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Identification of optimal locations for green space initiatives through GIS-based multi-criteria analysis and the analytical hierarchy process

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Abstract

Urban green spaces play a vital role in enhancing the well-being of communities and mitigating environmental challenges such as air pollution and global warming. Despite their importance, effective models to allocate these green spaces are often overlooked, particularly in developing countries. This study utilises GIS-based Multi-Criteria Analysis and the Analytical Hierarchy Process to recommend optimal locations for green space interventions in Lilongwe City, Malawi, based on nine factors: population density, proximity to roads, slope, Digital Elevation Model (DEM), Normalized Difference Vegetative Index (NDVI), land cover, existing green space, proximity to water bodies, and nitrogen dioxide concentration. The results show that 0.57% (23,776 hectares) of Lilongwe city is highly suitable while 14.50% (604,596 hectares) is unsuitable for green space interventions, where population density was the most determining factor. The suitability varied across the city, with highly suitable areas predominantly located in the southern part. The study highlights the importance of informed decision-making in urban green space planning, setting a standard for equitable access to green spaces and sustainable urban development.

Keywords GIS, Multi-criteria analysis, Analytical hierarchy process, Urban green spaces, Spatial planning

Introduction

Green spaces are vegetated areas within urban environments, encompassing parks, gardens, playing fields, children's play areas, woods, natural areas, grassed areas, cemeteries, allotments, green corridors, and even derelict or vacant land with potential for transformation (Natural England 2010). These spaces are crucial for urban biodiversity, mitigating heat island effects, and enhancing residents' well-being (Aronson et al. 2014; Rizwan et al. 2008; Li et al. 2021; Wang et al. 2021; Hartig et al. 2014; Nawrath et al. 2021 cited in Guenat et al. 2021). Effective management of green spaces is essential for maximising their benefits. Green space establishment and management in developed countries are carried out by collaborating with the government and public or private bodies, following specific models (Kwon et al. 2021). For instance, in England, Local Authorities manage urban green spaces with a focus on ecosystem services, biodiversity conservation, and community engagement, including local "Friends of the Park" groups (Natural England 2010), while in the United States, cities like New York and San Francisco use advanced strategies such as public–private partnerships and innovative urban planning, exemplified

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by New York City's "MillionTreesNYC" project (Mustafa et al. 2023).

In contrast, green space creation and management practices in developing regions such as sub-Saharan Africa, undergoing rapid urbanisation, face challenges such as poor planning, limited institutional resources dedicated to green spaces, insufficient prioritisation of green areas, uncooperative attitudes from local communities, and political instability (Anderson et al. 2013; Alabi 2020; Mensah 2014). For instance, in countries like Kenya and Nigeria, urban green spaces are frequently threatened by infrastructural development (Mwanzu et al. 2023; Alabi 2020). As urbanisation continues globally, with over 6.3 billion people expected to live in urban areas by 2050 (United Nations Development Programme, 2022), the demand for green spaces increases. Understanding their value and addressing obstacles in their planning and management is critical (Haaland and Bosch 2015). Therefore, incorporating green spaces into urban planning is essential for improving the quality of life and mitigating the environmental impacts of urban expansion (Paudel and States 2023).

Studies have highlighted the ecological and social importance of urban green spaces (Jabbar et al. 2022) and supporting human well-being (Farkas et al. 2023; Guenat et al. 2021; Dennis et al. 2020; Ridgley et al. 2020). However, these spaces are being reduced in Lilongwe City due to various challenges, including inappropriate urbanisation, population growth, and a lack of coordination, participation, and public engagement (Ngalande and Odera 2023). The Global Urbanisation Trends indicate that over half of the world's population, surpassing 4 billion people now resides in urban areas (ICLE-UNA 2020; Alabi 2020). This shift, marking the point where the urban population exceeded the rural population, was recognised in 2007 by the United Nations (Bowen, and Lynch 2017). However, the proportion of urban dwellers compared to rural inhabitants varies significantly from one country to another (Güneralp et al. 2018). The rapid urbanisation of Malawi has positioned it as one of the world's fastest-growing urban nations. According to the United Nations (2019), urban areas in Malawi are expanding at a rate exceeding 5% annually, leading to a significant increase in the urban population, which is projected to surpass rural growth by 2025. This unprecedented urbanisation trend raises pressing concerns, particularly regarding the scarcity of green spaces in urban environments (Niemelä 2014; Bowen, and Lynch 2017) like Lilongwe City.

As one of the world's rapidly expanding urban centres, Lilongwe's population is expected to nearly double from 1.12 million in 2020 to 2.21 million people by 2035 (Afionis et al. 2020). This swift urban growth leads to significant environmental degradation, pollution, loss of biodiversity, and unregulated development within the city (Ngalande and Odera 2023). The loss of green spaces in urban areas contributes to various environmental challenges, including air and water pollution, heat island effects, and loss of biodiversity (Castelli et al. 2021). Moreover, green spaces play a crucial role in enhancing the quality of life for urban residents, providing opportunities for recreation, relaxation, and physical activity (Giannico et al. 2021; Jabbar et al. 2022).

The Government of Malawi, in partnership with the Lilongwe City Council (LCC), is spearheading the Greening Lilongwe Campaign, a transformative initiative aimed at enhancing the environmental sustainability and resilience of Lilongwe City. The campaign focuses on restoring degraded open spaces and riverine buffer zones, as well as establishing green infrastructure in schools, offices, and homesteads. Additionally, the initiative prioritises the planting of avenue trees along major roadsides and the restoration of the city's Area 18 Cemetery (Lilongwe City Council 2019).

