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Geospatial multi-criteria analysis for identifying optimum wind and solar sites in Africa: Towards effective power sector decarbonization

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ABSTRACT

Africa has the potential to provide for its growing energy needs with renewable electricity sources. We implement a multi-criterial geospatial optimization to locate the most favorable sites for utility-scale, grid-connected onshore wind and solar PV. Legal, technical, political, environmental, socio-economic and investment risk factors were incorporated in the model. Analysis of the whole African continent revealed South Africa and Egypt to be amongst the most favorable countries for renewable investment, so these were subject to more in-depth analysis. The analysis revealed the favorable conditions offered by Egypt for solar energy installations are attributable to high yearly average insolation (278.3 W/m^2), grid reliability, terrain appropriateness and political stability. Current heavy dependence on fossil fuels (165.7 billion kWh) means that there is great potential for emissions reduction from the power sector. South Africa, on the other hand, offers favorable conditions for wind installations due to high wind speeds (12 m/s at 100 m height), high fossil fuel electricity reliance (213 billion kWh), good political stability, and adequate techno-economic factors. The levelized cost of constructing wind farms in propitious sites in South Africa is 16.7% lower than building coal-fired power stations, while the levelized cost of constructing solar farms in optimum zones in Egypt is 29.7% lower than investing in combined-gas turbines and 37% lower than investing in diesel generators.

1. Introduction

The population of Africa is expected to double by 2050, reaching an estimated 2.4 billion in a world where population growth is declining [1]. Predicted to be the fastest urbanizing region in the world, the continent is expected to witness more than 80% of its population growth to occur in cities over the next two decades [2]. This population boom in the burgeoning cities of Africa is foreseen to have significant economic repercussions that would entail profound changes in energy demand. The current lion's share of the electricity generation in Africa comes from fossil fuel (40% Natural gas, 30% Coal and 9% Oil), which makes up 79% of the centralized electricity grid, with a generation potential of 870 TWh [3]. While electricity access in Northern Africa reaches nearly 99% of the population, primarily generated from oil and gas, Sub-Saharan Africa (excluding South Africa) has an electricity access of about 29%, more than half of which is generated from hydropower [4]. South Africa, on the other hand, has an electricity access of 77%, and is heavily reliant on coal [4,5]. In 2018, renewable energy generation capacity in Africa stood at about 50 GW, primarily derived from hydropower (35 GW), wind (5.5 GW), solar PV (4.5 GW) and geothermal (0.7 GW) [3]. However, as stated by Rodriguez-Manotas et al. [6], several East African countries which are heavily reliant on hydro for electricity generation, are shifting towards other renewable energy sources due to the depletion of water resources and successive droughts. The IRENA [7] reported global weighted average cost reductions of 69% in the electricity generation of utility-scale solar PV plants and 18% for onshore wind electricity generation between 2010 and 2016. Hence onshore wind and solar PV represent viable alternatives that can ensure a cost-effective and economically robust, continent-wide energy transition.

Power sector reform is much needed in Africa since, on the one hand, over-reliance on fossil fuel imports has economic repercussions on net-importing countries caused by fossil fuel price fluctuations on international markets, while on the other hand, economies dependent on fossil fuel exports are subject to increased fiscal pressures caused by dwindling export revenues [8,9]. Consequently, diversification of the energy mix is an important step in achieving energy security and ensuring an economically robust energy transition. The long-term international goal of net zero emissions will rely on major renewable energy investments to replace fossil fuels. Even in the medium term, several African countries aim to meet their emission reduction targets by transforming their

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Nomenclature

Abbreviations

AHP	Analytical Hierarchy Process
CO_2	Carbon Dioxide
CI	Consistency Index
CMSAF	Climate Monitoring Satellite Application Facility
CR	Consistency Ratio
ECM	Environmental Change and Management
EIA	Energy Information Administration
GIS	Geographic Information System
IRENA	International Renewable Energy Agency
LCOE	Levelized Cost of Electricity
MCDA	Multi-Criteria Decision Analysis
METEOSAT	Meteorological Satellite
NASA	National Aeronautics and Space Administration
NOAA	National Oceanic and Atmospheric Administration
NPP	Net Primary Productivity
OECD	Organization for Economic Co-operation and Development
PPA	Power Purchase Agreement
PV	Photovoltaic
RCMRD	Regional Centre for Mapping of Resources for Development
RI	Random Index
SDG	Sustainable Development Goals
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
WFP	World Food Programme
WLC	Weighted Linear Combination
WWF	World Wide Fund for Nature

Symbols

%	Percentage
$	US Dollars
λ_{max}	Maximum Eigenvalue
μ	Efficiency
σ_U	Standard deviation
A	Scale factor
A_f	Area factor
A_T	Total parcel of land
E	Annual electricity generation potential
$f(U)$	Probability density function
G	Global horizontal irradiation
i	Discount rate
k	Shape factor
K_c	Capital cost
K_{RF}	Capital recovery factor
m	Factor
N	Row/column number
O_f	Fixed annual operating costs
S	Aggregated value
t	Economic life
U	Wind speed
U_{avg}	Average of wind speed
v_c	Cut-in speed
v_r	Rated speed
v_f	Cut-out speed
w_i	Weight of factor
x_i	Standardized value
Z	Category

Units

$/MWh	US Dollar per Megawatt-hour
GW	Gigawatt
km^2	Kilometer square
kWh	Kilowatt-hour
kWh/m^2day	Kilowatt-hour per meter square per day
m/s	Meter per second
MW	Megawatt
MWh	Megawatt-hour
TWh	Terawatt-hour
W/m^2	Watt per meter square
°C	Degree Celsius

carbon-intensive power sectors to low carbon energy systems [10]. However, the costs of renewable energy are spatially variable for a range of geographical, environmental, economic and political reasons. In this context, it is important that renewable energy investments are made at spatially appropriate sites. The last decade has seen the tripling of international investments channeled to the energy sector in the continent, attaining $8 billion in 2015 [11]. The main investor over the 2005–2015 period was the World Bank Group with a financial assistance of $17.6 billion, primarily in fossil fuel energy (notably coal) where its contribution was more pronounced in both Sub-Saharan Africa and South Africa. The European Union on the other hand invested $16.8 billion, mainly in hydroelectricity, solar and wind, predominantly in North Africa. A quarter of the investments over the period 2005–2015 came from the African Development Bank with a share of $14.4 billion, mostly in electricity distribution infrastructures [11]. Africa was the recipient of the highest spatial density of the climate funds, with South Africa having the largest number of investments over the 2013–2016 period in the continent [12].

However, as stated by the Africa Progress Panel [13], excessive fragmentation coupled with poor coordination are major roadblocks in ensuring efficient investments in the African power sector. Investments made by the European Union in the continent has been distinctly uncoordinated with 26 different initiatives coming from member states and institutions [14]. Such a fragmented system results in efficiencies and overlaps in the investment process. Consequently, coordination among the donors and knowledge of where to invest in order to make a significant impact, are crucial. Numerous market barriers exist in Africa which tend to dampen the attractiveness of investments across the continent. Some countries have started to establish adequate policy and regulatory frameworks to spur renewable energy growth and address these investment barriers.

This paper seeks to geolocate the potential of the African continent for utility-scale, grid-connected solar PV and onshore wind farms. As indicated by Gies [15] despite the fact that Egypt, Ethiopia, Kenya, Morocco and South Africa are driving renewable energy development, a significant barrier to project implementation in the African continent is the unavailability of high-resolution wind and solar resource potential maps that would allow investors to make informed decisions pertaining to investments. Consequently, it would be useful to develop a high-resolution mapping of the solar and wind resource potentials in Africa in order to bridge this knowledge gap and attract investments for utility-scale solar and wind energy projects at spatially optimum sites to help avert a fossil fuel lock-in.

Determination of optimum sites for utility-scale wind and solar farm installations necessitates the integration of multiple factors that affect the costs of both generation and the transfer of electricity to users, whilst meeting legal requirements [16]. Consequently, in this paper, we use Multi-Criteria Decision Analysis (MCDA) coupled with GIS, to incorporate environmental, economic, legal, social and technical criteria, in order to determine spatially optimum sites for utility-scale wind and

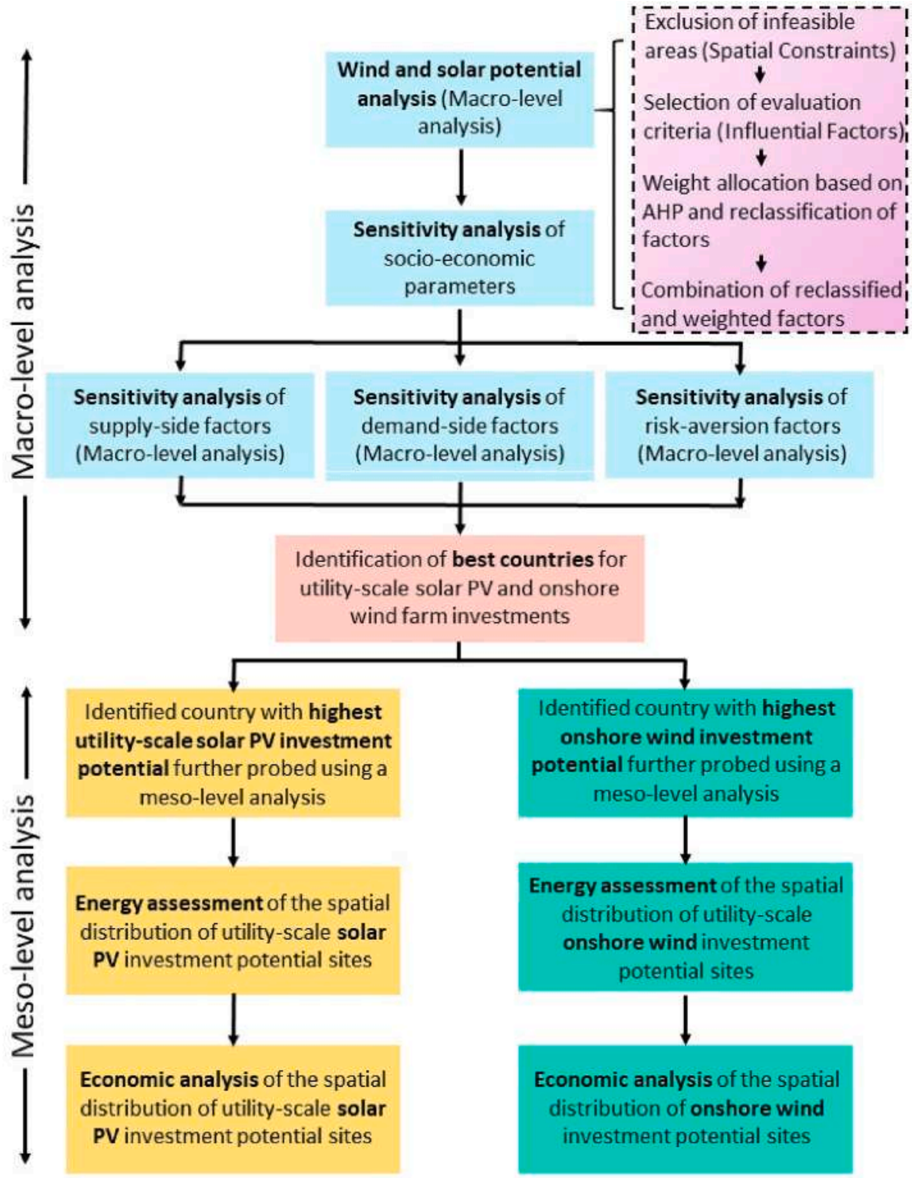

Fig. 1. Methodological flowchart illustrating the main steps adopted in the current study.

Table 1
Preference scale for AHP (Source: Saaty [25]).

Intensity of Importance	Definition	Explanation
1	Equal importance	Two activities contributing equally to the objective
3	Moderate importance	Experience and judgement slightly favor one over another
5	Strong importance	Experience and judgement strongly favor one over another
7	Very strong importance	Activity is strongly favored and its dominance is demonstrated in practice
9	Absolute importance	Importance of one over another affirmed on the highest possible order
2,4,6,8	Intermediate values	Used to represent compromise between priorities listed above
Reciprocal of above non-zero numbers	If activity *i* has one of the above non-zero numbers assigned to it when compared with *j*, then *j* has the reciprocal value when compared with *i*	

solar installations. The objective of the analysis is to identify countries having abundant solar and wind resources and which rely heavily on fossil fuel electricity, which should be priorities for investments in utility-scale wind and solar so as to phase out fossil fuel reliance.

Regional studies from different areas in Africa using the MCDA GIS-based approach have mainly focused on revealing the technical potential for wind and solar installations. In the tropical savanna climate of Mauritius, Doorga et al. [17] identified optimum sites for solar farms using a multi-criteria model consisting of climatological, topographic and economic-based factors. In the Mediterranean climate of Southern Morocco, Mensour et al. [18] implemented a multi-criteria model, incorporating climatological, environmental, topographic and economic-based factors to locate ideal sites for solar farm placements. Hamid [19], on the other hand, explored the wind energy potential in the desert climate of Egypt using a multi-criteria model comprising of climatological, environmental, topographic and economic-based factors. In the oceanic subtropical highland climate of the Amhara Region in Ethiopia, Dereje [20] identified ideal sites for wind farm placements using a multi-criteria model consisting of climatological, social, environmental, topographic and economic-based factors. However, while

Table 2
Description of criteria used in solar PV and onshore wind spatial optimization models.

