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Optimizing solid waste management using a GIS-based smart decision framework: A case study of Khartoum State, Sudan

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ABSTRACT

Accelerating urbanization in Khartoum State has placed considerable pressure on solid waste management (SWM) infrastructure. Inadequate landfill site selection and inefficient collection planning have created environmental risks, economic inefficiency, and public health concerns. This study proposes an integrated GIS-based decision-support framework combining Multi-Criteria Decision Analysis (MCDA) and the Analytic Hierarchy Process (AHP) to improve waste management in Khartoum, Omdurman, and Khartoum North. Seven spatial criteria were weighted using AHP and integrated in ArcGIS to produce a three-class suitability map. Location-Allocation analysis identified three suitable sites, confirming the suitability of the existing Khartoum North site and designating the other two as transfer stations. Service Area Analysis assessed accessibility, while container locations and capacities were optimized according to household walking distances (maximum 250 m) and building density. Python simulations compared two collection scenarios for February 2026: a fixed daily schedule and a demand-driven schedule triggered when containers reached 80% capacity. The demand-driven approach reduced total travel distance by 19.4%, working hours by 44%, and operational costs by 19%. The proposed framework provides a transparent, reproducible, and cost-effective approach to urban solid waste management, particularly in resource-constrained settings.

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1. Introduction

Solid waste management represents one of the most pressing environmental challenges confronting rapidly urbanizing centers in the developing world. Across Sub-Saharan Africa, municipal solid waste generation is projected to more than double by 2050, placing severe pressure on existing infrastructure and institutional planning frameworks (Kaza et al., 2018). Khartoum State, the capital of Sudan, exemplifies this crisis: with a population exceeding six million across the tri-city metropolitan area comprising Khartoum, Omdurman, and Khartoum North, the state confronts mounting challenges characterized by poor landfill siting, inefficient collection logistics, and a persistent absence of data-driven decision-support mechanisms (Guerrero et al., 2013; Kaza et al., 2018).

Traditional approaches to landfill site selection have historically relied on subjective assessments that fail to integrate complex spatial and environmental variables. In many developing countries, site decisions have been driven primarily

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by land availability rather than rigorous environmental suitability criteria, resulting in facilities positioned near water bodies, residential communities, or ecologically sensitive areas, generating long-term liabilities including groundwater contamination and elevated disease burden (Gbanie et al., 2013; Şener et al., 2010).

Geographic Information Systems (GIS) function as more than cartographic tools; they constitute integrated frameworks for the acquisition, management, and spatial analysis of georeferenced data. When coupled with MCDA, GIS becomes a robust Decision Support System (DSS). MCDA provides a structured approach to evaluating multiple, often conflicting criteria in planning decisions. Among MCDA techniques, the AHP developed by Saaty (1980) enabled decomposition of complex problems into hierarchical structures, using pairwise comparisons to derive objective criterion weights. The combination of GIS and MCDA transforms raw spatial data into actionable planning intelligence through a rigorous, mathematically grounded process (Demesouka et al., 2013).

Conventional waste collection operations typically follow rigid daily schedules regardless of actual container fill levels, resulting in unnecessary fuel consumption, excessive labor costs, and systemic inefficiency. Trucks collecting near-empty containers on some days while bypassing overflowing ones on others represent a dual failure degraded service quality coupled with resource waste. Integrating GIS, MCDA, and advanced spatial simulation provides a robust methodological framework for addressing these shortcomings (Bányai et al., 2019; Catania and Ventura, 2014; Karadimas et al., 2005).

This study addresses these interrelated challenges through a multi-stage integrated methodology encompassing three components of SWM within the Khartoum context. Specifically, it applies GIS-based suitability analysis for optimal landfill siting using AHP, followed by spatial optimization of waste container distribution through Location-Allocation modelling. Finally, a comparative simulation of two collection scenarios is presented: a conventional fixed-route schedule versus a smart, sensor-triggered, demand-driven system implemented through a Python-based model within the ArcGIS Pro environment (Ghiani et al., 2014). This study makes the following principal contributions to the field of GIS-based solid waste management:

1. Integrated multi-component GIS framework: This work is among the first to unify landfill suitability analysis, transfer station designation, container network optimization, and smart collection simulation within a single replicable pipeline applied to a Sub-Saharan African context.
2. Quantitative validation of demand-driven collection: Through a Python-scripted ArcGIS simulation over a full operational month, the study provides empirical evidence of cost, distance, and labor savings achievable through IoT-triggered collection relative to fixed scheduling.
3. Evidence-based reclassification of existing facilities: The suitability analysis validates one existing landfill site and identifies two others for redesignation as transfer stations, a directly actionable finding for current municipal planning.
4. Reproducible methodology for developing nations: The approach, data sources, and simulation parameters are fully documented to enable replication in comparable urban environments across Africa and the Global South.

The remainder of this paper is organized as follows: Section 2 reviews relevant literature; Section 3 details the methodology and multi-criteria weights; Section 4 describes the study area; Section 5 reports the experimental results; Section 6 discusses the findings and their practical implications; and Section 7 presents conclusions and recommendations for future research.