While research on the role of urban green spaces in improving the well-being of urban social-ecological systems is expanding, most studies focus on developed nations (Dennis et al. 2020; Reyes-Riveros et al. 2021). There has been less attention on urban green spaces in developing countries, especially in sub-Saharan Africa (SSA), where rapid urbanisation poses significant challenges for urban planners In Malawi, studies point to infrastructure development, including roads and buildings, as key factors contributing to the decline of green spaces, particularly in cities like Lilongwe, Blantyre, Mzuzu, and Zomba (Afionis et al. 2020; Ngalande and Odera 2023).

Recent studies have shown that creating a public green space, such as the Botanical Garden in Lilongwe City, has positively impacted the well-being of residents and visitors (Ngalande and Odera 2023). However, access to this space is restricted due to its location on the city's outskirts and the presence of steep mountains in certain areas (Afionis et al. 2020). Also, despite efforts invested in urban greening, the vegetated areas aren't designed for public recreational purposes, which impairs their accessibility and direct contribution to wellbeing improvement. Despite efforts to expand green spaces in Lilongwe City, there remains a lack of multi-criteria models meeting the green space accessibility and contribution to ecological and societal challenges brought about by urban expansion.

The lack of scientific evidence provided by methodological studies presents a significant obstacle in efforts to expand green spaces in Lilongwe City (Lilongwe City

Council 2019; ICLE-UNA 2020). To address this gap, this study utilises a Geographic Information Systems (GIS)-based Multi-Criteria Analysis (MCA) approach to predict the suitability of different areas within Lilongwe City for public green space interventions. The study aims to provide scientific evidence that can support strategic decision-making and enhance urban green infrastructure development, ultimately promoting improved well-being and equitable access to green spaces in Lilongwe City.

Materials and methodology

Study area

The study focuses on Lilongwe City, situated at 13°59′S, 33°47′E, and 1,050 m.a.s.l. (Fig. 1c) within Malawi (Fig. 1b). It was declared the capital in 1975, chosen for its central strategic position and flat terrain. With a total population of 1227100 in 2020, exhibiting a growth rate of 3.8% between 2008 and 2018, and covering an area of over 41,705.46 hectares according to the National Statistics Office (2020), Lilongwe is the most populated city in Southern Africa (United Nations 2019). The city predominantly engages in various economic activities, such as finance, banking, retail trade, transportation, public administration, tourism, and tobacco manufacturing (Kamusoko 2017). Lilongwe has faced a significant reduction in green spaces, with only about 8% of the city's area currently designated for green space (Malawi Country Environmental Analysis 2019). Rapid population growth and urbanisation, coupled with a weak legal framework in Malawi's urban centres, have resulted in the loss and degradation of the quality of natural environments (Afionis et al. 2020). Malawi faces challenges related to land degradation, deforestation, and the loss of forests and woodlands (Malawi Country Environmental Analysis 2019).

Research design

The methodology of this study involved five key steps: spatial data collection (Table 1), establishment and rating of criteria, creation of maps for each criteria used, standardisation of factors, determination of weights for each sustainability factor, and subsequent analysis through weighted overlaying (Briassoulis et al. 2019). ArcGIS Pro 3.3 was used and served as the primary analytical tool

