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Combining AHP and ROC with GIS for Airport Site Selection: A Case Study in Libya

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Abstract: Choosing airport locations requires thorough and comprehensive decisions to be made. To do so in a professional and logical manner is crucial for the social, economic, and logistic settings intended for any region. The present research takes place in Libya, where airports are just as vital for the economy in terms of tourism and investment by allowing for improved transportation throughout the developing market and supplier locations as well as trading between the industrial and financial sectors. For this reason, using the geographic information system (GIS) to determine the appropriate airport site, twenty-three criteria were considered. In addition, two different methods—analytic hierarchy process (AHP) and rank order centroid (ROC)—were utilized to derive the related weights. The comparison of the output maps from these two distinctive approaches shows that both approaches provide identical results. Finally, a sensitivity analysis was carried out to evaluate the reliability of the method used and select the best site among the proposed ones based on the result of the highest suitability index for each candidate site. This research provides a siting approach and substantial support for decision-makers in the issue of airport locations selection in Libya and other developing countries.

Keywords: airport; Libya; GIS; AHP; ROC; sensitivity analysis

1. Introduction

Airports are major foundations, playing prominent and critical parts for any country's economy. An airport represents a considerable project in infrastructure, and its participation in communications expansion will be an important motivation to regional development.

For this, proper plans in this respect can greatly influence logistics at the local level and improve the economic prosperity and social settings.

The present work investigates airport site selection in the country of Libya, which is found in the north of the Africa continent, bordering the Mediterranean Sea on its 1770-km-long coastline.

Libya will be open in the future for tourists and investment, and the main center for connection between Europe and African countries, especially due to the fact that the African region is vast and is characterized by sparse passenger demand [1].

Such developments are of great significance as they help to accelerate developments in market–supplier and manufacturer–financier ties and dealings. Other establishments can also flourish as a result of tourism to production, to the service sector and beyond.

Also, the construction of a new airport in the selected study zone will serve people living there without nearby airport services. All such developments can, at the same time, improve regional welfare and prosperity using proper location and stability in transportation.

In this paper, we focus on airport service locations, whose cost and sustainability make them vital to be selected as carefully as viable. Airport construction is related to economy, national politics, technology, military affairs, geographical environment, transport networks, tourism, industrial enterprises [2], and so on, and is interlaced with a large and complicated system; hence, site selection is the most vital stage for the creation of a new airport. This task is considered a challenging task for decision-makers and planners due to the existence of a large volume of spatial data from different sources [3].

To solve the problem of selecting suitable sites for airports, the integration of the geographic information system (GIS) software and multi-criteria decision-making (MCDM) methods can be utilized, which represent a fast approach to achieve this aim. GIS is ideal for this type of study due to its high ability for processing and analyzing a large amount of spatial and nonspatial data from different sources in a short time [4–9].

MCDM methods were utilized to derive the selected criteria weights. After that, these weights were applied on the input layers (criteria maps) in GIS. The analytic hierarchy process (AHP) and rank order centroid (ROC) methods were two examples of MCDM methods used to derive the weights of criteria maps.

AHP was first proposed by Saaty [10], and it is one of the very common methods in MCDM (multi-criteria decision-making), which is a very powerful tool to tackle complicated decision-making processes that include numerous choices and alternatives [11]. Its main properties rely on the pairwise comparison matrix. AHP helps to decompose a complicated problem with numerous choices to several one-to-one comparisons. It is a powerful and easy tool for a qualitative and quantitative analysis of multi-criteria issues [12]. It is more convenient than the direct selecting of the weights since an expert could examine weights consistency by computing the consistency ratio (CR) in a pairwise comparison. Many researches used AHP with GIS to assess the criteria weights in the determining of suitable sites [4,13–19].

Among different weighting strategies recommended in the decision-making, rank-based strategies that change a criterion ranking order into algebraic weights have been asserted as a great practical choice between the ease of usage and quality of the choice result [20].

According to Barron and Barret, the weights obtained in this way are likely to be more accurate compared to those by decision-maker individuals who can easily and reassuringly disregard the minor changes in basically classifying the significance of each criterion, in particular should the outcomes appear close to that regarded acceptable by them.

Due to this consideration, some techniques have been devised to make ranking more possible for the so-called 'surrogate' weights to estimate the actual values of the weights; one is ROC [21].

The ROC weight method provides an approximation of the weights to reduce the maximum error of every weight by differentiating the centroid of all potential weights preserving the rank order of objective significance. It is more accurate than the other rank base formula and its based analysis is highly simple and efficient and supplies suitable implementation tools [22].

The integration of GIS and MCDM could effectively improve the capabilities and solve complicated spatial decision-making problems [23].

Lastly, a sensitivity analysis was carried out to evaluate the reliability of the method used and select the best site among the proposed ones. Sensitivity analysis is utilized for assessing how sensitive outputs are to small changes in the inputs. If the changes do not influence the outputs considerably, then the ranking is presumed to be robust and satisfactory. Otherwise, one has to return to the problem formulation stage [24].

The present study initially aims to create a methodology incorporating both ArcGIS 10.5 and the AHP and ROC methods (MCDM methods) and to apply this methodology to a region in the north of Libya. Besides, the comparison method was used to calculate the pixel percentage of matching and non-matching areas for the output maps resulted from AHP and ROC methods, and to select the best site among the proposed sites, a sensitivity analysis was used.

This study was carried out in several stages according to the following:

- A spatial and non-spatial analysis was carried out to obtain some information and characteristics about the area and narrow the area under research to determine the study zone.

- The relevant data were collected based on the local features of the study zone, applicable rules, regulations, a literature review of previous researches, expert opinion, and availability of the data including maps, documents, etc.
- All the collected data (23 criteria) were geo-referenced, rectified, manipulated, rasterized, and reclassified.
- The relative importance weights of criteria and sub-criteria were evaluated, respectively, using AHP and ROC methods based on experts' opinions.
- All the weighted input layers were entered into the weighted overlay model of GIS to produce the suitability index map.
- Comparison analysis was carried out to determine the matching and non-matching area between the two output maps resulted from the applied AHP and ROC methods.
- Finally, sensitivity analysis was implemented to evaluate the reliability of the method used and select the best site among the proposed ones based on the result of the highest suitability index for each candidate site.

2. Background

Many studies have been conducted by several researchers to find the best location for airports; some have viewed this issue from the perspective of civil airport site selection, using GIS [25], evaluating passengers' choice [26], utilizing different evaluative approaches to compare programs with each other [27], or initiating the models of airport location based on different indicators [28].

From the literature review for selecting the best airport location from past to present, Bambiger and Vandersypen [29] mainly applied a qualitative multi-criteria evaluation to the airport site problem, followed by Neufville and Keeney [30], who researched airport location and applied the multi-attribute utility (MAU) method to assess two alternative airport locations near Mexico City.

Horner [31], who applied the location-allocation algorithm technique to review the location of airports and airstrips in Ireland, considered distance minimization with respect to population distribution. Saatcioglu [32] used three approaches of programming models to determine airport site location with different attributes for each model. Neufville [33] used an approach which provides insurance against risks and was associated with a strategy to cope with uncertainties.

Janic and Reggiani [34] found the same outcomes when applying three methods of multi-criteria decision making, including AHP, simple additive weighting (SAW) and the technique for order preference by similarity to the ideal solution (TOPSIS) on seven preselected airport sites as potential locations to select a new hub airport for a hypothetical European Union airline.

Again, Wang [35] established the index system of the model and used the expert knowledge system. Sur and Majumder [36] used the mathematical entropy model and construction cost per person as criteria to assist the alternatives for the determination of airport site location in developing countries. Yang et al. [37] expanded a quantitative technique to determine optimal airport locations by taking into consideration the accessibility to airports by airside and surface transportation. Hammad et al. [38] developed an optimization model of a multi-objective, mixed integer linear programming (MILP) model used to solve a problem formulated as a bi-level program.

Sennaroglu et al. [39] performed a study to select the best location for the military airport among several candidate locations using MCDM methods. The AHP method was used to determine the criteria weights. VIKOR, PROMETHEE, Multi-Attributive Border Approximation Area Comparison (MABAC), Multi-Attributive Ideal-Real Comparative Analysis (MAIRCA), and Complex Proportional Assessment (COPRAS) methods were used for the ranking process. After the comparison of the result, they found that all methods provide the same result.

Lastly, Zhao et al. [13] focused on the importance of bird ecological conservation when selecting an airport location by avoiding the construction of an airport on bird migration routes. They carried out a study to decide either to extend the existing airport or relocate to the planned one. The authors assessed the effect of the two airports on the birds' environment using the AHP approach to derive the chosen criteria weights and an expert-based approach to evaluation. The overall environmental impact assessment showed that the planned airport was a favorable choice because it had less impact on the birds' environment.

From the literature above, two different approaches of solutions relating to the problem of airport location were found, namely a ranking approach (factor assessment) and an optimization approach (mathematical approaches). Some drawbacks were found in both approaches, as summarized as follows:

- In ranking problems, it is mainly to predefine the potential locations of airports which are to be subsequently evaluated, despite it being possible to unintentionally overlook some potentially better locations [40].
- In the optimization problem, the criteria being used seem to be too narrow, which in most cases consists of the population size and the distance to the airport [40].
- Objective analysis and subjective judgment are the main components of the methods which require weighted computation. The defect of subjective judgment is that it is too dependent on the experience of experts.
- On the other hand, the disadvantage of objective analysis is that the experts' experience and knowledge is disregarded and the results which are obtained via computing devices may deviate from the actual [41].
- In models using grids, the defect is that it cannot disregard grids that are unsuitable for the location of an airport because of geographical factors such as buildings and mountains, etc., or considerations of urban density such as proximity to very densely populated regions [37].

To overcome the drawbacks of the approaches mentioned above and to improve the quality of solving the problem of the airport location, integrating GIS software with MCDM methods is proposed for the following reasons:

- Advanced analytical tools and new technology such as the GIS have been considered as the most significant factors in supplying better information and acquiring greater reliable outcomes when applied in the decision-making process for site selection. Thus, the main purpose behind GIS's notoriety is that it integrates spatial data such as satellite images, aerial photographs besides maps with qualitative, quantitative, and descriptive info databases [42]. Regarding the assessment of appropriate locations for airport site selection, GIS contributes as the main decision tool for perceiving economically and environmentally viable sites, making use of large quantities of spatial data associated with diverse technical, economic, social and environmental criteria.
- The integration of GIS and AHP extremely facilitates the decision-making task [43].
- GIS-based Multi-Criteria Decision Making provides a combination of powerful tools and methods converting non-spatial and spatial data into information in the decision maker's rule [44].
- Using the GIS, the defect of not eliminating the grids which are unsuitable for an airport location due to geographical factors or urban density considerations will be controlled [37].
- MCDM, which deals basically with evaluating decision issues and assessing the choices depend on a decision maker's values and inclinations, needs the ability to handle spatial data (for instance, buffering and overlay) that are necessary to spatial analysis.

