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Optimal wind-solar site selection using a GIS-AHP based approach: A case of Tunisia

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ABSTRACT

Constructing large wind power plants (WPPs) and solar photovoltaic plants (SPVPs) is a significant long-term investment. Due to the various conflicting factors involved in the selection process, determining the most appropriate locations prior to deploying such facilities is of paramount importance. In this paper, we propose a preliminary assessment of the most promising sites in Tunisia to host large-scale WPPs and SPVPs using geographical information systems (GIS) and multi-criteria decision-making (MCDM). A study of this kind, focusing on both resources, has not been conducted in Tunisia. An in-depth literature review has been conducted in order to determine suitability criteria as well as constraint factors. The analytical hierarchy process (AHP) is used to assign weights to the considered criteria; then, the final suitability maps are generated using the weighted overlay tool under ArcGis 10.8 software. The study findings indicate that there are large areas that are suitable for the deployment of large-scale WPPs and SPVPs, covering 3335 km^2 (2.15 % of the total area) and 3815 km^2 (2.57 %), respectively. The most suitable wind sites are scattered northwest to southwest, southeast, and to a lesser extent north. In contrast, ideal solar sites are mainly distributed in the central and southern regions of the country. Furthermore, it has been demonstrated that these designated locations are capable of providing an estimated annual energy of 40.896 TWh and 781.83 TWh for wind and solar, respectively. As a result of the adopted model in this study, policymakers could be more proactive in developing solar and wind farms. This would increase the possibility of Tunisia achieving its 2030 target.

Introduction

As the world's population continues to grow and modern societies have become increasingly digitized, the quest for energy is set to increase in intensity over the coming decades. Nearly 80 % of current electricity is generated from burning fossil fuels, such as coal, oil, and natural gas [1]. These resources have been directly related to the issue of climate change. They account for nearly 99 % of greenhouse gas emissions notably CO2 and methane as of 2019 [2]. Consequently, the transition to renewable energy sources (RES) has gained significant attention in an effort to highlight the immense contribution RES can make to safeguarding the energy status and fighting the disastrous consequences of climate change [3–8]. In this context, a considerable amount of research has been intensively conducted on exploiting these RES, solar and wind. This is owing to their vital role in increasing energy independence as well as mitigating the harmful impact of climate change [9–13]. Driven by a tremendous decline in costs and impressive technological advancements [1], both technologies have been regarded as the most viable options for a green transition [9,14]. Given Tunisia's hydrocarbon scarcity, the status of the country's energy has always been a major issue on a national scale. In fact, Tunisia has become a net importer since 2000. The energy mix is almost non-existent as the Tunisian power system remains exclusively reliant on natural gas which accounts for nearly 97 % of the mix whereas renewables (solar, wind, and hydro) represent only 3 % of the mix [15]. Demand has been consistently increasing over the last decade reaching nearly 19.8 terawatt hours (TWh) in 2020 [15]. The total installed fleet in Tunisia reached 5934 megawatts (MW). The lion's share of electric capacity (91.5 %) and electricity production (82 %) is controlled by the state power utility company (STEG) while the remaining 18 % is generated by the two Independent Power Producers (CPC & PTT) [15]. However, despite this current situation, Tunisia is among the few countries that have significant solar and wind potentials due to its meteorological and geological conditions. Solar radiation varies between 1800 and 2600 kWh/m2 per year while wind speed ranges between 6 and 8 m/s across vast areas of the country [16–20].

Therefore, harnessing these untapped solar and wind potentials

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Nomenclature

WPPs	Wind power plants
SPVPs	Solar photovoltaics plants
GIS	Geographical information system
MCDM	Multi-criteria decision making
AHP	Analytical hierarchy process
RES	Renewable energy sources
FAHP	Fuzzy analytical hierarchy process
TOPSIS	Technique for Order preference by similarity to ideal solution
ANP	Analytic network process
VIKOR	VIseKriterijumska Optimizacija I Kompromisno Resenje
ELECTRE	ELimination Et Choix Traduisant la REalité
DEA	Data envelopment analysis
WASPAS	Weighted aggregated sum-product assessment
DEMATEL	Decision-Making Trial and Evaluation Laboratory
SWARA	Step-wise Weight Assessment Ratio Analysis
EDAS	The evaluation based on distance from average solution
MABAC	Multi-attributive border approximation area comparison
OWA	Ordered weighted averaging
CR	The Consistency Ratio
CI	Consistency's value Index
RI	Random Consistency Index
n	Number of criteria
λ^{max}	Maximum eigenvalue

Table 1
The commonly used criteria for developing SPVP and WPP in the literature.

Criteria	Reference
Solar irradiation (GHI)	[24,28,32–38]
Wind Speed	[11,28,30,33,36,38–42]
Average temperature	[24,34–37]
Slope	[11,24,28,32–35,37,40–42]
Land Aspect	[11,24,28,32–33,35–37]
Proximity to power lines	[24,28,30,32–39,42]
Proximity to main roads	[11,24,28,30,32–35,37–42]
Proximity to residential areas	[11,24,28,30,32–35,37–42]
Elevation	[28,29–34,37,38–40]
Land use	[11,28,32–33,35,36,38,39,41]
Population density	[43,44]
Distance to wildlife designations	[43,45]
Plot Area	[23,28,38,40,43–45]
protected Bird areas	[30,46,47]
Distance to airports	[28,30,40]
Dust storm	[48]
Distance to water resources	[28,35,37–38,40]
Relative humidity	[35,48–50]

Table 2
Summary of GIS-MCDM methods used in literature.

MCDM Technique	Renewable Technology	Location	Reference
AHP	Solar PV, Onshore wind, and Biomass	Thailand	[38]
FAHP	Offshore wind	Morocco	[66]
AHP	Solar PV and Onshore wind	India	[67]
AHP	Onshore Wind	Knjazevac-Serbia	[68]
FAHP and FAD	Onshore wind	China	[69]
FDEA	Onshore Wind	Indonesia	[70]
Fuzzy Logic Modeling	Solar PV and onshore wind	Mauritius	[71]
AHP	Offshore wind	Egypt	[72]
FTOPSIS	Solar PV and Onshore wind	Fars, Iran	[73]
AHP, ELECTRE, TOPSIS, and VIKOR	Solar PV	Anatolian Region, Turkey	[74]
AHP - OWA	Solar PV	Chile	[75]
DEMATEL, ANP, and MABAC	Onshore wind	Serbia	[76]

would not only allow the country to secure its energy supply but also ensure its energy independence. In addition, it could benefit from the significant economic implications in terms of increased production and employment. In this context, the government has vowed to deploy a third (4.7 GW) of its electricity generation from renewable energy by 2030 in an attempt to ensure its energy security, diversify its mix, and decrease its imports [21]. However, to achieve such a target, it is crucial to determine the most feasible geographical locations in the country before developing a solar or wind farm [22,23]. Allocating a well-suited site is among the most strategic decisions, as it is a critical and complex process. It is insufficient to construct a solar or wind farm just because the resources are abundant. In fact, there are many factors that can directly affect output power, costs, social, and environmental influences [23–25].

This current study integrates the technique of the analytical hierarchy process (AHP) and GIS with a view to exploring the optimal locations for developing SPVPs and WPPs. This combination approach would offer further insights into a variety of subjective and conflicting factors which would assist decision-makers in screening potential locations. To the best of the author's knowledge, a GIS-based multi-criteria scheme has not been exploited for allocating sites considering both solar and wind facilities in Tunisia. Therefore, this article represents the first contribution in this direction.

Literature review

Identifying the most viable location prior to developing an SPVP or WPP is absolutely crucial [23,26]. However, allocating a suitable site is a complex task, given the multidisciplinary data and multiple conflicting criteria involved in the selection process [25,26] as depicted in Table 1. In this regard, integrating MCDM approaches with the GIS has been widely used in the field of renewable energy site selection due to their ability in tackling issues associated with decision-making problems [24,25,27]. A combination of such tools has proven to be an extremely useful tool in deciding on the most appropriate option among several alternatives [28–31].

