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Landfill Site Suitability Assessment Based on GIS and Multicriteria Analysis: A Case Study of Kirkuk City

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Abstract:

This study looks at the environmental and socioeconomic aspects of possible landfill locations in Kirkuk City, Iraq, as well as their spatiotemporal appropriateness. This study used different types of data, including Landsat satellite imagery, soil texture, groundwater level, and slope. The Analytic Hierarchy Process (AHP) was utilized for multi-criteria decision analysis of possible landfill sites, linear regression was employed for population projection, and a Convolutional Neural Network (CNN) was utilized for Normalized Difference Vegetation Index (NDVI)/ Normalized Difference Built-up Index (NDBI) prediction. The suitability ratings for prospective dump sites were produced using the AHP-based Geographic Information Index (GIS) techniques. The results reveal that the selection of landfill locations minimizes environmental effects and advances environmentally sound waste management. The technique provides a framework for assessing the appropriateness of dump sites in various geographical areas. Moreover, the projections for the future emphasize Kirkuk City's need for upgraded waste management facilities. Furthermore, urban planners and politicians in Kirkuk City may benefit greatly from this research's data-driven approach to landfill site selection, which takes social and environmental concerns into account and has implications for sustainable waste management techniques.

Keywords*:* Landfill, Geographic Information System (GIS), Analytic Hierarchy Process (AHP), Convolutional Neural Network (CNN), Kirkuk, Multicriteria Analysis, Suitability Assessment.

تقييم مدى ملاءمة موقع المكب بناء على نظم المعلومات الجغرافية وتحليل متعدد المعايير: دراسة حالة مدينة كركوك

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الخلاصة:

نظرت هذه الدراسة في الجوانب البيئية والاجتماعية والاقتصادية لمواقع مدافن النفايات المحتملة في مدينة كركوك بالعراق، فضلا عن ملاءمتها الزمانية المكانية. تم استخدام أنواع مختلفة في هذه الدراسة بما في ذلك صور الأقمار الصناعية لاندسات، وملمس التربة، ومستوى المياه الجوفية، والمنحدر. واستخدمت عملية التسلسل الهرمي التحليلي (*AHP*) لتحليل القرار متعدد المعايير لمواقع المكب المحتملة، واستخدمت الانحدار الخطي لإسقاط السكان، واستخدمت الشبكة العصبية التلافيفية (*CNN*) للتنبؤ ندفي/ندبي. وأنتجت تقييمات الملاءمة لمواقع التفريغ المرتقبة باستخدام تقنيات نظم المعلومات الجغرافية القائمة على برنامج التكيف الهيكلي. تم الكشف عن النتائج أن اختيار مواقع مدافن النفايات يقلل من التأثير البيئي ويعزز الإدارة السليمة بيئيا للنفايات. وتوفر هذه التقنية إطارا لتقييم مدى ملاءمة مواقع تفريغ النفايات في مختلف المناطق الجغرافية. علاوة على ذلك، تؤكد التوقعات المستقبلية على حاجة مدينة كركوك إلى تحسين مرافق إدارة النفايات. علاوة على ذلك، قد يستفيد المخططون والسياسيون الحضريون في مدينة كركوك بشكل كبير من نهج هذا البحث القائم على البيانات لاختيار مواقع دفن النفايات، والذي يأخذ في الاعتبار الاهتمامات الاجتماعية والبيئية وله آثار على تقنيات الإدارة المستدامة للنفايات.

الكلمات المفتاحية: مكب النفايات، نظم المعلومات الجغرافية، التسلسل الهرمي التحليلي، الشبكة العصبية التلافيفية، كركوك.

1. Introduction:

Every nation on the planet deals with a variety of environmental issues [1]. Municipal solid waste management is becoming a global concern that many municipalities are facing, especially in hilly cities. Additionally, the UN's goal for global sustainability now includes municipal waste management as an emerging problem because of the population increase [2–4].