3. Study Area

This area is located in the northern part of Libya between the longitude lines from 18°00′00″ to 20°30′00″E and latitude lines from 29°00′00″ to 31°00′00″N, as depicted in Figure 1. It is about 42,254 km^2, which represents 2.4% of the total land area of Libya with a population of approximately 350,000 inhabitants in 2019 [45], which represents 5.133% of the total population in Libya. The main income sources of this population are petroleum industries. The study zone, one of the most important industrial areas and closest to the coast of the Mediterranean Sea, is considered to be the main location for the petrochemical industries in Libya, with a rather dry climate, in particular between the months of April and October, and more precipitation between November and March. There is about 320 mm of rain in this region the year around at a temperature varying between 5 °C in the cold season to as high as 40 °C in the warm season, averaging 21 °C annually.

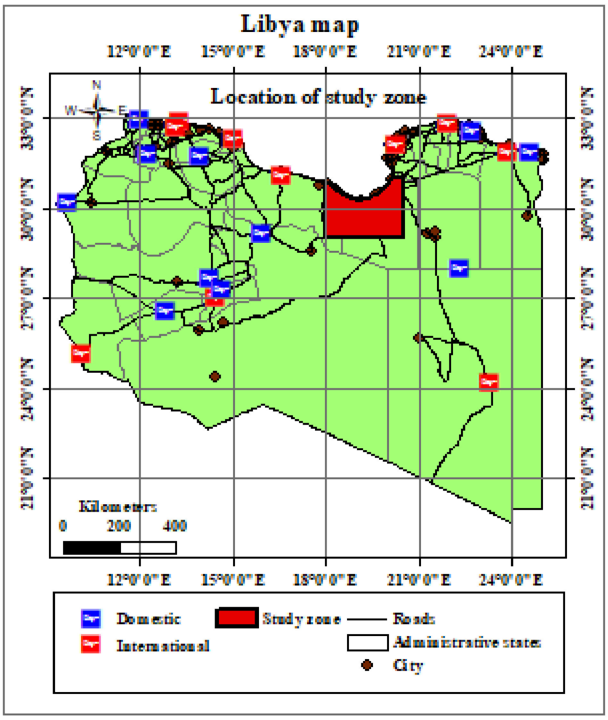


Figure 1. Location of the study zone.

In general, site selection begins utilizing several stages, initially applying spatial analysis to the already acquired data and features related to the region in point to limit its size into smaller zones that can be handled more easily [46]. The resulting zones are more likely to accommodate the right site qualities. Next, these zones are assessed more intricately to choose the best ones. Lastly, these shortlisted zones are examined by pre-determined and site-specific parameters to single out the most appropriate one for airport construction. All this, naturally, implies that the entire process is intensive as narrowing down continues. Such a stage-by-stage approach is quite common for choosing the right spot due to clarity and the economy of time and financing. What is more, and mostly in advancing countries, the absence of the right information and pre-requisites to choose a location quickly call for a phased method as described here and regarded most efficiently.

Applying spatial statistics, we can know the modeling of spatial distributions, processes, patterns, and correlation.

- By determining the location of the mean and median of all cities, we find the location of mean and median are close to each other which means the outlier cities do not affect the location of the mean center of cities. Consequently, this location will serve most cities located beside it.
- By determining the location of the mean of international airports, we find that it is close to the location of the mean of all cities.
- The result of calculating the standard distance of the cities (to show concentration or dispersion of cities) shows the most cities are concentrating and distributing inside the standard distance along the coastal strip.
- The calculated directional distribution of cities (measuring the directional trend in the data along with the central tendency and dispersion) shows the x-axis is longer than the y-axis, which means

the distribution of the population density is higher in the direction of the x-axis from east to west and vice versa.

- Average nearest neighbor (ANN) measures the distance between each city centroid and its nearest neighbor's centroid. If the ANN ratio is less than 1, we can say that the data exhibit a clustered pattern, whereas a value greater than 1 indicates a dispersed pattern in the data. From the spatial analysis result, as depicted in Figure 2, the ANN ratio is equal to 0.635 which means a clustered pattern. So, we may construct an airport in each cluster or construct it in the middle of all the clusters.
- Line density analysis of the main roads shows the heavy density of roads is located in the coastal strip where there is a high percentage of the population, so the construction of a new airport will mitigate the way of transportation between cities.
- The linear directional mean analysis of the roads (identifying the mean direction or the mean orientation for a set of roads) indicates the linear directional mean of the roads is from east to west and vice versa, which means heavy traffic in that area.

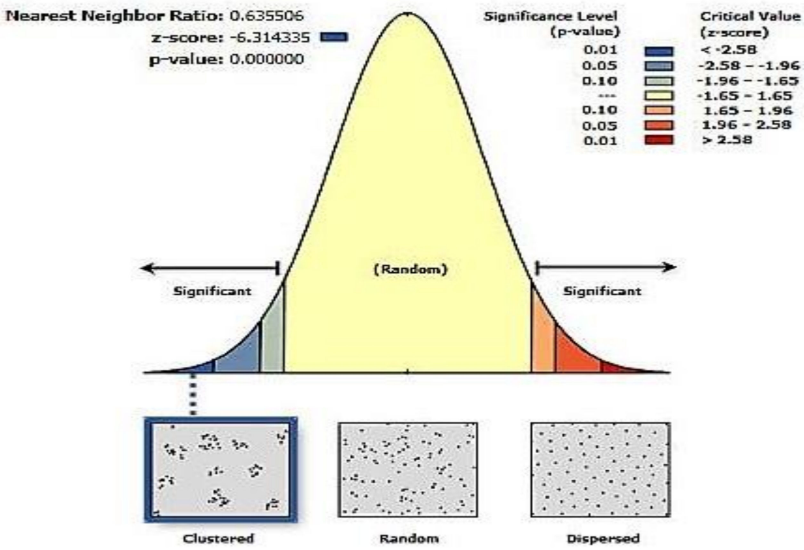


Figure 2. Average nearest neighbor result.

From the previous analyses, the obtained results are collected in Figure 3, and notice that the vital region is located in the middle of the north nearest to the coastal strip.

From the literature, the factors most commonly considered for selecting airport locations are the population size and the airport service cover distance [40]. Considering that a maximum radius of 150 km has been selected to identify airports close to each other [47], any existing airport can serve the people of neighboring cities located within that area of such radius.

It was observed that there are about eleven cities with an aggregated population of more than 350,000 inhabitants located out of the range of the circle (see Figure 4). It should be noted that the study zone is situated in the north part of Libya, where more than 80% of the total inhabitants of the country live; the location is near the mean center of cities, near the mean center of Libyan national airports, within the standard distance and directional distribution (68% of cities lie within the standard distance), in the direction of linear directional mean of major roads and all roads, and located between two existing airports with a distance of about 600 km between them.

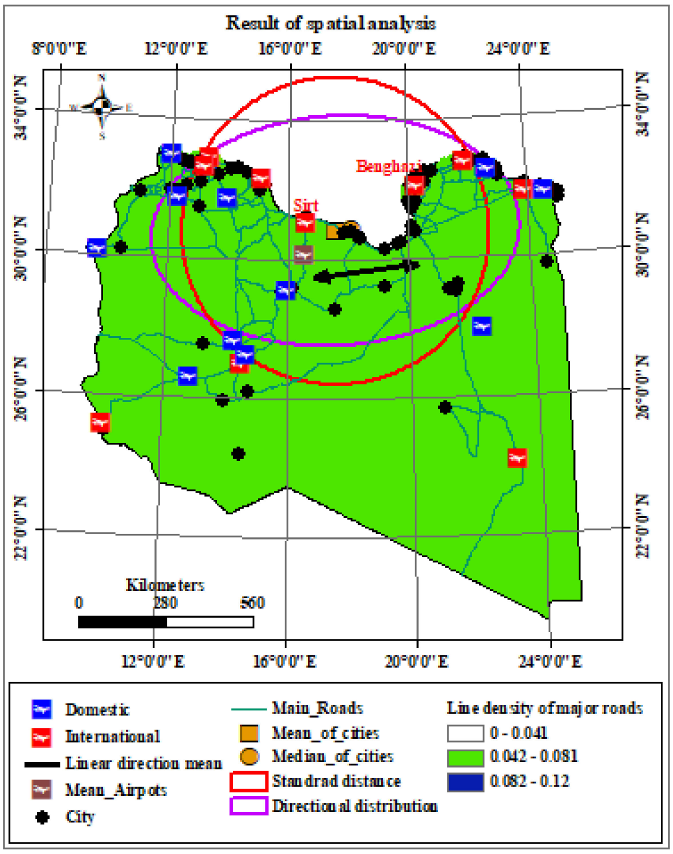


Figure 3. Result of spatial analysis.

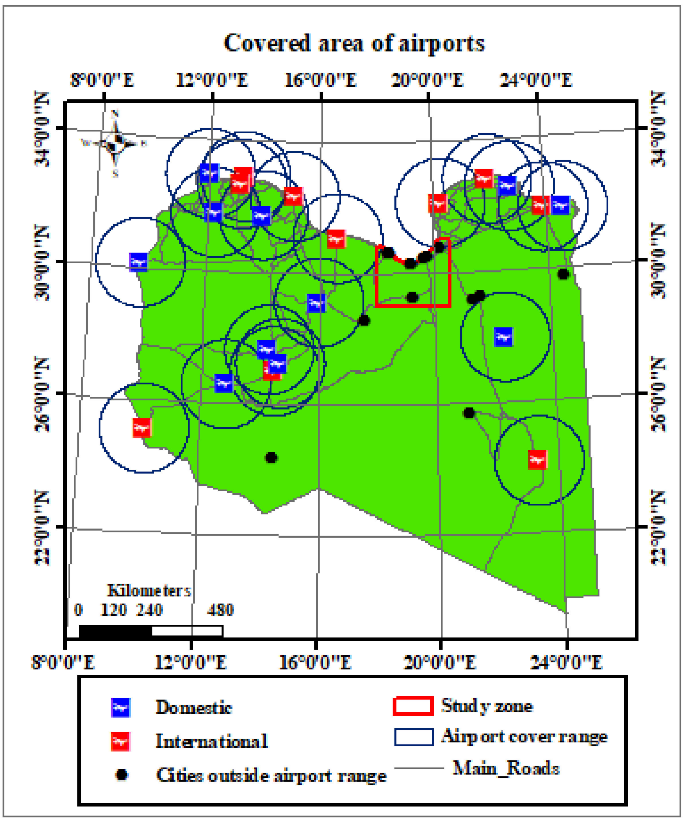


Figure 4. Cities outside the airports' range area.