Numerous scholars have developed and utilized a variety of MCDM methods to determine the optimal locations for WPPs and SPVPs, such as AHP, TOPSIS, fuzzy AHP (FAHP), fuzzy TOPSIS, DEA, ELECTRE, VIKOR, WASPAS, SWARA, and other approaches. Recently, more robust decision-making models have been introduced on the topic. For instance, Wang et al. [26] proposed a hybrid model of the DEA, Grey-AHP, and Grey-TOPSIS to determine the optimal locations for solar power plants in Vietnam. Also in Vietnam, Wang et al. [51] used DEA, FAHP, and fuzzy-weighted aggregated sum-product assessment (FWASPAS) to identify the most suitable areas for wind farms. In another study, a two-stage DEA-AHP approach was developed by Wang et al. [52] to construct solar PV farms in 20 cities in Taiwan. In an Iranian case, Rezaei-Shouroki et al. [53] introduced a hybrid multi-criteria model of DEA, AHP, and FTOPSIS to determine the suitability of 13 cities in order to host wind farms in the province of Fars. Khanjarpanah et al. [54] investigated the possibility of installing hybrid wind and solar PV power plants in Iran by utilizing a novel network data envelopment analysis (NDEA). Badi et al. [32] investigated the feasibility of developing solar parks in western Libya by combining GIS with the Decision-Making Trial and Evaluation Laboratory (DEMATEL) and SWARA. In

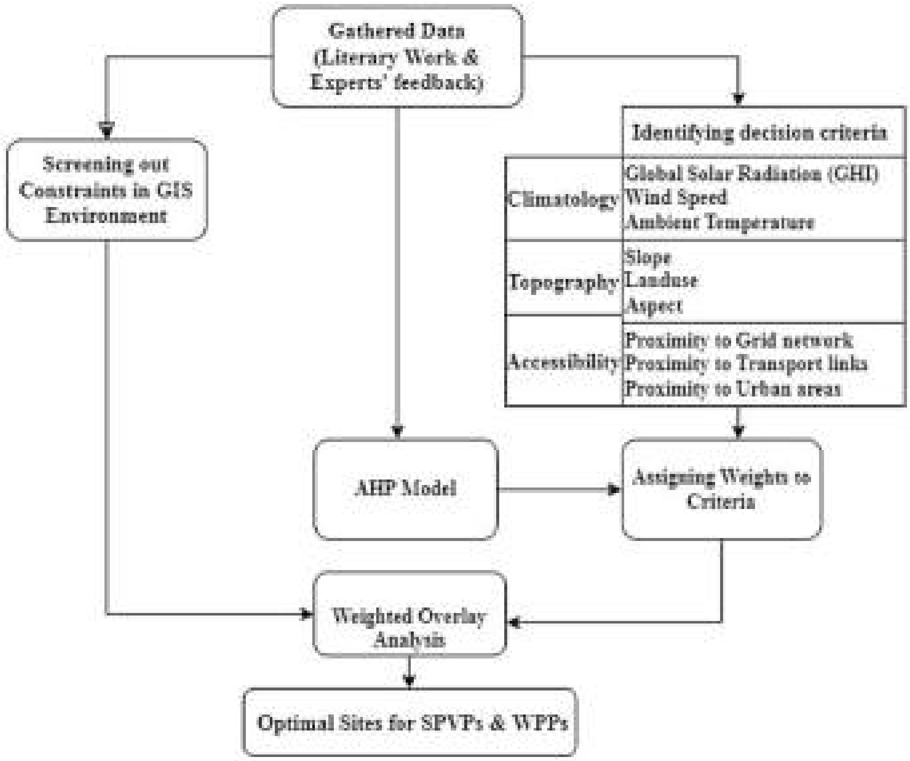

Fig. 1. The steps for selecting the most suitable area of WPPs and SPVPs.

Table 3
Saaty's Nine-Point Weighting Scale.

Intensity of importance	Description
1	i is equally important as j
3	i is moderately more important than j
5	i is strongly more important than j
7	i is very strongly more important than j
9	i is extremely more important than j
2,4,6,8	Intermediate values
Reciprocals	j has greater importance than j

order to identify optimal wind power locations in Greece, Konstantinos et al. [55] constructed an integrated model of AHP, TOPSIS, and GIS. In Pakistan, F-VIKOR and AHP were successfully applied by Solangi et al. [56] to determine the ideal location for a solar PV power plant. In another work, Xu et al. [42] combined FAHP and VIKOR with GIS to optimize wind sites in the Wafangdian region, in China. In a recent paper, Effat and El-Zeiny [33] incorporated classical AHP and GIS to determine the suitable locations for installing hybrid solar PV and wind power plant site selection in Assiut, Egypt. Table 2 depicts a variety of recently published studies addressing the application of GIS-MCDM in solar and wind site selection. In this paper, the AHP technique is used despite its shortcomings in dealing with uncertainties and ambiguities unlike fuzzy models such as FAHP, FTOPSIS, and FVIKOR [57–59]. Nevertheless, AHP is still the most widely applied method either alone or integrated with other MCDM models [60–62] owing to the following:

It is simple, easily implemented, and could be integrated with other techniques such as TOPSIS, EDAS, fuzzy sets, etc. [63]. Additionally, it is capable of handling both quantitative as well as qualitative data. This technique enables a variety of sensitivity analyses to criteria and considers the consistency and inconsistency of alternatives, which is the core advantage of this technique [40,64]. Moreover, when dealing with allocating optimal locations, the AHP is considered adequate as there are no significant differences in results from other complex techniques such as FAHP [65].

It is deduced from the exhaustive literature survey that research concerning solar PV and onshore wind site selection in Tunisia is missing. Moreover, in terms of methodology, the integration of AHP in the GIS environment has not been exploited in this kind of problem. To address this research gap, the key factors were initially identified based on an extensive review of the literature, similar research experiences, and experts' opinions. Subsequently, the combined model of GIS-AHP will be utilized to screen the most potential locations for developing WPPs and SPVPs in Tunisia.

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Data and methods

The main purpose of this study is to provide a preliminary evaluation of qualified candidate sites that could host large WPPs and SPVPs in

Table 4
Random index for different values of number of elements.

n	2	3	4	5	6	7	8	9	10	11	12
RI	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48

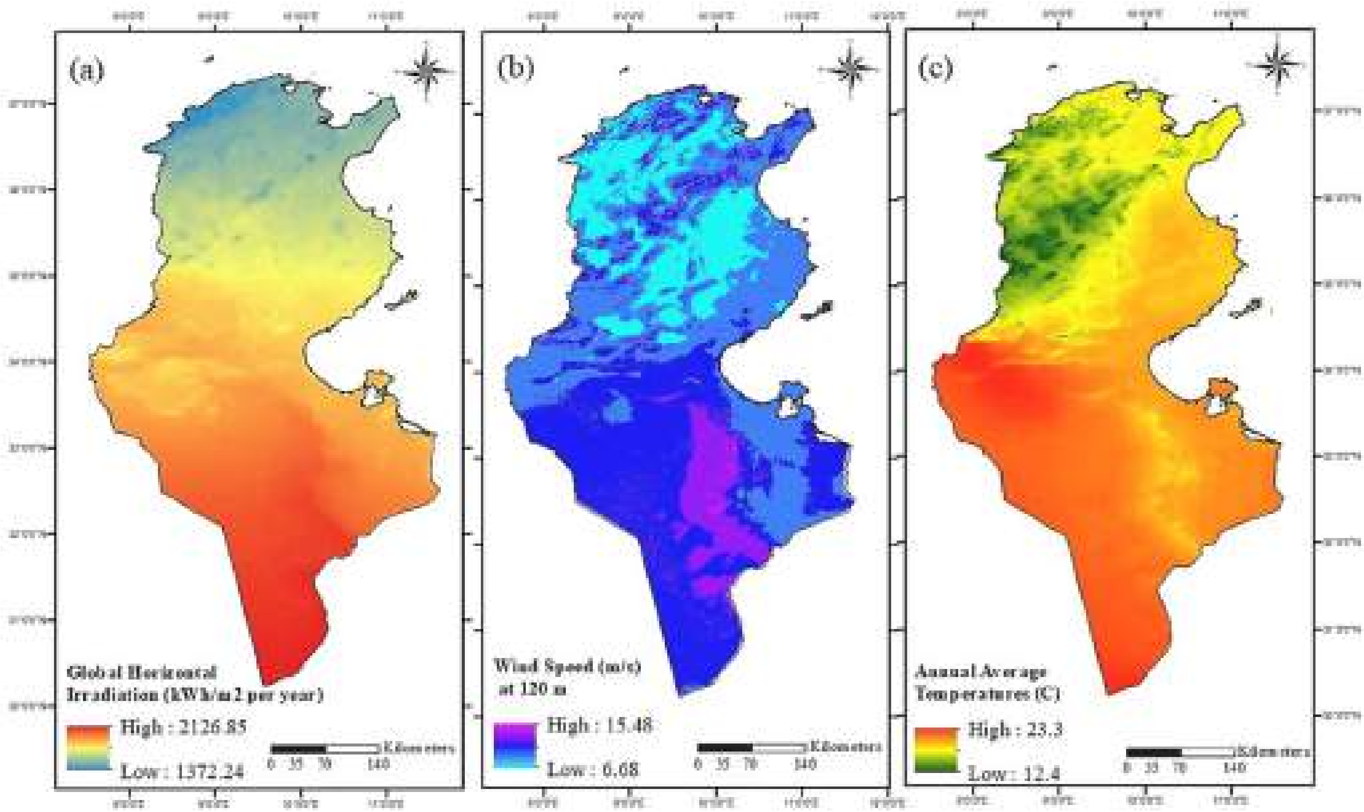

Fig. 2. Thematic maps for climatology criteria (a) Global Horizontal Irradiation (kWh/m^2 per year) (b) Wind Speed (m/s) at 120 m (c) Annual Average Temperatures (C).