The aim of solid waste management is to dispose of waste in the most environmentally friendly way feasible [5]. The locals who are immediately touched by a region's solid waste program help to achieve this. Households, workplaces, small businesses, and commercial establishments all have their solid trash collected. This is regarded as a unique waste stream in the EU. The term "MSW" refers to this type of trash as well as waste produced during building, restoration, and demolition. MSW includes items like glass, bricks, concrete, inert materials, paper and cardboard, yard trash, metal, plastic and rubber, electronic waste, and miscellaneous garbage. Municipalities across the world classify MSW in different ways. It is composed of both biodegradable and non-biodegradable elements as well as organic and inorganic components. Many different approaches are used worldwide to reduce the production of solid waste. The most popular strategies for reducing solid waste are garbage disposal, recovery, reuse, recycling, and prevention. Another tactic used to prevent any environmental problems is the regular storage of solid waste. One of the major worldwide concerns that is particularly noticeable in developing countries is the disposal of municipal solid waste (MSW) **[6]**. Finding, evaluating, and planning for landfill sites is one of the most important steps in the MSW disposal process **[7,8]**.

According to their research, the number of households, employment, and population expansion all have a big influence on trash generation rates. Predicting a 70.6% rise in garbage by 2031, the LSTM model proved to be the most accurate in predicting future trends in waste. Planning effective waste management systems to accommodate the predicted rise in trash creation would need careful consideration of this forecast.

The aim of this study is to provide a framework for assessing the appropriateness of dump sites in various geographical areas. This framework is based on the Analytic Hierarchy Process (AHP) **[9],** which was utilized for multi-criteria decision analysis of possible landfill sites, linear regression was employed for population projection, and a convolutional neural network (CNN) **[10]** was utilized for NDVI/NDBI prediction **[11–13]**.

2. Literature Review

A number of review papers discussed GIS-based multicriteria spatial decision support systems for landfill siting suitability analysis. The factors considered for utilizing MCDA for landfill site suitability assessment **[16]**. The use of MCDA in tackling waste management problems emphasized the increasing complexity of waste management due to growing waste volumes and environmental concerns **[17]**. The review covered various MCDA techniques used in real-life waste management scenarios, highlighting their advantages and disadvantages compared to other approaches .

In **[18]** it was discussed that the challenges in solid waste management due to the increasing quantities and complexity of waste generated worldwide. They presented the importance of MCDA models in addressing the various dimensions and conflicting criteria involved in waste management. The study reviewed the current practices and methods of MCDA in SWM, emphasizing the need for tools to assess system performance comprehensively **[18]**.

Abujayyab et al. (2016) discussed GIS modelling for landfill site selection, focusing on the criteria and methods used for selection as the key challenges in determining landfill-siting input criteria, as discussed in the article, include the complexity of procedures, the need to consider environmental, economic, and social impacts, compliance with regulations, public acceptance, and the extensive evaluation required for selecting suitable landfill sites [19].

Abujayyab et al. (2017) explored the use of MCDA in GIS modeling for landfill site selection from 1997 to 2014 as the study focused on stages such as the selection of weights and decision rules in the models [20]. It identified strengths and limitations of using MCDA for landfill site selection and suggested the potential use of Artificial Neural Networks (ANN) for enhanced validation and accuracy [20].

Mat et al. (2017) discussed the criteria and decision-making techniques used in solving landfill site selection problems, it highlighted the importance of selecting appropriate landfill sites and the use of GIS and MCDA techniques in this process [21]. More recently, the review by Mohammed et al. (2019) discussed how the combination of GIS-based tools and decision analysis techniques has significantly expanded in various fields of research over the last few decades, allowing for the automation and analysis of spatial data [22].

3. Materials and methods:

3.1 Overview: The process for determining whether possible landfill sites are suitable and analyzing the spatiotemporal dynamics of several elements' influence is shown in **Figure 1**. The technique incorporates many data sources, such as population data from 2004 to 2024, Landsat satellite photos from 2004, 2014, and 2024, and climatic data including air temperature, rainfall, relative humidity, wind speed, and wind direction. Furthermore, soil texture, steady groundwater level, and slope GIS data are used.