Country	Optimization	Technique	Constraint factor/Rejection areas	Criteria and Weight	Reference
UK	Wind Resource	• AHP; • WLC;	• Agricultural land with high fertility • Historical site (<1 km away from cultural heritage site) • Landscape designation (<1 km away from national parks) • Settlement areas (<0.5 km away from built-up areas) • Wildlife designation (<1 km away from conservation sites) • Aspect and slope (>10% slope and North, East and West facing slopes)	• Wind speed (55.5%) • Distance from historical site (7.8%) • Distance from settlement area (13%) • Distance from conservation area (13%) • Distance from transport network (4.6%) • Distance from grid network (6.2%)	Watson and Hudson [32]
Iran	Wind Resource	• AHP	• Elevation (>2 km) • Slope (>30%) • Distance from protected area (<2 km) • Distance from airports (<2 km away from airports) • Distance from historical sites (<0.7 km) • Distance from lakes, water bodies and rivers (<1 km) • Distance from urban area (<2.5 km) • Distance from rural area (<0.5 km)	• Wind energy (38.9%) • Distance from grid network (27.7%) • Distance from transport network (14.4%) • Distances from substations (8.4%) • Distance from urban areas (6.8%) • Slope of land (3.9%)	Moradi et al. [33]
Germany	Wind Resource	• AHP	• Distance from residential area (<0.55 km) • Distance from mixed-use area (<0.4 km) • Distance from road and transmission lines (<0.1 km) • Distance from natural resource areas where there are presence of bats and birds (<0.3 km) • Distance from water bodies (<0.05 km) • Slope of terrain (>30%)	• Wind energy (21.6%) • Distance from natural areas (20.4%) • Distance from urban areas (18.5%) • Distance from grid network (8%) • Distance from road network (7.4%) • Distance from points of interest (7.2%) • Landscape architecture (6.2%) • Land cover type (6%) • Slope of land (4.6%)	Höfer et al. [34]
Spain	Solar Resource	• AHP • TOPSIS	• Cultural heritage sites • Archaeological and Paleontological sites • Watercourses and streams • Military areas • Conservation areas • Sites of interest • Cadastral municipalities • Inappropriate slopes and orientation • Mountains	• Solar radiation (23.8%) • Average temperature (4.8%) • Distance to grid lines (32.5%) • Distance to substations (8.9%) • Distance to road networks (4.3%) • Distance to villages (2.8%) • Land slope (11.2%) • Land orientation (4.8%) • Plot areas (1.2%) • Agrological capacity (5.6%)	Sánchez-Lozano et al. [35]
Serbia	Solar Resource	• AHP	• Permanent water bodies • Protected natural areas • Airports • Transportation and grid networks • Mineral extraction and dump sites • Vegetation areas • Built-up areas	• Solar radiation (30.5%) • Sunshine duration (18.4%) • Air temperature (11.1%) • Relative humidity (4.8%) • Slope (15.3%) • Aspect (7.7%) • Vegetation (12.2%)	Doljak and Stanojević [36]
Egypt	Solar Resource	• AHP	• Slope (>5%) • Distance from grid lines (<0.5 km) • Distance from road lines (<0.15 km) • Distance from railway lines (<0.15 km) • Distance from settlement areas (<1.5 km) • Dark pixel values excluded • Slope orientation (North facing) • Low insolation values (<4.5 kWh/m^2day) • Land types including urban areas, water bodies and agricultural lands • Air temperatures (>24.5 °C)	• Solar radiation (22.1%) • Slope (11.5%) • Distance from grid lines (3.5%) • Distance from road networks (5.6%) • Distance from railway lines (1.9%) • Distance from settlement areas (5.4%) • Shadow (7.7%) • Aspect (8.2%) • Relative humidity (4.1%) • Wind speed (2%) • Air temperature (3%) • Land cover (12.5%) • Land capability (12.5%)	Habib et al. [37]

regional, meso-scale multi-criterial studies tend to involve limited factors for optimum wind and solar site identifications, a continent-wide, macro-scale analysis would require the scope to be broadened in order to account for political and investment risk factors which dictate renewable energy investments. However, there is no comparable analysis at the continental scale.

The geographical limitations of previous resource assessment studies are mainly due to the lack of high-density and temporally consistent long-term in-situ measurements, particularly in sub-Saharan Africa, which pose a major problem to conduct a geospatial analysis at the

Table 3
Description of spatial constraint data.

Model	Data	Temporal coverage	Spatial resolution	Data source
Macroscale solar/ wind	Disputed territories	2018	Meso-scale	Natural Earth
	Net primary productivity	2016	0.1°–0.1°	NASA satellite
	Settlement areas	2020	0.008°–0.008°	WorldPop
	Elevation >2 km	2000	0.1°–0.1°	NASA satellite
	Slope >10%	2000	0.1°–0.1°	NASA satellite
	Protected areas	2020	Meso-scale	Protected Planet
	Water bodies	2003	Meso-scale	WWF
Mesoscale solar/ wind	Places of interest	2020	Meso-scale	OpenStreetMap
	Airports and heliports	2020	Meso-scale	WFP
	Settlement areas	2020	0.008°–0.008°	WorldPop
	Slope >10%	2017	0.0003°–0.0003°	RCMRD Geoportal
	Elevation >2 km	2017	0.0003°–0.0003°	RCMRD Geoportal
	Protected areas	2020	Meso-scale	Protected Planet
	Conservation areas	2020	Meso-scale	DEA South Africa

continental level [21]. However, the recent availability of high-resolution and continent-wide solar and wind datasets recorded by METEOSAT satellite has enabled us to conduct a continent-wide analysis. Moreover, besides the larger-scale analysis, the proposed multi-criteria analysis is the first to integrate political and institutional factors to reflect the variations in prevailing politico-institutional regimes across Africa. Investors rank political concern as the major factor influencing investments while an adequate institutional structure comprising of an established supply chain, expertise and attractive policy landscape influence the rate of renewable energy investments [22]. The importance of the current study is that it will provide knowledge of where investments in renewables should be taking place in Africa, to assist investors in making informed decisions for effective power sector decarbonization.

2. Methodology

2.1. Framework overview

The methodological framework is shown in Fig. 1. Initially, a macro-level analysis is performed to identify the countries having high wind and solar energy investment potentials. Consequently, a wind/solar potential model is implemented, integrating factors found to influence the placements of wind and solar farms (influential factors). Weights are allocated to each influential factor based on its degree of influence. The weighted factors are thereafter combined and infeasible areas (spatial constraints) for project implementation are identified and removed. The aim of the proposed model is to identify countries witnessing high solar/wind resources and which are heavily dependent on fossil fuel electricity so as to attract investments in utility-scale solar/wind and phase out fossil fuel reliance.

Table 5
AHP results showing the (a) factor weights and (b) decision matrix for the solar potential analysis.

(a) Factor weights

Cat	Criteria	Weight	Rank
Z_1	Solar radiation	21.8%	1
Z_2	Temperature	5.8%	6
Z_3	Country risk classification	21.8%	1
Z_4	Fossil fuel electricity generation	21.8%	1
Z_5	Slope	8.8%	5
Z_6	Proximity to settlement areas	2.7%	8
Z_7	Proximity to grid lines	13.5%	4
Z_8	Proximity to road network	3.9%	7

(b) Decision matrix

	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8
Z_1	1	4.00	1.00	1.00	3.00	6.00	2.00	5.00
Z_2	0.25	1	0.25	0.25	0.50	3.00	0.33	2.00
Z_3	1.00	4.00	1	1.00	3.00	6.00	2.00	5.00
Z_4	1.00	4.00	1.00	1	3.00	6.00	2.00	5.00
Z_5	0.33	2.00	0.33	0.33	1	4.00	0.50	3.00
Z_6	0.17	0.33	0.17	0.17	0.25	1	0.20	0.50
Z_7	0.50	3.00	0.50	0.50	2.00	5.00	1	4.00
Z_8	0.20	0.50	0.20	0.20	0.33	2.00	0.25	1

Table 4
Description of evaluation criteria data used in model implementation.

Model	Case	Data	Temporal coverage	Spatial resolution	Data source
Macroscale solar/wind	Wind/Solar model	Monthly average of daily global horizontal radiation	1982–2015	0.05°–0.05°	CMSAF satellite
		Monthly average of daily land surface temperatures	1981–2010	0.5°–0.5°	NOAA
		Monthly average of wind speed	1970–2000	0.2°–0.2°	WorldClim
		Country risk classification	2020	Country-scale	OECD
		Fossil fuel electricity generation	2017	Country-scale	EIA
		Slope (Derived from elevation data)	2000	0.1°–0.1°	NASA satellite
		Proximity to settlement areas	2020	0.008°–0.008°	WorldPop
		Proximity to grid/road network	2020	Mesoscale	OpenStreetMap
	Supply side	Solar PV/onshore wind total capacity	2020	Country-scale	IRENA
	Demand side	Electricity access	2018	Country-scale	World Bank
		Monthly outages	2006–2019	Country-scale	World Bank
	Risk-aversion	Fossil fuel pre-tax subsidy	2019	Country-scale	SDG
		Monthly mean precipitation	1998–2016	0.25°–0.25°	NASA satellite
Mesoscale wind	Conventional	Wind speed	2008–2017	0.0025°–0.0025°	World Bank
		Slope (Derived from elevation data)	2017	0.0003°–0.0003°	RCMRD Geoportal
		Proximity to settlement areas	2020	0.008°–0.008°	WorldPop
		Proximity to grid/road network	2020	Mesoscale	OpenStreetMap
Mesoscale solar	Conventional	Monthly mean of daily global horizontal radiation	1994–2018	0.0025°–0.0025°	World Bank
		Slope (Derived from elevation data)	2000	0.0003°–0.0003°	NASA and NGA
		Aspect (Derived from elevation data)	2000	0.0003°–0.0003°	NASA and NGA
		Monthly average of daily land surface temperatures	1981–2010	0.5°–0.5°	NOAA
		Proximity to settlement areas	2020	0.008°–0.008°	WorldPop
		Proximity to grid/road network	2020	Mesoscale	OpenStreetMap

Table 6
AHP results showing the (a) factor weights and (b) decision matrix for the wind potential analysis.

(a) Factor weights

Cat	Criteria	Weight	Rank
Z_1	Wind speed	22.9%	1
Z_2	Country risk classification	22.9%	1
Z_3	Fossil fuel electricity generation	22.9%	1
Z_4	Proximity to grid lines	13.6%	4
Z_5	Proximity to road network	8.5%	5
Z_6	Slope	5.5%	6
Z_7	Proximity to settlement areas	3.7%	7

(b) Decision matrix

	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7
Z_1	1	1.00	1.00	2.00	3.00	4.00	5.00
Z_2	1.00	1	1.00	2.00	3.00	4.00	5.00
Z_3	1.00	1.00	1	2.00	3.00	4.00	5.00
Z_4	0.50	0.50	0.50	1	2.00	3.00	4.00
Z_5	0.33	0.33	0.33	0.50	1	2.00	3.00
Z_6	0.25	0.25	0.25	0.33	0.50	1	2.00
Z_7	0.20	0.20	0.20	0.25	0.33	0.50	1

A sensitivity analysis is conducted on the socio-economic and political factors that were integrated in the wind/solar potential model in order to cater for future uncertainties in the infrastructural and social criteria. Owing to the underlying uncertainties in the formulation of the wind/solar potential model itself, three additional sensitivity tests are proposed on the supply-side, demand-side and risk-aversion factors, as presented in Appendix A, so as to offer three additional perspectives on power sector decarbonization.

The identified best countries are then further investigated using a meso-level test in order to refine the analysis. An energy assessment is thereafter conducted to examine the relationship between energy yield and investment potential site selection. To close the analysis, an economic appraisal is performed to determine the viability of the project.

2.2. Analytical Hierarchy Process (AHP)

We apply the Analytical Hierarchy Process (AHP) to combine the multiple criteria that influence wind and solar energy investments. AHP is a semi-quantitative method which involves pair-wise comparisons among criteria in order to determine relative weights so as to guide the decision process [23]. As stated by Contreras et al. [24], the four main stages in AHP are: (1) Decomposition of the problem (section 2.6.1); (2) Pair-wise comparisons among elements (section 2.5) using 'Saaty's Fundamental Scale' (Table 1); (3) Generation of a decision matrix (Tables 5b and 6b); (4) Determination of relative weights for each element (Tables 5a and 6a).

The AHP relies on consistent judgement from decision makers. However, judgements are not always consistent and therefore a consistency check is useful. The consistency of decisions is determined through the consistency ratio (CR) which is a ratio of the inconsistency (CI) of the decision maker to a randomly generated index (RI), as shown below:

$$CR = \frac{CI}{RI} \tag{1}$$

where the inconsistencies obtained through the Consistency Index (CI) are derived as follows:

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{2}$$

and λ_{max} denotes the maximum eigenvalue; n represents the row/column number in the decision matrix.

To deal with the randomness of the AHP method, the consistency check was applied in the analysis and a consistency ratio of less than 10% was regarded as acceptable while values exceeding 10% implied that the process ought to be repeated until a satisfactory value was obtained.

2.2.1. Weighted linear combination (WLC)

Each layer element with an associated weight, based on the output of the AHP method, is then combined using the equation below to generate a suitability map. The WLC method permits the generation of a composite layer in the GIS platform which takes into consideration the weights of individual criterion [26]. It is derived using the equation:

$$S = \sum_{m=1}^{n} w_i x_i \tag{3}$$

where S is the aggregated value; w_i represents the weight of factor i; and x_i denotes the standardized value of factor m.