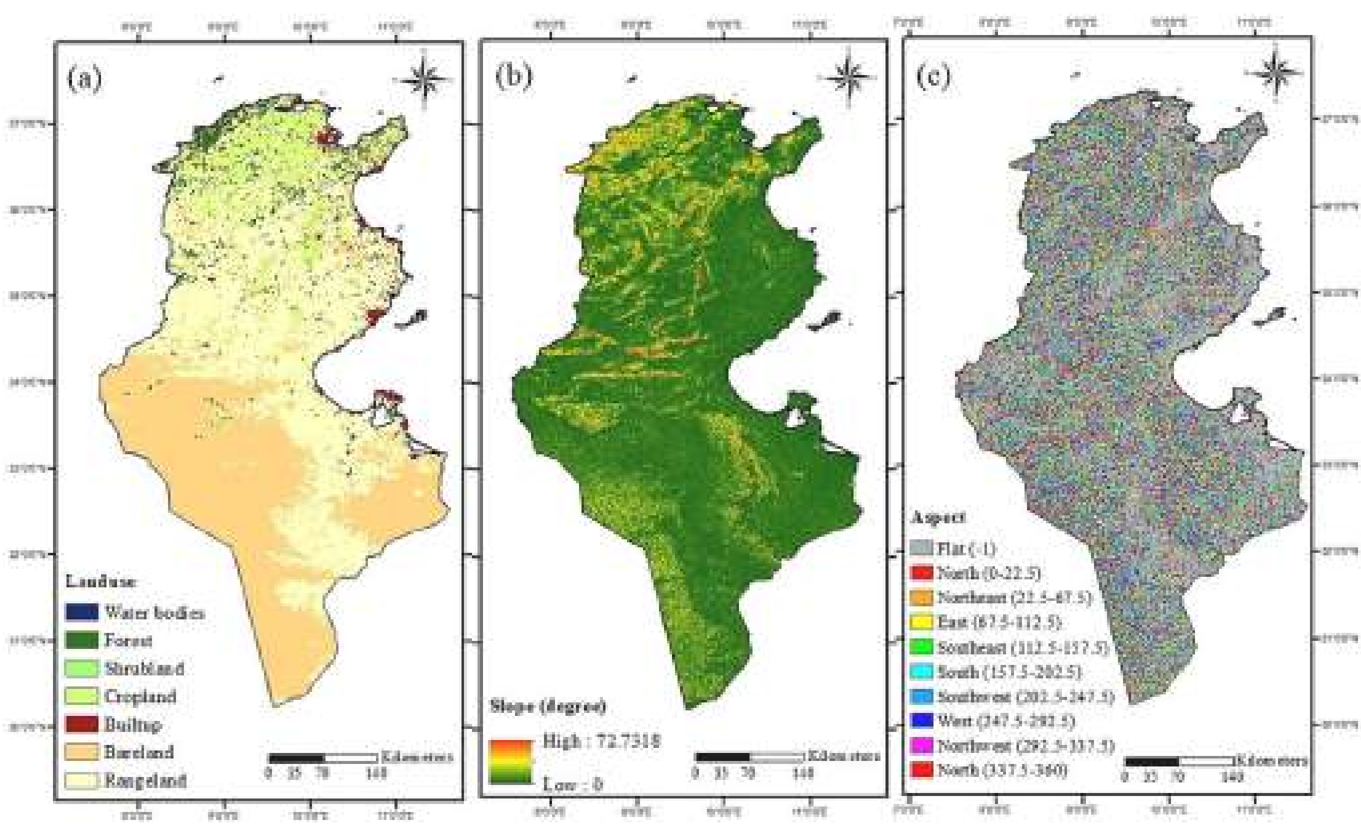

Fig. 3. Thematic maps for the topographic criteria (a) Landuse (b) Slope (degree) (c) Aspect.

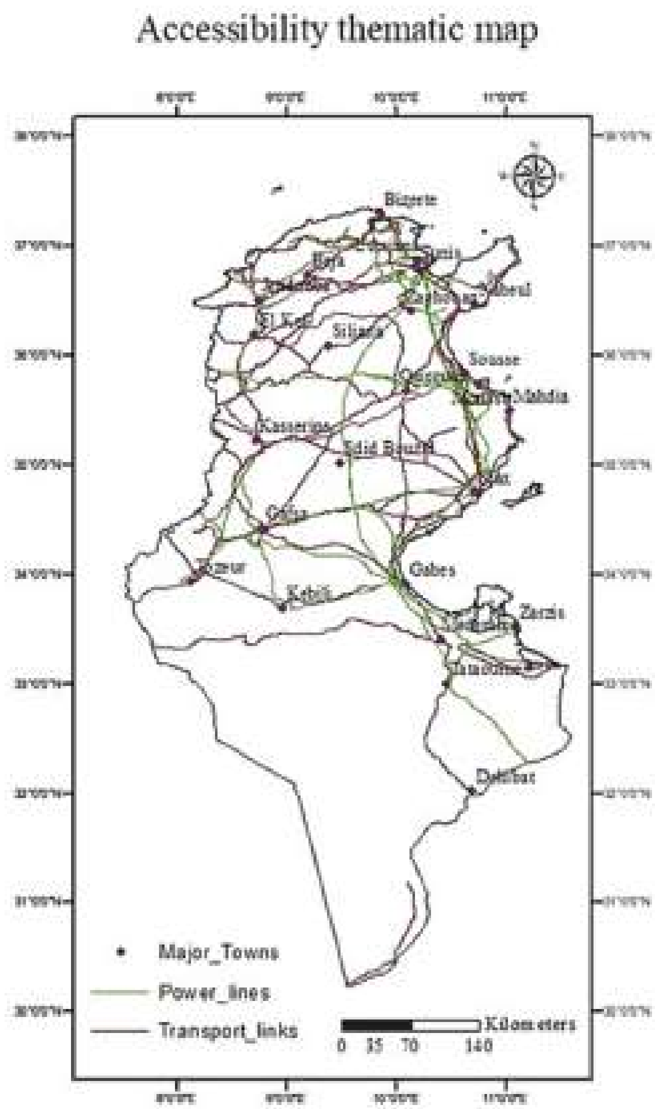

Fig. 4. Thematic map for accessibility criteria (Major Towns, Power lines, and Transportation links).

Table 5
Constraints considered for developing SPVPs and WPPs.

Constraints layer	Boolean algebra restriction
Slope percentage	$x > 10\%$
Distance to protected areas	$x < 500m$
Distance to roads	$x < 500m and x > 1500m$
Distance to residential areas	$x < 1000m and x > 25000m$
Landuse	$x \neq$ *Bare land, shrubland, and medium grassy or sparse vegetation*

Tunisia. The present study uses a variety of datasets that were gathered from various governmental organizations, open sources, and similar literary works. After consulting with experts and referring to related literature, climatology, topography, and accessibility were identified as the main factors, whereas wind speed, global solar irradiance (GHI), temperature, slope, aspect, landuse, proximity to the grid network, transport links, and residential areas were designated as criteria (see Tables A.1 and A.2 in Appendix A).

Afterward, a methodological framework was developed based on the integration of GIS with the AHP technique. Then, a four-step analysis was conducted to assist in the decision-making process for the WPPs and SPVPs site selection.

- First step: Identify the constraint thematic layers to eliminate the unsuitable sites, using the Boolean algebra in the integrated tools of ArcGis 10.8.
- Second step: Apply the AHP approach to assign the relative weight of each criterion.
- Third step: Rescale the layers' input data along with their weights obtained from AHP.
- Fourth step: generate the final suitability maps using the weighted overlay tool within the ArcGis

All the steps followed in the study are illustrated in Fig. 1.

Study area

Tunisia is a relatively small country located between 32° – 38° north latitude and 7° – 12° east longitude in northern Africa and the Mediterranean basin. The country is bordered by the Mediterranean Sea to the north and east, Algeria to the west, and Libya to the southeast. Tunisia is a lower middle-income state with an area of approximately 163,610 km2 with a population of nearly 12 million inhabitants of whom 70 % are settled in urban coastal areas [77,78]. Tunisia has a Mediterranean climate, with mild rainy winters and hot dry summers in the north, semi-arid conditions in the center, and arid conditions in the south. The average annual temperature and sunshine hours vary between 30 °C in July and 12 °C in December, and 2500 to 3400 h respectively.

The GIS-AHP model

GIS is a valuable tool that has been widely used in exploiting geographical information to develop spatial analyses that offer an in-depth assessment of the site suitability of solar and wind locations [25,79]. However, despite its spatial databases, and analytical capabilities, the GIS, on its own, still lacks the ability to select the optimal sites [32]. As such, coupled GIS and MCDM are considered ideal techniques for solving problems with multiple factors [24].

Analytical hierarchy process (AHP)

Among the most frequently used MCDM models, AHP stands out as an effective technique. This tool has been successfully applied to determine the suitability of sites for wind and solar PV installations. It is a mathematical approach developed by Saaty [80] that can also be utilized as a decision analysis tool. It is used to rank various alternatives taking into account multiple factors and provide the optimum compromise in case of conflicting objectives [81].

AHP offers a variety of attractive features including its flexibility in handling unstructured and multi-attribute issues by breaking the complex problem into smaller segments, its applicability to quantitative and qualitative data, and validating the procedure by measuring its consistency [23,37,81,82]. Thus, it has been chosen for this study.

Once the overall goal is set, criteria and sub-criteria are identified. The following key steps of AHP are summarized briefly as follows [23,81]:

Prepare pairwise comparison matrices in which the importance of the criteria and sub-criteria is scored by experts. The element x_{ij}, of matrix (k) of size (n × n), denotes the importance of criterion i to criterion j based on a fundamental scale from 1 to 9 [24], as shown in Table 3.