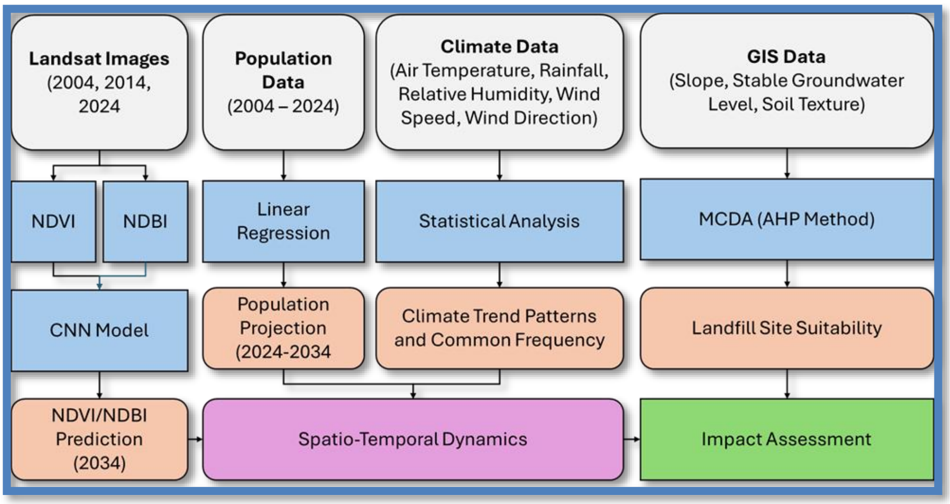

Figure 1: Flowchart of the proposed methodology overview

3.2 Study Area: This research focuses on Kirkuk City, the capital of the Kirkuk Governorate, which is situated in northern Iraq, along with its surrounding neighborhoods, including Taza and Leylan. Situated between the flat plains and the foothills of the Zagros

Mountains, Kirkuk City is located at 35°28'N 44°25'E. With a population that is expected to surpass 1.1 million by 2023 due to both natural growth and migration, this large metropolitan area is experiencing tremendous population increase. Significant urban sprawl has occurred in the city and its environs, with industrial zones primarily located on the periphery and residential and commercial sectors predominating in terms of land use. Figure 2 shows the study area.

Geographically, Kirkuk City is bordered to the north by the Zagros Mountains, to the east by the city of Sulaymaniyah, to the south by the Hamrin Mountains, and to the west by the Lower Zab Mountains. The area is around 250 kilometers away from Baghdad. The three districts of Kirkuk City, Laylan, and Taza comprise the 1368.34 km2 that make up the Kirkuk study area. Its landscape is varied, with heights ranging from 192 to 713 meters above sea level and features both flat sections and quite steep hills.

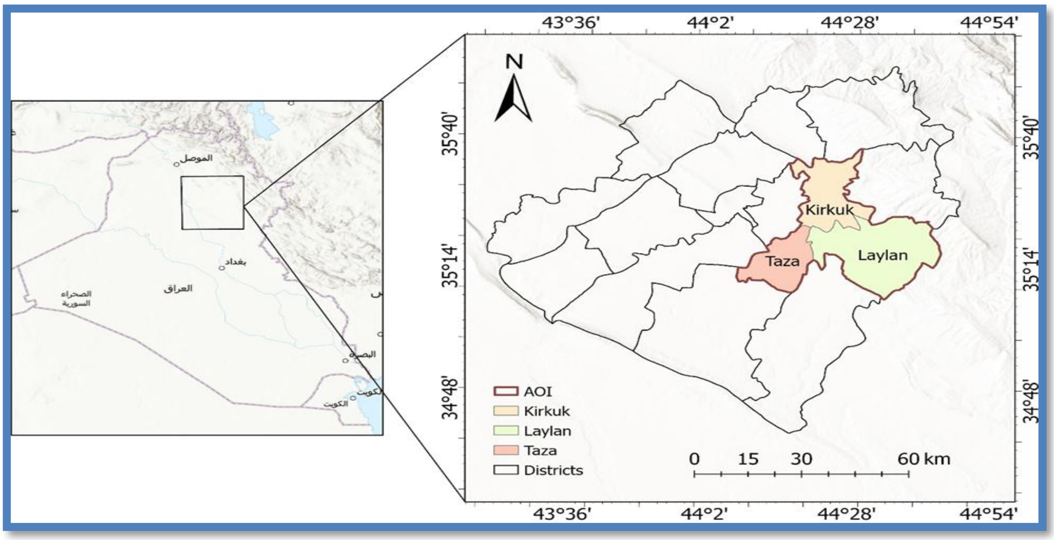

Figure 2: Map of the study including three districts of Kirkuk province (Kirkuk city, Laylan, and Taza).

3.3 Datasets

3.3.1 Landsat Data: Four images total from Landsat satellites were used in the investigation. As shown in **Table 1**. The dataset contains atmospherically corrected surface reflectance and land surface temperature derived from the data produced by the Landsat 8 OLI/TIRS sensors.

Table 1: Information on Landsat images obtained for this study.