2. Literature review

2.1. GIS-based landfill site selection

The application of GIS in landfill site selection is well established in the literature. Şener et al. (2010) and Gbanie et al. (2013) demonstrated the effectiveness of combining GIS with MCDA for municipal disposal site selection, identifying suitable zones based on geological and land-use criteria. In African contexts, recent studies conducted in Kinshasa and Ethiopia (Kang et al., 2024) have confirmed that AHP integrated with GIS outperforms single-criterion evaluation approaches (Demesouka et al., 2013). AHP remains the preferred method for criterion weighting owing to its capacity to process both quantitative and qualitative inputs through structured pairwise comparison matrices (Saaty, 1980). Additional studies in Jordan, Ghana, and Turkey have similarly validated GIS-MCDA as a reliable and transparent spatial planning tool (Al-Hanbali et al., 2011).

2.2. Waste collection optimization

Vehicle routing and waste collection optimization have been addressed using a range of operations research methods. Karadimas et al. (2005) combined GIS with operations research techniques to optimize collection routes in Athens, achieving notable reductions in both travel distance and operational costs. Ghose et al. (2006) further demonstrated that GIS-based routing substantially improves fleet efficiency. More recently, sensor-driven smart waste collection systems have attracted growing attention as IoT technologies become progressively more affordable (Aleyadeh and Taha, 2018; Hannan et al., 2011).

Catania and Ventura (2014) developed an intelligent waste management system employing fill-

level sensors to dynamically route collection vehicles, demonstrating potential cost savings of 20%–40% relative to fixed schedules. Bányai et al. (2019) corroborated these findings through simulation modelling, noting that demand-driven collection substantially reduces fuel consumption and working hours in urban settings. Han and Ponce Cueto (2015) and Hemmelmayr et al. (2014) provided comprehensive reviews of vehicle routing problem (VRP) formulations for solid waste, while Akhtar et al. (2017) applied metaheuristic algorithms to the capacitated VRP for collection optimization. Faccio et al. (2011) demonstrated that real-time traceability data further enhances multi-objective collection planning. Vu et al. (2019) examined machine learning approaches for waste generation prediction, a key input for sensor-driven dispatch systems. However, limited research integrates GIS-based spatial optimization with Python-driven collection simulation in developing-country contexts, particularly for Sub-Saharan African cities (Guerrero et al., 2013).

2.3. Artificial intelligence and IoT in waste management

Abdallah et al. (2020) conducted a systematic review of AI applications in solid waste management, identifying machine learning and IoT-based sensing as particularly promising for collection route optimization and waste forecasting. Hannan et al. (2011) demonstrated the operational viability of RFID-based bin monitoring for tracking container fill levels and truck locations. Aleyadeh and Taha (2018) proposed an IoT architecture capable of real-time waste container monitoring, enabling demand-driven dispatch. Ghiani et al. (2014) provided a broader survey of operations research applied to strategic and tactical SWM decisions, underscoring the value of integrating sensor data with optimization models. Guerrero et al. (2013) and Kaza et al. (2018) further highlighted the institutional and financial barriers that make data-driven SWM especially critical in low-income urban settings.

Despite the growing body of literature on GIS-based SWM, few studies have integrated landfill site selection, transfer station designation, container network optimization, and smart collection simulation within a single unified framework. This study addresses this gap by presenting a comprehensive, replicable methodology applied to Khartoum State, Sudan, a context that has received limited attention despite its significant planning challenges.

3. Methodology

The methodology follows a four-stage integrated GIS framework: (1) landfill suitability analysis using AHP-weighted MCDA; (2) optimal site selection and transfer station designation using Location-Allocation; (3) container network optimization; and (4) waste collection route simulation using Python. The overall methodological framework is shown in Fig. 1.

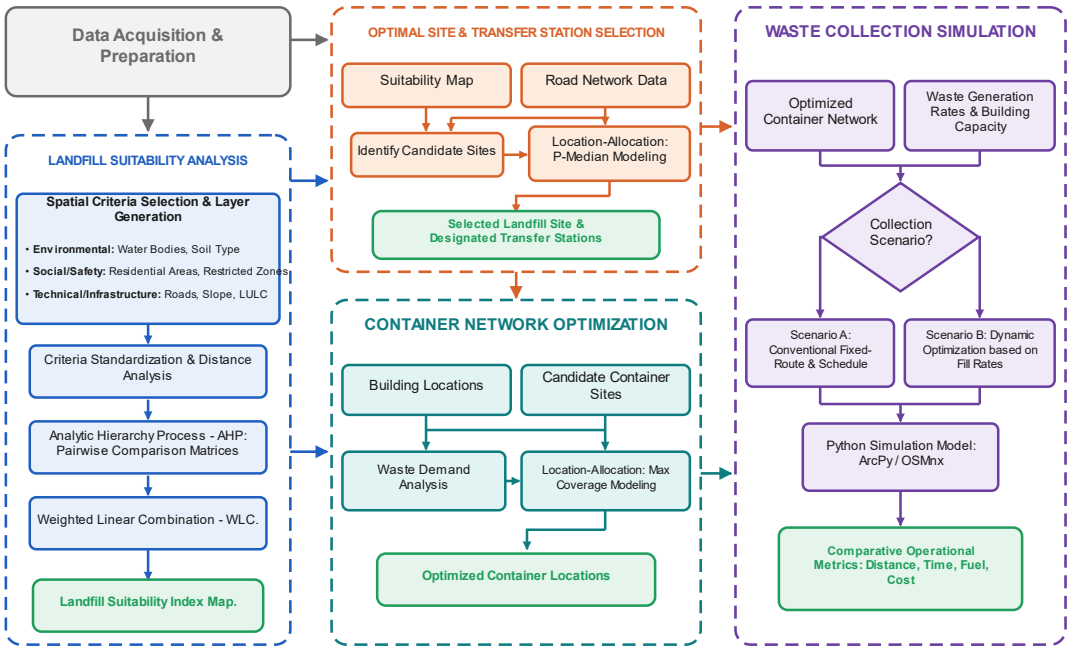


Fig. 1: Overall methodological framework of the study

3.1. Data sources and preparation

Spatial data were obtained from three primary sources. OpenStreetMap (OSM) provided road network data, land use layers, and building footprints for all three study cities, covering a combined total of 8,245 buildings (3,320 in Khartoum, 3,600 in Omdurman, and 1,325 in Khartoum North). High-resolution satellite imagery was employed for visual interpretation and