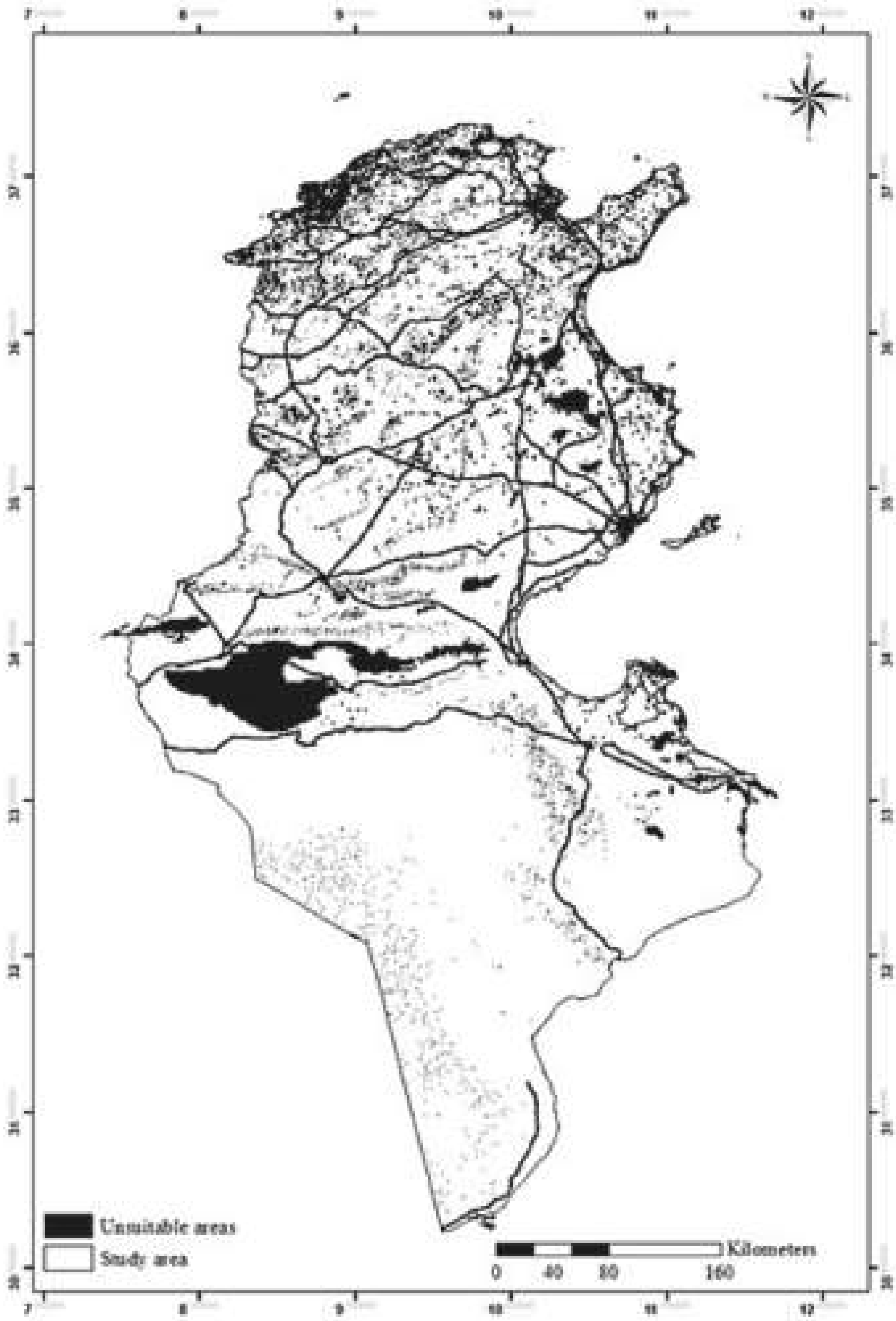

Fig. 5. Constraints layer map.

$$K = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{m2} & \cdots & x_{nn} \end{bmatrix} \quad (1)$$

where $i = 1, 2, \cdots n$ *and* $j = 1, 2, \cdots n$

2. Develop the normalized matrix to calculate the relative weights as follows:

a) Compute the sum of each column
b) Divide each entry by its column sum
c) Average the rows to obtain the relative weights

After obtaining the weights, compute the Eigenvector, maximum eigen value, and consistency index (CI) using Eq. (2).

$$CI = \frac{\lambda_{max-n}}{n-1} \quad (2)$$

where λ_{max} is the maximum eigenvalue for each matrix and n the number of criteria.

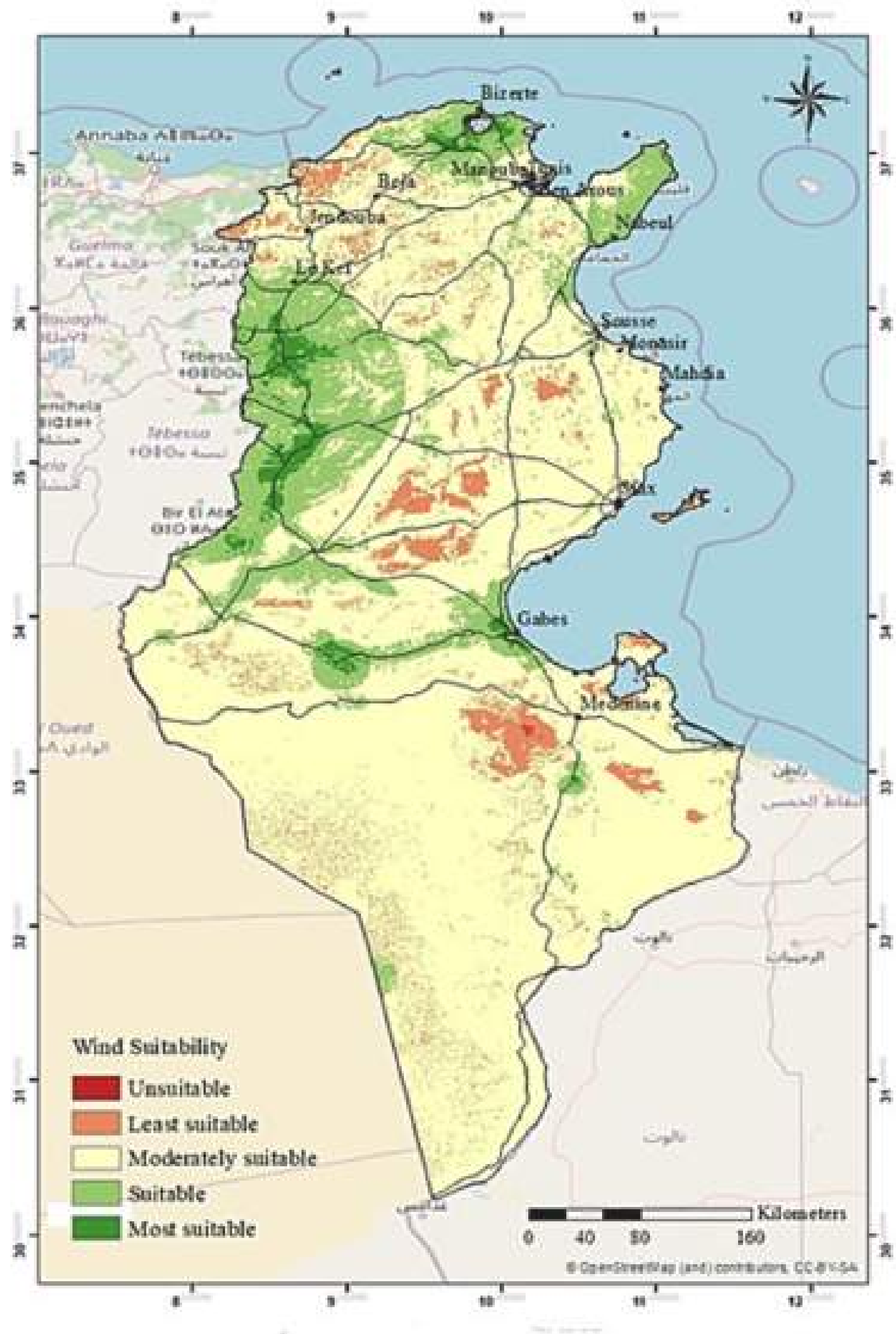

Fig. 6. Final suitability map for potential wind sites.

Finally, the consistency ratio (CR) is calculated to guarantee the consistency of the pairwise comparison matrix (K) using the following Eq. (3)

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

where RI is the random index (Table 4).

If $CR \leq 0.10$, the degree of consistency is acceptable; otherwise, serious inconsistencies exist in the pairwise comparison and therefore, the procedure has to be repeated.

Identification of decision criteria

The siting process of an SPVP or a WPP involves many factors as well as constraints. Accordingly, the factors should not only be analyzed from

Table 6
The final weights for wpps and spvps.

Factor	criteria	Relative weight	
		Onshore wind	Solar PV
climatology	**GHI**		**34.8 %**
	Wind speed	**38.0 %**	**–**
	Temperature	**–**	**5.3 %**
Topography	**Slope**	**15.9 %**	**18.1 %**
	Landuse	**15.7 %**	**12.3 %**
	Aspect	**–**	**4.7 %**
Accessibility	**Distance to transport links**	**12.7 %**	**12.4 %**
	Distance to grid network	**11.9 %**	**9.4 %**
	Distance to urban areas	**5.8 %**	**3.0 %**
	RI	**1.24**	**1.41**
	λ^{max}	**6.287**	**8.502**
	CI	**0.057**	**0.072**
	CR	**4.60 %**	**5.01 %**

an economic and technological standpoint, but also from a policy and environmental perspective. The identified criteria for this study have been finalized based on a comprehensive literature review, similar research experiences, and experts' opinions. Involving qualified experts in any MCDM approach is absolutely essential [23,83,84]. Assigning relative weights to a certain criterion to determine its importance over another is the most crucial part of such research activity. Hence, based on individual skills and expert knowledge in the domain, a panel of five experienced experts (more than fifteen years) was consulted to propose the most influential criteria applicable to the case of Tunisia. The summary of the experts' details is shown in Table A.3 in Appendix A. Then, the experts were asked to conduct a pairwise comparison.