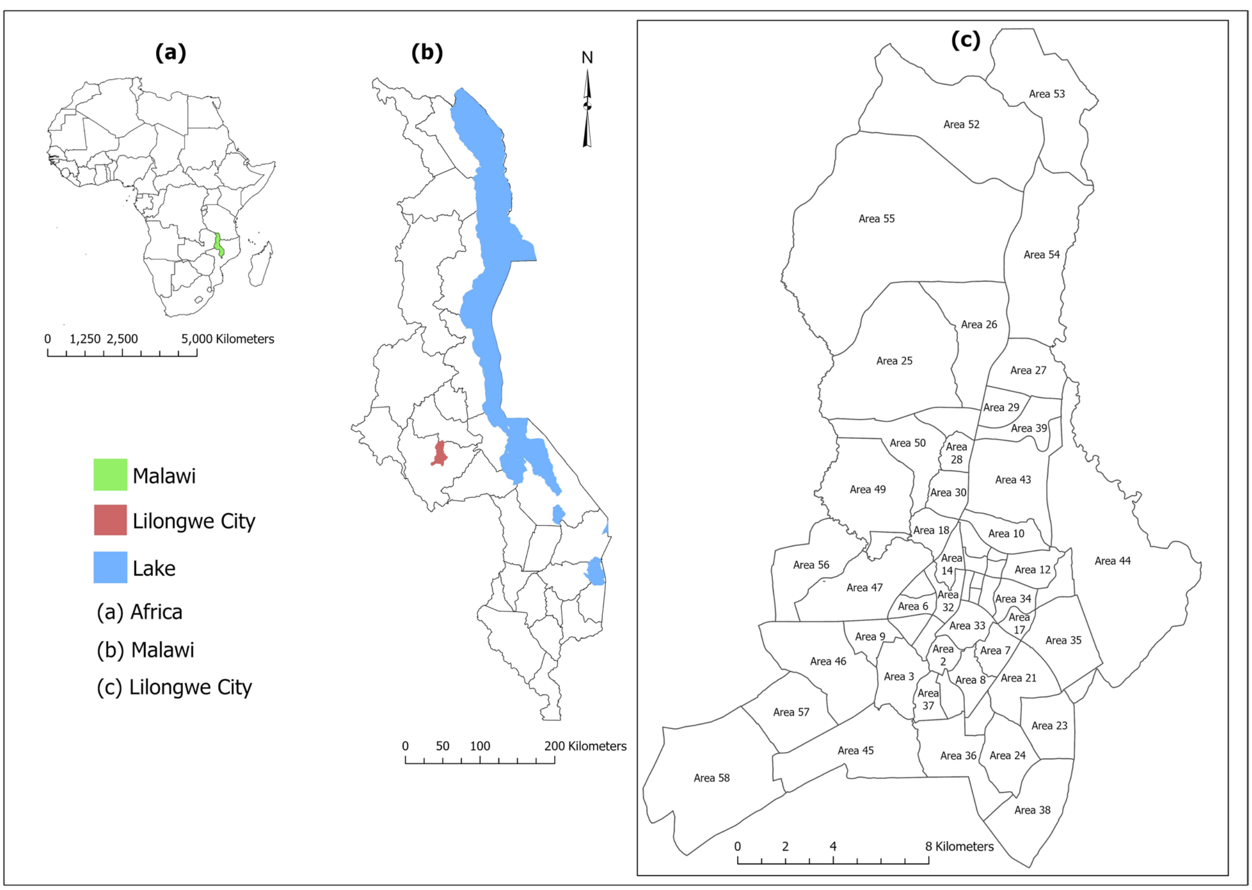

Fig. 1 Map of the study area

Table 1 Spatial data and its associated spatial analysis tool

No	Factors	Criteria	Source	Analysis tool
1	Social-Economic	Population density	Malawi National Statistics Office & the Department of Surveys and Mapping (2020)	Reclassify
		Proximity to roads	Malawi National Statistics Office & the Department of Surveys and Mapping (2020)	Multiple ring buffer
2	Geographic	30 m resolution DEM in raster format	LP DAAC—MOD13Q1 (usgs.gov)	Reclassify
		30 m resolution slope in raster format generated from the DEM	LP DAAC—MOD13Q1 (usgs.gov)	Reclassify
		Land cover	10 m spatial resolution Sentinel-2 image from Copernicus Open Access Hub in Google Earth Engine (GEE)	Reclassify
3	Environmental	Normalized Difference Vegetation Index (NDVI)	10 m spatial resolution Sentinel-2 image from Copernicus Open Access Hub in Google Earth Engine (GEE)	Reclassify
		Existing green space	Malawi National Statistics Office & the Department of Surveys and Mapping (2020)	Multiple ring buffer
		Nitrogen dioxide concentration (μg m^{-3})	3.5 kms spatial resolution Sentinel-5P image from USGS	Reclassify
		Proximity to water bodies	Malawi National Statistics Office & the Department of Surveys and Mapping (2020)	Reclassify

due to its ability to address location-based challenges using various geoprocessing tools (Li and Ning 2023; Wang et al. 2021). Its features facilitated geographic data management, pattern recognition, trend assessment, and decision-making support (Gelan 2021; Tripathi et al. 2022). Additionally, the integration of the Analytical Hierarchy Process (AHP) enhances decision-making for urban green space interventions by prioritising criteria (Saaty 1980 cited in Gelan 2021). It starts with defining the goal and identifying relevant criteria like environmental benefits, accessibility, and cost (Islam et al. 2024). These criteria are organised hierarchically and compared pairwise to assess their relative importance. Numerical weights are calculated from these comparisons, followed by a consistency check. The weighted criteria are then synthesized with option scores to generate a clear ranking, ensuring a comprehensive and balanced recommendation framework (Gelan 2021). The weights to the criteria were assigned based on the findings of the Analytical Hierarchy Process (AHP) (Dong et al. 2008).

Establishing and assigning ratings to criteria and sub-criteria

In identifying optimal locations for urban green spaces interventions, raster criteria maps were reclassified using the Reclassify spatial analyst tool into five suitability classes, ranging from 1 (unsuitable) to 5 (highly suitable) (Table 2 and Fig. 2) following the Food and Agriculture Organisation's classification scheme (Food and Agriculture Organisation [FAO] 2006). This structured approach provided a foundation for effective decision-making.

Population density, expressed as people per km^2, played a pivotal role in the analysis, designating high-density areas as highly suitable for new green spaces (Bille et al. 2023). This is because densely populated areas benefit most from green spaces due to the higher number of people who can access and utilise these areas, thus maximising the social and health benefits of urban green spaces (Gelan 2021). Suitability based on proximity to roads (PR) was also a critical factor, as suggested by Natural England guidelines (2010), which recommend that green spaces should be placed closer to roads for easy accessibility (Loja et al. 2021). Proximity to roads ensures that green spaces are easily reachable by the public, enhancing their usability and encouraging more frequent visits (Cardinali et al. 2024). This accessibility is particularly important for promoting physical activity, social interaction, and overall well-being among urban residents. Moreover, well-connected green spaces can help improve traffic flow and reduce congestion by offering alternative routes and spaces for non-motorised transport, such as walking and cycling. Environmental metrics like the Normalized Difference Vegetative Index (NDVI) contributed to suitability assessment by looking at the greenness areas of the city (Martinez and Labib 2023; Huang et al. 2021). Landscape impact was refined by considering Existing Green Spaces and Land Cover, with regulatory support ensured through Public Land Use (LU) guidelines (Bensouda 2013; Hamada and Ohta 2010; Natural England 2010). Areas with high Nitrogen Dioxide Concentration (μg m^{-3}) can be targeted for the establishment of green spaces, as these green areas can significantly reduce bioaerosol concentrations, including airborne particles from human respiration (Niepsch et al. 2022). The Digital Elevation Model (DEM) and slope categorized lower elevations and gradients