validation of land use classifications and existing landfill conditions. Soil type data, administrative boundaries, restricted zone delineations, and existing SWM facility locations were obtained from relevant Sudanese governmental sources. Shuttle Radar Topography Mission (SRTM) 30-metre Digital Elevation Model (DEM) data were used to derive slope maps. All datasets were projected to the Universal Transverse Mercator (UTM) Zone 36N coordinate system (WGS 1984) and resampled to a uniform 30-metre cell resolution for raster analysis.

3.2. Suitability analysis using AHP-weighted MCDA

The suitability analysis followed a standard GIS-based MCDA procedure consisting of three steps: criterion standardization, AHP weight derivation, and weighted overlay.

3.2.1. Criterion standardization

Seven spatial criteria were identified based on environmental regulations, international guidelines (EU Landfill Directive; UNEP guidelines), and local conditions. Each criterion raster layer was reclassified on a suitability scale of 1 (least suitable) to 9 (most suitable) using standard distance-based functions. The criteria encompassed: distance from water bodies, distance to residential areas, land use type, soil type, distance to roads, slope, and restricted zones. Full classification details are provided in Table 1.

Table 1: Spatial criteria used in the suitability analysis with classification schemes

Rank	Criterion	Weight (%)	Data source	Classification range	Class (1–9)	Class label
1	Distance from water bodies	28.2%	OpenStreetMap	< 500 m	1	Not suitable
				500–1,000 m	2	Very poor
				1,000–1,500 m	3	Poor
				1,500–2,000 m	5	Moderate
				2,000–3,000 m	7	Good
				3,000–4,000 m	8	Very good
				> 4,000 m	9	Excellent
2	Soil type	21.8%	ISRIC-world soil (soil grids)	Sandy (< 10% clay)	1	Not suitable
				Sandy loam (10–20%)	3	Poor
				Loam (20–30%)	5	Moderate
				Clay loam (30–40%)	7	Good
				Clay (> 40%)	9	Excellent
3	Distance to residential areas	17.5%	OpenStreetMap	< 200 m	1	Not suitable
				200–500 m	2	Very poor
				500–1,000 m	5	Moderate
				1,000–3,000 m	7	Good
				3,000–5,000 m	8	Very good
				> 5,000 m	6	Moderate–good
4	Land use type	15.2%	OpenStreetMap	Waterbody/wetland	1	Not suitable
				Agricultural	2	Very poor
				Urban/built-up	3	Poor
				Shrubland/grassland	6	Moderate
				Bare/sparse vegetation	8	Very good
				Desert/sand sheet	9	Excellent
5	Distance to roads	8.1%	OSM road network	< 0.2 km	1	Not suitable
				0.2–0.5 km	9	Excellent
				0.5–1.0 km	8	Very good
				1.0–2.0 km	7	Good
				2.0–5.0 km	5	Moderate
				5.0–10.0 km	3	Poor
				> 10.0 km	1	Not suitable
6	Slope	5.8%	SRTM 30 m DEM	0–2°	9	Excellent
				2–5°	8	Very good
				5–10°	6	Moderate
				10–15°	3	Poor
				15–20°	2	Very poor
				> 20°	1	Not suitable
7	Restricted zones	3.4%	Government environmental layers	Inside protected area	1	Not suitable
				0–500 m buffer	2	Very poor
				500–1,000 m buffer	5	Moderate
				> 1,000 m from boundary	9	Excellent

3.2.2. AHP weight derivation

Criteria weights were derived using the AHP methodology developed by Saaty (1980). The method entails constructing a pairwise comparison matrix (PCM) in which each criterion is evaluated against every other using a scale from 1 (equal importance) to 9 (extreme dominance). The pairwise comparison matrix A for n criteria is defined as:

$$A = [a_{ij}], \quad (1)$$

where, $a_{ij} = w_i / w_j, and\ a_{ji} = 1/a_{ij}$

The priority vector (weight vector) W is derived by normalizing the geometric mean of each row:

$$w_i = (\prod_j a_{ij})^{(\frac{1}{n})} / \sum_{i=0}^{n} (\prod_i a_{ij})^{(\frac{1}{n})} \quad (2)$$

The Consistency Ratio (CR) was computed to verify the logical consistency of the pairwise judgments:

$$CR = \frac{CI}{RI} \quad (3)$$

where the Consistency Index (CI) is:

$$CI = \frac{\lambda max - n}{n - 1} \quad (4)$$

and RI is the Random Consistency Index for a matrix of size n (Saaty, 1980). A CR < 0.10 is considered acceptable. In this study, the principal eigenvalue (λmax) was 7.19, yielding CI = 0.032 and CR = 0.024 (RI = 1.32 for n = 7), well below the threshold and confirming the consistency of the pairwise judgments. Results are presented in Tables 2 and 3.