Climatology criteria

- Global solar radiation
  Solar radiation is an influential factor to consider when designing solar PV, as it is the main source of energy for the panels. Therefore, the higher the solar irradiance, the more electricity is generated by cells, and hence, the better the site for placing SPVPs. It has been recommended that a minimum amount of 1300 KWh/m^2/year is required for a typical PV system to be economically feasible [33,34,85]. In this analysis, for the sake of obtaining highly accurate solar data, the solar radiation thematic map was adopted from the model developed by SOLARGIS Company (https://solargis.com) in the form of raster data (Fig. 2.a). The GHI values across Tunisia are high and ensure the successful deployment of SPVPs.
- Wind speed
  The average wind speed of a given region is the key factor in the process of selecting a suitable site for a wind farm. Higher wind speeds within an appropriate range indicate the presence of wind resources. Therefore, wind speed has been considered to be the most critical criterion in almost every study [28,30,42,86]. A raster dataset of detailed wind data was obtained from the global wind Atlas (https://globalwindatlas.info/area/Tunisia) as shown in Fig. 2.b.

The National Renewable Energy Laboratory (NREL) provides reliable information regarding Tunisia's wind resources since most of its wind speed falls within wind class 3 and 4 (above 6 and 7 m/s), which opens up the possibility of using wind power projects (https://www.nrel.gov/gis/wind_detail.html).

- Temperature
  This criterion is mainly associated with solar PV systems. It is known to have a significant impact on PV modules' efficiency and, therefore, on the total power output. Higher temperatures reduce significantly the system's performance as well as its components such as inverters and transformers which affect the modules' lifetime and durability [24,48,87]. As such, this criterion has to be well evaluated as it is a major limiting factor for PV systems. In this paper, the temperature parameter was obtained from SOLARGIS as a raster (Fig. 2.c).

Topographic criteria

- Landuse
  This is yet another crucial factor in the spatial planning for SPVPs and WPPs locations representing a challenge facing the selection process [24,28,41]. Accordingly, optimal locations are those types of areas where no significant restrictions related to land use exist such as forests, natural reserves, archaeological sites, military zones, etc. A 10 m high-resolution land cover map created by the European Space Agency (ESA) is used in this paper as shown in Fig. 3.a.
- Slope
  For economic feasibility, flat terrain or with gentle slopes are crucial for solar PV and wind farms since areas with steep slopes contribute to higher economic costs. Therefore, the lower the slope, the more appropriate it will be. However, thresholds varying between 3 % and 5 % have been widely accepted in the case of solar PV, while ranges varying between 10 % and 30 % have been considered for wind [28,33,42,87]. For this study, slope of 10 % was considered for both SVPPs and WPPs. This criterion was derived using the 30 m Digital Elevation Model (DEM) obtained from the Shuttle Radar Topography Mission (SRTM) provided by NASA (https://blog.arabnubia.com/2020/05/tunisia-nasadem-digital-elevation-model-1-arc-second) as illustrated in Fig. 3.b.
- Aspect
  According to the literature, this criterion has been mostly applied to solar PV plants. It determines the slope in a clockwise direction from the north from 0 to 359.9°. The −1 dimension indicates flat cells with zero inclination. In the northern hemisphere, south-facing, southwest and southeast slopes receive the most sunlight, which makes them the most appropriate [88–90]. Fig. 3.c depicts this criterion.

Accessibility Criteria: distance to Power Lines, Transport links, and Residential areas

Proximity to road networks, power lines, and urban areas is perceived as a favorable factor playing a vital role in the sustainability of solar and wind facilities. Proximity to power lines is directly associated with the transmission and distribution costs of output power. Therefore, the shorter the distance to power lines is, the lower the connection cost and power loss will be [50,91,92]. Additionally, the ease of accessibility of the chosen location reduces the costs involved in the building and logistics process during the construction and operation phase [24,93]. Furthermore, being close enough to populated areas ensures power supply and avoids the distribution of energy over long distances, resulting in lower efficiency [94]. However, in some instances, it may pose a hindrance to future urban development [95,96]. In this paper, the Euclidean distance tool was used to generate the map layers associated with this factor. The major urban areas and transport links including the main roads as well as existing railroads were downloaded from the free available open Street Map project (https://download.geofabrik.de/africa/tunisia.html); whereas, the power lines were obtained from the data provided by SOLARGIS. These criteria are summarized in Fig. 4.

Identification of constraints

It is necessary to consider some economic, technical, and environmental constraints when analyzing the feasibility of selecting solar and wind farms. It is necessary to consider some economic, technical, and environmental constraints when analyzing the feasibility of selecting

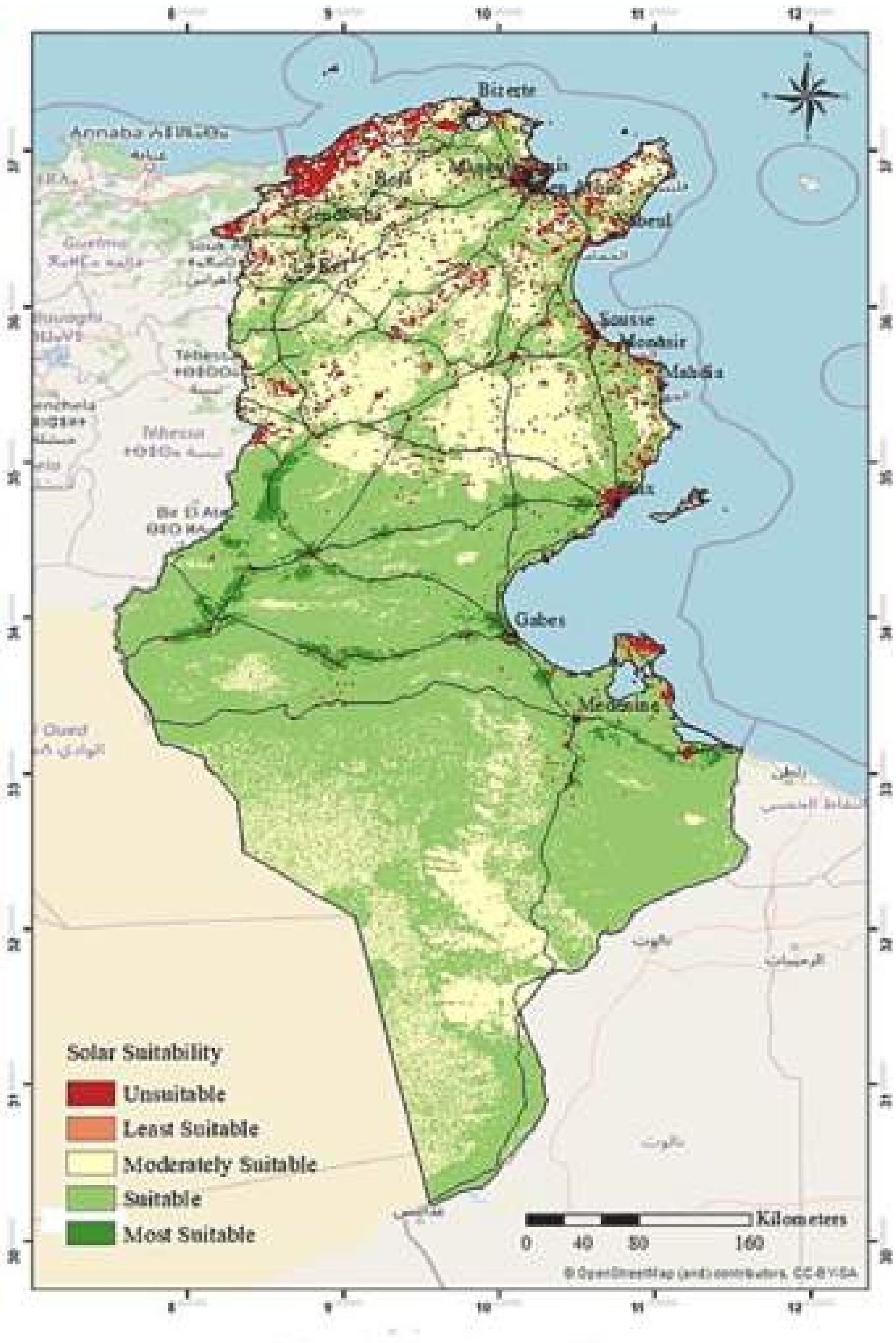

Fig. 7. Final Suitability map for potential solar sites.

solar and wind farms. The constraints illustrated in Table 5 were identified based on similar previous studies. The constraints depicted in Fig. 5 were produced and aggregated into one layer using Boolean algebra (1 and 0) in the integrated tools of ArcGis 10.8. “1″ corresponds to an absence of restrictions, allowing for the development of solar and wind farms, while ”0″ indicates constraints, which means such facilities cannot be developed.