To sum up, the study zone was determined based on the following:

1. The analysis of spatial distributions and patterns.
2. As this study region is approximately mid-way to the cities of Benghazi and Sirte that are about 600 km apart. Additionally, there is no civil airport in that zone, not to mention the population of about 306,863 inhabitants without any air transportation facilities.

4. Methodology

Environmental systems research institute GIS (Esri ArcGIS version 10.5 software) and two methods of MCDM (AHP and ROC) were used to determine an airport site according to the flowchart illustrated in Figure 5.

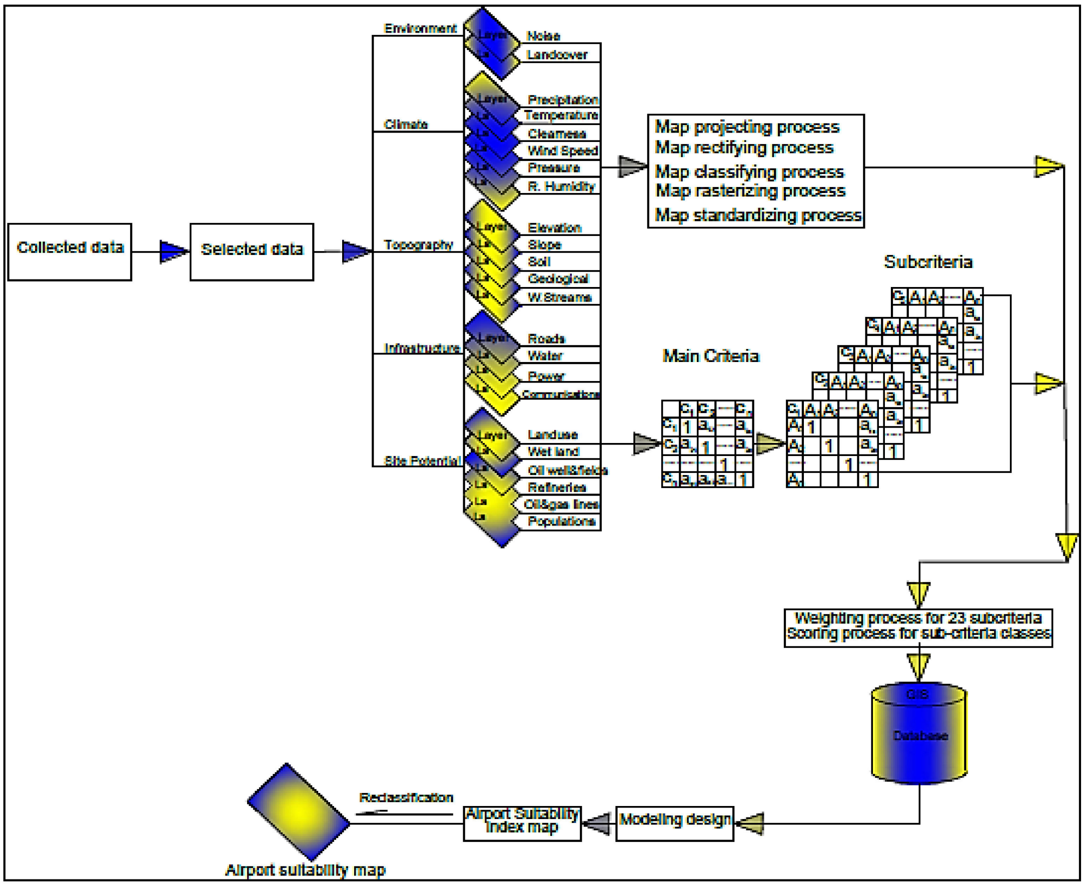


Figure 5. The flow chart of the methodology stages.

4.1. Selection of Criteria

The choice of the relevant criteria has been based totally on the local features of the study zone, applicable rules, regulations (International Civil Aviation Organization (ICAO) [48–50], Federal Aviation Administration (FAA) [51]), literature review of previous researches (e.g., Horner [31]; [32]; Min et al. [52]; Ballis [53]; Kassomenos et al. [54]; Hammad et al. [38]; Yang [37]), expert opinion, and availability of the data including maps, documents, etc.

The decision criteria used for selecting airport locations were classified into five main categories; namely, environmental considerations, topographical conditions, climatic factors, infrastructure facilities, and operational conditions. Each main criterion includes sub-criteria and each sub-criterion is classified as well. Thus, the total number of the applied criteria is 23, as depicted in Table 1.

Table 1. Criteria of study zone.

Number	Criterion	Number	Criterion
1	Distance from residential regions (noise and pollution)	13	Distance from water streams
2	Land cover	14	Proximity to roads
3	Precipitation	15	Proximity to water resources
4	Temperature	16	Proximity to power lines
5	Clearness index	17	Proximity to communications stations
6	Wind speed	18	Land use
7	Atmospheric pressure	19	Distance from wetland and wildlife
8	Relative humidity	20	Distance from oil wells and fields
9	Elevation above sea level	21	Distance from refineries and industrial factories
10	Slope of land	22	Distance from lines of oil and gas and
11	Soil characteristics	23	Proximity to cities centers
12	Distance from faults		

4.2. Data Collection and GIS Integration

All the input data utilized in this paper were collected from a wide diversity of sources that differ in resolution or scale, and prepared by digitizing, scanning, and geocoding the needed information. In addition, GIS methods such as intersection, union, buffering, interpolation, map algebra, and overlay were performed to prepare these maps (see Table 2).

Considering that the input data used in various organizations are usually developed and compiled intended for applications, they possess different formats and scales and utilize various systems of projections. All those data were geo-referenced within the GIS environment using the Transverse

Mercator projection system (LGD2006_Libya_TM_Zone_10 and Datum D_Libyan_Geodetic _Datum_2006). Afterward, numerous stages were followed in GIS to obtain the final required layers (such as extract, proximity, buffer, overlay, convert, and clip) and, finally, converting those vectors map (shapefiles) to a raster format.

Table 2. Criteria used, sources, format and scale/resolution factor.

Factor	Source	Format	Resolution or Scale	Utilized to Create Layer
Slope, elevations, water streams	United States geological Survey (USGS) Satellite Imagery [55] earthexplorer.usgs.gov	Digital	30 m x 30 m	Slope (%), elevation (m), distance from water stream
Roads, power lines poles, water resources, communication stations	Open Street Map Satellite Imagery [56] www.openstreetmap.org	Digital	Shapefiles	Proximity to roads, proximity to power lines poles, proximity to water resources, proximity to communication stations.
Precipitation, temperature, wind, atmospheric pressure, humidity, clearness index	National Aeronautics and Space Administration Satellite Imagery [57] power.larc.nasa.gov	Digital	Drawn by author. Data from 22 locations inside the area of study were entered into GIS software to implement interpolation between the point locations using the tool Kriging.	The appropriate degree of temperature (°C), the suitable wind speed (m/sec), the value of atmospheric pressure (KPa), the less value of relative humidity, the higher clearness index.
Oil and gas lines, oil fields and oil wells, refineries.	Petroleum geology of Libya [58]	Digital	Drawn by author	Distance from lines of oil and gas, distance from oil wells and discovery fields, distance from refineries and industrial factories
Land cover	Food and Agriculture Organization (FAO) Satellite Imagery lby_gc_adg [59]	Digital	Shapefiles downloaded, then prepared by the author	Selecting the appropriate land
Geological properties	Atlas Libya map 1:5,000,000 A field guidebook to the geology of Sirte Basin, Libya [60]	Hardcopy	Drawn by author	Distance from faults

Table 2. *Cont.*

Factor	Source	Format	Resolution or Scale	Utilized to Create Layer
Soil characteristics	Atlas Libya map 1:5,000,000	Hardcopy	Drawn by author	Select the suitable type of soil
Land use	openstreetmap.org [56]	Digital	1:2500	Select the appropriate land
Wetland and wildlife	openstreetmap.org [56]	Digital	1:2500	Distance from wetland and wildlife

For infrastructure data: Starting from version 10 Esri company developed a tool ArcGIS Editor OSM which we can download directly to the software. Using this tool, it is simple to download shapefiles of infrastructure for the required study zone. In addition, shapefiles can be downloaded directly from the site [61]; For climate data: (precipitation, temperature, wind, atmospheric pressure, humidity, clearness index), it was downloaded from NASA Imagery Satellite (power.larc.nasa.gov) and preparing the layers as the following: 1. Making grid of points for all study zone was done (22 points). 2. From the NASA satellite, we got an Excel file that contains the required data. 3. For every point in the grid, we calculate the average of the required data. 4. Entering the data for every point on the grid to GIS software and apply the command from Arc toolbox (3D analyst tools - Raster interpolation - Kriging). 5. Raster layer is obtained. For landcover layer: 1. The layer of Libya's landcover was downloaded from the source [59]. 2. Using the mask layer of the study zone and applying the command Extract- Clip from Arc Toolbox. 3. Geocoding the layer of landcover according to Libyan datum.

4.3. Criteria and Sub-Criteria Reclassifying and Weighing

Since every criterion layer has a unit that differs from the others, to carry out a weighted overlay process they need to be in typically the same units and, as such, require standardization to make the dimension units uniform—through which process, the scores typically lose their dimensions as well as their measurement unit [62]. All the input layers were converted to raster layers and reclassified to be entered into the weighted overlay to produce the suitability index map (see Figure 6). The information collected from the literature review, experts' opinions, and particular specifications about the safe distances and buffering zones to an airport site are used to determine the reclassifying task by assigning rating values from 1 to 9 (from the least to the most suitability), as highlighted in Table 3.

Table 3. Reclassification of input layers.