Landsat Image	Sensor	Row	Path	Date	Cloud Cover	Processing Level
Image 2004-1	LANDSAT 5 TM	035	169	2004-03-18	18.00	L1TP
Image 2004-2	LANDSAT 5 TM	036	169	2004-03-18	2.00	L1TP
Image 2014	LANDSAT 8 OLI TIRS	035	169	2014-03-28	30.88	L1TP
Image 2024	LANDSAT 8 OLI TIRS	035	169	2024-03-01	1.35	L1TP

3.3.2 Population Data: The Department of Urban Planning in Kirkuk provides the demographic figures. The information was collected annually between 2004 and 2023. In terms of population, Kirkuk is the largest of the three cities. Between 2004 and 2023, the population grew gradually, from 566,000 to 1,075,000. According to the data, the population is growing by between 30,000 and 40,000 people every year on average. Although Taza is a smaller city than Kirkuk, its population has been increasing more quickly. The population of Taza rose from 12,715 in 2004 to 51,119 in 2023. With the population growing by about 2,000 per year in the earlier years and then by about 3,000 to 4,000 per year in the more recent years, the growth rate seems to be quickening. In terms of population, Laylan is the smallest of the three cities. Between 2004 and 2023, its population grew from 14,887 to 20,881. The population of Laylan is growing by a few hundred each year, which seems to be a slower pace of growth than that of Kirkuk and Taza.

3.3.3 Climate Data: The Kirkuk station's meteorological section provides climatic data. The monthly statistics were collected between 2014 and 2023. Included in the climatic variables are air temperature, precipitation, relative humidity, wind direction, and wind speed.

3.3.4 GIS Data: Three primary factors—the soil texture and steady groundwater level—were taken into consideration while determining the viability of a landfill site. The research area's DEM data was used to derive the slope. With a spatial resolution of 30 m, the DEM was acquired from ASTER GDEM (https://gdemdl.aster.jspacesystems.or.jp/). The soil texture was taken from a 1:250000 scale raster map of the Iraqi Geological Survey.

3.4 Methods

3.4.1 Remote Sensing Indices: This investigation made use of several indices. These consist of NDBI and NDVI. The density of greenness on the ground surface is indicated by the NDVI measure, which is why it was chosen in this study. As such, it is an important factor to take into account while choosing a suitable landfill site. Equation (1) was utilized to create the NDVI using the Landsat-8 OLI dataset, as shown in reference **[13]**.

$$\mathrm{NDWI} = \rho_{\mathrm{green}} - \rho_{\mathrm{NIR}} / \rho_{\mathrm{green}} + \rho_{\mathrm{NIR}} \qquad \textbf{(1)}$$

Where ρ_{green} and ρ_{NIR} are the green and the near infrared satellite image bands, respectively.

The size and geographic distribution of the research area's urban built-up areas are evaluated using the NDBI and related computations. It also offers a thorough overview of the land cover in cities. This study's NDBI map was produced using the Landsat-8 OLI dataset. For relevant computations, the near-infrared (NIR) and shortwave infrared (SWIR) bands were used, as shown in Equation (1) **[14]**.

3.4.3 CNN

3.4.3.1 CNN Background: Convolutional operations are used on 2D input data, such as photographs or spatial grids, in order to extract significant features and patterns. This is the fundamental theory of CNNs **[15]**. In a regular Neural Network, there are three types of layers:

Input Layers: It's the layer in which we give input to our model. The number of neurons in this layer is equal to the total number of features in our data (number of pixels in the case of an image). Hidden Layer: The input from the Input layer is then fed into the hidden layer. There can be many hidden layers depending on our model and data size. Each hidden layer can have different numbers of neurons, which are generally greater than the number of features. The output from each layer is computed by matrix multiplication of the output of the previous layer with learnable weights of that layer and then by the addition of learnable biases, followed by an activation function, which makes the network nonlinear. Output Layer: The output from the hidden layer is then fed into a logistic function, like sigmoid or softmax, which converts the output of each class into the probability score of each class.

3.4.3.2 Patch Extraction: The input images are usually processed in discrete areas, known as patches, using CNNs. The input image is divided into smaller patches, or tiles, as part of the patch extraction process. These patches are then fed into the CNN's convolutional layers. The input picture is frequently padded with zeros around the borders prior to patch extraction. The purpose of this padding is to guarantee that patches close to the image's edge may be removed without running out of data. The size of the patches being extracted determines how much padding is needed.