Results and discussion

The perusal of the constraint layer reveals that only 19.14 % (26618 km^2) is deemed unsuitable which indicates the abundance of substantial solar and wind potentials across Tunisia. After ruling out the constraints, spatial suitability analysis was used to screen the optimal locations for WPPs and SPVPs. In this study, spatial suitability analysis was conducted using the Spatial Analyst tools within ArcGIS 10.8.1, which is one of the most useful tools for solving multi-criteria problems such as site selection [24,32,35,93]. To perform the integrated analysis, the derived data, associated with the diverse layers, were transformed to a common scale and then reclassified. Accordingly, each reclassified input layer was multiplied by its relative weight obtained from the AHP technique. Finally, the final suitability maps, for solar and wind, were generated using the raster calculator tool (Fig. 6). Maps were classified into five classes based on the pixel values, with class 5 representing the most suitable sites and class 1 the least suitable ones. In order to determine ideal locations, a minimum threshold of 1 km^2 was considered for both SPVP and WPP sites.

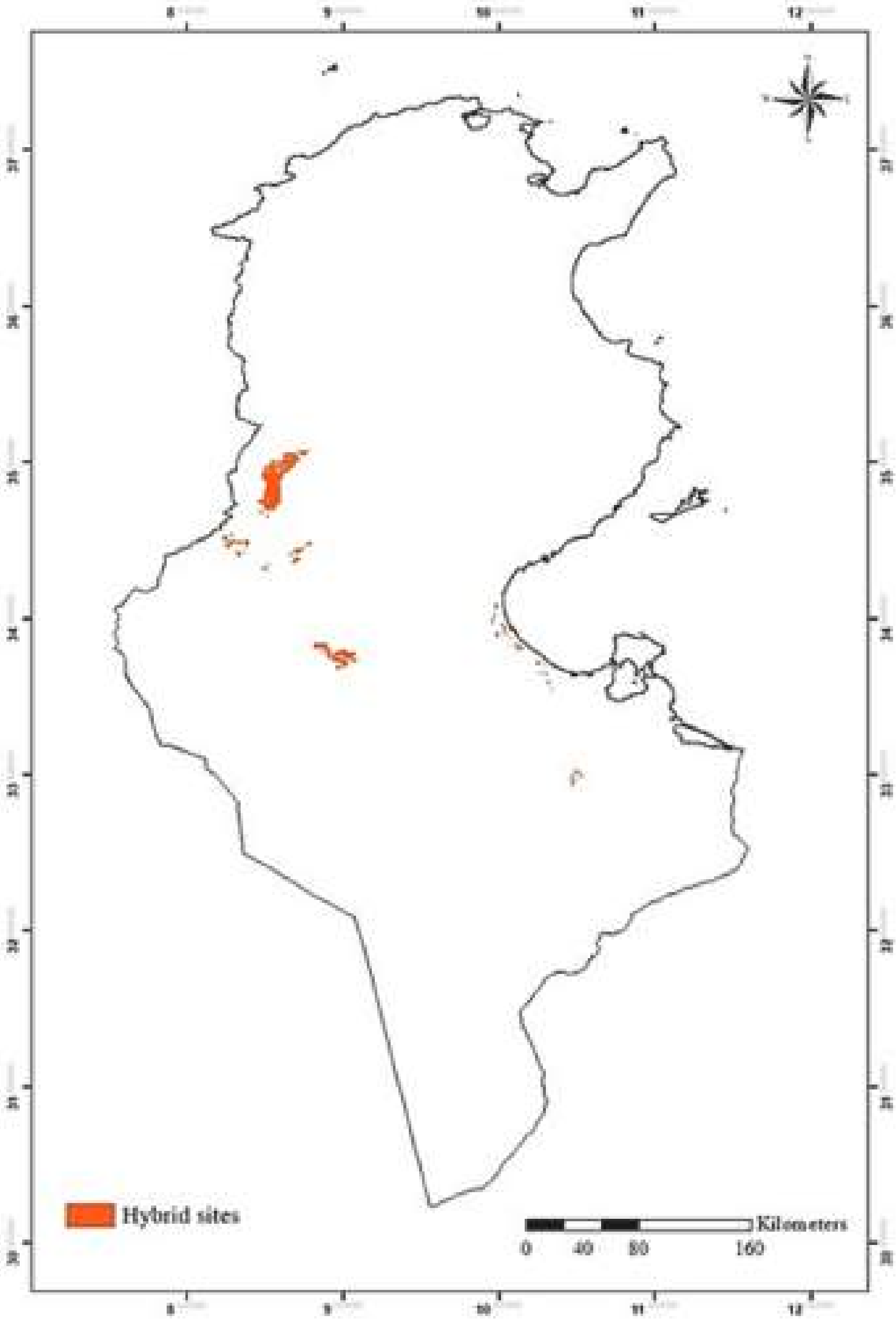

Fig. 8. Potential hybrid sites.

4.1. AHP comparison analysis

The individual pairwise comparisons of each expert were computed separately and then aggregated into a final synthesized matrix performed by means of the geometric mean using a traditional Excel sheet. The assigned weights for the evaluation of WPPs and SPVPs applied in this study using AHP pairwise comparisons are illustrated in Table 6. In both cases, the values of consistency ratios (CRs) were less than 10 % (4.60 and 5.03 %) which is considered acceptable. More details are included in Appendix B.

The AHP model indicated that the resource criteria of solar radiation and wind speed were the major determining factors. These criteria scored nearly 38 % and 35 % for wind and solar, respectively. As a rule of thumb, the greater the available resources, the greater the electricity generated. The next most influential criteria were slope and land use with both technologies ranking second and third. These criteria had scores of 15.9 % and 15.6 % for wind and 18.1 % and 12.3 % for solar, respectively. Transport and power lines under the accessibility criteria were yet significant factors for both technologies with almost similar weights of 12.7 %; for solar, the criterion of grid network was slightly lower scoring 9.4 %, though. As a result, it is essential to locate solar or wind facilities away from transport links and grids, as well as on a flat or gentle slope; otherwise, further costs will be incurred. The literature has shown that solar PV systems are highly sensitive to temperature and aspect factors due to their direct impact on power output. As a result, they were mainly used in solar technology. Higher temperatures significantly reduce the cells' efficiency, while choosing the right direction maximizes the generation of power and minimizes the cost of

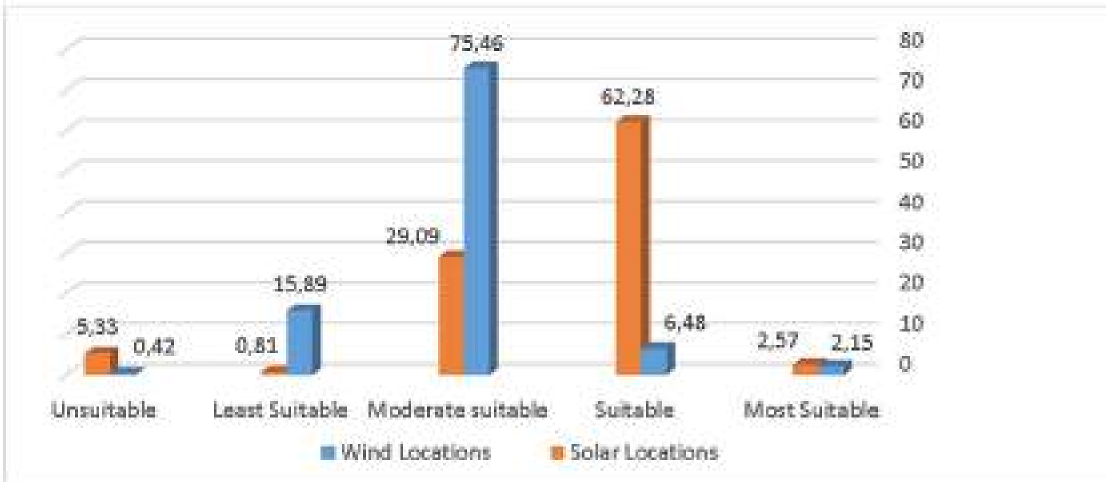

Fig. 9. Land Suitability distribution for solar and wind.

Table 7
Sample of the large wind turbines available in the market [26].

Turbine		Hub height (m)	Rotor diameter (m)	Name plate capacity (MW)	Area per turbine (Km^2)	installed capacity per unit area (MW/km^2)
Vestas	III	84/94/119	112	3.8	0.794	4.157
Vestas	III	80/95/105	90	1.8	0.405	4.444
Eno	III	92/128/142	126	3.5	0.794	4.409
Siemens	IIB	80	108	2.3	0.583	3.944
Gamesa	III	109	97	2.0	0.470	4.251
Mitsubishi	II	80	100	2.4	0.500	4.800
Nordex	III	164	116.8	2.4	0.682	3.518

technical modifications. However, they were given lower scores of 5.3 % and 4.7 % respectively. As for the vicinity of residential areas, it was deemed to be more influential considering the site location of a WPP 5.3 % compared with an SPVP 3 %.