Main Criteria	Sub-Criteria	Reclassification	Score	Source
Environment considerations	Noise and pollution (distance from residential regions)	< 18,000 m 18,000 m– 25,000 m 25,000 m– 40,000 m > 40,000 m	1 9 7 3	[48,52,63]
	Land cover	Bare area Consolidated bare area Non-consolidated bare area Herbaceous sparse vegetation Sparse grassland Natural and semi natural vegetation Salt hardpans Closed to open shrubland Artificial surfaces and associated areas Water bodies	9 8 6 4 3 3 2 1 1 1	[64]
Climatic factors	Precipitation (mm/day)	0.522– 0.799 0.799– 0.977 0.977– 1.21	9 8 7	[49]
	Temperature (°C)	27.7– 33.3 33.4– 36.8	9 8	[49]
	Clearness index	0.081–0.185 0.185–0.263 0.263–0.31	7 8 9	[48]
	Wind speed (m/s)	3.8–4.02 4.03–4.22 4.23–4.56	9 8 7	[48,50,51]
	Atmospheric pressure (KPa)	98.75–99.98 99.98–100.84 100.84–101.54	7 8 9	[49]
	Relative humidity %	42.48–50.78 50.78–58.26 58.26–68.77	9 8 7	[49]

Table 3. *Cont.*

Main Criteria	Sub-Criteria	Reclassification	Score	Source
Topographical	Elevation (m)	< 0 0–131 131–227 > 227	1 9 8 7	[49]
	Slopes (%)	< 1.15 1.15–1.622 1.622–3.55 3.55–8.55 > 8.55	9 8 7 5 3	[49]
	Soil properties	Dry soil Shallow soil over compact rocks Desert soil Sedimentary soil Shallow soil over incoherent rock material Sand dunes with moving sands Salt soil	9 7 6 6 5 3 2	[48]
	Distance from faults	< 1000 m > 1000 m	1 9	[65]
	Distance from water streams	< 300 m > 300 m	1 9	[66]
Infrastructure	Proximity to major roads	< 100 m 100 m–5000 m 5000 m–10,000m 10,000 m–25,000 m > 25,000m	1 9 8 5 3	[47,48]
	Proximity to water resources	< 3000 m 3000 m – 6000 m 6000 m – 9000 m > 9000 m	9 7 5 2	[48]
	Proximity to power lines	< 3000 m 3000 m–6000 m 6000 m–12,000 m > 12,000 m	9 7 5 2	[48]
	Proximity to communications stations	< 5000 m 5000 m–10,000 m 10,000 m–15,000 m > 15,000 m	9 7 5 3	[48]
Operational conditions	Land use	Bare land Industrial Agricultural Sebka Residential Water tank	9 3 3 2 2 1	[48,67]
	Distance from wetland and wildlife	< 8000 m > 8000 m	1 9	[48,68]
	Distance from Oil wells and fields	< 8000 m > 8000 m	1 9	[69]
	Distance from Refineries	< 8000 m > 8000 m	1 9	[48,70]
	Distance from Lines of oil and gas	< 500 m > 500 m	1 9	[48,71]
	Proximity to cities centers	< 10,000 m 10,000 m–20,000 m 20,000 m–30,000 m 30,000 m–40,000 m > 40,000	9 8 7 5 3	[48]

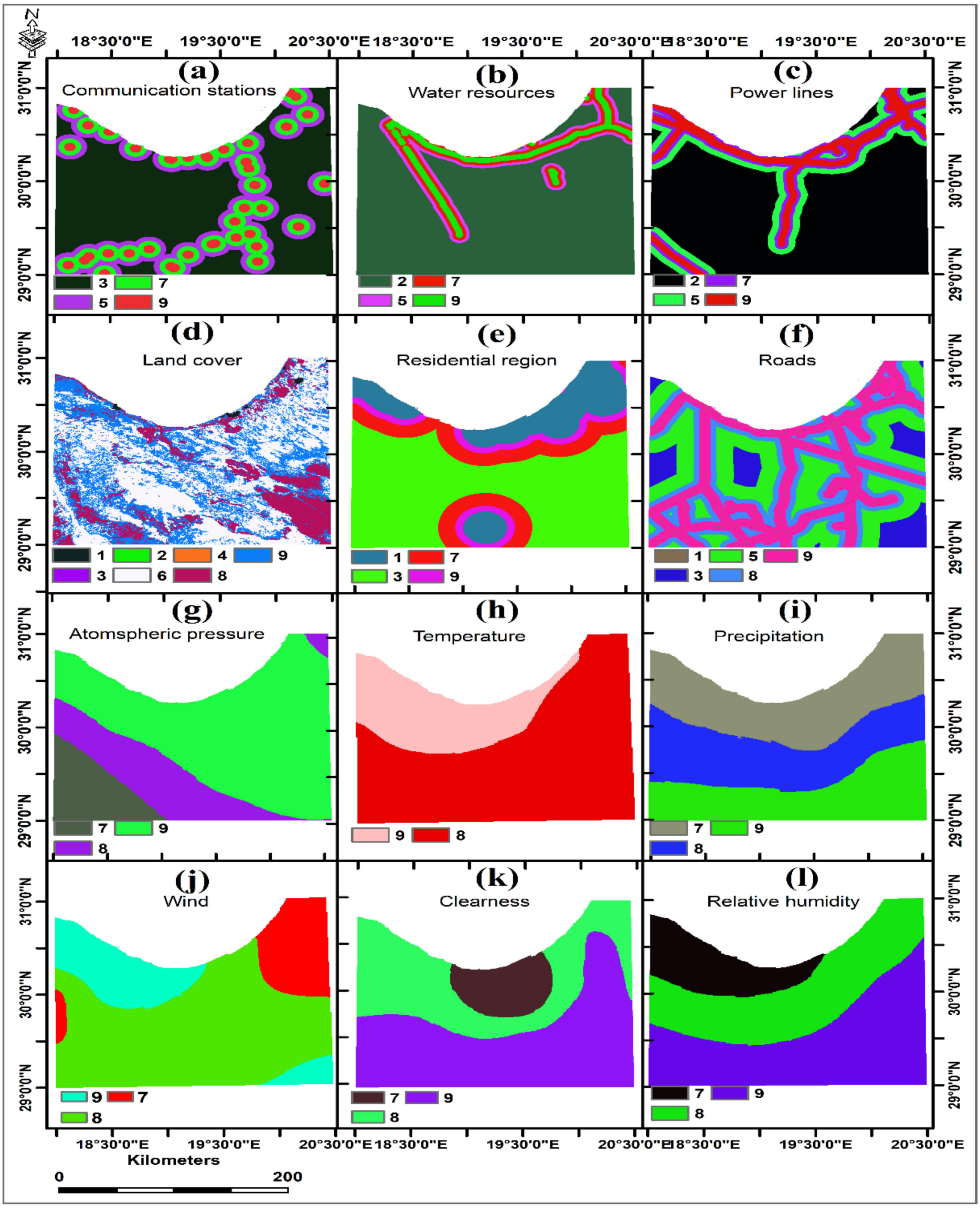


Figure 6. *Cont.*

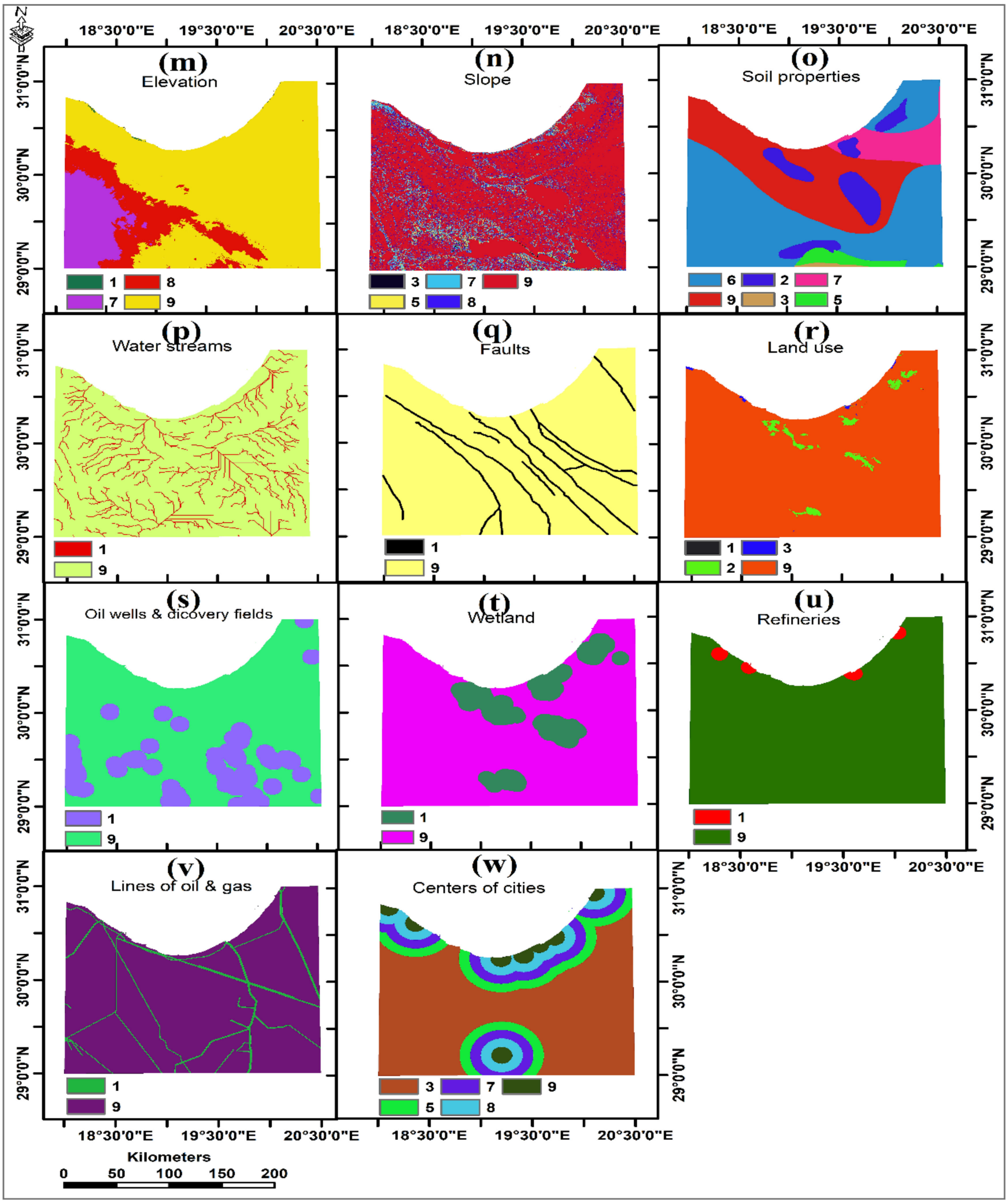


Figure 6. Classes determined for (**a**) communication stations; (**b**) water resources; (**c**) power lines; (**d**) land cover; (**e**) residential region; (**f**) roads; (**g**) atmospheric pressure; (**h**) temperature; (**i**) precipitation; (**j**) wind; (**k**) clearness; (**l**) relative humidity; (**m**) elevation; (**n**) slope; (**o**) soil properties; (**p**) water streams; (**q**) faults; (**r**) land use; (**s**) oil wells and discovery fields; (**t**) wetlands; (**u**) refineries; (**v**) lines of oil and gas; (**w**) centers of cities.

