied exclusion criteria. In contrast, the hybrid model produces a more differentiated suitability surface, allowing variation in suitability across the study area. AHP-derived weights indicate that land-use and LPG proximity criteria have greater influence on suitability outcomes than biophysical factors. Comparison with existing LPG stations shows that most facilities are located in less suitable and unsuitable classes, with no stations located in the highest suitability classes. Overall, the findings demonstrate the value of integrating Boolean logic with multi-criteria evaluation in urban infrastructure planning,

as the hybrid framework provides a more realistic and spatially nuanced basis for guiding the siting of hazardous energy infrastructure in rapidly growing urban environments.

Author Contributions: Conceptualization, methodology, writing—review and editing, Dorothy Onchagwa and Felix Mutua; software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, visualization, Dorothy Onchagwa; supervision, project administration, Felix Mutua. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The datasets used in this study are from multiple sources. Publicly available datasets are cited in the References and can be accessed via the provided URLs. Digitized and processed datasets will be made available by the corresponding author on request. Restrictions apply to the availability of LPG Refill Station data. These data were obtained from a third-party source and are available from the authors with the permission of the data provider.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Appendix A.1

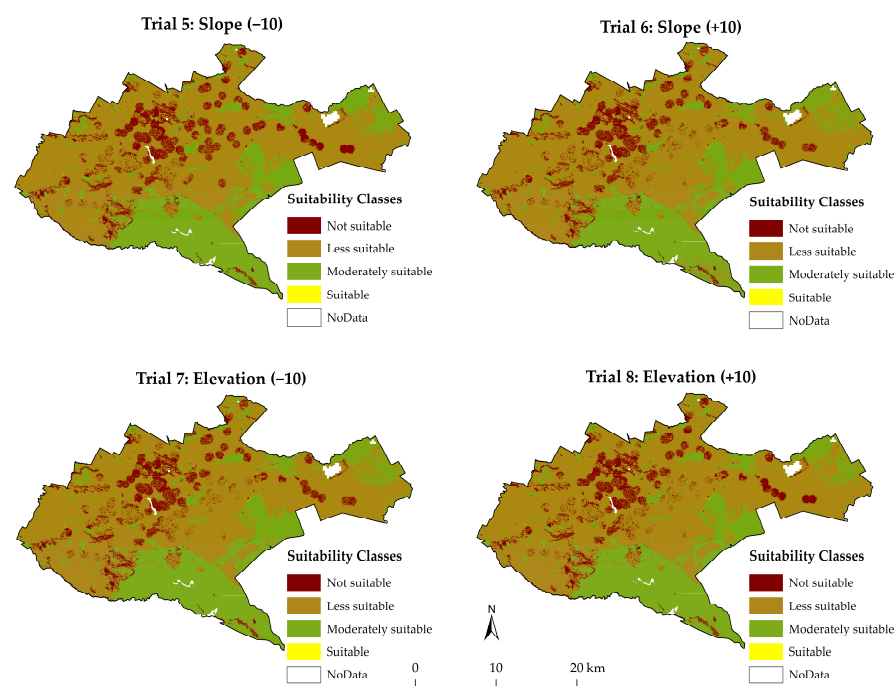


Figure A1. Sensitivity analysis maps for slope and elevation, illustrating how $\pm 10\%$ changes in weights affect the spatial distribution of suitability classes.

Appendix A.2

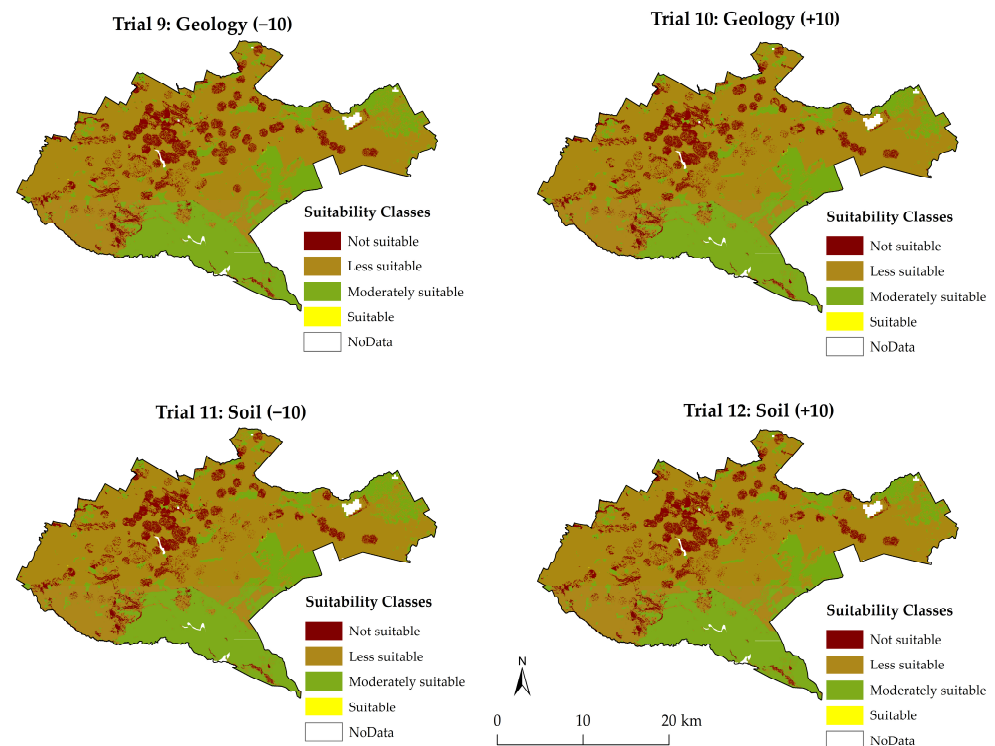


Figure A2. Sensitivity analysis maps for geology and soil, illustrating how $\pm 10\%$ changes in weights affect the spatial distribution of suitability classes.

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