4.2. Spatial distributions of wind and solar PV sites

The final wind suitability map (Fig. 6) has shown that the category of 'highly suitable' locations represents 2.15 % of the total surface area and covers 3335 km^2, while areas that fell under "suitable", "moderately suitable," and "least suitable" areas were 6.48 %, 75.46 %, and 15.89 %, respectively. It has also been found that the most suitable areas were located northwest to central west, southeast, and utmost north. According to the model findings, 46 sites were identified as optimal locations to deploy WPPs. This is owing to significant wind resources, and proximity to major roads, grid lines, and urban areas. Among these regions, Thala, Kasserine Sud, Feriana, and Majel Belabbes stood as the most favorable candidate sites accounting for nearly 38 % of these most suitable areas.

Likewise, according to the solar suitability map (Fig. 7), the potentially viable areas were categorized as follows: 2.57 % (nearly 3815 km2) are classified as 'most suitable', 62.28 % 'suitable', 29.79 % 'moderately suitable', 0.11 % 'least suitable', and 5.33 % 'unsuitable'. Solar locations of most suitability were mainly scattered in the central and southern regions of the country, as opposed to wind patterns. This is mainly due to the high solar insolation, gentle slope, and bareland prevailing in those regions. On this map, Benguerdane, Degueche, Kebili Nord, and Majel Belabbes represent over 30 % of the 45 local regions identified for this cluster. In addition, using the intersection function in ArcMap, 15 locations, 0.88 % (1351 km^2), were delineated as potential sites for hosting hybrid wind and solar systems (Fig. 8). In those regions, the average wind speed ranged between 8.79 and 15.38 m/s, whereas the average solar radiation varied between 1880 and 2048 kWh/m^2/year.

Therefore, being near the densely populated cities, having the necessary infrastructure, and enjoying significant wind and solar resources, such designated sites could offer a high potential for ultimate performance of onshore wind and solar PV systems. In the category of 'suitable' locations, it was evident that solar locations significantly outweighed those of wind. The solar sites under this category were densely scattered on the southern, central, and to a lesser extent on the eastern coast, representing nearly 62 % compared to nearly 6.5 % for wind (Fig. 9). Thus, by improving the efficiency of grid networks and transport infrastructure, there could be significant potential to have even more suitable locations to generate electric power.

4.3. Estimated energy production

From a theoretical perspective, wind and solar power generation could be defined as the availability of wind and solar resources within a promising and best-suited area for deploying WPPs and SPVPs based on the technical characteristics of the available commercial technologies. Thus, wind and solar potential are determined using GIS and the AHP technique, by screening out all the constraints from the final suitability maps. For this section, only the most suitable areas for both wind and solar were considered. However, owing to the low resolution of maps, this estimated area may not be entirely usable.

Estimated wind energy production

In order to generate utility-scale output power from large wind farms, large turbines are required as they have higher performance, and produce more energy even in low and medium winds [97]. However, the proper placement of turbines within the allocated farm has a direct impact on installation cost, operation, and energy yield. Generally, typical wind farms are designed with a spacing of 3–15 times the turbine's rotor diameter [29,98]. In this study, an equal spacing factor of 10D was selected as wind direction data was not available, where D is the turbine diameter. The installed capacity potential was computed based on a sample of commercial large wind turbines available in the market as illustrated in Table 7.

This capacity ranged between 3.518 and 4.8 MW/km^2, therefore, the installed capacity potential of 4 MW/km^2 was assumed to calculate the wind energy potential. The height of 120 m was chosen as it correlates best with the average hub heights of the considered turbines, which vary between 80 m (Siemens IIB) and 164 m (Nordex III). The measurements at 120 m were extrapolated using the power law equation [29]:

$$V_z = V_{ref}\left(\frac{Z}{Z_{ref}}\right)^P \quad (4)$$

where V_z is the wind speed at height Z, V_{ref} is the reference wind speed at height Z_{ref}, and p is the power law exponent.

Then, the wind annual energy production was estimated based on the following Eq. (5).

$$AEP(GWh) = \sum(\mathrm{ICP} * 8760 * \mathrm{Capacity\ Factor}) \quad (5)$$

where AEP is the annual energy production and ICP is the installed capacity potential. A wind turbine's capacity factor, which is a parameter usually used to measure its technical performance, depends on wind speed distribution as well as the type of wind machine, according to [99]. In the literature, the most commonly assumed capacity factors range from 20 to 30 % [100]. In Tunisia, Maatallah et al. 2013 [101], who investigated wind energy at different heights, found that the capacity factor of eight different turbines varied between 24 % and 45 %. Therefore, an average of 35 % was adopted as a capacity factor in this study.

The obtained results reveal that the estimated total wind energy could reach as high as 40.896 TWh per annum (see Table C.1 in Appendix C), which is nearly twofold the entire demand as of 2020 [15].

Estimated solar energy production

In order to compute the solar potential, the various technical characteristics of solar PV technologies have to be considered such as efficiency, system performance, and capacity factor [87,102]. Accordingly, the estimated annual solar output power could be computed as follows:

$$\mathrm{AEP} = \mathrm{SR} * \mathrm{CA} * \mathrm{AF} * \eta \quad (6)$$

where AEP is the annual generated power (TWh/year), SR is the annual solar radiation (kWh/m2/year), CA is the total area of suitable locations (km^2); AF is the area factor of total CA that could be covered by solar panels (%), and η is the PV system's efficiency (%). Solar power potential was calculated based on the technical characteristics of monocrystalline silicon technology and PV modules tilted at latitude angles with the south surface orientation [87]. According to the results, Tunisia has an impressive solar energy yield estimated at 781.83 TWh/year. Even considering 10 % of the most suitable sites, it would generate almost 78 TWh of solar energy annually (see Table C.2 in Appendix C), which is roughly-four times the total consumption in 2020 [15].

Discussion

It is evident that Tunisia enjoys enormous solar and wind potential. Therefore, the obtained results can be very encouraging for policymakers and investors and can offer very competitive opportunities compared with similar studies [29,33,67].

Even though the Tunisian government has set itself an ambitious goal of making 30 % of its electric power from renewable sources by 2030 with a view to ensuring its energy independence, diversifying its energy mix, and reducing fossil fuel imports as well as emission intensity. However, very little appears to have changed. The social and political impasse, lack of funding, and the absence of a welcoming investment climate are among the major factors that hindered the acceleration of such a plan. Surprisingly, the designated potential sites lie within the least developed regions of the country such as Kasserine, Gafsa, and Kebili. Therefore, to bring these deprived communities into the development fold, concrete actions are required to boost investment in solar and wind projects. The process of identifying optimal locations usually involves improving grid and transportation infrastructure, manufacturing facilities, and educational as well as training centers [67]. As a result, this will have positive implications for social welfare and living standards.

Conclusion

With the advent of renewable energy sources, solar and wind energy have become ideal options for power generation with a sustainable, secure, and environmentally-friendly future. As this sector continues to expand, identifying optimal sites for energy generation has become paramount, especially in light of the lack of supportive policies and regulatory frameworks. Thus, the main objective of the study was to propose a preliminary assessment of land suitability for deploying SPVPs and WPPs in Tunisia using the GIS-based MCDA methodology. This combination of GIS with MCDA was employed with a view to screening out the optimal candidate sites for such energy exploitation. This was done taking into account climatological, topographic, and economic factors. The assessment model was developed based on a comprehensive review of literature, similar research works, and experts' opinions. After conducting spatial analysis for both solar and wind, the potential sites were assessed and clustered into five categories: "highly suitable", "suitable", "moderately suitable", "least suitable", and "Unsuitable".

The study indicated that the entire territory of Tunisia was well suited to both solar and wind development as the country has significant potential. Based on the spatial analysis, the area to install WPPs was categorized as follows: 2.15 % (3334.65 km2) of the total available area was delineated as 'highly suitable', 15.78 % (9960.84 km2) fell under the 'suitable' cluster, 74.76 % and 7.28 % belonged to the categories of 'moderately suitable' and 'least suitable', respectively. Similarly, for deploying SPVPs only 3814.75 km2 (2.57 % of the available area) was classified as 'highly suitable', 61.86 %, 30.09 % and 5.35 % of the total surface area fell under the 'suitable', 'moderately suitable', and 'unsuitable' categories, respectively. In addition, the theoretical annual energy was estimated at 40.896 TWh for wind and 783.81 TWh for solar. Furthermore, it was concluded that the regions of Kassérine, Kebili, Gabès, and Gafsa were found to be ideal locations to host SPVPs as well as WPPs. Additionally, implementing research results can aid in tackling the pressing issue of unemployment. As a result, more jobs will be created at the local and regional levels. This is especially true in underdeveloped communities such as Kassérine, Gafsa, and Kebili where unemployment rates vary between 15.7 % and 20.2 %. Therefore, taking concrete actions to accelerate the deployment of solar and wind facilities will have positive implications for social welfare and living standards as infrastructure and income levels improve locally.

As for future works, it is recommended to carry out further local research on a finer scale to address the issue of site selection. Such research could be enriched with criteria such as hourly and daily data, wind directions, load information, dust storms, land cost, and land ownership; as this present paper falls short of this kind of data. Furthermore, it is also recommended to consider the possibility of installing hybrid systems such as PV-wind in more detail. Accordingly, the study's outcomes can be used by policymakers to be more proactive in developing solar and wind farms, which will help Tunisia achieve its 2030 strategic plan.