5. Analysis

After the preparation of all required criteria layers, two methods, AHP and ROC, were implemented to assign the suitable criteria weights. These weights of criteria have been based totally on previous studies, and experts' opinions. Two groups of experts were formed to give their opinions. The first group for the AHP method and the other group for the ROC method. Each group consisting of ten experts of university professors, aviation engineers, planning engineers, geologists, and experienced individuals in the field of environmental management. Questionnaires were prepared and sent to each group of experts for determining the rank and level of importance for all selected criteria.

5.1. AHP Implementation

It is obvious that the task of assessing the factor weights is primarily based on the understanding of the factor features and the characteristic of the study zone, in addition to the expert's experience associated with the weight assessment process. However, an effort has been made to improve the weight assigning process as objectively as possible by using techniques such as AHP [19].

The process begins by forming a hierarchy (see Figure 7) as a way to define the issue, comprising a general objective on top, a series of choices for every objective, and finally a set of standards or features that relate the options and objectives together. In many scenarios, such standards are narrowed down further to form sub-criteria at different stages, and depending on the issue and its requisites. When it is completed, users employ the AHP model to determine precedence or priorities for every node. A series of pairwise comparison matrices (PCM) are formed and the experts are asked to evaluate the relative importance to the criteria for each pairwise comparison matrix by using the nine points of scale as indicated in Table 4. Saaty [10] represented the indicated nine-item measure, in which 9 represents absolute preference, 7 highly probable, 5 as probable, etc. until 1 to stand for identical importance.

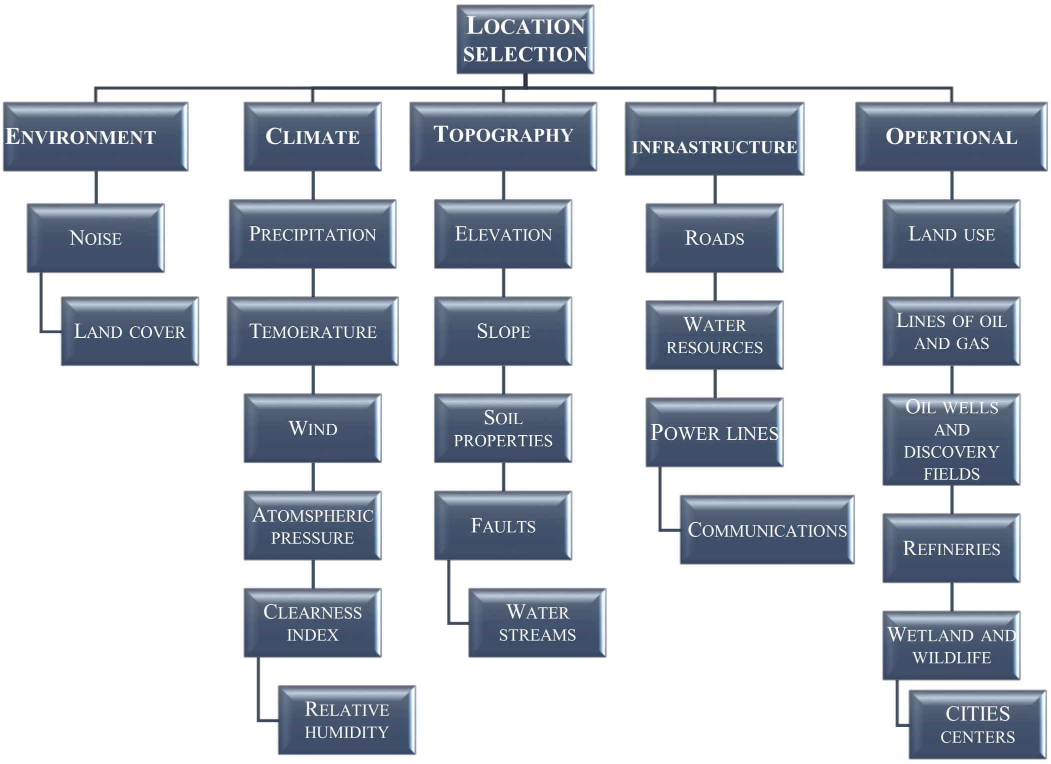


Figure 7. Hierarchy structure of the inputs criteria.

Table 4. The comparison scale in AHP method (source [11]).

Value of a_{ij}	Interpretation
1	Objective i and j are of equal importance.
3	Objective i is moderate importance than objective j.
5	Objective i is strong importance than objective j.
7	Objective i is very strong importance than objective j.
9	Objective i is extreme importance than objective j.
2,4,6,8	Medium values

Such an approach makes free assessment possible to determine the degree of significance of each factor—in this way, facilitating the arrival at a reliable decision [72]. The pair-wise comparisons of different criteria were arranged as a square matrix, whose diagonal elements are one as highlighted in Table 5. The main eigenvalue along with the related normalized right eigenvector of the comparison matrix offers a certain degree of significance regarding the criteria under evaluation. Additionally, the components within the normalized eigenvector are assigned weights concerning the (sub) criteria for averaging based on the possible options [73].

$$A = \begin{bmatrix} 1 & 2 & 1 & 2 & 1 \\ 1/2 & 1 & 1/2 & 1/2 & 1 \\ 1 & 2 & 1 & 1/2 & 1 \\ 1/2 & 2 & 2 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \tag{1}$$

Table 5. Comparison matrix of the main criteria.

	Environment	Climate	Topography	Infrastructure	Operation
Environment	1	2	1	2	1
Climate	1/2	1	1/3	1/2	1
Topography	1	3	1	1/2	1
Infrastructure	1/2	2	2	1	1
Operation	1	1	1	1	1

The reciprocal matrix A implies that criteria weight is obtainable using certain techniques like arithmetic mean. Upon determining a normalized matrix (B), its factors can be identified in the manner below:

$$B = \left[b_{ij}\right],\ b_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{2}$$

$$B = \begin{bmatrix} 0.25 & 0.25 & 0.182 & 0.4 & 0.2 \\ 0.125 & 0.125 & 0.091 & 0.1 & 0.2 \\ 0.25 & 0.25 & 0.182 & 0.1 & 0.2 \\ 0.125 & 0.25 & 0.364 & 0.2 & 0.2 \\ 0.25 & 0.125 & 0.182 & 0.2 & 0.2 \end{bmatrix} \tag{3}$$

The calculation of the weights i.e., eigenvector w= $[w_i]$ form the normalized matrix B is performed by calculating the arithmetic mean for each row of the matrix according to formula 4. (The obtained result is indicated in Table 6).

$$w_{i=} \frac{\sum_{j=1}^{n} b_{ij}}{n} \tag{4}$$

$$Weights\ of\ criteria = \begin{bmatrix} \frac{0.25+0.25+0.182+0.4+0.2}{5} = 0.256 \\ \frac{0.125+0.125+0.091+0.1+0.2}{5} = 0.128 \\ \frac{0.25+0.25+0.182+0.1+0.2}{5} = 0.196 \\ \frac{0.125+0.25+0.364+0.2+0.2}{5} = 0.227 \\ \frac{0.25+0.125+0.182+0.2+0.2}{5} = 0.191 \end{bmatrix} \tag{5}$$

Table 6. The weighs of main criteria.

	Environment	Climate	Topography	Infrastructure	Operation	Weights
Environment	1	2	1	2	1	**0.256**
Climate	1/2	1	1/3	1/2	1	**0.128**
Topography	1	3	1	1/2	1	**0.196**
Infrastructure	1/2	2	2	1	1	**0.227**
Operation	1	1	1	1	1	**0.191**

The AHP method permits identification and takes into consideration the inconsistencies of the decision-makers as experts are scarcely consistent in their decisions about factors of qualitative nature [74]. To confirm the comprehensive consistency of the PCM, the consistency ratio (CR) is estimated according to Equation (6) as follows:

$$CR = CI/RI \tag{6}$$

CR is a measure of the decision-makers' mistake or an indication of the degree of consistency or inconsistency [75], relying on the index of consistency (CI) and the index of random (RI).

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{7}$$

where λ_{max} is the principal eigenvalue of the judgement matrix, and n is the matrix order

RI is a constant depending on the element number being compared, as shown in Table 7.

Table 7. Random inconsistency indices RI (source [10,76]).

n	RI	*n*	RI	*n*	RI
1	0	6	1.24	11	1.51
2	0	7	1.32	12	1.48
3	0.58	8	1.41	13	1.56
4	0.9	9	1.45	14	1.57
5	1.12	10	1.49	15	1.59

Calculation of λ_{max}

$$AxW = \begin{bmatrix} 1 & 2 & 1 & 2 & 1 \\ 1/2 & 1 & 1/2 & 1/2 & 1 \\ 1 & 2 & 1 & 1/2 & 1 \\ 1/2 & 2 & 2 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 0.256 \\ 0.128 \\ 0.196 \\ 0.227 \\ 0.191 \end{bmatrix} = \begin{bmatrix} 1.356 \\ 0.659 \\ 1.014 \\ 1.196 \\ 1 \end{bmatrix} \tag{8}$$

$$\lambda_{\max} = \left(\frac{1}{5}\right)\left[\left(\frac{1.356}{0.256}\right) + \left(\frac{0.659}{0.128}\right) + \left(\frac{1.014}{0.196}\right) + \left(\frac{1.196}{0.227}\right) + \left(\frac{1}{0.191}\right)\right] = 5.216 \tag{9}$$

$$CI = \frac{5.216 - 5}{5 - 1} = 0.054 \tag{10}$$

From Table 7 RI = 1.12 for n = 5

$$CR = \frac{CI}{RI} = \frac{0.054}{1.12} = 0.048 < 0.1 \quad (11)$$

If CR < 10 %, then the PCM is acceptable and the value of the weights is valid. Should the CI not achieve a threshold level, in that case, certain pairwise figures require a re-arrangement, after which the cycle is followed a number of times up to the point that an ideal value of CR < 0.10 can be obtained. In general, for the matrix to be compatible, CR less than or equal to 0.1 should be retained. A homogeneity associated with variables within each group, a lower number of variables in the group, and a stronger understanding of the problem of decision-making improve the particular index of consistency [77].

Applying the same steps for the sub-criteria.

Tables 5–12 shows the method of calculating the CR value and the weights of criteria for every comparison matrix. Table 13 summarizes all values of CR and weights of criteria.

Table 8. Comparison matrix and significance weight of sub- criteria of environment.

	Noise and Pollution	Land Cover	Weights
Noise and pollution	1	2	**0.67**
Land cover	0.5	1	**0.33**

λ_{max} =2, CI = 0, CR = 0.

Table 9. Comparison matrix and significance weight of sub- criteria of climate.