2.3. Energy modelling

The annual electricity yields from solar PV and onshore wind energy technologies are computed as follows:

The annual electricity generation potential, E [MWh], of solar PV technologies installed on a parcel of land is given by Ref. [27]:

$$E = G \times A_T \times A_f \times \mu \tag{4}$$

where G represents the global horizontal irradiation [$MWh/km^2 year$]; A_T denotes the total parcel of land [km^2]; A_f is the area factor representing the fraction of land that is solar exploitable; and μ represents the efficiency of the solar PV system.

The distribution of wind speeds at a site may be approximated by a Weibull distribution, describing the probabilistic variation of wind speed. It is given by the following probability density function, $f(U)$ [28]:

$$f(U) = \frac{k}{A}\left(\frac{U}{A}\right)^{k-1} exp\left[-\left(\frac{U}{A}\right)^{k}\right] \tag{5}$$

where U represents the wind speed; while the shape factor k; and the scale factor A can be calculated as follows:

$$k = \left(\frac{\sigma_U}{U_{avg}}\right)^{-1.086} \tag{6}$$

$$A = \frac{U_{avg}}{\tau\left(1 + \frac{1}{k}\right)} \tag{7}$$

where σ_U is the standard deviation; and U_{avg} is the average wind speed. Using the probability density function, the electricity generation of the wind turbine can be modelled as follows [29]:

$$P(v) = P_r \begin{cases} 0 \; for \; v < v_c \\ \frac{v^3 - v_c^3}{v_r^3 - v_c^3} for \; v_c \leq v \leq v_r \\ 1 \; for \; v_r \leq v \leq v_f \\ 0 \; for \; v \geq v_f \end{cases} \tag{8}$$

where v_c, v_r and v_f are the cut-in, rated and cut-out speeds of the wind turbine, respectively.

2.3.1. Economic modelling

The Levelized Cost of Electricity (LCOE) represents the full life-cycle costs, whether fixed or variable, of electricity generation technologies per MWh of electricity produced [30]. It provides a way of comparing the generation costs of different technologies. Under the assumption of

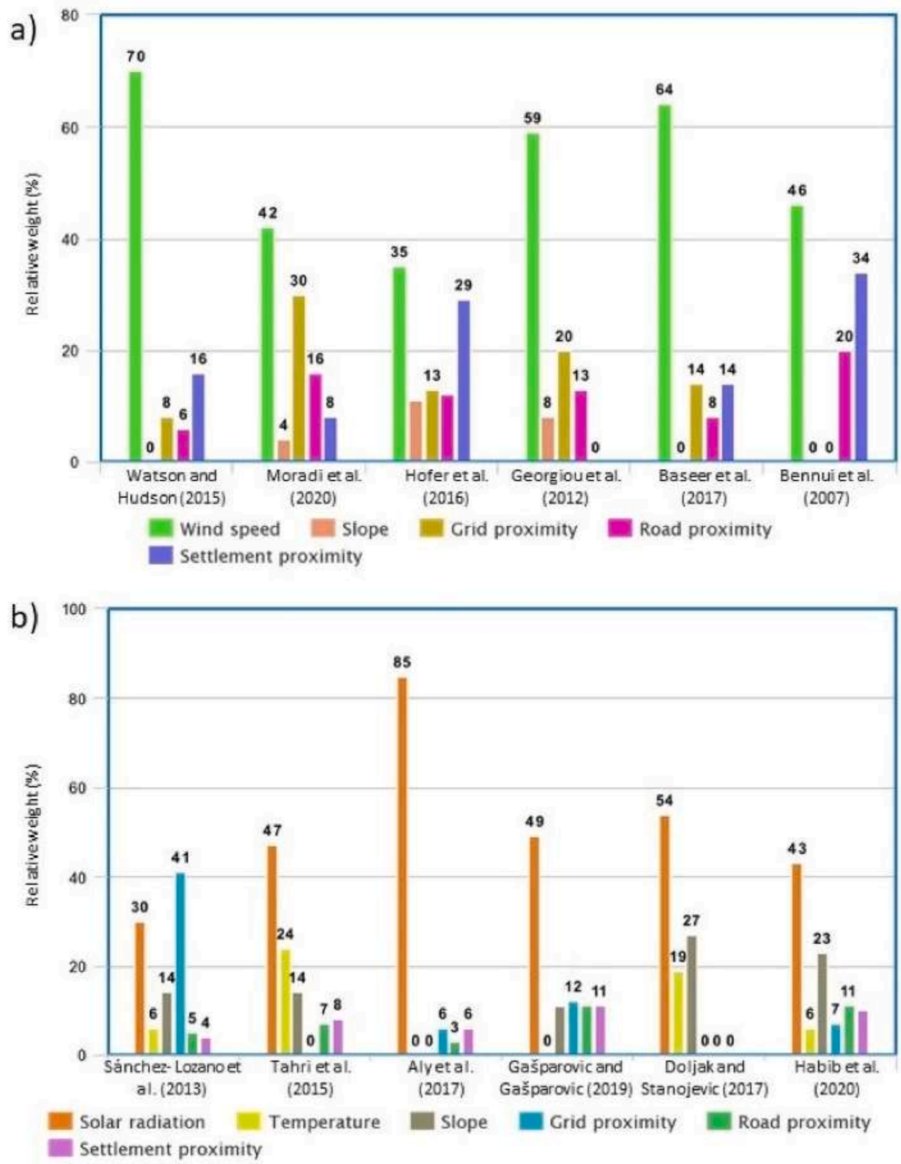

Fig. 2. Relative weights attributed to each criterion in the (a) wind and (b) solar multi-criteria case studies analyzed.

constant annual maintenance costs and energy generation throughout the life-cycle of the project, the LCOE [$/*MWh*] may be estimated using [31]:

$$LCOE = \frac{K_c K_{RF} + O_f}{E} \tag{9}$$

where K_c represents the capital cost [$]; K_{RF} is the capital recovery factor; O_f denotes the fixed annual operating costs [$]; while E is the annual electricity generation [*MWh*]. The expression for K_{RF} is given by:

$$K_{RF} = \frac{i(1+i)^t}{(1+i)^t - 1} \tag{10}$$

where i is the discount rate [%]; and t represents the economic life [*years*] of the solar PV and wind technology investigated.

2.4. Criteria selection and weighting scheme for model optimization

To guide the selection of factors for the model being implemented, Table 2 synthesizes results from six studies from distinct geographical regions.

In addition to the wind modelling case studies of UK, Iran and Germany presented in Table 2, wind multi-criteria models of Cyprus [38], Saudi Arabia [39] and Thailand [40] have also been analyzed, which revealed that the most common criteria in wind modelling case studies are wind speed, slope of terrain, proximity to grid lines, road networks and settlement areas. Similarly, three additional solar case studies were investigated besides the ones shown in Table 2, in Morocco [41], Tanzania [42] and Croatia [43]. The common criteria used in solar multi-criteria studies are solar radiation, temperature, slope, proximity to grid lines, road networks and settlement areas.

We adopt the criteria that are most widely and consistently employed in wind and solar multi-criteria models. However, since the objective of the model being implemented is to identify countries heavily dependent on fossil fuel so as to attract investments that would dampen this reliance, the fossil fuel electricity generation of African countries is another criterion considered. Finally, to reflect the political regime prevailing that could impinge on investments, the country risk classification is also taken into consideration, as described in section 2.5.1.

Despite the subjective nature of the weights attributed to the criteria

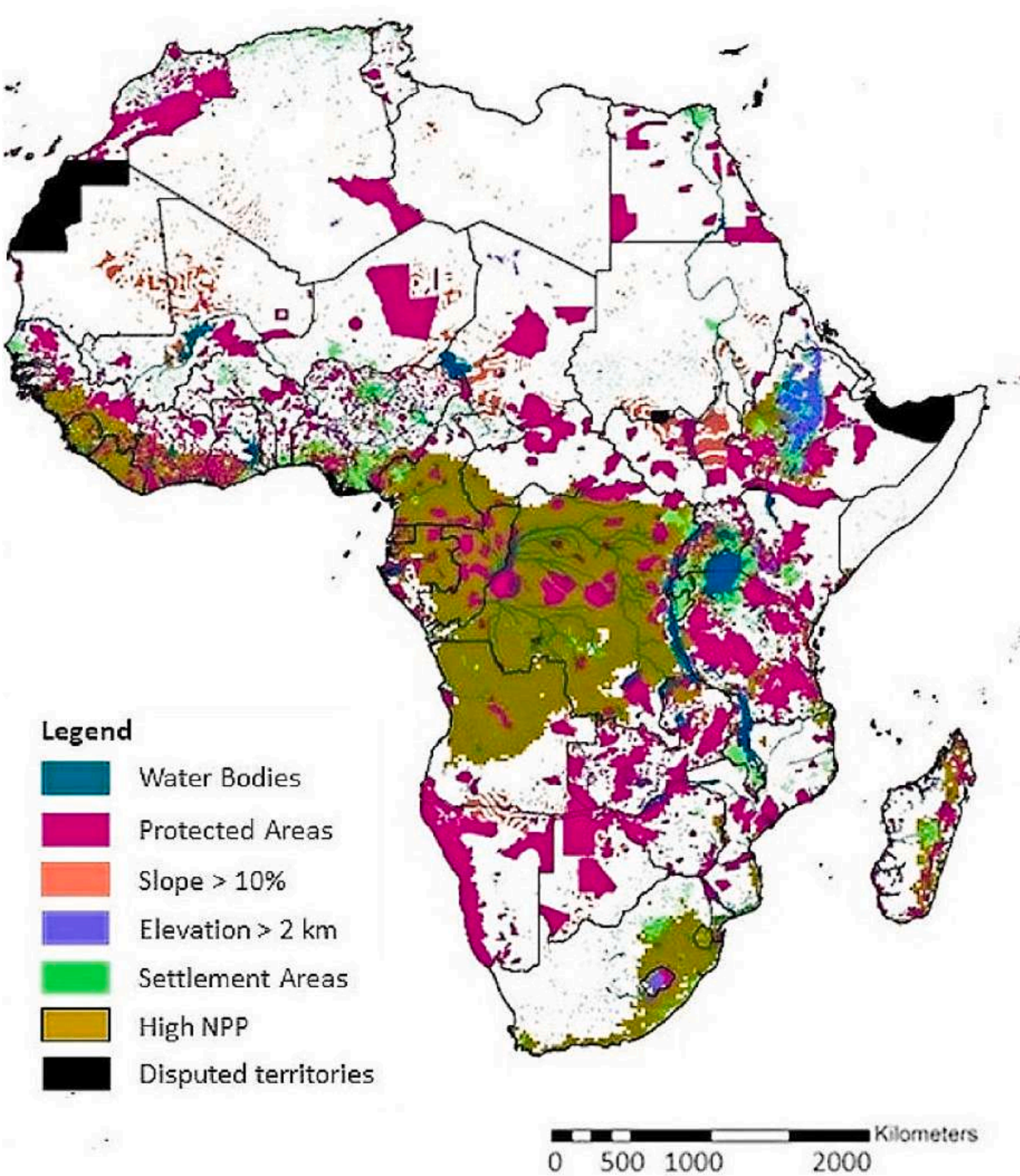

Fig. 3. Constraint map of Africa for solar and wind farm placements.

employed in the studies considered, it can be observed from Fig. 2 that, in general, wind speed and solar radiation criteria are regarded as the most influential factors contributing in the determination of optimum sites for wind and solar farms, respectively. Proximity to grid lines is considered as the next highest influential factor in the wind models implemented by Moradi et al. [33] and Georgiou et al. [38] while it is regarded as being a highly influential factor in the solar model implemented by Sánchez-Lozano et al. [35]. Expert evaluation in the study conducted by Sánchez-Lozano et al. [35] revealed that slope is the third highest influential factor used in determining optimum solar farm sites, followed by proximity to road network and settlement areas.

The outputs of these studies that applied the AHP process were used to implement the wind and solar models. The political regime and the fossil fuel electricity generation criteria are given equal importance to the solar radiation and wind speed factors owing to their high influence in attracting renewable energy investments with high decarbonization potentials at spatially optimum sites in Africa. A description on how the AHP weights were arrived at, is presented in Table B.1 in Appendix B.