Table 2: AHP pairwise comparison matrix and derived criterion weights

Criterion	Water bodies	Soil type	Urban prox.	Land use	Road dist.	Slope	Protected areas	Weight (dec.)	Weight (%)
Water bodies	1.00	1.294	1.611	1.855	3.481	4.862	8.294	0.282	28.2%
Soil type	0.77	1.00	1.24	1.43	2.69	3.76	6.41	0.218	21.8%
Urban proximity	0.62	0.80	1.00	1.15	2.16	3.02	5.15	0.175	17.5%
Land use	0.54	0.70	0.87	1.00	1.88	2.62	4.47	0.152	15.2%
Road distance	0.29	0.37	0.46	0.53	1.00	1.40	2.38	0.081	8.1%
Slope	0.21	0.27	0.33	0.38	0.72	1.00	1.71	0.058	5.8%
Protected areas	0.12	0.16	0.19	0.22	0.42	0.59	1.00	0.034	3.4%

λmax = 7.19 | CI = 0.032 | RI = 1.32 | CR = 0.024 < 0.10

Table 3: Summary of AHP criterion weights and rankings

Criterion	Weight (%)	Rank	Justification
Distance from water bodies	28.2%	1	Environmental protection – highest priority
Soil type	21.8%	2	Clay content provides a passive leachate barrier
Urban proximity	17.5%	3	Health impact vs. transport cost trade-off
Land use	15.2%	4	Legal compliance; conflicts negotiable
Distance to roads	8.1%	5	Operational efficiency factor
Slope	5.8%	6	Low discriminating power in flat terrain
Protected areas	3.4%	7	Hard exclusion constraint
Total	100%	—	CR = 0.024 (λmax = 7.19, RI = 1.32)

3.2.3. Weighted overlay and suitability classification

The Weighted Linear Combination (WLC) method was applied to compute the final Suitability Index (SI) for each raster cell:

$$SI = \sum_i Wi \times Xi \quad (5)$$

where, Wi is the normalized AHP weight of criterion (i) and Xi_i is the standardized suitability score (1–9) for that criterion at each cell. The resulting continuous suitability raster was reclassified into three discrete zones:

- Unsuitable (SI = 1–3): Areas where landfill development is prohibited due to environmental or regulatory constraints.
- Moderately Suitable (SI = 4–6): Areas meeting minimum requirements but subject to limitations.
- Suitable (SI = 7–9): Areas with high environmental compatibility and operational feasibility.

3.2.4. Sensitivity analysis

To assess the robustness of the suitability classification to the AHP weighting scheme, a sensitivity test was performed by varying the weight of the highest-ranked criterion, distance from water bodies (baseline = 28.2%), by ±10% relative to its baseline value (25.4% and 31.0%), with the remaining criteria weights re-normalized proportionally so that all weights summed to 1. The resulting suitability classification was compared against the baseline map on a cell-by-cell basis, yielding 84% agreement in final class assignment (Unsuitable / Moderately Suitable / Suitable). Disagreement was concentrated at the boundary between the Unsuitable and Moderately Suitable classes, while classification of the Suitable zones, which determine candidate landfill locations in the subsequent Location-Allocation step, remained largely stable. This result indicates that the site-selection outcome is not highly sensitive to moderate uncertainty in the dominant criterion weight, supporting the robustness of the AHP-MCDA framework.

3.3. Location-allocation analysis for landfill site selection

The Location-Allocation (LA) tool in ArcGIS Network Analyst (pro.arcgis.com) was applied to identify the optimal number and placement of landfill sites. The Maximize Coverage problem type was selected to ensure that the maximum demand (weighted by population density) is served within a defined impedance cutoff. Three candidate sites were required to serve the three study cities.

Input demand points were derived from population-weighted centroids of residential blocks extracted from OSM building footprints. Only cells classified as Suitable in the suitability analysis were eligible as candidate facility locations. The objective function minimized the weighted sum of network distances:

$$Z = \min \sum_i \sum_j d_{ij} \times Y_{ij} \times W_j \quad (6)$$

where, d_{ij} is the network distance from demand point j to facility i, Y_{ij} is a binary assignment variable (1 if j is assigned to i, 0 otherwise), and W_j is the demand weight at point j.

Existing landfill sites found to lie within Unsuitable zones were subsequently redesignated as intermediate transfer stations consolidation points where collected waste is temporarily stored prior to final transport to selected landfill sites.

3.4. Service area analysis

Service Area Analysis (ArcGIS Network Analyst) (pro.arcgis.com) was conducted around all transfer stations to assess spatial accessibility and service coverage. Network-based service area polygons were computed representing areas reachable within 5, 10, and 15 km road-distance thresholds from each station.

3.5. Container location optimization

Three study zones, one per city, were selected as representative residential areas for container placement analysis. Building footprints from OSM were used to extract household locations within each zone (3,320 buildings in Khartoum, 3,600 in Omdurman, and 1,325 in Khartoum North, totaling 8,245 buildings). A 250-metre maximum walking distance was adopted as the design threshold for this study. While this parameter is derived from common household waste container placement standards in medium-density urban planning literature (Ghiani et al., 2014; Hemmelmayr et al., 2014), it is noted that this was not empirically derived from local Khartoum-specific walking behavior. Consequently, this parameter is acknowledged as a study limitation, and future research should conduct surveys to determine context-specific acceptable walking distances for Khartoum.