	Precipitation	Temperature	Clearness Index	Wind Speed	Atmospheric Pressure	Relative Humidity	Weights
precipitation	1	1	0.5	0.5	1	0.5	**0.111**
Temperature	1	1	0.5	0.5	1	0.5	**0.111**
Clearness index	2	2	1	1	2	1	**0.222**
wind speed	2	2	1	1	2	1	**0.222**
Atmospheric pressure	1	1	0.5	0.5	1	0.5	**0.111**
Relative humidity	2	2	1	1	2	1	**0.222**

λ_{max} = 6, CI = 0, CR = 0.

Table 10. Comparison matrix and significance weight of sub- criteria of topography.

	Elevation	Slopes	Soil Characters	Geological Layers	Water Stream	Weights
Elevation	1	0.5	0.5	0.5	1	**0.120**
Slopes	2	1	1	0.5	0.5	**0.175**
Soil characters	2	1	1	1	3	**0.264**
Geological layers	2	2	1	1	3	**0.294**
Water stream	1	2	0.34	0.34	1	**0.147**

λ_{max} = 5.328, CI = 0.082, RI = 1.12, CR = 0.07 < 0.1.

Table 11. Comparison matrix and significance weight of sub- criteria of infrastructure.

	Roads	Water	Electricity	Communications	Weights
Roads	1	0.5	0.5	1	**0.17**
Water	2	1	1	2	**0.33**
Electricity	2	1	1	2	**0.33**
Communications	1	0.5	0.5	1	**0.17**

λ_{max} = 4, CI = 0, CR = 0.

Table 12. Comparison matrix and significance weight of sub- criteria of operational.

	Land Use	Distance from Wetland	Distance from Oil Wells and Fields	Distance from Refineries	Distance from Lines of Oil and Gas	Population	Weights
Land use	1	1	2	1	2	0.5	**0.180**
Distance from lakes	1	1	2	1	2	1	**0.198**
Distance from Oil wells and fields	0.5	0.5	1	0.5	1	0.5	**0.099**
Distance from Refineries	1	1	2	1	2	1	**0.198**
Distance from Lines of oil and gas	0.5	0.5	1	0.5	1	0.5	**0.099**
Population	2	1	2	1	2	1	**0.226**

$\lambda_{max} = 6.054$, CI = 0.011, RI = 1.24, CR = 0.008 < 0.1.

Table 13. Main criteria, sub-criteria, and their relative weights computed by using AHP method.

Stage 1			**Stage 2**			**Stage 3**
Main Criteria	**Weight**	**CR**	**Sub-Criteria**	**Weight**	**CR**	**Total Weight**
Environment	**0.2564**	0.048			**0**	
			Noise and pollution (Distance from residential regions)	**0.67**		**0.172**
			Land cover	**0.33**		**0.085**
Climate	**0.1282**				**0**	
			Precipitation (mm/day)	**0.11**		**0.014**
			Temperature °C	**0.11**		**0.014**
			Clearness index	**0.22**		**0.028**
			Wind speed (m/s)	**0.22**		**0.028**
			Atmospheric pressure (KPa)	**0.11**		**0.014**
			Relative Humidity %	**0.22**		**0.028**
Topography	**0.1964**				**0.073**	
			Elevation of land above sea level (m)	**0.12**		**0.024**
			Slopes of land %	**0.175**		**0.034**
			Soil Properties	**0.264**		**0.052**
			Distance from faults	**0.294**		**0.058**
			Distance from water streams	**0.147**		**0.029**
Infrastructure	**0.2277**				**0**	
			Proximity to roads	**0.167**		**0.038**
			Proximity to water resources	**0.333**		**0.076**
			Proximity to power lines	**0.33**		**0.076**
			Proximity to communications stations	**0.167**		**0.038**
Operational	**0.1914**				**0.008**	
			Land use	**0.179**		**0.034**
			Distance from wetland and wildlife	**0.198**		**0.038**
			Distance from oil wells and discovery fields	**0.099**		**0.019**
			Distance from Refineries and industrial factories	**0.198**		**0.038**
			Distance from Lines of oil and gas	**0.099**		**0.019**
			Proximity to cities centers	**0.226**		**0.043**
				Total weight		**1**

Generating and performing the suitability model is carried out by using ArcMap GIS 10.5 modeler and adding all the re-classified maps of criteria and overlaying all criteria weights. The final output map, which is generated after overlaying the weighted (AHP) factor layers of the study zone, was divided into six classes—4 to 9—of suitability indices including average suitability, average-to-good suitability, good suitability, very good suitability, excellent suitability, and perfect suitability, as shown in Figure 8.

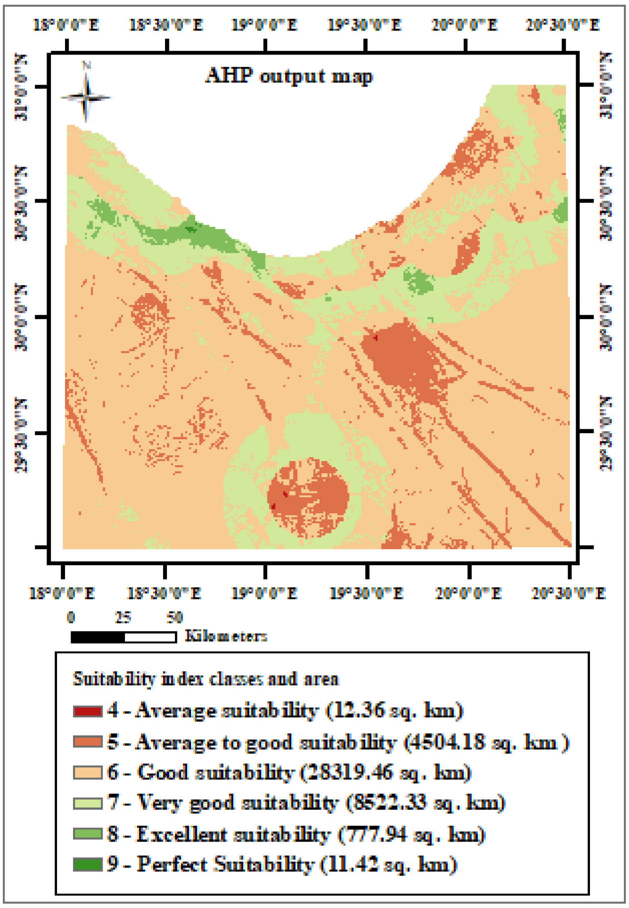


Figure 8. Output map of applying AHP method.

5.2. ROC Implementation

The ROC weight method provides an approximation of the weights to reduce the maximum error of every weight by differentiating the centroid of all potential weights preserving the rank order of objective significance. Barron and Barrett [22], in essence, came to the understanding that the values gained in this way prove to be highly stable. Next, only aware of the rank order related to the actual weight and without any other data whatsoever, we may say that the obtained weights are evenly distributed along the simplex of rank order [78].

$$w_i = \frac{1}{n}\sum_{j=i}^{n}\frac{1}{j},\ i = 1,\ 2,\ \ldots,\ n \tag{12}$$

The purpose of the ROC weights approach is to determine one group of weights to stand for all likely, acceptable, and reliable combinations regarding the identified linear inequality limitations on the weights,

$$k = w : w_1\ \geq\ w_2\ \geq w_3 \geq \ldots\ w_n\ ,\ \sum_{i=1}^{n} w_i = 1, \quad w_i\ \geq 0,\ i = 1,\ \ldots,\ n \tag{13}$$

The k boundaries can be obtained using

$$ext^i = \left(\frac{1}{i}\ ,\ \frac{1}{i},\ \ldots\ \frac{1}{i}\ ,\ 0,\ \ldots,0\right),\ i = 1,\ldots\ldots n \tag{14}$$

In which ext^i is the i^{th} extreme point with i positive elements and n – i zeros.

Edwards and Barron [79] offered a simple equation to determine a centroid in k through the approximation of coordinates related to the boundaries:

$$w_1^{ROC} = \frac{1+\frac{1}{2}+\frac{1}{3}+\ldots.+\frac{1}{n}}{n},\ w_2^{ROC} = \frac{0+\frac{1}{2}+\frac{1}{3}+\ldots+\frac{1}{n}}{n},\ w_n^{ROC} = \frac{0+0+0+\ldots\ldots+\frac{1}{n}}{n} \quad (15)$$

where w_1^{ROC} represents the most significant feature, W_2^{ROC} the second most significant feature, etc. [80]. Also, i represents the i^{th} rank order while n represents the option number.

ROC is advantageous owing to the steepness and non-linear processing of the weights, which can show a lot of agreement as regards the decision-makers 'views [20]. Lee [81] considered the ROC method practical for determining the weights of the criteria because of its simplicity and ease-of-use compared to AHP and fuzzy methods. Moreover, the weights resulted by applying the method of maximum entropy display an equally convenient performance with the ROC weights under some conditions, which is explained by theoretical and simulation analysis [80]. According to [22], the ROC weights method is more accurate than the other rank base formula and its based analysis is highly simple and efficient and supplies suitable implementation tools; hence our adoption of this approach in the present study.

Questionnaires were aggregated from the experts, identifying the rank of each criterion, then applying the method of ROC to calculate the weights for each criterion as shown in Table 14.

Table 14. Weights of criteria and sub-criteria using the ROC method.

Criterion	**Rank**	**Weight=w_i=$\frac{1}{n}\sum_{j=i}^{n}\frac{1}{j}$**
Noise and pollution (Distance from residential regions)	1	w_1 = (1/23) (1/1 + $\frac{1}{2}$ + 1/3 + ... + 1/23) = 0.162
Land cover	2	w_2 = (1/23) (1/2 + 1/3 + ... + 1/23) = 0.119
Distance from faults	3	0.097
Soil Properties	4	0.083
Land use	5	0.072
Proximity to power lines poles	6	0.063
Proximity to water resources	7	0.056
Proximity to roads	8	0.050
Proximity to cities centers	9	0.044
Distance from wetland and wildlife	10	0.039
Distance from Refineries and industrial factories	11	0.035
Distance from Lines of oil and gas	12	0.031
Distance from Oil wells and discovery fields	13	0.027
Wind speed (m/s)	14	0.024
Clearness index	15	0.021
Slopes of land %	16	0.018
Precipitation (mm/day)	17	0.015
Temperature °C	18	0.013
Atmospheric pressure (KPa)	19	0.010
Distance from water streams	20	0.008
Relative Humidity %	21	0.006
Elevation of land above sea level (m)	22	0.004
Proximity to communications stations	23	0.002
Total weights		1.000

The final output map, which is generated after overlaying the weighted (ROC) factor layers of the study zone, was divided into six classes—4 to 9—of suitability indices, included average suitability, average-to-good suitability, good suitability, very good suitability, excellent suitability, and perfect suitability as shown in (Figure 9).