2.5. Spatial constraints

Besides the obvious spatial constraints such as settlement areas and water bodies, other spatial limitations are presented in Fig. 3 and described as follows:

2.5.1. Disputed territories

As stated by Frynas [44], foreign investors are reluctant to invest in disputed territories. An example would come from the Western Sahara

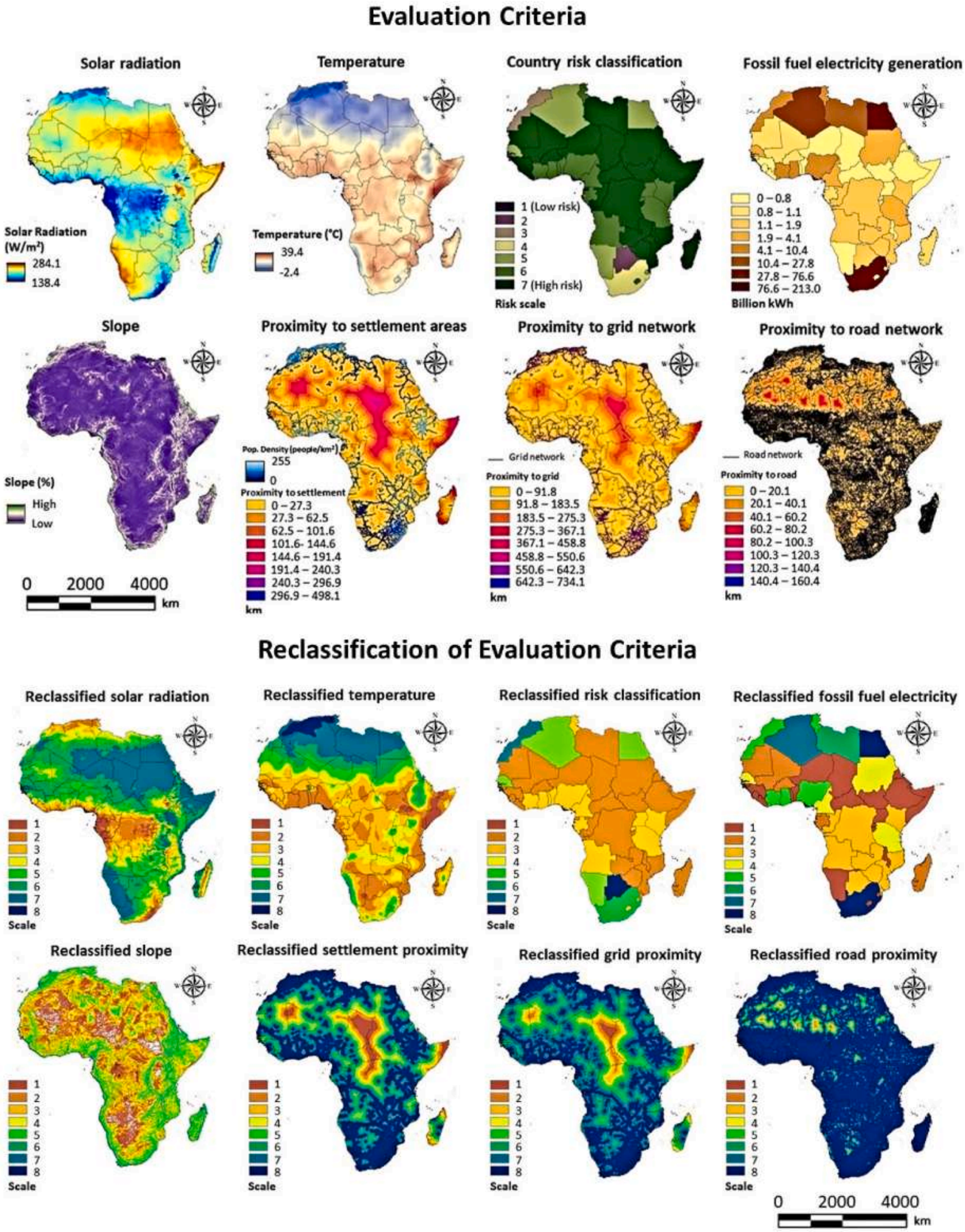

Fig. 4. Evaluation criteria and reclassification of factors influencing solar farm investments.

where it was reported that disputes with Morocco over land resources resulted in substantial investment risks [45].

2.5.2. High net primary productivity (NPP) areas and protected areas

According to Rehbein et al. [46], solar PV, onshore wind and hydro power stations have been constructed in or near biodiversity hotspots, potentially impacting 886 protected areas and 749 important biodiversity areas. In the current study, areas of high NPP, synonymous with enhanced carbon sequestration by terrestrial ecosystems, are excluded from the surface analyzed. Moreover, protected areas are secured by strict legal frameworks and excluded in the current analysis [47].

2.5.3. Inadequate slopes

As mentioned by Giamalaki and Tsoutsos [48], extensive land-levelling works need to be performed in order to accommodate these renewable energy technologies, which further increases the project's capital expenditure. To comply with the range of values used in literature, a conservative slope limit of 10% was used, above which the

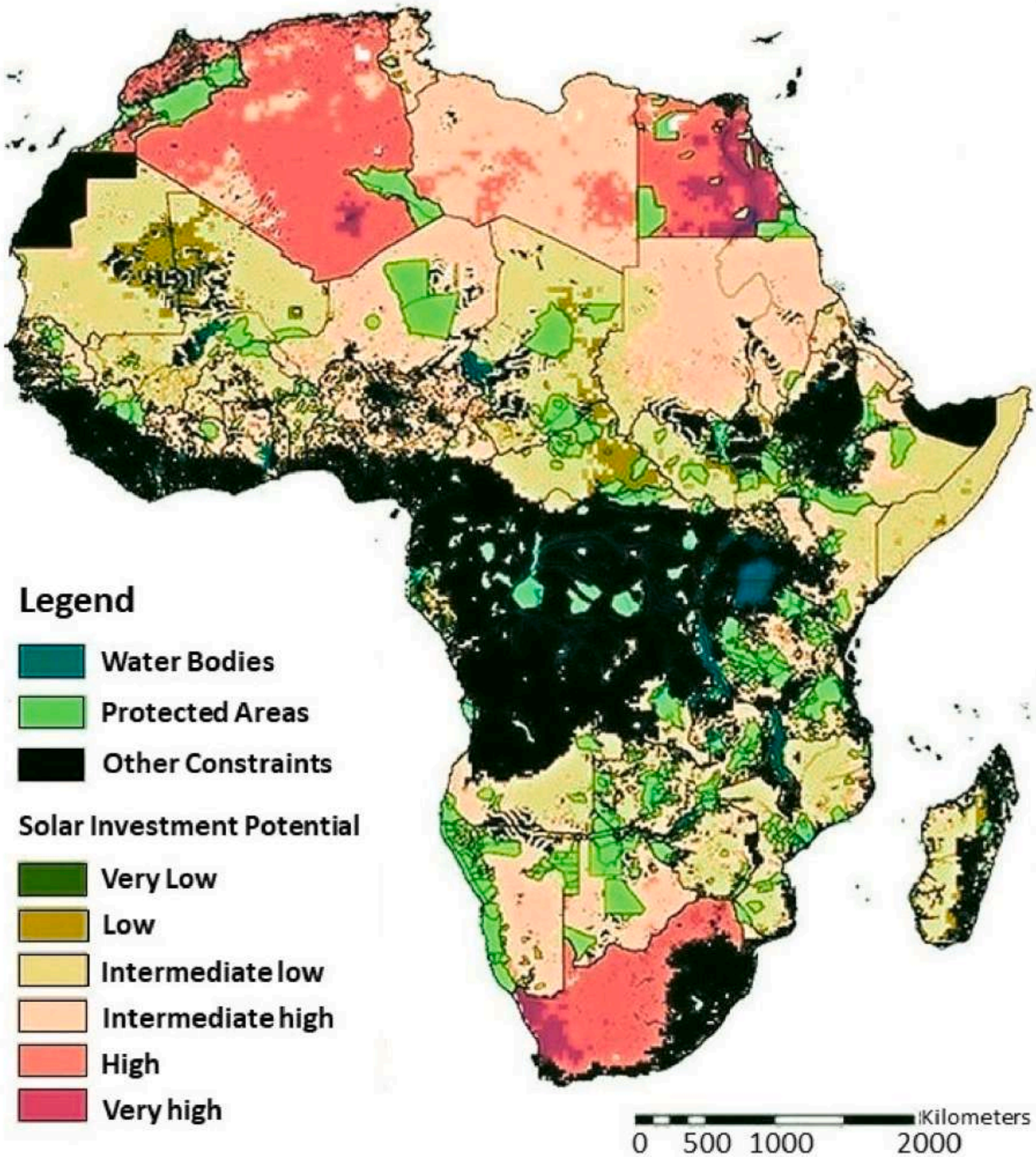

Fig. 5. Solar farm investment site identification using the solar potential model.

regions were excluded. Land slopes less than 10% are graded for site construction.

2.5.4. Unsuitable elevations

Mentis et al. [49] mentioned that technological implementation on higher elevations would involve additional investment costs due to higher construction and transportation costs. A conservative value of 2 km altitude was chosen as the threshold, beyond which regions were deemed unsuitable for solar and wind farm constructions.

2.5.5. Influential factors

A description of the factors selected above, to be integrated in the wind and solar models, is presented in this sub-section. Besides the obvious factors such as wind speed and solar radiation, other influential factors include:

2.5.5.1. Country risk classification. Foreign investments involve supplementary risks that are not present in domestic investments. These risks are referred to as country risks and incorporate risks that emerge as a consequence of differences in economy, policy and socio-political settings across states [50]. The OECD's country risk classification is used as a proxy for political stability, and captures the transfer/convertibility risk associated with the investment structure in place as well as cases of *force majeur* due to war, civil disturbance, flood and earthquake [51].

2.5.5.2. Fossil fuel electricity generation. Since the objective of the current study is to study decarbonization of Africa's power system, the strategy is to identify the countries that are heavily reliant on fossil-fuel for electricity generation in order to drive utility-scale renewable energy investments in those countries and diversify their energy mix.

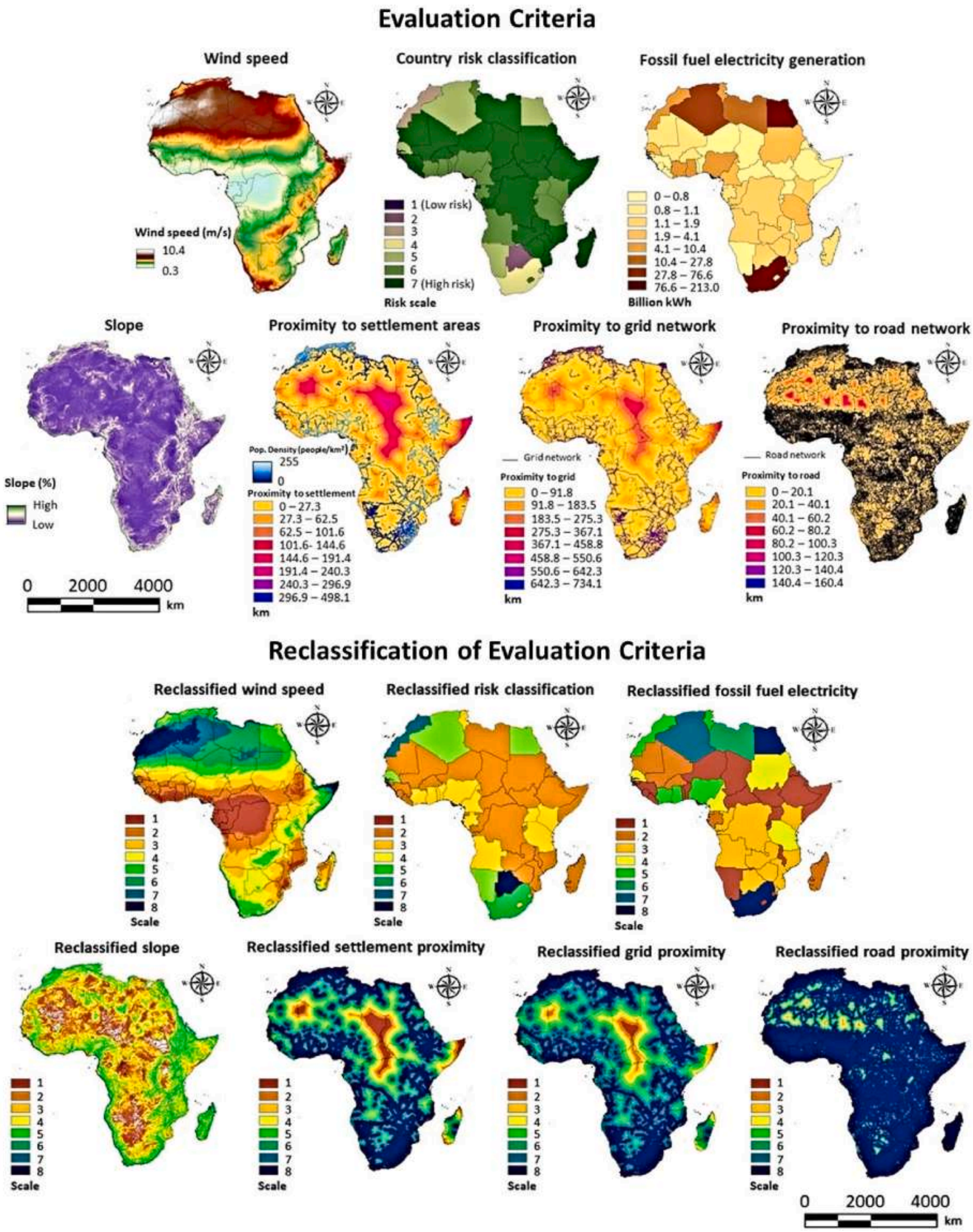

Fig. 6. Evaluation criteria and reclassification of factors influencing wind farm investments.

2.5.5.3. Temperature. The performance of PV panels diminishes with increasing temperature. As stated by Huld and Amillo [52], an increase of 1 °C for PV modules having temperatures greater than 25 °C, results in an associated decrease in energy production of about 0.4%–0.5%. Therefore, the effect of temperature is taken into consideration in determining optimum investment potential sites.

2.5.5.4. Proximity to settlement areas. As stated by Tabassum et al. [53], the shorter the distance between supply and demand, the lower the energy losses and cost of transmission network required. The closer the farm to the existing settlement areas, the higher the probability for construction. A buffer of 1 km is used around settlement areas to prohibit construction near residential places.

2.5.5.5. Proximity to grid network. The use of existing infrastructure instead of having to build new ones cuts down on capital costs and diminishes transmission losses arising from having to transmit electricity over longer distances [54]. Higher probabilities for construction are given to sites located closer to existing electricity transmission networks.