Table 2 Standard scores of criteria and subcriteria

Criteria used	Sub-criteria	Standardisation score	Factor suitability rating
Proximity to Roads (PR) in metres	≤ 300	5	Highly suitable
	300–600	4	Suitable
	600–900	3	Moderate suitable
	900–1200	2	Poorly suitable
	≥ 1200	1	Unsuitable
Normalized Difference Vegetation Index (NDVI)	−0.24 to −0.05	1	Unsuitable
	−0.05 to 0.14	2	Poorly suitable
	0.14–0.33	3	Moderate suitable
	0.33–0.52	4	Suitable
	0.52–0.71	5	Highly suitable
Population density (people per km^2)	1–2249	4	Suitable
	2249–2264	5	Highly suitable
Digital Elevation Model (DEM) in metres	982–1040.6	5	Highly suitable
	1040.6–1099.2	4	Suitable
	1099.2–1157.8	3	Moderate suitable
	1157.8–1216.4	2	Poorly suitable
	1216.4–1275	1	Unsuitable
Slope (%)	0–5.74	5	Highly suitable
	5.74–11.48	4	Suitable
	11.48–17.22	3	Moderate suitable
	17.22–22.97	2	Poorly suitable
	22.97–28.71	1	Unsuitable
Nitrogen dioxide concentration ($\mu g\ m^{-3}$)	3.99E-05 to 4.10E-05	1	Unsuitable
	4.10E-05 to 4.20E-05	2	Poorly suitable
	4.20E-05 to 4.30E-05	3	Moderate suitable
	4.30E-05 to 4.40E-05	4	Suitable
	4.40E-05 to 4.50E-05	5	Highly suitable
Existing green space (metres)	0–500	1	Unsuitable
	500–1000	2	Poorly suitable
	1000–1500	3	Moderate suitable
	1500–2000	4	Suitable
	≥ 2000	5	Highly suitable
Proximity to water bodies (metres)	0–250	5	Highly suitable
	250–500	4	Suitable
	500–1000	3	Moderate suitable
	1000–2000	2	Poorly suitable
	≥ 2000	1	Unsuitable
Land cover	Built-up	5	Highly suitable
	Vegetation	4	Suitable
	Arable	3	Moderate suitable
	Water	2	Poorly suitable

as highly suitable (Rees and Wackernagel 2012). These areas are easier to develop and maintain, making them ideal for creating green environments (Ferreira and Panagopoulos 2014; Okolie and Smit 2022). Collectively, these factors informed a comprehensive decision-making process, considering socio-economic, environmental, and geographical factors in this urban green space selection process (Gelan 2021).

The Normalized Difference Vegetation Index (NDVI) for this study was calculated using Eq. 1.