The minimum number of container sites (F_{min}) required for full coverage was determined by:

$$F_{\min} = \min F: \forall j \in D, \exists i \in F\ s.t.\ d_{ij} \leq 250\,m \quad (7)$$

where, D is the set of demand points, and F is the set of selected container sites. For each site i, the required number of containers was determined based on daily waste generation per household (G_h = 0.6 kg/person/day × 5 persons/household) and container volume (VC = 2.5 m^3):

$$N_i = (H_i \times G_h \times F_days) / VC \quad (8)$$

where, F_days is the maximum number of days between collections (set to 2 for Scenario A and variable for Scenario B). The nearest transfer station to each study zone was designated as the assigned collection depot.

3.6. Collection route simulation (Python)

A Python script was developed using ArcPy within ArcGIS Pro (pro.arcgis.com) to simulate two waste collection scenarios over February 2026 (24 working days, excluding Fridays). Daily fill rate per container was estimated as:

$$FR_i = (H_i \times G_h) / (N_i \times Vc) \times 100\% \quad (9)$$

Container fill level on day t was computed as:

$$FL_i(t) = min(FL_i(t-1) + FR_i, 100\%) \quad (10)$$

3.6.1. Scenario A: Fixed daily collection

Under Scenario A, all containers within each study zone were collected every working day irrespective of fill level. Three trucks, each starting and ending at the assigned transfer station depot, serviced all containers before returning for unloading. Total operational cost was calculated as:

$$Cost_A = (D_total \times CR \times C_n) + (T_hours \times (S^d + 2 \times S_l)) \quad (11)$$

where, D_total is total distance travelled (km), CR is fuel consumption rate (55 L/100 km), C_n is fuel price (4,000 SDG/L), T_hours are total working hours, S^d is driver salary (40,000 SDG/month), S_l is labor cost per worker (36,000 SDG/month × 2 workers), and an operational overhead of 20% was applied to total direct costs.

3.6.2. Scenario B: Smart demand-driven collection

Scenario B simulates an IoT sensor-based system in which containers are collected only when specific triggering conditions are satisfied:

- Rule 1 (Overflow prevention): Collect if $FL_i(t) \geq 80\%$.
- Rule 2 (Pre-overflow): Collect if $FL_i(t) + FR_i \geq 100\%$ (predicted overflow before next working day).
- Rule 3 (Friday prevention): On Thursday, collect any container predicted to reach 100% before Saturday (the next working day after the Friday holiday).

The combined decision rule for Scenario B on day t is:

$$Collect_i(t) = 1\ if\ FL_i(t) \geq 80\%, OR\ FL_i(t) + FR_i \geq 100\%, OR\ Thursday\ AND\ FL_i(t) + 2 \times FR_i 100\% \quad (12)$$

4. Study area

Khartoum State is situated in central Sudan at the confluence of the Blue and White Nile rivers as shown in Fig. 2. The state encompasses three interconnected cities: Khartoum (the national capital), Omdurman (the most populous city), and Khartoum North (Bahri), collectively forming a metropolitan area of approximately 22,142 km^2 with a combined population exceeding six million.

The state experiences a hot desert climate (Köppen BWh), characterized by extreme summer temperatures exceeding 45°C and scarce annual rainfall of approximately 157 mm. The predominantly flat topography of the central urban core, interspersed with wadis and flood-prone zones, imposes specific constraints on both landfill siting and waste transport logistics.

Currently, SWM in Khartoum State is administered by State and locality governments with

limited inter-agency coordination. Three main landfill sites serve the three cities; however, field assessments conducted in this study revealed that two of these sites are situated in zones classified as unsuitable under environmental and regulatory criteria. Daily waste generation is estimated at 0.5–0.7 kg per capita (Kaza et al., 2018), yielding a total daily volume of approximately 3,000–4,200 tones across the state.

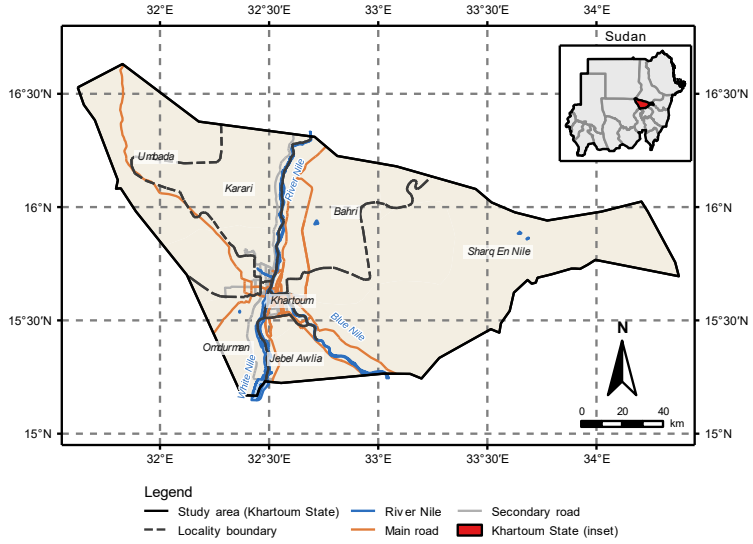


Fig. 2: Study area: Khartoum State, Sudan

5. Results

5.1. Suitability analysis

The AHP-weighted overlay analysis produced a continuous suitability index across Khartoum State. After reclassification, approximately 10.42% of the state's land area was designated as Suitable, 46.65% as Moderately Suitable, and 42.93% as Unsuitable for landfill development (Fig. 3). Unsuitable zones were concentrated along the Nile River corridor, existing urban areas, and agricultural land.