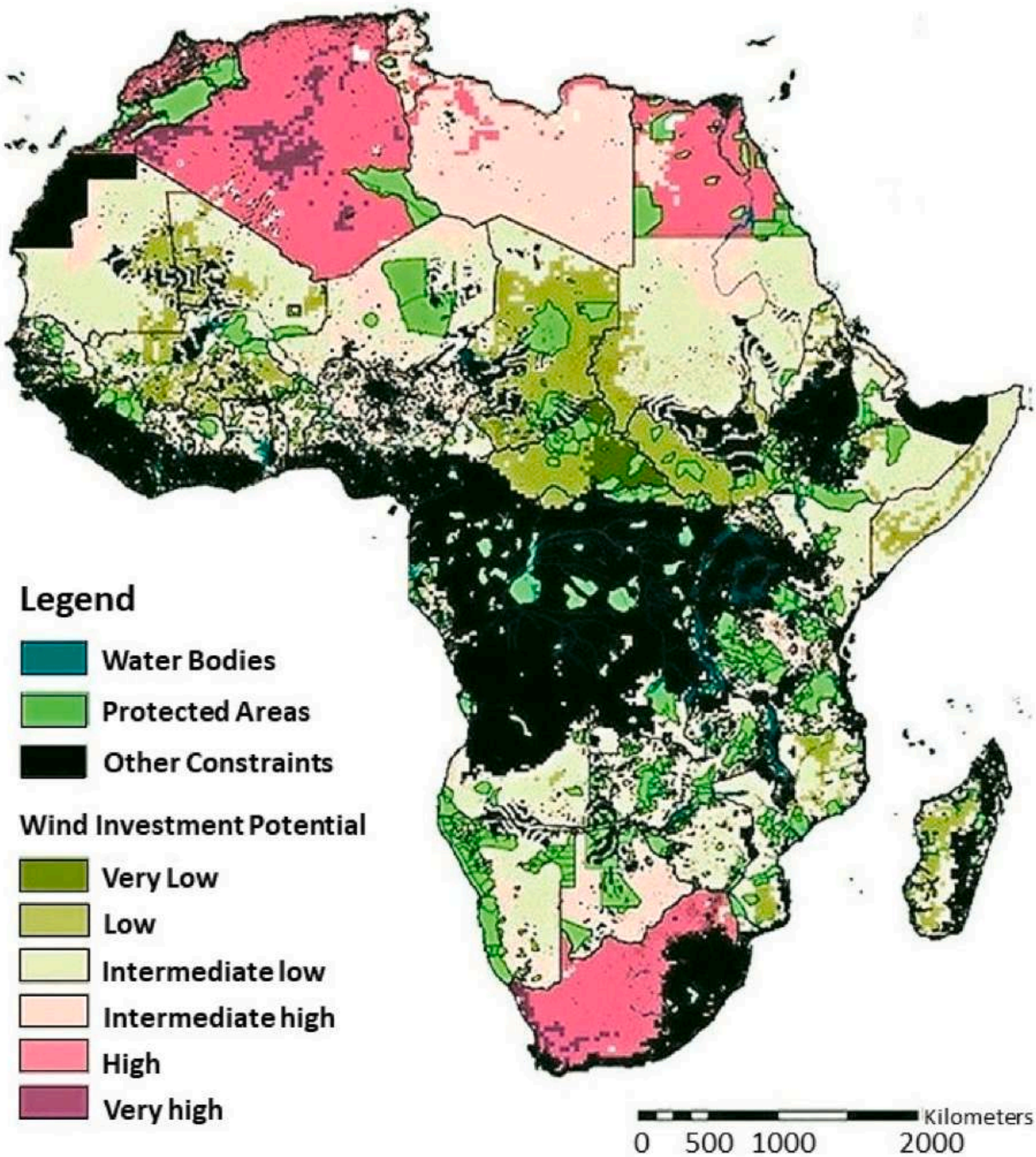

Fig. 7. Wind farm investment site identification using the wind potential model.

2.5.5.6. Proximity to road network. Implementation of renewable energy farms near roads diminishes transportation costs and improves access to the farms for construction and maintenance [54]. Higher probabilities for farm placements are attributed to sites situated closer to road networks.

2.6. Data and analysis

A description of the spatial constraint and evaluation criteria dataset used in the current study is presented in Tables 3 and 4, respectively.

The geospatial dataset was analyzed using ArcMap (Version: 10.3.1), while criteria weights were determined using the BPMSG AHP priority calculator. A wind energy simulation model was constructed in MATLAB (Version: R2015a) while the economic modelling was performed using the NREL LCOE calculator. Details of the analysis tools and techniques are presented in Appendix C.

3. Results

3.1. Utility-scale solar PV

Factors influencing the placement of solar farms, as described in section 2.5.1, are mapped and illustrated in Fig. 4. The solar potential model aims at identifying countries that have abundant solar resources, rely heavily on fossil fuel for electricity generation, and are politically stable so that investments would offer the highest electricity decarbonization potentials. An important stage in the multi-criteria analysis process prior to combining the different factors, is the rescaling of the evaluation criteria into comparable units through a standardisation process [55]. Consequently, the standardisation of factors to bring them on a common scale (1–8) is also presented in Fig. 4. The weights for the evaluation criteria identified, as derived using AHP, are shown in Table 5a.

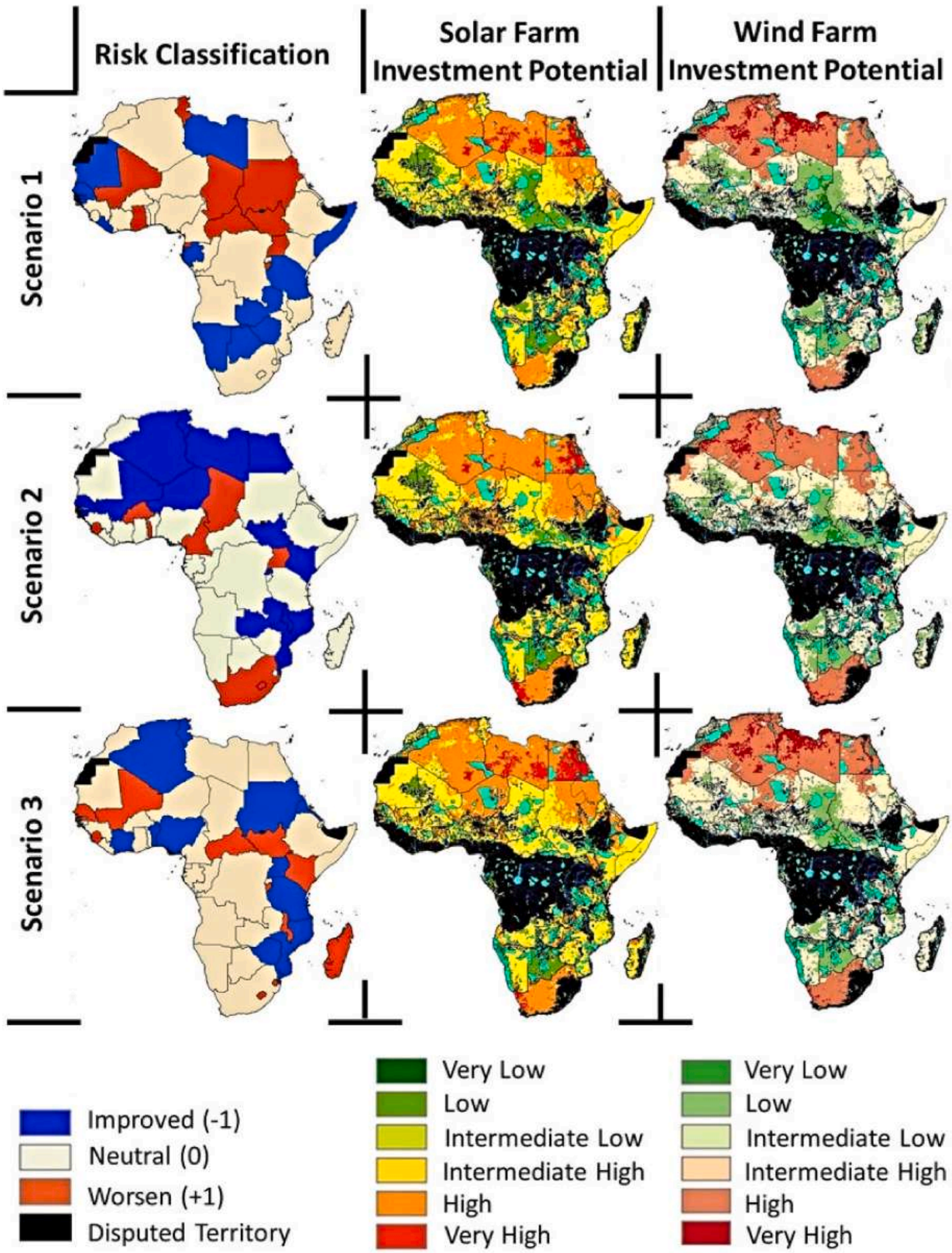

Fig. 8. Sensitivity analysis of country risk classification.

The reclassified factors are graded as presented in Table D.1 (Appendix D). The mapping of the output from the combinatorial process, which involves the weighted and standardized factors, is presented in Fig. 5. The figure portrays the very high investment potential sites located in the western part of South Africa and the eastern region of Egypt. Both of these sites are characterized by high insolation (>250 W/m^2), high fossil fuel electricity generation (76.6–213.0 billion kWh), and relatively stable political regimes.

3.2. Utility-scale onshore wind

The wind potential model is tailored to identify sites having adequate wind regimes, high fossil fuel electricity generation and good political stability to drive utility-scale wind energy investments in those countries

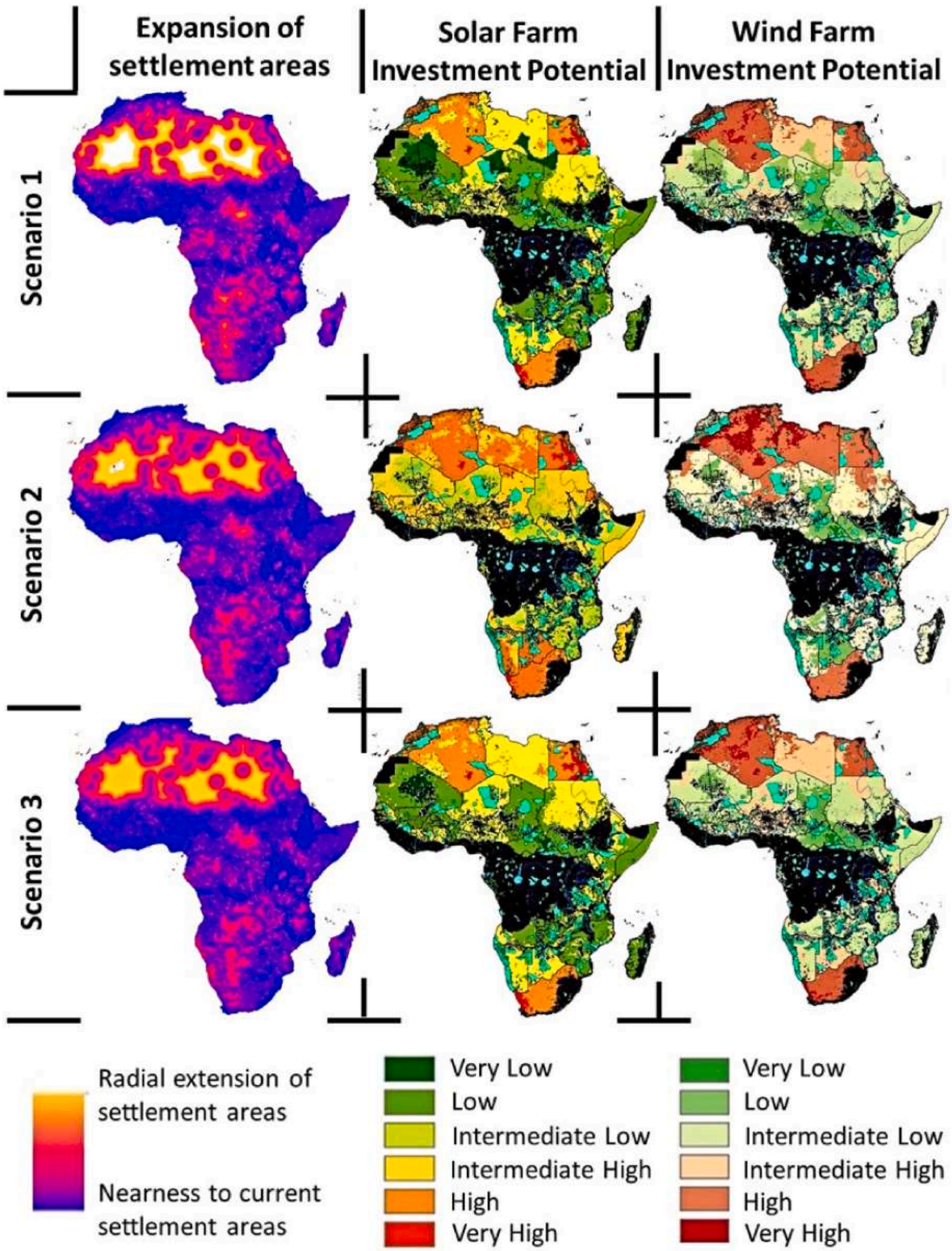

Fig. 9. Sensitivity analysis of population expansion.

and decarbonize the power sector. The evaluation criteria influencing wind farm investments, as described in section 2.5.1, are mapped as illustrated in Fig. 6. Also presented in Fig. 6 is the standardisation of these criteria to bring them on a common scale (1–8). The factor weights derived from AHP are presented in Table 6a and are based on the decision matrix shown in Table 6b. The score attributed to the reclassified classes are presented in Table D.2 found in Appendix D.