3.4.3.3 Proposed CNN Architecture: One convolutional layer, one flattening layer, and two fully connected dense layers make up the CNN design that the study suggests. With data from 2014 and 2024, this CNN model is intended to forecast the NDVI and NDBI for the year 2034. The input data is passed through 32 convolutional filters of size 2x2 by the model's first layer, a 2D convolutional layer. The input shape is (3, 3, 2), where the number of channels (corresponding to NDVI and NDBI data) is represented by 2 and the spatial dimensions of the input data are represented by 3x3. This layer's output is subjected to the ReLU activation function. The convolutional layer's output is flattened into a 1D vector by the flattening layer, which prepares it for the fully connected layers that follow. The ReLU activation function is applied to the output by the following fully connected layer in the model, which consists of 16 neurons.

3.5 Validation: The actual observed data for 2024 was compared with the model's predictions as part of the validation procedure. The NDVI and NDBI values for 2024 were predicted by the algorithm after it had been trained using data between 2004 and 2014. The performance of the model was then assessed by comparing the projected values for 2024 with the actual observed values for 2024.

4. Results and Discussions

4.1 Results of NDVI/NDBI Prediction: Figure 1 shows the NDVI changes for a study region in 2004, 2014, and 2024. Higher values (darker green) in the NDVI indicate denser vegetation, whereas lower values (yellow/brown) indicate scant or no vegetation, such as in urban or desolate environments. A variety of plant densities were observed in the study region in 2004. Some areas, especially in the northern and southern parts, have extremely thick vegetation (dark green). Significant regions with moderate to low plant cover, which are represented by yellow and lighter green hues, are found as well; these areas are thought to be urban or developed areas. The research area's total vegetation density seems to have decreased by 2014. Particularly in the central and eastern sections, the forested areas have given way to urban or arid areas. The size of the dark green, high NDVI zones has shrunk, suggesting more urban or arid territory. The trend of declining vegetation density is expected to continue in 2024. A reduced percentage of the study area is currently covered by the highest, darkest green NDVI values, especially in the central and eastern parts. Comparing this year to last, there has been greater growth in the yellow, arid/urban regions. The NDVI variations between 2004 and 2024 indicate that the study area's vegetation is gradually getting less dense and dispersed. This may be brought on by things like changes in farming techniques that result in less plant cover, deforestation, or urban growth.

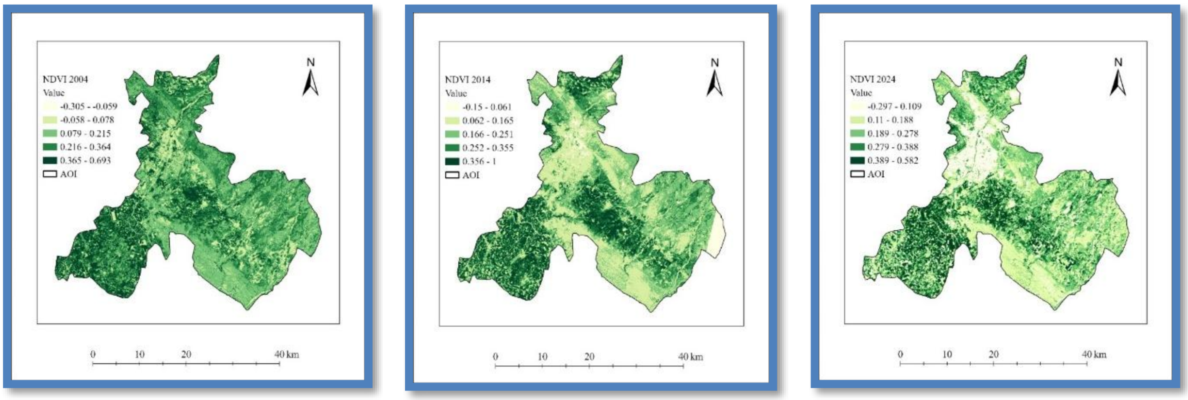

Figure 3: NDVI maps of the study area, (a) 2004, (b) 2014, and (c) 2024.