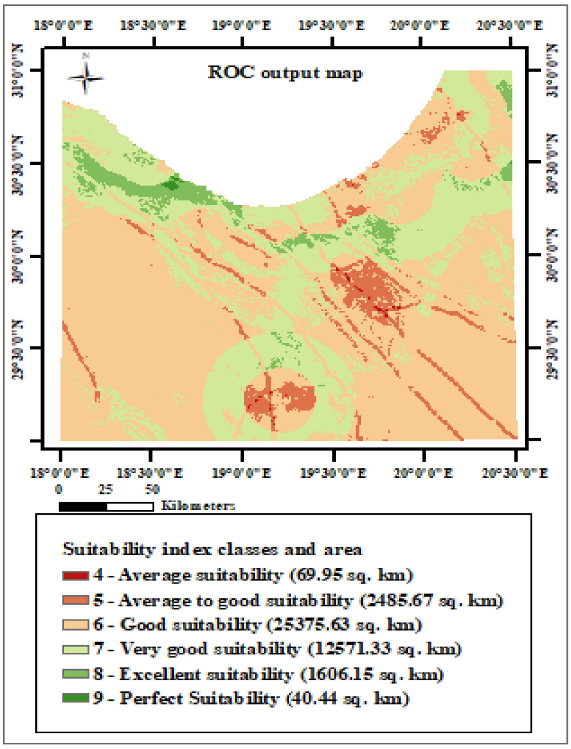
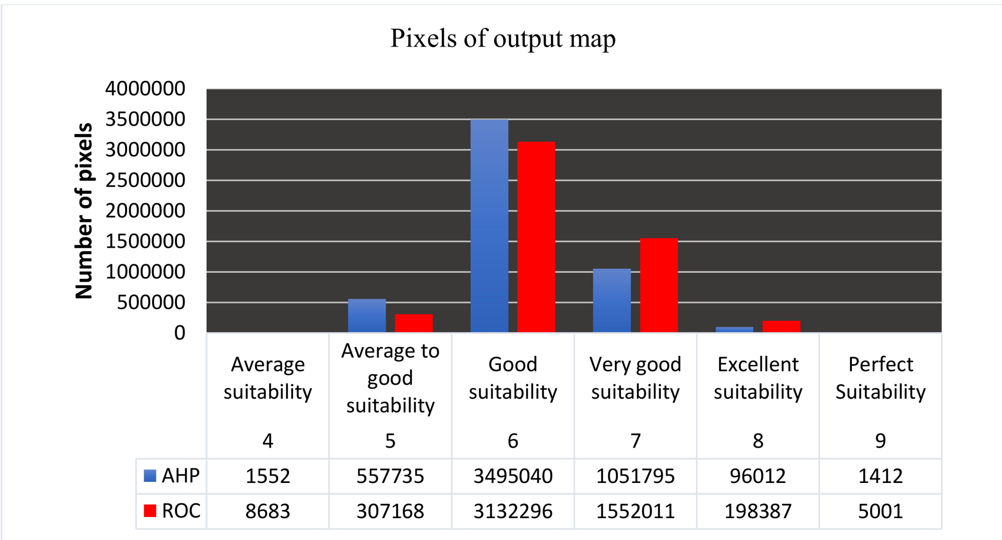


Figure 9. Output map of applying the ROC method.

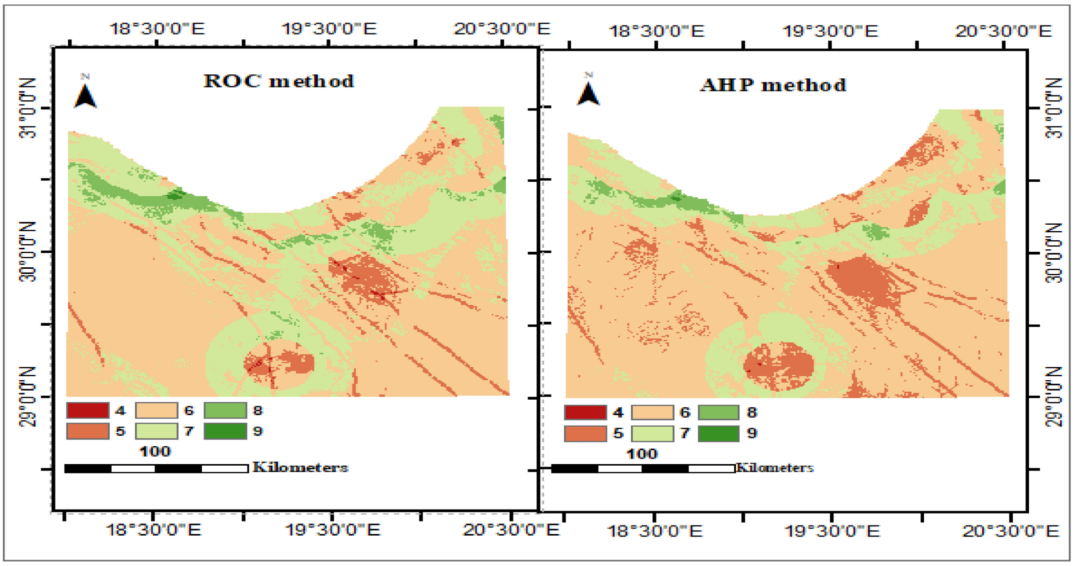
From the obtained result by applying AHP and ROC methods, we found that each output map includes six categories of suitability index categories but, the difference was in pixels units for each as indicated in Figure 10a,b.



	Average suitability 4	Average to good suitability 5	Good suitability 6	Very good suitability 7	Excellent suitability 8	Perfect Suitability 9
AHP	1552	557735	3495040	1051795	96012	1412
ROC	8683	307168	3132296	1552011	198387	5001

(a)

Figure 10. *Cont.*

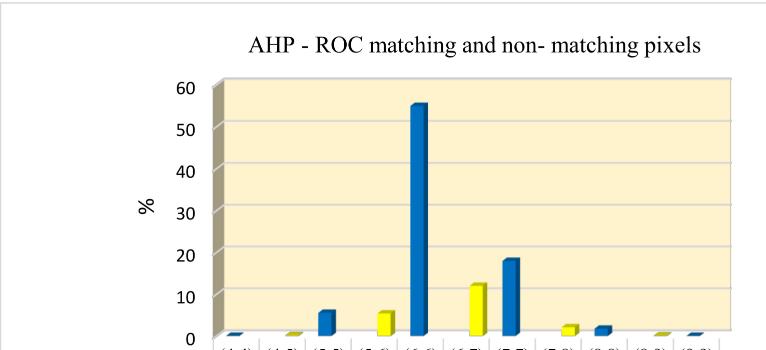


(b)

Figure 10. (**a**) Number of pixels and suitability index resulting from the two output maps. (**b**) Output map of AHP and ROC.

5.3. Comparison of the Results from the AHP and ROC Used

To know the percentage of matching and non-matching between the output maps, we used the spatial analysis tool "Map Algebra" and applied the command raster calculator to combine the two output maps (the AHP raster map and the ROC raster map). A final comparison map is, then, obtained including the number of pixels for each suitability index class and the raster categories combined number for AHP and ROC, along with the conformable ratios for each suitability index class used for matching. In this final comparison map, [(4, 4), (5, 5), (6, 6), (7,7), (8,8) and (9, 9)] refer to the pixels of correct classes in both methods, and [(4, 5), (5, 6), (6, 7), (7, 8), (8, 9) and (9, 8)] were considered as acceptable classes. Figure 11 indicates the percentage of matching and non-matching classes of suitability index pixel values.



	(4,4)	(4,5)	(5,5)	(5,6)	(6,6)	(6,7)	(7,7)	(7,8)	(8,8)	(8,9)	(9,9)
% of matching	0.0298		5.5459		54.979		17.969		1.7497		0.0271
% of non-matching		0.137		5.3925		12.012		2.0893		0.069	

Figure 11. The percentage of matching and non-matching classes of suitability index pixels values.

Reclassifying the output map of comparison, and later the classes of the identical output number of raster classes, we combined the pixels to arrive at a category of matching zones, and the other classes were combined to produce the category of non-matching areas (acceptance area), as shown in Figure 12. The matching pixels in the output map amount to 80.3%, while the non-matching pixels comprise

19.7%. If we summed the matching and non-matching pixels percentages, it can be concluded that the two techniques are compatible with a percentage of 100%.

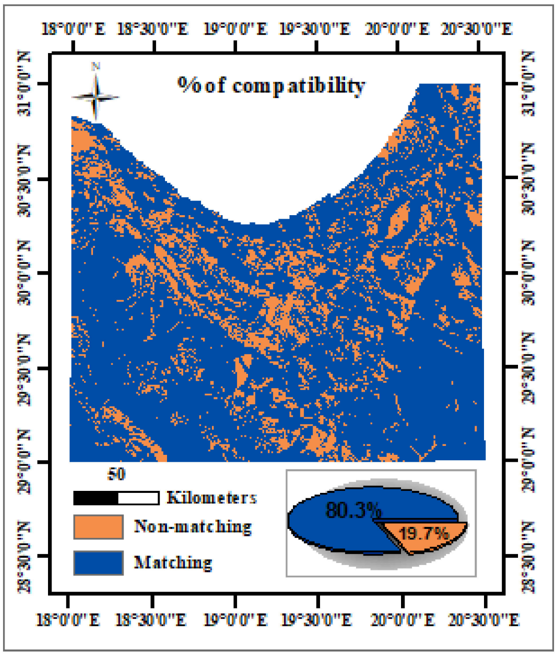


Figure 12. The comparison map of ROC and AHP methods and its percentages.

One of the conditions for the weighting method to be applicable is that the obtained result should be similar or almost the same as the results of various methods evaluated. If the different methods provide different results, the causes for the variance require being analyzed so that a suitable method should be selected to conform with decision-making [81].

To check the correlation between the two methods used for the determination of the criteria weights, correlation coefficients between the ROC and AHP methods were calculated. The correlation coefficient was 0.867, as depicted in Figure 13. Consequently, this result indicates a strong relationship between the two different methods evaluated and used in this study. We can say the small differences that occurred between the results of the two used methods were due to the ability of AHP to fine-tune weights more precisely [82]. Also, the results show that the determination of criteria weights by the different teams of experts with the same aim in the decision-making issues will yield almost the same result as long as the experts' evaluation is close together.