Fig. 7 illustrates the mapping of the output from the combinatorial

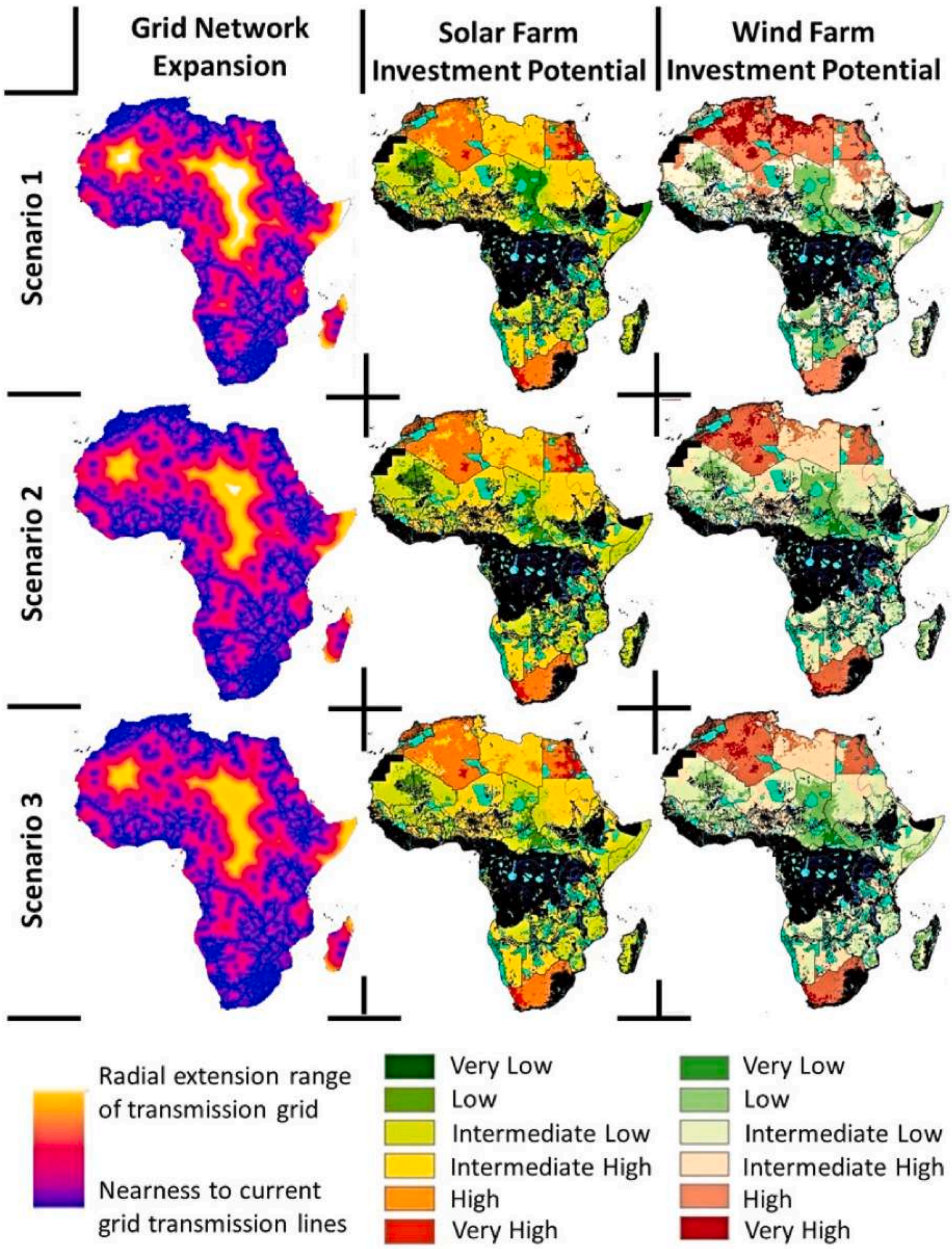

Fig. 10. Sensitivity analysis of grid network expansion.

process involving the weighted and standardized factors influencing wind farm placements. The very high wind farm investment potential sites are located in the central region of Algeria and near the southern and western coasts of South Africa. These regions witness high wind speed values of about 13.3 m/s at 100 m height, rely heavily on fossil fuels for electricity generation (27.8–213.0 billion kWh), and have good political stability.

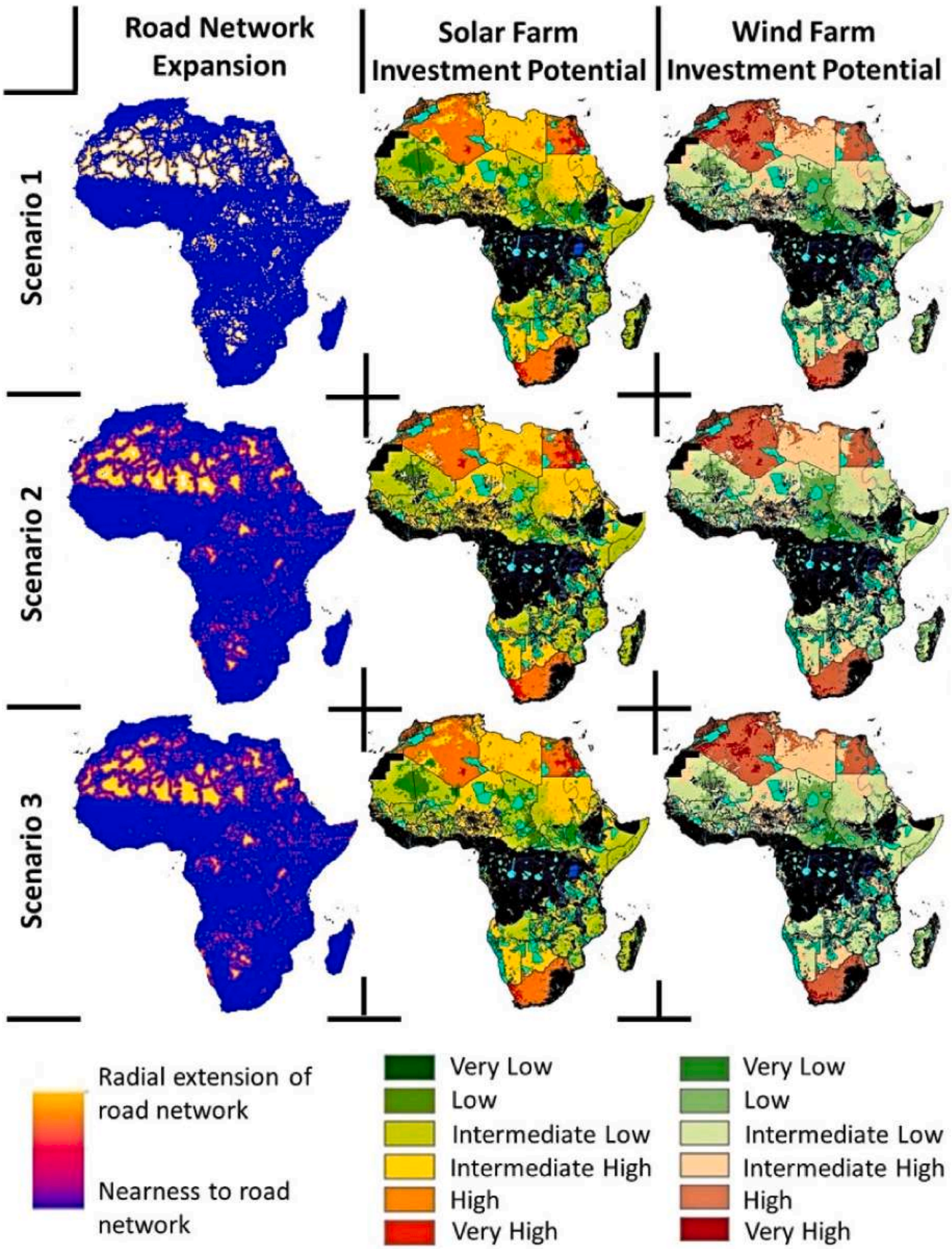

Fig. 11. Sensitivity analysis of road network expansion.

3.3. Sensitivity analysis and synthesis of results

Due to the uncertainties in future political and socio-economic factors, a sensitivity analysis is conducted to assess the impact of uncertain future conditions on project investment decisions.

A sensitivity analysis is performed by randomly incrementing, decrementing or keeping unchanged, the country risk classification values as shown in Fig. 8. The results indicate that the change in spatial

Table 7
Synthesis of results for the wind/solar potential model and additional sensitivity tests.

Model and sensitivity tests	Solar PV		Onshore wind	
	Best site	Next best site	Best site	Next best site
Wind/solar potential model	Egypt	South Africa	South Africa	Algeria
Supply-side sensitivity test	Egypt	South Africa	South Africa	Egypt
Demand-side sensitivity test (High grid access and reliability)	Egypt	South Africa	South Africa	Algeria
Demand-side sensitivity test (Low grid access and reliability)	Niger	Chad	Niger	Chad
Risk-aversion sensitivity test	South Africa	Morocco	South Africa	Morocco
Selection for refined analysis on spatial scales	**Egypt**		**South Africa**	

variations of the investment potentials due to the change in country risk classifications were insignificant.

To account for future population expansion and further build-out of transmission and road networks, a sensitivity analysis is conducted on the socio-economic factors of the model. This sensitivity analysis shows that the variations in population expansion and further build-out of grid and road networks have marginal effects on the spatial distributions of investment potentials as illustrated in Figs. 9–11.

In addition to performing a sensitivity analysis on political and socio-economic factors, sensitivity tests are also performed on supply-side, demand-side and risk-aversion factors so as to cater for the underlying uncertainties present in the combinatorial process. The additional sensitivity test results are presented in Appendix A.

Including institutional capacity factors in the form of solar PV and onshore wind total capacities which influence the smoothness of investments on the supply side due to established supply chains and local expertise, revealed again the favorable nature of Egypt and South Africa for solar and wind farm investments, respectively. The inclusion of demand-side factors, on the other hand, to identify countries having high electricity access and low power outages for investors interested in pursuing economic gains once again reported that Egypt and South Africa stand out for solar and wind farm investments, respectively. However, looking at the demand-side sensitivity test from another angle and instead aiming at identifying countries having low electricity access and high power outages to improve their electricity landscapes rather than to make profits, concluded that Niger offers high wind and solar farm investment potentials. Finally, risk-averse investors would prefer to make investments in South Africa due to the lower fossil fuel subsidies which guarantee competitive renewable energy investments and higher rates of successful solar and wind projects.

Table 7 presents the summary of results. It can be observed that among the 5 different variants of the solar/wind potential model analyzed, Egypt was identified best on 3 occasions for the solar analysis, while South Africa was identified best on 4 occasions for wind analysis.

3.4. Wind farm investment potential of South Africa

Appendix E elaborates on the spatial constraints and evaluation criteria that influence the wind farm investments on spatial scales for South Africa. The weights for the reclassified criteria, acquired through the AHP method, are applied to the individual layers in the combinatorial process while the factors are graded as shown in Table D.11 (Appendix D). A mapping of the combination of reclassified and weighted factors using the WLC method, is presented in Fig. 12. The very high investment potential sites witness high wind speeds (>10 m/s), have relatively gentle slopes, are near settlement areas, and are close to grid and road networks.

The very high investment potential sites are extracted and superposed on a layer containing existing wind farms and grid networks in South Africa as shown in Fig. 13. The majority of existing wind farms lie on very high investment potential sites, indicative of good farm planning by local authorities. To model the annual energy yield from wind turbines in the locality, the Noupoort wind farm (Fig. 13) is chosen as a case study, as elaborated in Appendix E. Using equations (5)–(8), the variations in annual energy as derived from wind farms for the different investment potential sites are estimated, as shown in Table 8.

Using equations (9) and (10) and adopting the assumptions of Lazard [56] for capital cost ($1,500,000/MW), annual fixed and operating costs ($35,000/MW), discount rate (8%) and useful project lifetime of 20 years, yielded the Levelized Cost of Energy (LCOE) values presented in Table 8 for the different investment potential sites. A plot showing the variation of LCOE with investment potential sites is illustrated in Fig. 14. The marginal cost for implementing the wind farm in the very high investment potential zone is $50/MWh which is within the $30–60/MWh range estimated by Lazard [56]. In contrast, the LCOE of building new coal stations in South Africa is estimated at $60/MWh [57] which lies at the lower end of the $60–143/MWh range provided by Lazard [56]. Consequently, wind farms present an economically viable and environmentally safe alternative to new coal power stations. Additionally, incorporating tax exemptions and other energy subsidies would bring the cost of wind technologies even lower.

3.5. Solar farm investment potential of Egypt

The spatial constraints and evaluation criteria that influence solar farm investments on spatial scales in Egypt are presented in Appendix E. The gradings attributed to the reclassified factors are presented in Table D.12 (Appendix D), while the weights derived from AHP are applied to the individual reclassified criteria prior to proceeding with the combinatorial process. The combination of the reclassified and weighted factors led to the solar investment map of Fig. 15. The very high investment potential sites represent regions having high insolation (>6.4 kWh/m^{2}day), suitable temperatures, adequate land characteristics while being close to settlement areas, grid and road networks.

Superposing the extracted layer containing very high investment potential sites on the layer containing an existing solar farm in Egypt (Fig. 16), again indicates proper planning by local authorities. Equation (4) is used to model the variations in annual energy derived from solar farms for the different investment potential sites, as shown in Table 9. The computations leading to the estimations are detailed in Appendix E.