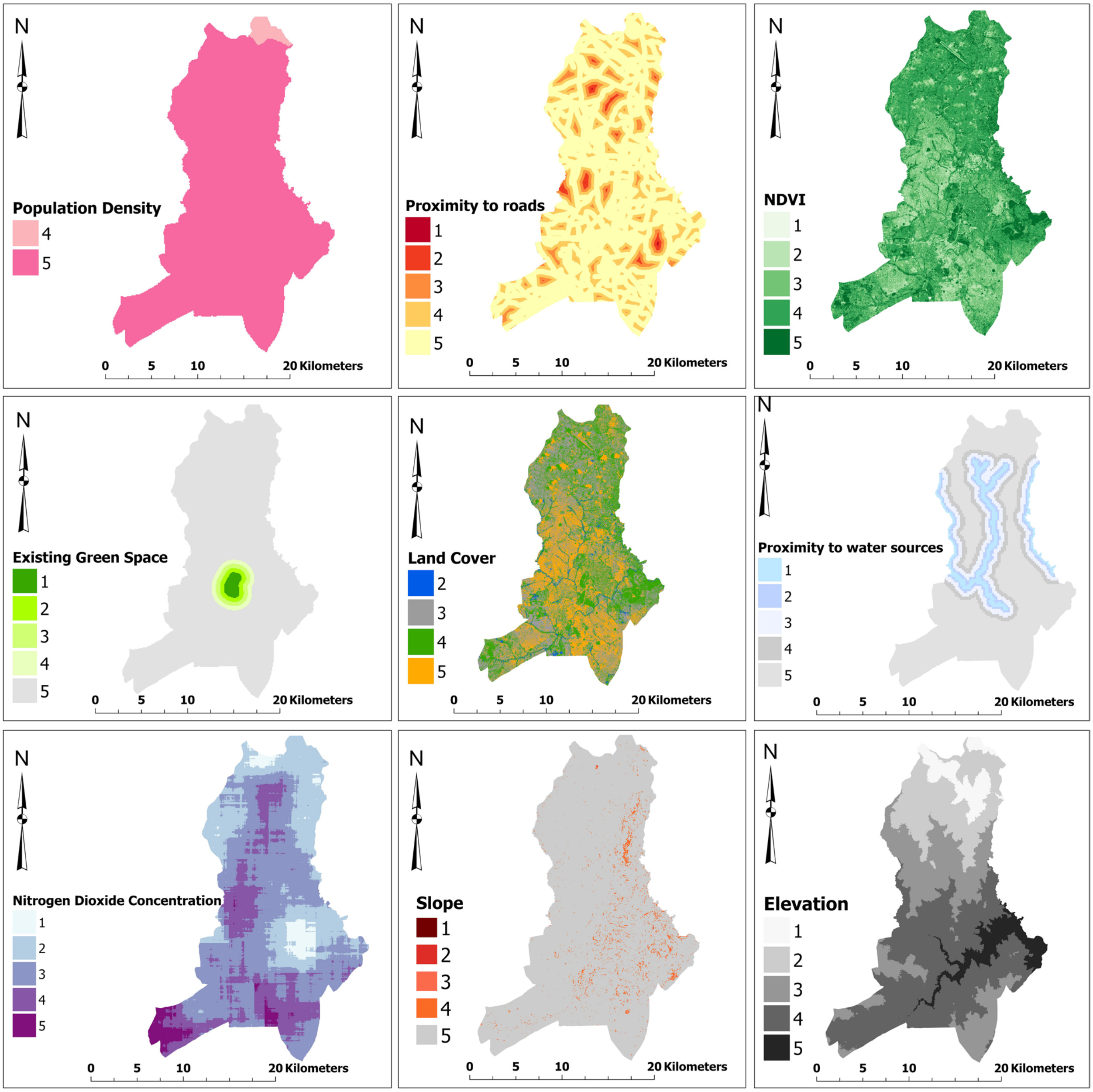

Fig. 2 Reclassified criteria maps

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \quad (1)$$

Utilising Band 8 (Near Infra-red; NIR) and Band 4 (Red) from Sentinel-2 satellite imagery with 30 m resolution, the ArcGIS Pro raster calculator was used for the calculation of NDVI. This was done to quantify vegetation greenness and density in the study area. According to Beck et al., (2005), and Evangelides and Nobajas, (2020), higher NDVI values signify high greenness.

Calculating weight for the selected factors

In this study the GIS-based multi-criteria decision-making analysis involved assigning weights to each factor map, crucial for expressing the importance of each criterion in

Table 3 Saaty's (1980) foundation scale used in pairwise comparison cited in Gelan (2021)

Intensity of importance on an absolute scale	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance of one over another	Experience and judgment strongly favour one activity over another
5	Essential or strong importance	Experience and judgment strongly favour one activity over another
7	Very strong importance	An activity is strongly favoured, and its dominance demonstrated in practice
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation
2,4,6,8	Intermediate values between the two adjacent judgments	When compromise is needed

influencing urban green areas (Saaty 1980 cited in Liaqat et al. 2021; Gelan 2021). The weights were determined through the AHP with pairwise comparison matrices (Islam et al. 2024; Gelan 2021). Following Saaty's (1980) nine-degree preferences scale (Table 3), the AHP process involved pairwise comparisons of criteria, with the results entered into a comparison matrix. The scale's hierarchy demonstrated the increasing importance of each level. This systematic approach ensures the incorporation of weighted criteria, facilitating the decision-making process. Saaty's (1980) consistency principal guides pairwise comparisons, ensuring self-consistency, with scores reflecting equal (1), high (9), or low (1/9) importance.

Criterion weights were subsequently determined by normalising the eigenvector of the reciprocal ratio matrix, leading to the creation of a Normalised Pairwise Comparison Matrix (PCM). The standardisation of these weights involved dividing each element by the total columns. The following steps were used to identify the criteria weight through the AHP process. From the PCM m = (n*n) for n criteria. Where p_{ij} is the value of the cell located at the i-th row and j-th column of PCM (Eq. 2) (Tripathi, Agrawal and Gupta, 2022).

$$P_{ij}.P_{ji} = 1 \quad (2)$$

Following the pair-wise comparison and factor weight calculation, a consistency ratio (CR) was computed to identify any differences and determine the ideal weights for the complete pair-wise comparison matrix. The consistency ratio was calculated for every pairwise comparison matrix using the following Eq. 3 (Gill et al. 2018).

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

where CR = Consistency Ratio, CI = Consistency Index, and RI = is the Random Inconsistency Index whose value depends on the number of factors being compared (Table 4) (Saaty 1980). The consistency index (CI) (Table 5) was calculated by the following Eq. 4:

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

where n = the number of items being compared in the matrix, λmax = Average value of the consistency vector (Table 5).

Data analysis

A multi-criteria analysis decision rule was applied after the weights and criteria reclassified maps were created and set. Three common decision rules in multi-criteria analysis include weighted linear overlay, Boolean overlay, and ordered averaging, as noted by Jiang and Eastman (2000) and Malczewski (2004). The standardised layers in this investigation were aggregated using the weighted linear combination technique utilising a raster calculator in ArcGIS Pro software (Fig. 3). The weight of the suitability parameters (Wi) was multiplied by factors and parameters (Xi) in the weighted linear combination technique to obtain composited weights, which were then summed (Malczewski 2004; Romano et al. 2015) (Eq. 5).