The maps in **Figure 1** depict the NDBI for the research area for the years 2004, 2014, and 2024. Oranges and reds denote greater values, indicating the presence of urban and arid areas. The NDBI values are represented using a color scale. Over the course of the three years, the mapped area's two main regions, the center and the southeast, have seen the greatest concentration of urban and desolate lands, shown by orange and red. These areas probably belong to large cities or metropolitan areas. The greater regions covered in orange and red on the 2014 map compared to the 2004 image indicate an increase in the size of urban and desolate lands between 2004 and 2014. The growth of urban and arid regions is evident in the 2024 image, which has even more areas covered in orange and red than the 2014 map had. The temporal variations point to a continuous pattern of urban sprawl and the spread of arid areas over time, with the pace of expansion seeming to be faster between 2014 and 2024 than it was between 2004 and 2014.

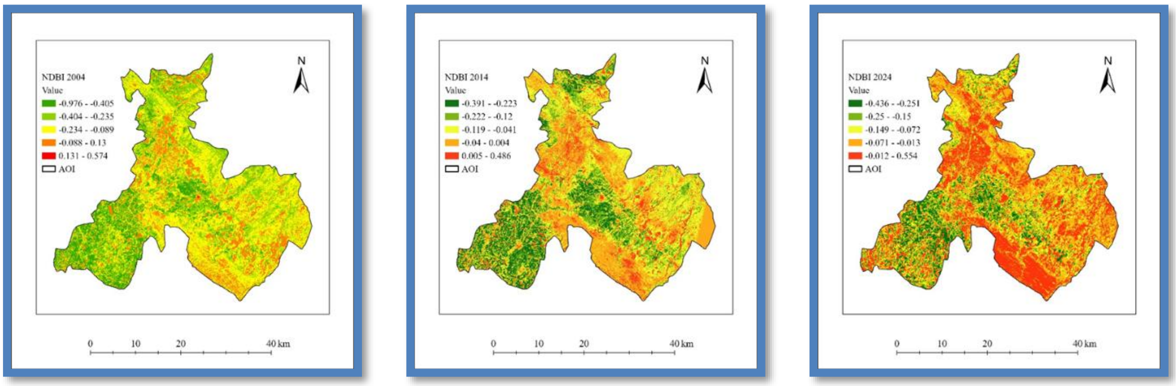

Figure 4: NDBI maps of the study area, (a) 2004, (b) 2014, and (c) 2024.

The NDVI for the research region in 2024 and the expected NDVI for 2034 are displayed in Figure 3. The NDVI readings show different degrees of plant density and health, ranging from -0.297 to 1 (green to red hues). Lower values (redder colors) denote scant or stressed vegetation, whereas higher values (greener shades) indicate denser and healthier plant cover. In comparison to 2024, the regional distribution of vegetation appears to have shifted dramatically, with some places seeing a loss of vegetation and others seeing a gain. The yellow/beige tint indicates where certain regions with moderate to high NDVI values in 2024 are expected to have little to no vegetation in 2034. The 2034 NDVI forecast shows that there won't be any appreciable changes to the plant cover.

These plant cover changes may have an influence on landfill siting because of the following possible effects. Because of possible ecological effects, places with sparse vegetation can be a better fit for landfill development than those with extensive vegetation. The anticipated alterations in the plant cover can be a result of infrastructure growth, urbanization, or other changes in land use that could affect whether possible landfill locations are suitable. To reduce soil erosion and regulate surface runoff, vegetation cover is essential. Variations in plant types may have an impact on surface water runoff and leachate management at landfills. During the site selection process, it may be necessary to take vegetation into account since it might affect the visual effect and public impression of a possible landfill site. Significant changes in the amount of vegetation might have an influence on the surrounding ecosystems, sometimes necessitating mitigation strategies or careful site selection to reduce effects on species or habitats that are vulnerable.

The NDBI for 2024 and the expected NDBI for 2034 are depicted in Figure 4. Warmer hues (yellow, orange, and red) indicate higher amounts of built-up or barren regions, whereas cooler colors (green) indicate vegetated areas. The NDBI values vary from -0.436 to 0.1. Compared to 2024, there seems to have been a considerable shift in the geographic distribution of developed and undeveloped regions, with certain places becoming more urbanized. It is anticipated that certain places with moderate to low NDBI values in 2024 will have high NDBI values (red) in 2034, suggesting a rise in built-up or bare areas, most likely because of urban growth or expansion. It is anticipated that certain regions with high 2024 NDBI values would have lower 2034 NDBI values (green), indicating a possible reduction in built-up areas or opportunity for revegetation or redevelopment.