Combining equations (9) and (10) with the assumptions of Lazard [56] for capital cost ($1,200,000/MW), annual fixed and operating costs ($10,500/MW), discount rate (8%) and useful project lifetime of 20 years, yielded the LCOE values presented in Table 9 for the different investment potential sites. The variation of LCOE with investment potential sites is portrayed in Fig. 17. Comparing Fig. 17 with Fig. 14, indicates that the range of LCOE for solar PV ($58–69/MWh) is less than that for onshore wind ($50–1073/MWh). This reflects the lower geographical dependence of making cost-effective solar farm investments as compared to wind farms. This is principally due to the fact that the wind resource potential is much more variable on spatial scales

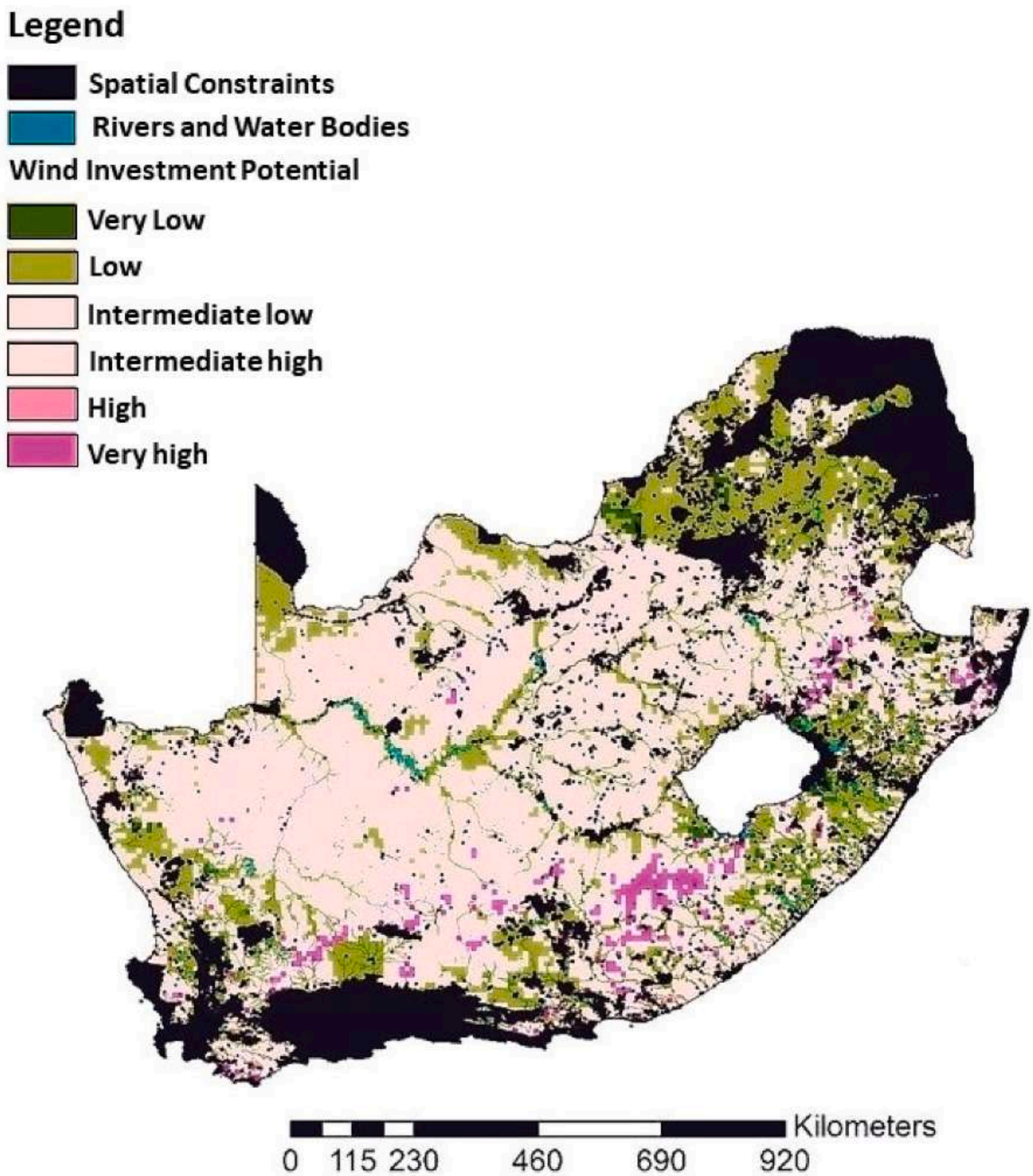

Fig. 12. Wind farm investment potential map of South Africa.

than the solar resource.

4. Discussions

Through the multi-criteria GIS-based technique, multiple variables that influence the investment decisions can be integrated to optimize solar and wind farm placements. The continental-scale analysis revealed that Egypt displays high solar farm investment potential to achieve significant power sector decarbonization, owing to its favorable insolation (278.3 W/m^2), high fossil fuel electricity dependence (165.7 billion kWh), political stability and other suitable investment factors. Natural gas is the main contributor to Egypt's electricity generation but uncertainties over the dwindling national reserves are exacerbated by policies to expand natural gas use as a substitute for petroleum and plans to increase natural gas exports [58]. With a projected population increase of 69.5 million by 2050, the country needs a major power sector reform to meet its energy demand while complying with the obligations set out in the Paris Agreement [59]. A diversification of the energy mix away from fossil fuels by channeling investments towards utility-scale solar farm constructions would not only improve energy security, but also constitute a milestone in the power sector decarbonization strategy owing to the high carbon intensity of the current Egyptian grid.

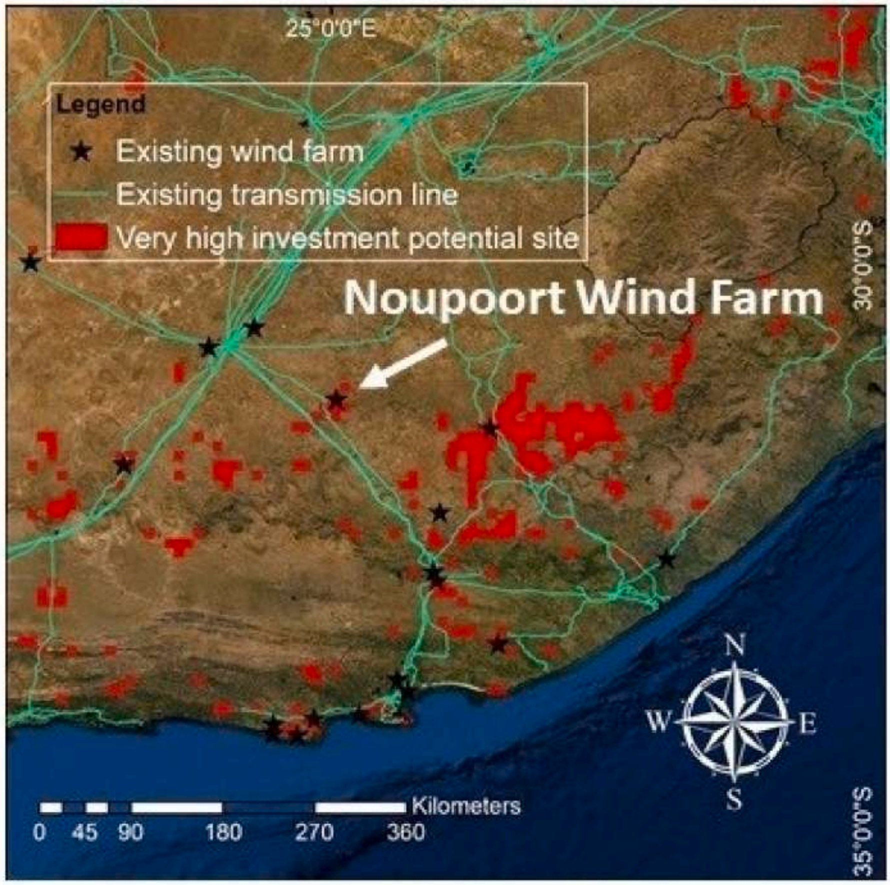

Fig. 13. Wind farm investment sites in South Africa.

Table 8
Cost and energy variations with investment potential sites in South Africa.

Investment potential site	Number of turbines	Maximum power (MW)	Wind speed (m/s)	Estimated annual energy (MWh)	Capacity factor	LCOE ($/MWh)
Very high	35	80.5	9.2	301,601	0.43	50
High	35	80.5	8.1	194,134	0.28	77
Intermediate high	35	80.5	7.2	133,472	0.19	113
Intermediate low	35	80.5	6.6	83,967	0.12	179
Low	35	80.5	5.3	32,449	0.05	429
Very low	35	80.5	4.4	12,665	0.02	1073

The continent-wide wind optimization analysis, on the other hand, revealed propitious regions for utility-scale wind farm constructions near the southern coasts of South Africa. In addition to the high wind speeds of around 12 m/s at 100 m height near the locality, the country has a high fossil fuel electricity reliance (213 billion kWh) and good political stability to ensure significant electricity decarbonization per wind farm investment. While the population of South Africa is projected to rise to around 63 million by 2050, there is increasing pressure on the power sector to meet the rising demand for energy [60]. South Africa had experienced major security-of-supply challenges in the past due to its inefficient fleet of ageing coal power stations, resulting in national load shedding and regular power outages [61]. As reported by Fawthrop [62], coal will remain an integral part of the power sector of South Africa over the upcoming decade, with plans to integrate 1500 GW of coal-based power, representing 59% in the energy mix by 2030. However, wind farms represent an economically viable substitute to coal power stations in South Africa and therefore investments in the wind sector would not only guarantee future security-of-supply, but also contribute in dampening the reliance on a carbon-intensive energy source to meet energy demand.

The placements of solar and wind farms influence the revenue per MWh of electricity generated to recover the construction and operation costs. The LCOE of constructing wind farms in very high investment potential sites in South Africa is $50/MWh, which is about 95.3% lower than building in very low investment potential sites ($1073/MWh). Similarly, constructing solar farms in very high investment potential sites in Egypt has an LCOE of $58/MWh which is about 15.9% lower than investing in very low potential sites ($69/MWh). The optimum

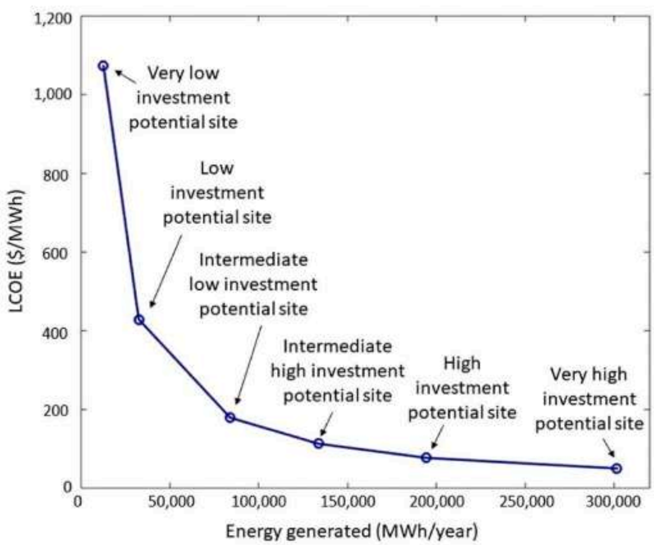

Fig. 14. Variation of LCOE with energy generation for different investment potential sites in South Africa.

sites being strongly influenced by insolation for solar farms and wind speeds for wind farms, imply that the low LCOE values on spatial scales for high investment potential sites are reflective of the higher annual energy generated by the power plants being constructed in sites blessed with high insolation and wind speeds. However, as noted in the results section, there is a lower geographical dependence in making cost-effective solar farm investments than investing in wind farms as the solar resource across Egypt does not vary much while wind investments will only be economic at high wind speed sites, and wind resources vary significantly on spatial scales in South Africa.

As estimated by Bischof-Niemz and Fourie [63], the LCOE of coal-fired power stations in South Africa is $60/MWh, which is around 16.7% higher than constructing wind farms in very high investment potential sites. In Egypt, the construction of a solar farm in a very high investment potential site is $58/MWh, which is around 29.7% lower than investing in combined-cycle gas turbines (LCOE of $78–87/MWh [64]) and 37.0% lower than investing in diesel generators (LCOE of $90–94/MWh [64]). Moreover, it is still cheaper to invest in solar farms in the worst sites in Egypt (LCOE of $69/MWh) than to invest in combined-cycle gas turbines and diesel generators. Consequently, investing in wind farms in South Africa and solar farms in Egypt represent low-risk and cost-effective solutions for phasing out fossil fuel dependence. The optimum sites identified in Figs. 12 and 15 represent strategic regions to invest in wind and solar farms, respectively, in order to cost-effectively decarbonize the electricity grids.

The results presented in this paper relate specifically to Africa. However, wind and solar energy are likely to be the major future resources for power generation in almost all continents and regions and siting constraints and implications are important everywhere. The methodology developed and used here could be used in any other jurisdictions for which the relevant input data are available. As reported by Institut Montaigne [65], Asia and Africa are the two continents most likely to shape future global energy owing to their high growth rates. In contrast to the African power sector, characterized by its slow economic growth (3.7% in 2020) and lack of energy efficient infrastructures, the increasing energy demand in Asia is being satisfied with supply-side investments at a higher pace [65]. Identification of optimum wind and solar sites on the Asian continent using the methodology proposed in the current paper would therefore be likely to have a more immediate impact on the environment and global temperature level than the African continent. A wide range of technical, economic and political conditions in Asia are very different from those in Africa, but similarly variable across the continent. It is therefore the methodology rather than particular results that is transferable. African countries may learn from the European power sector and benefit from their experience to leapfrog the highly carbon intensive pathway adopted by earlier developers [66]. In this context, the African continent, with its relatively high rural population and less developed existing grids than Europe, will not need to be as reliant on centralized electricity grids, and instead use decentralized mini grids to increase their capacity to integrate wind and solar energies at spatially optimum sites.