Table 4 Random inconsistency index

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	**1.45**	1.49

Where n is the number of factors used in the study and RI is the Random Inconsistency Index

Bold value indicates the Random Inconsistency Index (1.45) used in this study for 9 factors

Table 5 Factor weight computation and consistency ratio estimations

Factors	PD	PR	NDVI	EGS	LC	PW	NO_2	SLP	DEM	Weights	λ	CI	RI	CR
PD	0.419	0.576	0.481	0.356	0.379	0.310	0.232	0.237	0.225	0.357	9.807	0.101	1.450	0.070
PR	0.105	0.144	0.240	0.133	0.227	0.155	0.145	0.237	0.200	0.176				
NDVI	0.105	0.072	0.120	0.222	0.227	0.155	0.174	0.142	0.150	0.152				
LC	0.084	0.048	0.040	0.178	0.076	0.116	0.145	0.142	0.150	0.109				
EGS	0.052	0.048	0.024	0.044	0.019	0.077	0.087	0.142	0.075	0.063				
SLP	0.084	0.029	0.024	0.015	0.025	0.116	0.116	0.047	0.050	0.056				
PWS	0.052	0.036	0.030	0.022	0.019	0.039	0.058	0.016	0.075	0.039				
NO_2	0.052	0.029	0.020	0.015	0.015	0.019	0.029	0.012	0.050	0.027				
DEM	0.047	0.018	0.020	0.015	0.013	0.013	0.014	0.024	0.025	0.021				

PD Population Density, *PR* Proximity to Roads, *NDVI* Normalized Difference Vegetative Index, *LC* Land Cover, *EGS* Existing Green Space, *SLP* Slope, *PW* Proximity to Water, *NO2* Nitrogen Dioxide Concentration (μg m-3), and *DEM* Digital Elevation Model, *CI* Consistency Index, *RI* Random Inconsistency, *CR* consistency ratio

Fig. 3 Suitability for Green spaces implementation in Lilongwe City analysis workflow through ArcGIS Pro 3.3 Model Builder tool

$$s = \sum_{i=1}^{n} (WiXi) \quad (5)$$

where S = total suitability score, Wi = weight of the selected suitability criteria layer, Xi = assigned sub-criteria score of suitability criteria layer i, n = total number of suitability criteria layer.

Results

The AHP analysis in this study reveals varying impacts of different factors on urban green spaces. Population density emerges as the most crucial factor with the highest importance weight of 0.357, followed by proximity to roads (0.176) and NDVI (0.152). Land cover ranks fourth with a weight of 0.109, followed by distance from existing green space (0.063) and slope (0.056). Proximity to water sources (0.039) and nitrogen dioxide (0.027) are assigned the seventh and eighth priorities, respectively, while the Digital Elevation Model

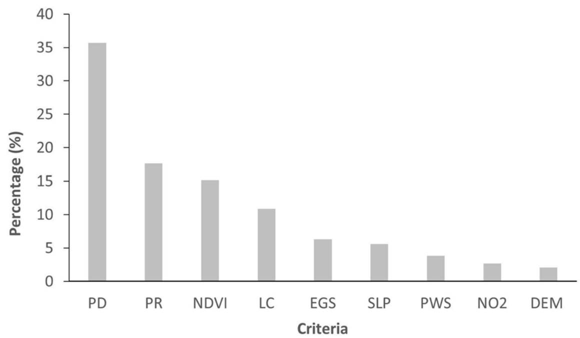

Fig. 4 Criteria weights in percentage. *PD* Population Density, *PR* Proximity to Roads, *NDVI* Normalized Difference Vegetative Index, *LC* Land Cover, *EGS* Existing Green Space, *SLP* Slope, *PW* Proximity to Water, *NO2* Nitrogen Dioxide Concentration (μg m-3), and *DEM* Digital Elevation Model)

(DEM) has the lowest weight (0.021). These findings indicate that factors with higher percentage weights have a greater influence on selecting suitable locations for urban green space interventions (Fig. 4).

In this study, the AHP analysis indicates a Consistency Ratio (CR) of 0.070, consistent with Saaty's (1980) threshold of 0.1 or less. The resulting map illustrates the suitability of various parts of Lilongwe City for green space interventions (Fig. 5). Specifically, 0.57% (237.76 ha) and 5.58% (2329.10 ha) of the study area are highly suitable and suitable, respectively, while 14.50% (6045.96 ha) is deemed unsuitable (Table 6).

The findings highlight the southern part of the city as having highly suitable locations for green space interventions, including areas 44, 1, 36, 37, 45, and 58, while the northern part features areas 52, 53, and 54. However, areas 30, 18, 49, 43, 26, and 55 present limited highly suitable locations. Notably, Area 55 contains many unsuitable areas for green space interventions.

Discussion

The resulting suitability map indicates that around 33.46% of the city is appropriate for green space development (summing up highly suitable, suitable, or moderately suitable areas), whereas 14.50% is deemed unsuitable, which notably surpasses the original allocation of 8% designated for such interventions. This difference highlights the importance of employing advanced multi-criteria analysis and decision-making models like AHP in illustrating intervention areas that general planning approaches would otherwise overlook. The importance of strategically planning green space interventions in Lilongwe City is further emphasised this study's findings, where the model indicated the densely populated southern and northern regions to be most suitable for green space interventions. This highlights the potential of promoting green spaces' accessibility by reducing the distances travelled by the city inhabitants to reach the green spaces and relevant costs (Gelan 2021; Kaźmierczak et al. 2013). These predictions align with previous research emphasising the necessity of optimising green space accessibility to enhance urban well-being and community health (Natural England 2010; Gelan 2021; Kaźmierczak et al. 2013).