Distance from water bodies received the highest weight (28.2%), reflecting the severe and irreversible consequences of Nile and groundwater contamination from poorly sited facilities. Soil type followed at 21.8%, as clay content provides a passive leachate barrier that engineered liner systems cannot fully substitute. Urban proximity was assigned 17.5%, encoding the planning trade-off between minimizing health impacts and reducing transport costs. Land use accounted for 15.2%, road distance for 8.1%, slope for 5.8%, and protected areas for 3.4%, the latter functioning primarily as a hard exclusion constraint rather than a graded suitability factor. Together, the two highest-weighted criteria (water bodies and soil type) constitute 50% of the total, confirming environmental containment as the dominant design objective.

5.2. Optimal landfill sites and transfer stations

Location-Allocation analysis identified three optimal landfill sites corresponding to the three study cities (Fig. 4). Notably, one selected site coincided with the existing Khartoum North (Bahri) landfill, validating its current location as spatially appropriate (Şener et al., 2010). The two remaining existing sites in Omdurman and central Khartoum were situated in Unsuitable zones, confirming the need for their redesignation.

These two sites were reclassified as transfer stations. Their central urban positions, while unsuitable for final waste disposal, proved advantageous as consolidation points, minimizing collection distances between residential areas and the nearest transfer depot.

5.2.1. Validation against existing site conditions

As an indirect validation check, the model's classification was compared against the known operational status of the three existing landfill sites. The Khartoum North (Bahri) site, which field assessments did not flag for major siting complaints, was independently confirmed as Suitable by the Location-Allocation analysis. The Omdurman and central Khartoum sites, both associated in field assessments with community and environmental complaints, fell within Unsuitable zones. This agreement between model output and observed site performance provides qualitative support for the suitability model, though quantitative validation against groundwater or leachate monitoring data was not possible within the scope of this study and is recommended for future work.

5.3. Service area coverage

Service Area Analysis revealed that the three main landfills, integrated with six transfer stations, provided network-based coverage for specific urban residential areas within a 15 km road-distance

threshold (Fig. 5). In Khartoum North (Bahri), combined operations of the landfill and its single transfer station covered the eastern districts. In Khartoum city, the two designated transfer stations served central sectors. In Omdurman, three transfer stations targeted densely populated western neighborhoods. However, significant coverage gaps were identified across many districts where services remain absent. Accordingly, this study focused on optimizing container locations exclusively within currently served zones, ensuring a maximum walking distance of 250 meters per household.

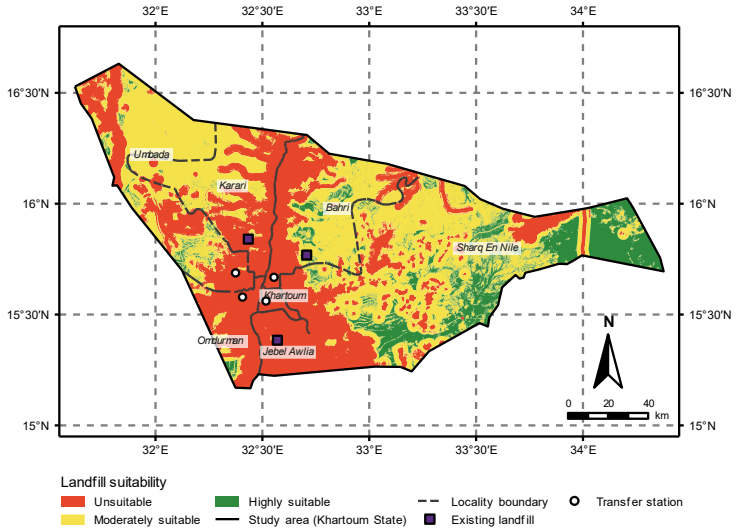


Fig. 3: Landfill suitability map of Khartoum State derived from AHP-weighted MCDA