The alterations in developed and undeveloped regions may have consequences for the location of landfills because of the subsequent elements and their effects. While locations with less built-up areas may provide more possible sites, areas with rising urbanization may have limited acreage available for landfill construction. Transportation networks and infrastructure may be easier to reach in urbanized regions, which might make it easier to move garbage to possible disposal locations. Higher densities of impermeable surfaces may be found in highly developed regions, which might increase surface runoff and require more thorough stormwater management at landfill sites. Potential landfill locations may get closer to residential areas because of increased urbanization, which might cause residents to worry about noise, odor, and other annoyances. Redevelopment of brownfields and the cleanup of previously constructed sites might be opportunities in regions with declining built-up areas and should be taken into consideration when choosing where to locate landfills.

4.2 Results of Landfill Site Suitability Assessment: A weighted average of the soil type weights, stable groundwater level, and criteria slope from earlier studies is used to assess the area's appropriateness for landfills. A map illustrating the research region's landfill suitability is shown in Figure 5. The appropriateness is broken down into five categories, as indicated by the map: very low, low, moderate, high, and very high. Several colored zones on the map represent different degrees of appropriateness for the establishment of a landfill. The areas for the five appropriateness levels—219.25, 305.30, 181.49, 304.10, and 354.84 km2—are displayed in the chart. The research region's northern regions exhibit varying degrees of eligibility for disposal locations. The red and yellow hues indicate that the region's eastern and southeast have very low and low suitability ratings, respectively. The land's southernmost portion is more favorable—in fact, exceptionally suited. Four landfill sites were chosen based on the suitability map and the accessible lands (**Figure 5**).

Site 3 is the ideal option since it implies typically flat terrain with low population density and a shallow water table, among other critical features. It has the largest population (16.922), the lowest slope (1.955), the highest landfill compatibility score (0.316), and a stable groundwater level (204.159m). It is also the closest to cities (3522.0m) and water (817.6m), which may or may not be useful depending on the circumstances. Even yet, the present landfill is rather far away (15120.5m). Site 1 is feasible as well, having the lowest slope (1.867), population (9.909), and NDVI (0.101, indicating little vegetation), in addition to having an intermediate landfill suitability (0.283). Although it is closer to water (1192.2m) than Sites 2 and 4, its closeness to towns and cities (2878.6m and 3735.4m) may provide issues.

Table 2: Weights for the landfill site suitability criteria provided by the experts questioned in this study and AHP methodology.

Main Criteria	Weight	Sub–criteria	Sub–Weights
Slope	0.310	0 – 3	0.163
		3 – 6	0.111
		6 – 9	0.034
		9 – 35.638	٠
Groundwater stable level	0.333	0.388 - 112	0.173
		113 - 224	0.136
		225 - 336	0.018
		337 - 448	0.005
		449 - 560	٠
Soil types	0.356	Injana Formation	0.050
		Kirkuk group	0.011
		Valley Fill Deposits	0.038
		Sheet Runoff Deposits	0.072
		Bai Hassan Formation	0.026
		Slope Deposits	0.074
		Poly Genetic	0.072
		Jaddala and Avanah Formation	0.011
Sum	1		1