Apart from population density, the model considered proximity to roads, which also ensures green space accessibility, making it easier for residents and visitors to reach these spaces, which is essential for maximising the benefits of urban green infrastructure (Moisa et al. 2023; Zhang and Chen 2024). According to Mueller et al. (2022), a green space between a road and a dense residential area decreases the negative effects of air pollution from vehicles. These green spaces help distance residents from exhaust fumes and road dust, thereby improving local air quality (Public Health England 2020; Bikis 2023). Furthermore, the suitable regions exhibit higher greenness values, as indicated by elevated Normalized Difference Vegetation Index (NDVI) scores, suggesting substantial existing vegetation cover that can be enhanced and preserved (Bagherzadeh et al.2020). However, it is also essential to consider other factors like soil quality, and drainage when planning green spaces (Bünemann et al. 2018).

The study's methodology, which integrates GIS and MCA, particularly the AHP, proves to be an effective tool for urban planning and green space development (Anteneh et al. 2023). This approach facilitates the systematic evaluation of multiple criteria, assigning weights based on their relative importance, thus providing a rational decision-making framework (Josselin and Maux 2017; Chen 2014). This method's applicability in developing cities like Lilongwe yielded effective results, showcasing its potential to address accessibility issues and reduce transport costs for residents, consistent with recommendations from previous studies (Romano et al. 2015; Gelan 2021).

Comparing the results with previous studies reveals both similarities and differences. For instance, Anteneh et al. (2023) and Gelan (2021) highlighted the significance of population density and accessibility in green space planning, supporting the current study's findings. However, differences in regional contexts and specific urban dynamics might account for variations observed in other studies (Kaźmierczak et al. 2010; Gelan 2021). According to Gelan (2021), site selection research provides strong support for this kind of multi-criteria methodology. To evaluate and select the best