CRediT authorship contribution statement

Sassi Rekik: Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Visualization. **Souheil El Alimi:** Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Appendix A

Table A.1
Onshore Wind power plant site selection criteria

Climatology	Topography		Accessibility			Suitability Score
Wind Speed (m/s)	Slope (degree)	Land use	Grid network (km)	Transport links (km)	Urban areas (km)	
< 5	> 10	Settlements, water bodies, Forests	> 15	> 15	20 – 25	1
5 – 6	8 - 10	Cropland and trees	10 - 15	10 - 15	15 - 20	2
6 – 7	5 - 8	shrubs	5 - 10	5 - 10	10 - 15	3
7 – 8	2 - 5	Grass land & Sparse vegetation	1 - 5	1 - 5	5 - 10	4
> 8	0 - 2	Bare land	0.3 - 1	0.5 - 1	2- 5	5

Sources: (Ali et al, 2019;Effat & El-Zeiny, 2022;Ghasemi et al, 2019;Koc et al, 2019)

Table A.2
Solar PV power plant site selection criteria

Climatology		Topography			Accessibility			Suitability Score
GHI (kwh/m^2)	Temp (C)	Slope (degree)	Aspect	Landuse	Grid network (km)	Transport links (km)	Urban areas (km)	
< 1300	> 23	> 10	Flat	Settlements, water bodies, Forests	> 15	> 15	20 – 25	1
1700 - 1900	22 - 23	8 - 10	N, NE, NW	Cropland and trees	10 - 15	10 - 15	15 - 20	2
1900 - 2000	21- 22	5 - 8	E, W	shrubs	5 - 10	5 - 10	10 - 15	3
2000 - 2100	20 - 21	2 - 5	SE, SW	Grass land & Sparse vegetation	1 - 5	1 - 5	5 - 10	4
> 2100	< 20	0 - 2	S	Bare land	0.3 - 1	0.5 - 1	2- 5	5

Sources: (Alami Merrouni et al, 2018;Ali et al, 2019; Effat & El-Zeiny, 2022;Ghasemi et al, 2019;Koc et al, 2019)

Table A.3
Experts' Profile

	Designation	Organization	Field of experience	Years of experience
1	General Director	Alcor research and consulting firm	PhD, Economist specializing in energy and climate change	25
2	General Director	Solar Energy Department at Agence Nationale pour la Maîtrise de l'Energie ANME	Solar and Wind energy policies	27
3	University Professor	l'Ecole Nationale d'Ingénieurs de Tunis (ENIT)	Renewable Energies and Energy Efficiency	38
4	Senior Engineer	STEG (SociétéTunisienne de l'Electricité et du Gaz)	Research and Development	26
5	Senior technical manager of Solar and Wind Farms	STEG (SociétéTunisienne de l'Electricité et du Gaz)	Solar and Wind energy	27

Appendix B

Table B.1
Onshore normalized pairwise comparison matrix and criteria weights

	Wind speed	Slope	Landuse	Grid network	Transport links	Urban areas	Weight
Wind speed	1	3	4	3	3	4	38.0%
Slope		1	2	1	1	3	15.9%
Landuse			1	2	2	3	15.6%
Grid network				1	1	2	11.9%
Transport links					1	3	12.7%
Urban areas						1	5.8%
λmax = 6.287		CI = 0.057		CR = 4.6%			

Table B.2
Solar PV normalized pairwise comparison matrix and criteria weights

	GHI	Slope	Landuse	Temperat	Aspect	Grid network	Transport links	Urban areas	Weight
GHI	1	3	5	6	7	4	3	5	34.8%
Slope		1	2	5	4	2	2	5	18.1%
Landuse			1	4	3	2	1	4	12.3%
Temperature				1	2	1/3	1/3	3	5.3%
Aspect					1	1/2	1/3	3	4.7%
Grid network						1	1/2	5	9.4%
Transport links							1	4	12.4%
Urban areas								1	3.0%
λmax = 8.502		CI = 0.072				CR = 5.1%			

Appendix C

Table C.1
Wind Annual Estimated Energy

Location	Most suitable AREA (km^2)	% of most suitable areas	ICP (MW)	AEP (TWh)
Thala	437.14	13.11%	1748.56	5.361
Kasserine Sud	402.45	12.07%	1609.8	4.936
Feriana	239.3	7.18%	957.2	2.935
Majel Belabbes	202.34	6.07%	809.36	2.481
Kebili Nord	181.43	5.44%	725.72	2.225
Mateur	157.29	4.72%	629.16	1.929
Hidra	130.5	3.91%	522	1.600
Souk El Ahed	126.83	3.80%	507.32	1.555
Tajerouine	122.47	3.67%	489.88	1.502
Kalaa Khesba	112.37	3.37%	449.48	1.378
Oum Larais	107.55	3.23%	430.2	1.319
Jerissa	102.15	3.06%	408.6	1.253
Kalaat Senan	97.96	2.94%	391.84	1.201
Foussana	91.98	2.76%	367.92	1.128
Metouia	80.88	2.43%	323.52	0.992
Kasserine Nord	67.46	2.02%	269.84	0.827
Menzel Bourguiba	64.46	1.93%	257.84	0.791
Jedeliane	63.78	1.91%	255.12	0.782
Gabès Ouest	58.26	1.75%	233.04	0.715
Ghazala	57.2	1.72%	228.8	0.702
Utique	54.71	1.64%	218.84	0.671
El Alia	51.49	1.54%	205.96	0.631
Gabès Sud	46.72	1.40%	186.88	0.573
Menzel Jemil	41.77	1.25%	167.08	0.512
Redeyef	38.68	1.16%	154.72	0.474
Tataouine Nord	27.07	0.81%	108.28	0.332
Ezzouhour	22.49	0.67%	89.96	0.276
Ghar El Melh	21.57	0.65%	86.28	0.265
Tinja	17.33	0.52%	69.32	0.213
Kef Ouest	17.27	0.52%	69.08	0.212
Makthar	14.82	0.44%	59.28	0.182
Bizerte Sud	12.96	0.39%	51.84	0.159
Ksour	10.77	0.32%	43.08	0.132
Mareth	9.95	0.30%	39.8	0.122
Ghannouch	8.75	0.26%	35	0.107
Dahmani	7.54	0.23%	30.16	0.092
Rouhia	4.59	0.14%	18.36	0.056
Lake Ichkeul	4.3	0.13%	17.2	0.053
Gabès Médina	4.0	0.12%	16	0.049
Kebili Sud	3.22	0.10%	12.88	0.039
Total	**3334.65**		**13338.06**	**40.896**

Table C.2
Solar Annual Estimated Energy

Location	Most suitable AREA (km^2)	% of most suitable areas	GHI ($Kwh/m^2/year$)	AEP (TWh)
Agareb	108.59	2.85%	1907.30	21.75
Belkhir	30.37	0.80%	1937.16	6.18
Ben Guerdane	346.95	9.09%	1982.89	72.24
Beni Khedache	1.14	0.03%	2013.31	0.24
Bir Ali Ben Khélifa	120.31	3.15%	1911.25	24.14
Bir Lahmar	10.68	0.28%	1986.24	2.23
Degueche	315.01	8.26%	1947.90	64.43
El Ghraiba	18.4	0.48%	1921.18	3.71
Feriana	103.89	2.72%	1907.34	20.81
Gabès Médina	3.95	0.10%	1915.78	0.79
Gabès Ouest	54.68	1.43%	1960.23	11.25
Gabès Sud	30.23	0.79%	1951.11	6.19
Gafsa Nord	24.01	0.63%	1945.07	4.90
Gafsa Sud	154.56	4.05%	1948.26	31.62
Ghannouch	12.19	0.32%	1919.54	2.46
Ghomrassen	5.71	0.15%	2019.35	1.21
Guetar	79.05	2.07%	1960.20	16.27
Hamma	169.24	4.44%	1968.30	34.98
Kasserine Sud	98.06	2.57%	1879.59	19.35
Kebili Nord	264.11	6.92%	1974.39	54.75
Ksar	57.29	1.50%	1950.94	11.74
Mahres	37.56	0.98%	1913.79	7.55
Majel Belabbes	240.61	6.31%	1941.35	49.05
Mareth	116.78	3.06%	1966.17	24.11
Mazzouna	14.71	0.39%	1915.24	2.96
Mdhilla	105.84	2.77%	1969.69	21.89
Médenine Nord	23.66	0.62%	1972.43	4.90
Médenine Sud	30.69	0.80%	1968.59	6.34
Meknassi	3.63	0.10%	1914.94	0.73
Menzel Bouzaiene	13.28	0.35%	1922.49	2.68
Menzel Habib	64.17	1.68%	1948.69	13.13
Metlaoui	188.34	4.94%	1959.77	38.76
Metouia	147.23	3.86%	1944.15	30.05
Nefta	85.38	2.24%	1947.46	17.46
Oum Larais	122	3.20%	1960.70	25.12
Redeyef	30.56	0.80%	1964.44	6.30
Sakiet Eddaier	1.28	0.03%	1892.55	0.25
Sened	80.5	2.11%	1944.50	16.44
Sfax Sud	9.4	0.25%	1901.64	1.88
Sidi Makhlouf	2.54	0.07%	1957.35	0.52
Skhira	32.67	0.86%	1928.96	6.62
Souk El Ahed	176.04	4.61%	1954.89	36.13
Tataouine Nord	70.47	1.85%	2014.05	14.90
Tataouine Sud	4.24	0.11%	2048.45	0.91
Tozeur	204.75	5.37%	1949.31	41.91
Total	**3814.75**			**781.83**

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