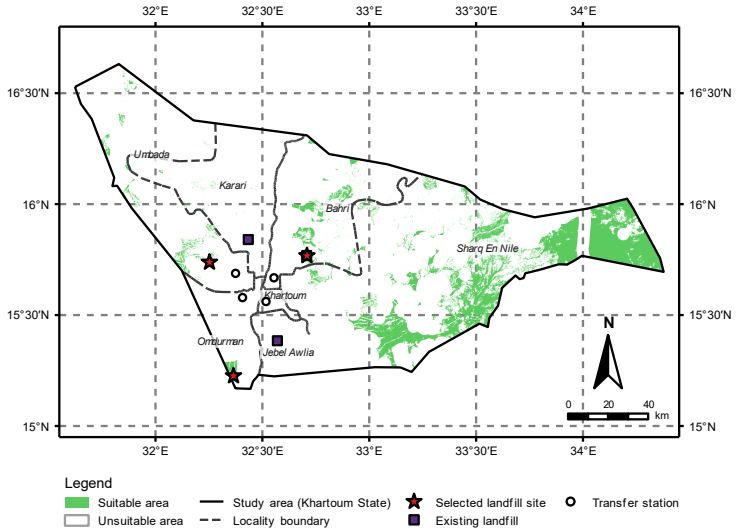


Fig. 4: Selected landfill sites and transfer stations

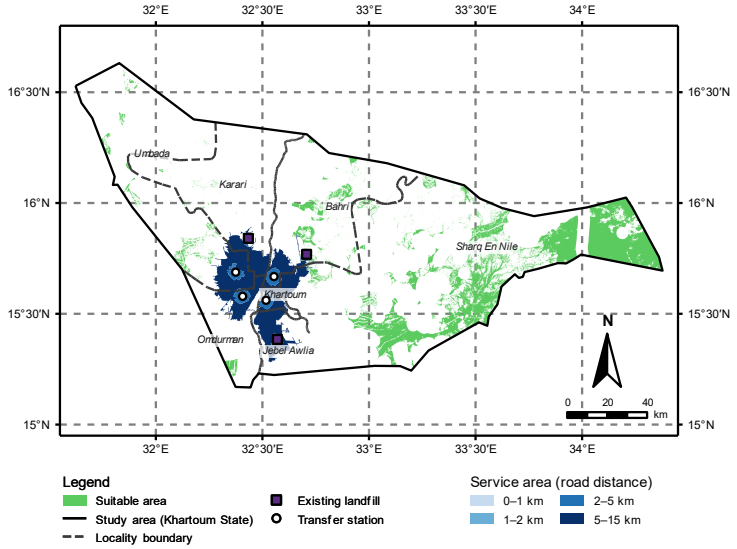


Fig. 5: Service area coverage map

5.4. Container network optimization

Container locations were successfully optimized across the three study zones. A total of 70 container sites were identified across all zones to achieve full coverage within the 250-metre threshold. The number of 2.5 m^3 containers per site ranged from 1 to 7, depending on the number of served buildings and their estimated daily waste output. Full results are summarized in Table 4.

5.5. Collection scenario comparison

The Python simulation produced a comprehensive comparison between Scenario A (fixed daily) and Scenario B (smart demand-driven) over the 24 working days of February 2026. Simulation parameters are listed in Table 5, and comparative results are presented in Table 6. Fuel price and salary figures were verified against prevailing Khartoum market rates at the time of data collection (January 2026).

Given the pronounced volatility of fuel prices and wages in Sudan's current economic conditions, absolute cost figures should be interpreted as indicative of relative efficiency gains between scenarios rather than fixed operational budgets; the 19% relative cost reduction is expected to remain broadly stable even if absolute input prices change, since both scenarios are computed under identical unit costs.

The results demonstrate that Scenario B achieved a 19.0% reduction in total operational cost, saving approximately 1,606,000 SDG over a single month. The most pronounced improvement was in total working hours, reduced by 44.0%, and in the number of individual container service events, reduced by more than half. Total distance travelled decreased by 604 km (19.4%), generating proportional fuel savings.

Table 4: Container optimization results by study zone

Study zone	Total buildings	Container sites selected	Total containers placed	Assigned transfer station
Khartoum	3,320	48	135	Khartoum transfer station
Omdurman	3,600	15	71	Omdurman transfer station
Khartoum North (Bahri)	1,325	7	32	Bahri landfill/station
Total	8,245	70	238	

Table 5: Simulation parameters for the February 2026 waste collection model

Parameter	Value	Notes
Simulation period	February 2026 (28 days)	24 working days, excluding Fridays
Waste generation rate (G^H)	0.6 kg/person/day×5 persons/household	Average household waste output
Container volume (Vc)	2.5 m^3	Standard municipal container
Fuel consumption rate (CR)	55 liters/100 km	Per truck
Fuel price (Cf)	4,000 SDG/liter	Current market rate
Driver salary (Sd)	40,000 SDG/month	Per truck
Labor cost (Sl)	36,000 SDG/month × 2 workers	Per collection crew
Overhead	20%	Applied to total direct costs
Smart trigger threshold	80% fill level	Scenario B only
Friday prevention rule	Thursday pre-collection if FL + 2×FR ≥ 100%	Scenario B only

Table 6: Comparative results: Scenario A (fixed daily) vs. Scenario B (smart demand-driven) for February 2026

Metric	Scenario A (fixed)	Scenario B (smart)	Improvement
Total distance traveled (km)	3,113	2,509	−604 km (−19.4%)
Total working hours	350	196	−154 h (−44.0%)
Total waste collected (tons)	Equivalent	Equivalent	—
Total depot trips	72	52	−20 trips (−27.8%)
Individual container service events	5,712	2,543	−3,169 (−55.5%)
Total operational cost (SDG)	8,468,467	6,862,498	−1,605,969 (−19.0%)

6. Discussion

The findings of this study affirm the value of integrating GIS-based spatial analysis with data-driven simulation for SWM planning. The AHP-MCDA framework successfully identified landfill sites consistent with both environmental protection requirements and operational accessibility needs. Validation of the existing Khartoum North site as spatially optimal provides evidence-based justification for its continued use, while the designation of the other two sites as transfer stations constitutes a pragmatic and cost-effective planning decision (Gbanie et al., 2013; Şener et al., 2010).

The three analytical components of this study form a single connected pipeline rather than independent analyses. The AHP-MCDA suitability analysis determines which of the state's existing landfills are validated for continued use and which are redesignated as transfer stations; these transfer-station locations in turn define the depots and network-distance baselines used in the Service Area and container-network optimization; and the resulting container network and assigned depots are the direct spatial inputs to the Scenario A/B collection simulation. Because each stage's output constrains the next, the reported cost and efficiency gains in Scenario B should be read as conditional on the upstream siting and network decisions, not as an independent finding

The 19% cost reduction achieved by Scenario B is consistent with findings reported in the literature. Catania and Ventura (2014) reported savings of 20–40% in European contexts, while Bányai et al. (2019) estimated 15–25% savings in simulated urban environments. The somewhat lower savings observed in this study may be attributable to the relatively high daily fill rates within the study zones,

which reduce the number of days on which containers can be skipped under the smart scenario.