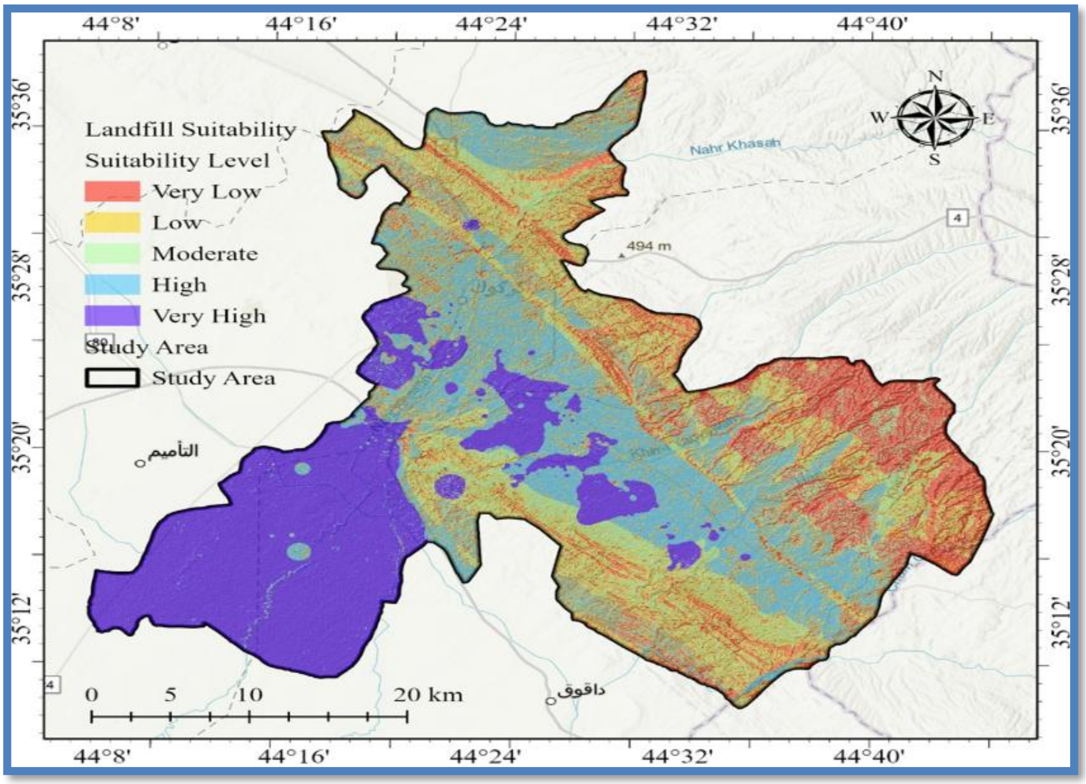

Figure 5: Map of landfill suitability in the study area.

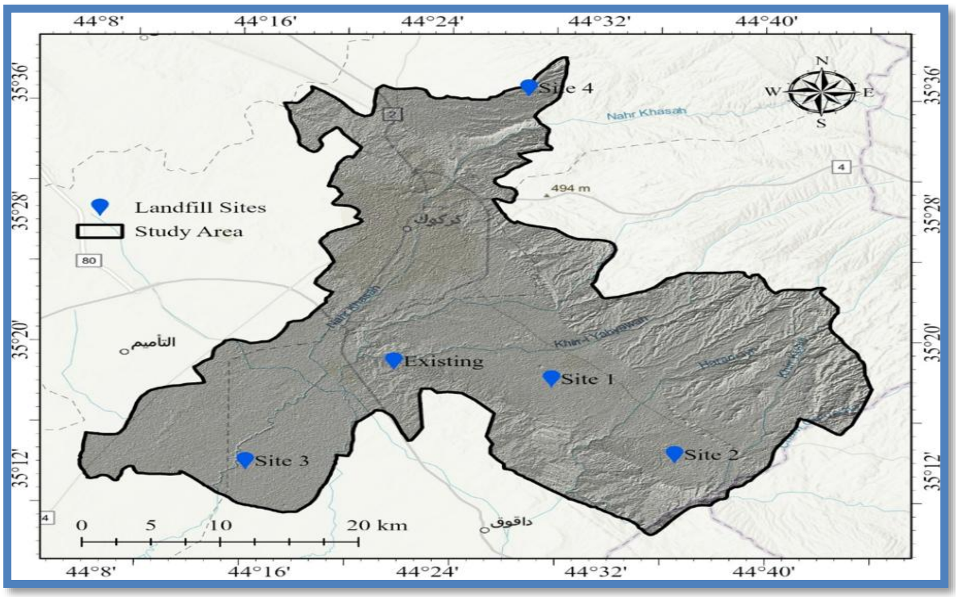

Figure 6: Map of landfill site locations including the existing and selected sites.

4. Conclusions

Significant trends in land use changes, climatic patterns, and population increase were found in Kirkuk City throughout our analysis. These patterns point to a significant rise in solid waste creation in the future, as do population estimates. The study developed a methodology for the spatiotemporal assessment of possible landfill sites to overcome this difficulty. This approach considers social, economic, and environmental aspects, such as land cost, population density, soil texture and groundwater levels. The study selected landfill locations that minimize environmental effects and enhance sustainable waste management by combining these through a multi-criteria decision analysis. For Kirkuk City urban planners, this study offers insightful information. The methodology of data-driven landfill site selection provides a model for comparable assessments in other areas. Moreover, the anticipated rise in trash production highlights the pressing necessity for enhanced waste management facilities inside the city. By putting our suggestions into effect, Kirkuk City's waste management procedures may have a more sustainable future.

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