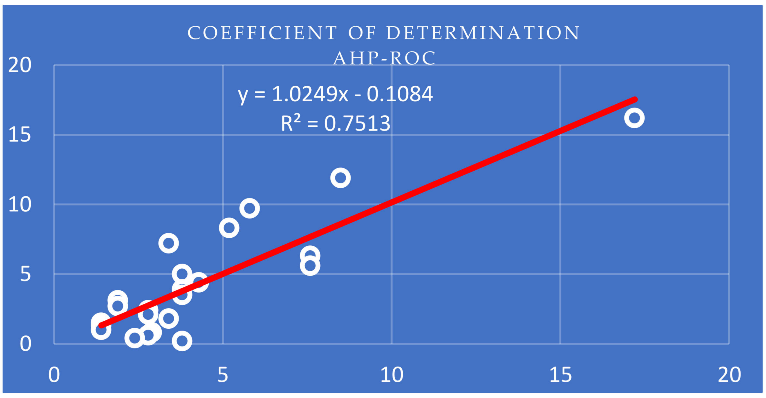


Figure 13. AHP-ROC Coefficient of determination.

6. Assessment of Suitability of Candidate Sites

Following the comparison process, three candidate sites were chosen as those meeting the full requirements and located in different locations within the regions of the highest suitability index (i.e., suitability index from 7 to 9). The stated sites were each assigned a letter—A, B, and C—and each covered approximately 50 sq. km (5000 hectares) (see Figure 14). In order to determine the best candidate site, a sensitivity analysis was performed.

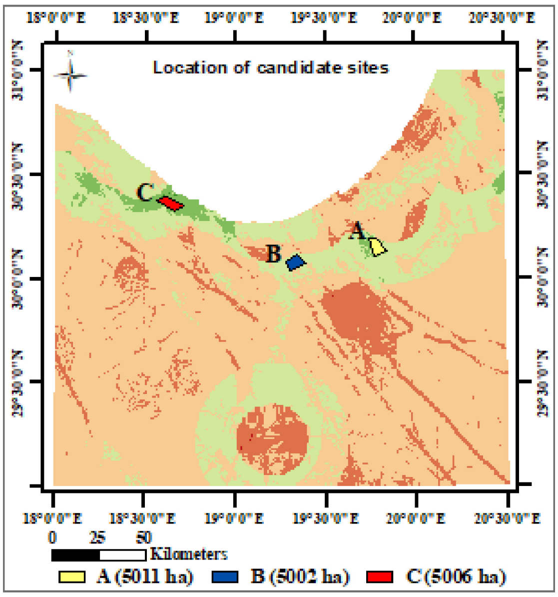


Figure 14. Location and area of candidate sites.

An overall review of several sensitivity analysis approaches can be found in Saltelli et al. [83] and Campolongo et al. [84]. Numerous analysts have proposed sensitivity analysis approaches that can be applied with particular MCDA strategies. These approaches are utilized to examine the relationship between changes in the weights of criteria and consequent changes within the alternatives rank, that taking after the completion of the decision analysis [85].

Chen et al. [75] determined the three most frequently utilized sensitivity analysis methods: specifically, changing the relative significance of criteria, changing the values of criteria, and changing the weights of criteria. Using the method of changes in criteria weights may be more common instead of testing for the changes regarding the criteria values.

Dabral et al. [86] considered that there are several basic approaches to evaluating sensitivity analysis, including one at a time (OAT), variance-based methods, and regression analysis.

Eldemir et al. [87] considered the sensitivity analysis as a tool that performed to reach a better realization of how the changes in decision criteria factors influence the direct area.

Minh et al. [88] conducted a sensitivity analysis to decrease the uncertainty by comparison of the weights of parameters in scenarios, relying on mean values and standard deviation (SD).

In this study (as suggested in Bahrani et al. [89]), the criteria weights related to the environment and infrastructure (input layers) are the highest weights among the rest. To perform the sensitivity analysis of the model, the weights related to these criteria were changed by (± 5%, ± 10%, and ± 15%) to construct six scenarios, with the remaining ones staying as they were initially [89].

The results obtained from the six scenarios show that the range of land suitability index for the intended study zone did not change and stayed within 4 and 9, whereas some changes were visible in the number of pixels in certain locations. To rank the candidate sites A, B, and C, we computed the area of each class of land suitability index in each candidate site for the six scenarios and, then, recorded the changes as shown in Table 15.

Table 15. Areas of candidate sites for six scenarios.

Sc. No.	%	Site A				Site B				Site C			
		Suitability Index 6	**Suitability Index 7**	**Suitability Index 8**	**Suitability Index 9**	**Suitability Index 6**	**Suitability Index 7**	**Suitability Index 8**	**Suitability Index 9**	**Suitability Index 6**	**Suitability Index 7**	**Suitability Index 8**	**Suitability Index 9**
Original	0%		330.63	4681.2	-	-	4118.7	883.8	-	-	-	4030.1	976.4
1	5%	-	-	5011	-	-	2923.1	2079.5	-	-	-	4023.7	982.7
2	−5%	-	508	4503.8	-	78.4	4802.8	121.3	-	-	-	4245.7	760.7
3	10%	-	-	5011.8	-	-	668.9	4333.7	-	-	-	3209	1791.3
4	−10%	-	1224.8	3787.1	-	335	4667.3	-	-	-	-	4545	461.2
5	15%	-	-	4909.7	102.11	-	274.9	4727.6	-	-	-	2641.7	2359
6	−15%	-	1563.9	3448	-	462.1	4540.5	-	-	-	-	4544.8	461.2
		Total area of site A = 5011 ha				Total area of site B = 5002 ha				Total area of site C = 5006 ha			

Accordingly, in scenarios 1, 3, and 5, with increasing the criteria weights, the areas belonging to the suitability index of classes 8 and 9 became better and more increased in site C. On the contrary, in scenarios 2, 4, and 6, with decreasing the criteria weights, those areas which belong to the suitability index of class 8 and 9 became smaller and were deleted from site B.

Comparing the changes that occurred in site A and site C, we noticed that in the latter within all the changes which occurred, scenarios maintained the highest suitability index of class 9, whereas the former (site A) did not have polygons of suitability index 9 except for in one scenario (see Figure 15). Finally, site C was selected as the best one among all the candidate sites because it is not affected by the changes in weights of criteria, followed by site A, then site B.

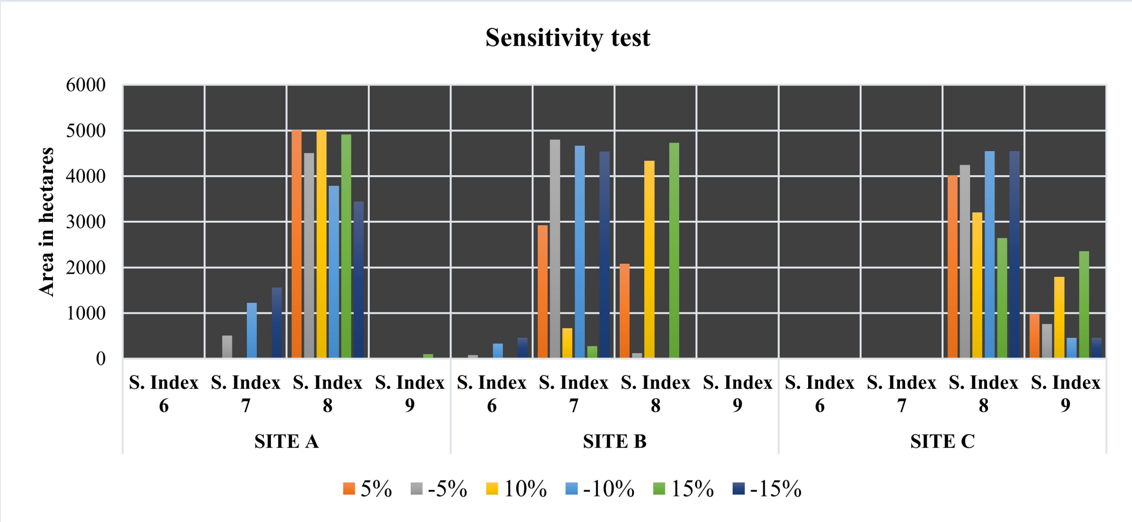


Figure 15. Distribution of suitability index resulting from sensitivity test.

7. Conclusions

This research presents the combination of AHP and ROC techniques, integrating GIS, and utilizing the environmental and multi-scientific criteria, which are pursued in the advanced countries, and represents an efficient and proficient technique in the process of selecting appropriate sites for the airport in Libya.

Twenty-three input layers were entered into the process of an overlaying analysis with GIS to solve the issue of airport site determination in the proposed region, with the ArcGIS 10.5 software technique having a high capacity to manipulate a huge volume of data from different sources [90]. These layers were the distance from residential regions (noise and pollution), land cover, precipitation, temperature, clearness index, wind speed, atmospheric pressure, relative humidity, elevation above sea level, the slope of the land (%), soil characteristics, distance from faults, distance from water streams, proximity to roads, proximity to water resources, proximity to power lines, proximity to communications stations, land use, distance from wetland and wildlife, distance from oil wells and fields, distance from refineries and industrial factories, distance from lines of oil and gas and the proximity to city centers.

The weights of criteria were derived from the AHP and ROC methods depending on the local features of the study zone, applicable rules, regulations, literature review of previous researches, and the opinion of experts. The resulting map included six categories from 4 to 9 of suitability indices. A comparison of the two resulting maps was made, and the proportion of matching pixels was found to be 80.3%, while the proportion of non-matching pixels was 19.7 %. Also, the correlation analysis indicates a positive relationship (R = 0.867) between the AHP and ROC methods. Thus, the ROC method is considered practical and effective.

Three sites were candidates for the airport location among several sites in the places which had the highest suitability index in the final map. Then, a sensitivity analysis was conducted to evaluate the reliability of the method used and the ranking of the candidate sites. The obtained results show that site C perfectly outranked the other candidate sites despite the differences in the decision weights within a range of ±15%. Field checks and a satellite image analysis confirm that the proposed sites agree well with the result of the model. The results of this study indicate the accuracy in the performance of the model applied here for airport site selection in Libya that is very compatible with the actuality in the field. Thus, it could be assigned as a decision-supporting tool for decision-makers and planners.

This study will contribute to the future of Libya in the following ways:

1. The proposed airport location between two existing airports, the distance between them is more than 600 km, will be very beneficial for the residents of that zone and oil companies' employees.
2. It must be taken into consideration that an airport represents an important investment in the infrastructure and that its contribution to communications development can be a significant motivation for regional expansion in that region.
3. As far as the authors know, using GIS to determine the appropriate location of an airport is considered one of a few research types in this field, especially with the use of layers such as climate, among the required criteria.
4. Applying an already-known method to a new area and a new scope of work that enhances the importance of using GIS. Furthermore, this study can serve as a pioneer work in future studies to be implemented for Libya.

For further future works, the cost factor could be added to the criteria to ensure the closest site concerning the resources of manpower and material of construction.

It has to be asserted that the GIS-based MCDA technique provides a local index of suitability, aiming to identify the best-required locations rather than areas that are inappropriate or restricted, in which additional geotechnical analyses need to be carried out before making the final decision.

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