The 50%+ reduction in individual container service events is particularly significant from an operational perspective. Fewer service stops per route translate directly into reduced vehicle idle time, lower labor strain, and extended vehicle lifespan indirect benefits not captured in the direct cost comparison but likely to be substantial over a full annual cycle (Ghiani et al., 2014; Han and Ponce Cueto, 2015).

Implementation of the proposed framework must also be considered against Sudan's current post-conflict context. Khartoum State sustained extensive infrastructure damage during the 2023–2025 conflict, including damage to power generation and road networks, and reconstruction following the government's administrative return to the capital in January 2026 remains active but resource constrained. This context has direct implications: currency instability and fuel-price volatility introduce uncertainty into the fixed cost parameters used in the collection-cost model; damaged or contested road segments may alter network-distance assumptions underlying the Location-Allocation and Service Area analyses; and limited inter-agency institutional capacity, already noted as a structural constraint in this study, is likely to slow coordinated adoption. Given these constraints, phased implementation prioritizing the redesignation of transfer stations and container relocation, which require comparatively modest capital investment, ahead of new landfill construction or sensor deployment represents a more realistic near-term pathway than full system rollout.

Several limitations of this study warrant acknowledgement. First, fill-level data used in the simulation were modelled rather than measured, as physical IoT sensors were not deployed; simulation accuracy therefore depends on the validity of waste generation rate assumptions (Vu et al., 2019). Second, the three study zones may not fully reflect the variability in waste generation patterns across the entire state (Guerrero et al., 2013). Third, the route simulation used static network distances and did not incorporate time-dependent traffic congestion, which can substantially affect travel time in Khartoum's central corridors during peak hours. Because both Scenario A and Scenario B were simulated under identical network-distance assumptions, the relative comparison between the two scenarios (percentage cost, distance, and time savings) is expected to be more robust to this omission than the absolute travel-time and cost figures reported for either scenario individually. Incorporating time-dependent traffic impedance into the routing model is identified as a priority direction for future work. Future research should address these limitations by validating the simulation against real sensor data, extending spatial coverage, and incorporating time-dependent traffic impedance (Ghose et al., 2006). The reported 19.0% cost reduction should be read as a simulation-based estimate grounded in literature-derived per-capita generation rates (0.5–0.7 kg/person/day; Kaza et al., 2018) rather than as a measured outcome from a deployed sensor network. The container-network optimization and collection simulation were conducted across three representative zones totaling 8,245 buildings, a small fraction of the residential building stock of the three-city metropolitan area; while the suitability analysis and site selection were performed at the state-wide scale, the simulation-based cost and efficiency findings should be interpreted as a proof-of-concept rather than a statistically representative estimate of state-wide savings. Because both Scenario A and Scenario B were simulated under identical network-distance assumptions, the omission of traffic congestion is expected to affect the relative comparison between scenarios less than it would affect either scenario's absolute travel-time and cost figures.

7. Conclusion and future work

This study presented a comprehensive GIS-based smart decision framework for optimizing solid waste management in Khartoum State, Sudan. The integrated methodology combined AHP-weighted multi-criteria suitability analysis, Location-Allocation optimization, Service Area Analysis, and Python-based collection simulation to address the full SWM chain from landfill siting through to daily collection operations (Bányai et al., 2019; Saaty, 1980).

The economic potential of smart waste collection demonstrated in this study is approximately 1.6 million SDG saved per month within the three representative study zones, indicating the potential pending validation at larger scale for substantial cumulative savings if extended city-wide. These findings should be interpreted as a proof-of-concept demonstration within three representative zones; validation at the full metropolitan scale, as outlined in Future Work, is required before these savings can be generalized state-wide.

Future work should prioritize the following directions:

- Validate and calibrate the simulation model against data from physically deployed ultrasonic or infrared fill-level sensors installed in actual containers across Khartoum, enabling more accurate fill-rate modelling and empirical grounding for smart collection thresholds.
- Develop a comprehensive operational dashboard displaying live sensor readings, container fill levels, and truck GPS positions simultaneously, enabling supervisors to monitor city-wide status and dispatchers to receive automated alerts at the 80% fill threshold.
- Extend the container optimization and simulation framework from the three representative study zones to all residential areas across the tri-city metropolitan area.

- Incorporate real-time traffic data into the Vehicle Routing Problem solver to refine route optimization in dense urban corridors where peak-hour congestion significantly affects collection time and fuel consumption.

List of abbreviations

AHP	Analytic hierarchy process
AI	Artificial intelligence
ArcGIS	ArcGIS geographic information system software
ArcPy	ArcGIS Python site package
CI	Consistency index
CR	Consistency ratio; fuel consumption rate (depending on context)
DEM	Digital elevation model
DSS	Decision support system
EU	European Union
GIS	Geographic information system
GPS	Global positioning system
IoT	Internet of Things
ISRIC	Not defined in the manuscript
LA	Location-allocation
MCDA	Multi-criteria decision analysis
OSM	OpenStreetMap
PCM	Pairwise comparison matrix
RFID	Radio frequency identification
RI	Random consistency index
SDG	Sudanese pound (currency)
SI	Suitability index
SRTM	Shuttle Radar Topography Mission
SWM	Solid waste management
UNEP	United Nations Environment Programme
UTM	Universal Transverse Mercator
VRP	Vehicle routing problem
WGS	World geodetic system
WLC	Weighted linear combination

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Compliance with ethical standards

Conflict of interest

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