To enable this energy transition in Africa, investment barriers need to be removed and an adequate policy framework, conducive to renewable energy investments at spatially optimum sites, needs to be established. Although the economics of wind and solar generation are potentially attractive in good locations, these are nascent industries in much of Africa. Policy makers may therefore need to offer fiscal incentives, such as tax relief and import duty exemptions on renewable energy components in the initial phases of sector growth. A buoyant renewable energy sector offers employment in development, construction and installation, which is a major consideration in many African economies. For these benefits to be realized, there needs to be a conduce enabling environment for project planning, approval, finance and implementation. This is lacking at the moment in many African countries, resulting in lengthy projects that are excessively costly and sometimes fail to be delivered [67]. Further work is needed on improving grid infrastructure and reliability to handle utility-scale renewable energy investments, notably in Sub-Saharan Africa. Multilateral financial institutions and local banks should improve capital markets in Africa that would support renewable energy investments. Governments (in partnership with international financial institutions) can provide the fiscal incentives, bank lending, guarantees, low-interest loans, and secure long-term funding opportunities for both the renewable energy sector and the electricity grid [68]. De-risking strategies should focus on how development banks could assist manufacturers and network companies in accessing capital, as well as government backing of Power Purchase Agreement (PPA) payments, facilitating the liaison with the private sector and removing policy risks [69].

5. Conclusions

A multi-criteria model has been implemented using a set of climatological, political, environmental, technical and socio-economic factors to determine optimum sites in Africa where wind and solar farm investments could have the most impact in decarbonizing the power sector. The methodology is novel in that it takes into account the geospatial variations in political and institutional regimes across the continent that influence utility-scale renewable energy investments.

The analyses revealed that Egypt offers propitious conditions for solar farm investments while South Africa provides favorable conditions for wind farm constructions. Those countries have an adequate level of institutional capacity and are politically stable in order to make best use of the renewable energy investments. The high renewable energy resources of these countries combined with their carbon intensive grids imply that investments in those countries have the potential of making significant cuts in carbon dioxide emissions per MWh of electricity generated. Investments in the continent aimed at making a significant

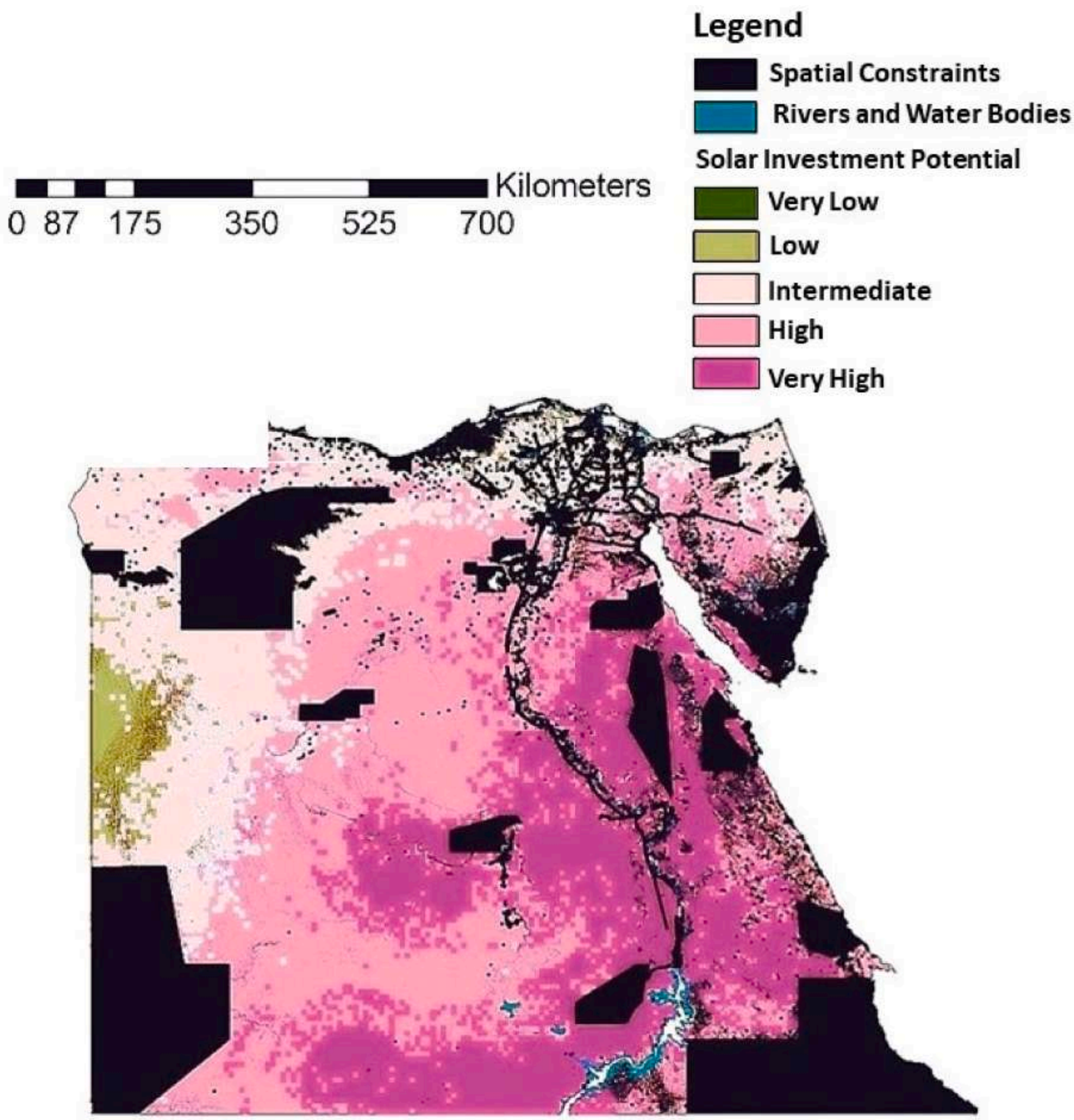

Fig. 15. Solar farm investment potential map of Egypt.

climate-related impact should therefore be directed towards Egypt for solar farm constructions and South Africa for wind farm placements.

Besides the favorable politico-institutional environment offered by these two countries, the economic benefits of investing in renewables in the hotspots identified in the research described in this paper outweighs the economic scenario of maintaining the current fossil fuel-reliant system. Actually, the economic prospects offered by the constructions of wind and solar farms in the strategic locations identified, present South Africa and Egypt, respectively, with an opportunity to phase out fossil fuel reliance for electricity generation and dampen the associated political and financial risks pertaining to renewable energy adoption. A diversification of the energy mix away from fossil fuels in those countries, brought about by strategic utility-scale renewable energy investments at spatially optimum sites, would help avert a potential fossil fuel lock-in and constitute a milestone in the African power sector decarbonization issue.

A more comprehensive view on African power sector decarbonization potential, would require the scope of this research to be broadened from utility-scale grid-connected solar and wind farms to include small and medium scales, on and off-grid solar PV and onshore wind facilities, including rooftop solar PV and off-grid wind turbines. Moreover, meso/micro-scale solar and wind analysis need to be conducted for the remaining 52 African countries while accounting for region-specific factors and constraints (e.g aeolian sand and dust in desert areas [70, 71]). Sustainable resource management should be a key priority in any strategy aiming to optimize resource use and a circular economy model

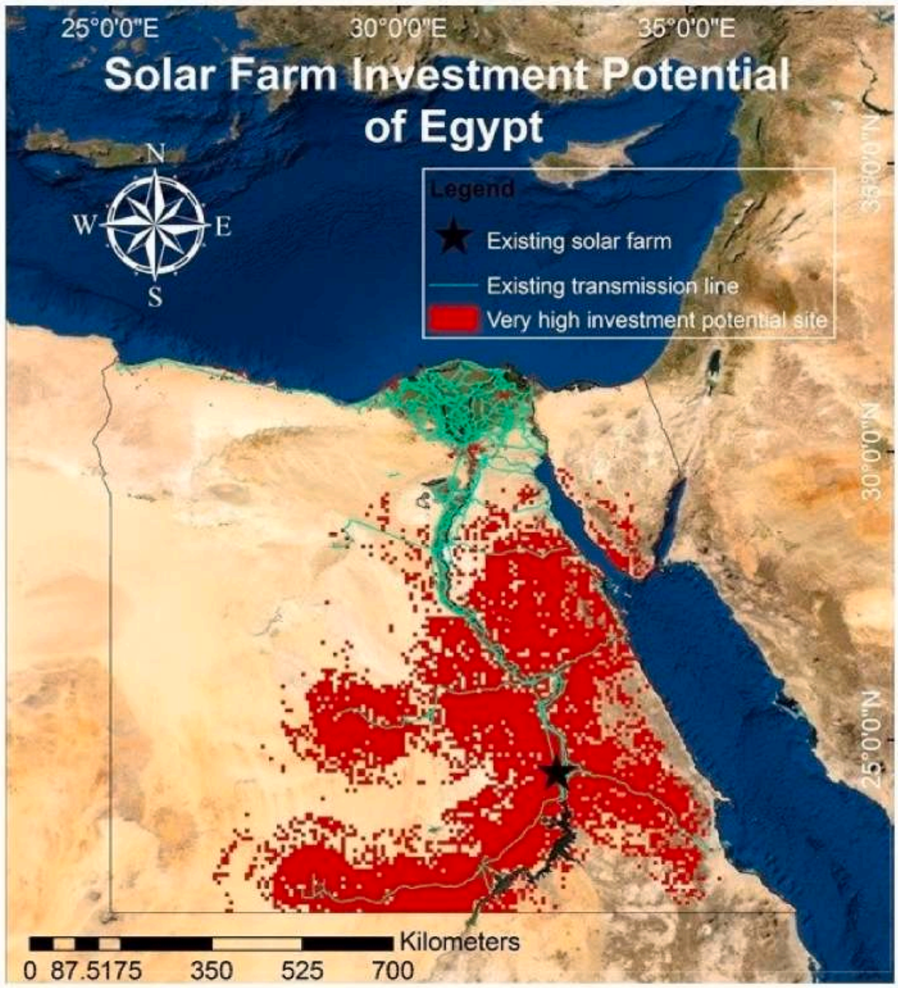

Fig. 16. Solar farm investment sites in Egypt.

Table 9
Cost and energy variations with investment potential sites in Egypt.

Investment potential site	Site area (km^2)	Maximum power (MW)	Solar irradiation (kWh/m^{2}day)	Estimated annual energy (MWh)	Capacity factor	LCOE ($/MWh)
Very high	37.2	1650	6.41	3,698,987	0.26	58
High	37.2	1650	6.20	3.577.803	0.25	61
Intermediate	37.2	1650	6.05	3,491,243	0.24	63
Low	37.2	1650	5.82	3,358,518	0.23	66
Very low	37.2	1650	5.53	3,191,169	0.22	69

which involves the recycling of turbine blades and solar panels during plant decommissioning phases, need to be a key endeavour.

Credit author statement

All authors contributed equally to this work.

Data availability

The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

Declaration of competing interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

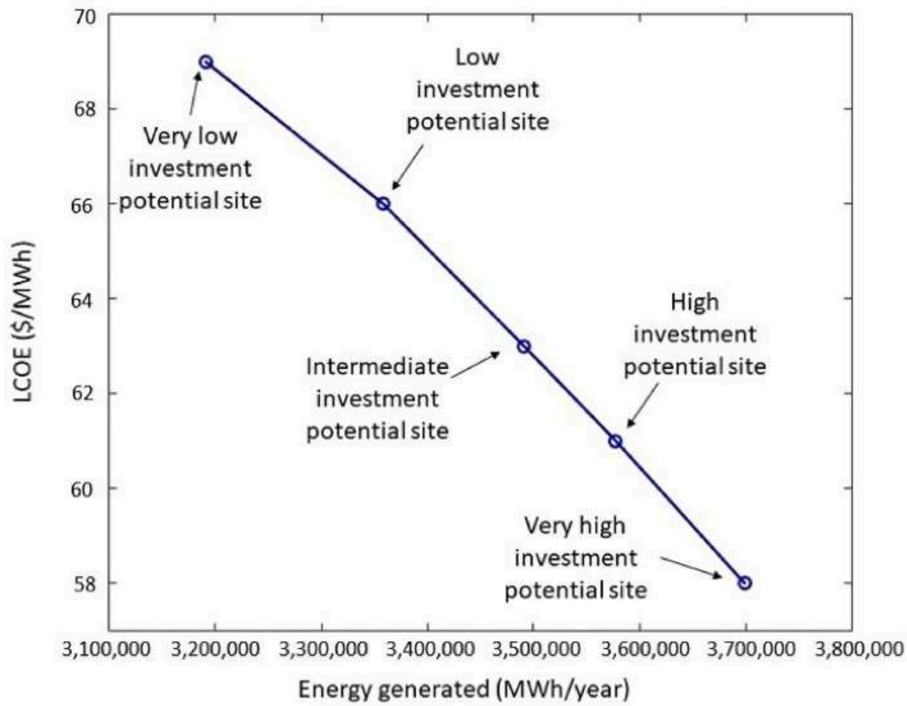

Fig. 17. Variation of LCOE with energy generation for different investment potential sites in Egypt.

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Appendix A. Supplementary data

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