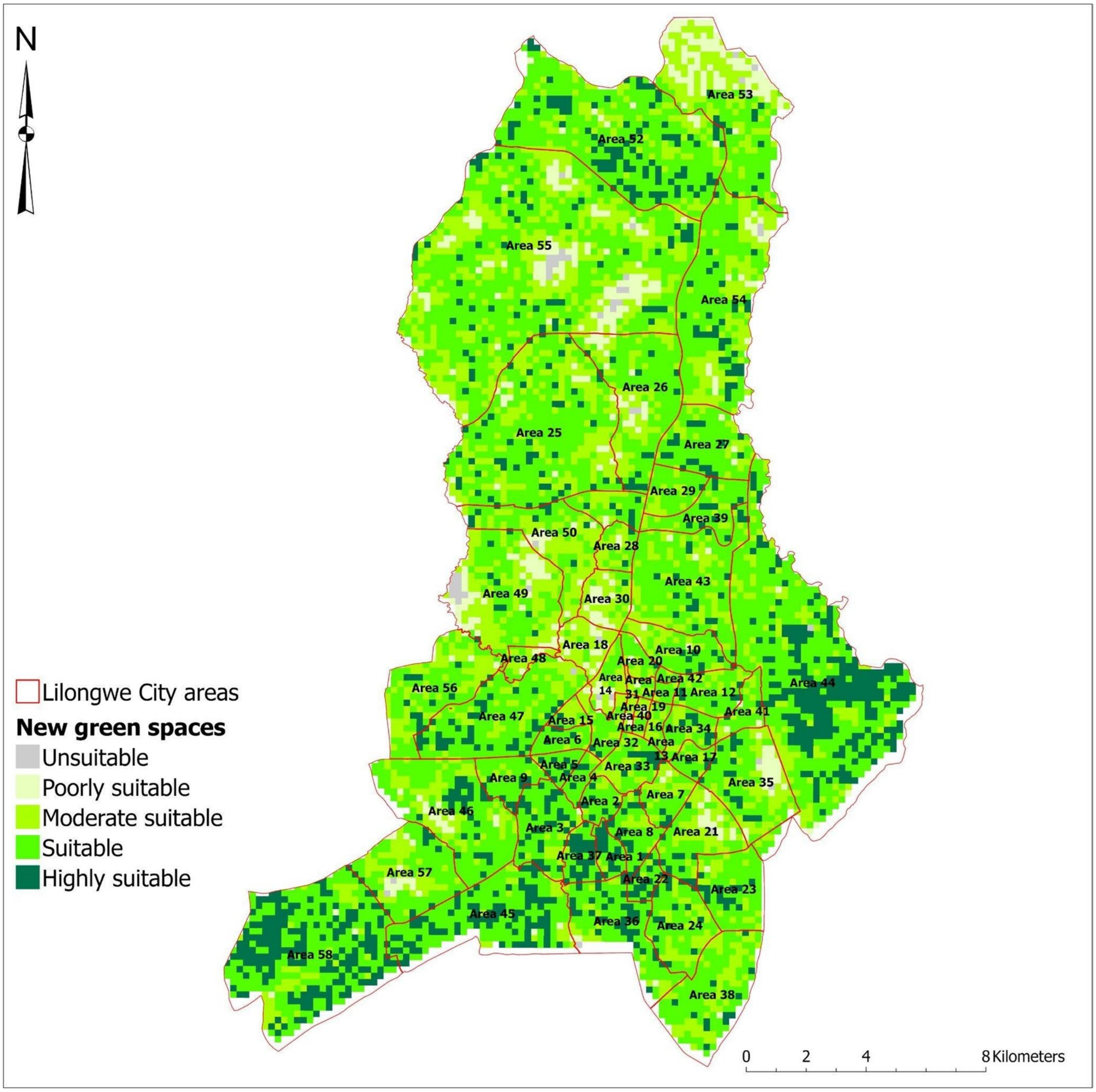

Fig. 5 Final suitability map across various areas in Lilongwe City

Table 6 Area coverage of classified land suitability map in Lilongwe City

Class	Area (Ha)	Percentage
Highly suitable	237.76	0.57
Suitable	2329.10	5.58
Moderately suitable	11388.33	27.31
Poorly suitable	21704.30	52.04
Unsuitable	6045.96	14.50

sites based on a variety of criteria, Greene et al. (2011) highlight the well-established practice of combining GIS with MCA methods in site selection. This involves using MCDA's decision-making frameworks and GIS's spatial analysis capabilities (Kaźmierczak et al. 2010; Gelan 2021). This study supports previous findings that GIS improves site selection accuracy and reliability by envisaging spatial relationships and patterns (Gelan 2021; Tripathi et al. 2022). It also reaffirms the usefulness of GIS in spatial analysis and visualisation, which is essential for informed decision-making (Hamada and Ohta 2010; Rees and Wackernagel 2012).

While the datasets provided valuable insights, their limitations suggest that future studies should aim to incorporate higher-resolution data and a broader range of factors to enhance the robustness of the suitability analysis. Additionally, considering the unique urban dynamics of Lilongwe, the methodologies applied in this study offer a viable framework for similar urban settings, although continuous monitoring and adjustment of strategies are essential for sustained benefits.

Conclusions

This study marks a significant advancement in using geospatial technologies and multi-criteria decision-making for green space planning in developing nations. The integration of GIS-based Multi-Criteria Analysis (MCA) with the Analytical Hierarchy Process (AHP) offers a precise evaluation of optimal locations for green space interventions, providing a replicable framework for other urban settings (Malczewski and Rinner 2015).

The findings highlight the critical importance of strategic urban green space planning in rapidly urbanising areas such as Lilongwe City, Malawi. The research reveals that 0.57% of the city is highly suitable for green space initiatives, while 14.50% is unsuitable. Significantly, the southern part of Lilongwe is identified as particularly favourable for green space development. These findings highlight the critical importance of population density and road accessibility in determining green space allocation, confirming recent scholarly discussions on the role of demographic and infrastructural factors in green space planning (Gelan 2021; Reyes-Riveros et al. 2021). A key methodological innovation is the integration of environmental parameters into the decision-making framework, surpassing traditional accessibility metrics (Romano et al. 2015). Beyond enriching the theoretical framework of green space geography, this study provides practical insights for policymakers. The generated suitability maps offer a data-driven foundation for strategic decision-making, with the potential to promote more equitable green space systems (Gelan 2021).

This study demonstrates that population density is the most influential factor in determining the suitability of areas for green space interventions, emphasising the need for urban planners to prioritise densely populated regions to enhance the overall well-being of residents. Additionally, the integration of various socio-economic, environmental, and geographical factors in the decision-making process ensures a comprehensive approach to urban green space planning. This research sets a standard for future studies and urban planning initiatives, advocating for informed and data-driven decision-making processes in the development of urban green infrastructure.

This study presents a practical framework for urban green space planning with global applicability. Using GIS-based Multi-Criteria Analysis (MCA) and the Analytical Hierarchy Process (AHP), it offers an accurate method to identify ideal locations for green space development. The approach emerges as particularly beneficial for rapidly expanding cities, highlighting the need to prioritise green spaces in densely populated areas. This adaptable methodology aids urban planners in enhancing green space networks and contributes to global sustainability and environmental health initiatives.

The findings of this study should be considered when implementing ongoing efforts to expand green spaces in Lilongwe City, and the collaborative model used in this study is recommended for future green space projects in other cities within Malawi. Additionally, incorporating additional criteria for similar studies in the future is proposed. Future research should concentrate on examining individual city areas to ensure the long-term benefits of urban green spaces. Additionally, studies should aim for results that are generalisable and suitable for contributing to a national framework. Advocating for development in highly suitable areas and devising optimisation strategies for less suitable regions, such as Area 55 in this study, is crucial. Collaborative planning involving planning authorities and communities is essential to foster public awareness and engagement in green space initiatives.

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Author contributions
Charles Bakolo: conceptualisation of the research idea, data collection, methodology development, formal analysis, preparation of the original draft manuscript, coordination, review, editing, and submission. Laban Kayitete: co-designed the methodology and assisted with review and editing. Jean de Dieu Tuyizere: assisted with data collection and review. James Tomlinson: contributed to the writing of the original draft. Jade Fawcett: contributed to the writing of the original draft. Richard Figueroa Alfaro: provided guidance in the implementation of the methodology and reviewed and edited all the versions of the manuscript. All authors were involved in revising and editing the manuscript and approved the final version submission.

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Availability of data and materials
The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare no competing interests.

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