Sustainable Energy Technologies and Assessments 86 (2026) 104749

Contents lists available at ScienceDirect

Sustainable Energy Technologies and Assessments

journal homepage: www.elsevier.com/locate/seta

Quantifying Africa's offshore wind energy potential using Multi-Criteria Decision Assessment

AbuBakr S. Bahaj *, Mostafa Mahdy

Energy & Climate Change Division & Sustainable Energy Research Group, (www.energy.soton.ac.uk), Faculty of Engineering and Physical Sciences, University of Southampton SO16 7QF, United Kingdom

ARTICLE INFO

Keywords:
Renewable energy
Offshore wind energy
Representative Cost Ratio (RCR)
MCDA
AHP
Africa

ABSTRACT

Global wind energy electrical power generation is expanding exponentially. It is a fundamental building block for decarbonising the energy supply to achieve net-zero carbon targets, as well as the sustainable development goals. Hence, quantifying the power generation from wind resources is of global interest. This research addresses the latter, focusing on the offshore wind potential for the African continent. A methodology based on the representative cost ratio (RCR) combined with fuzzy multi-criteria decision-making analysis, using appropriately selected criteria (wind speed, water depth, proximity to grid, etc), was used to arrive at the potential for offshore wind in Africa. The method was validated by predicting the large offshore wind development in China and the UK. The most suitable locations for offshore wind energy around Africa were identified. The results showed that the shallow water offshore wind potential is limited (~85 GW), restricting it to the use of depth-restrained seabed-fixed turbines. At greater depths, the wind resource can result in over 6665 GW of installed capacity, promoting exploitation through floating offshore wind turbine technologies. Such a continental-scale deployment will address energy access, create growth and employment, whilst reducing Africa's dependence on fossil fuel imports.

Introduction

The worldwide drive to achieve zero carbon in the energy sector, coupled with the current environmental impacts of fossil fuel utilisation, has created significant opportunities for exploiting non-polluting renewable energy resources. One such resource is offshore wind, which can be exploited by wind turbine technologies to provide clean and renewable energy. According to the Global Wind Energy Council 2023 report, approximately 64.3 GW of global offshore wind capacity was in operation by the end of 2022 [1].

The wind intensity in open seas reaches much higher and more constant speeds than on land, resulting in offshore wind energy yield, which is around twice that of onshore wind. Another advantage that offshore wind offers is the reduction in visual and acoustic impacts, minimising social impacts on the surrounding areas. It is also recognised that offshore wind energy farms have higher capacity factors than those onshore [2]. The average capacity factors of offshore wind farms are in the range 25 % to 60 %, while those for onshore wind are in the range 20 % to 34 % [3], depending on deployment sites. The capacity factor of a wind farm is the average power output of an installation divided by its installed capacity. Similar to solar energy, the wind resource is irregular, but unlike solar radiation, it is available 24 h a day, and when comparing hourly resource variations, offshore wind variability is less than a third of solar energy; see, for example, some areas of China [4]. In addition, in many cases (e.g. Europe), the peak time of the offshore wind power generation is in phase with the high demand for electricity during the heating season. While the cooling demand in many African countries occurs in the summer months, when air-conditioning loads are high. This is the case, for example, in Egypt, where its peak electricity demand occurs at high wind speed periods (hence higher power output), as evidenced by its existing three offshore wind farms [5,6]. Therefore, it is important to establish the benefit of such phasing when considering wind energy potential across regions.

To make the most of the offshore wind energy resource, large conversion structures (up to 260 m high) fixed to the seabed have been and are being installed worldwide. Currently, offshore wind farms typically have several hundreds of megawatts (MW) installed capacities. For example, in the UK, the Hornsea 2 wind farm is currently the world's largest operating installation with over 1.3 GW capacity, consisting of 165 turbines, each having a capacity of 8 MW. Hornsea 2 is supplying

* Corresponding author.
E-mail address: a.s.bahaj@soton.ac.uk (A.S. Bahaj).

https://doi.org/10.1016/j.seta.2025.104749
Received 10 July 2025; Received in revised form 5 November 2025; Accepted 1 December 2025
Available online 2 February 2026

power to over 1.4 million UK homes with low-cost, clean and secure renewable energy [7]. Furthermore, it is predicted that within the next 10 years, over 380 GW of offshore wind capacity, across 32 markets, will be deployed [8]. However, in Africa, there is currently no offshore wind energy development. As will be demonstrated here, such a renewable energy resource is also highly pertinent for enhancing and speeding the development of African countries [9,10].

Offshore wind is one of the renewable resources that will play a crucial role in the decarbonisation of the power supply. In the UK, for example, there is currently a plan to increase its installed offshore wind capacity from 15 to 60 GW by 2030 to achieve the country's net zero targets [12]. The main deployment of offshore wind farms currently relies on structures fixed to the seabed (seabed-fixed turbines). This has been extremely successful in deploying farms at scale in relatively shallow waters.

There are, however, ongoing activities to deploy floating turbines in deeper water where the wind resources are higher. For instance, the recent UK Floating Offshore Wind Leasing Round 5, seeks to build an additional 4.5 GW of floating offshore wind farms, catalysing new technology breakthroughs whilst creating social, economic, and environmental opportunities in the UK [13]. Unlike seabed-fixed turbines, floating offshore wind turbines are based on floating structures tethered to the seabed in deeper water, allowing the deployment of larger wind turbines in areas with much higher wind resources. However, in both technology cases, optimising the use of ocean space, reducing environmental impacts, and ensuring that offshore wind farms coexist with other maritime activities depend on effective spatial planning. Such issues sit at the core of this research.

Spatial planning is crucial for considering the best wind resources and any limitations to optimise the siting of a wind farm. It is essential to accurately identify good wind resources to maximise energy yield and establish the best coherent areas for deployment. A thorough evaluation of the pertinent issues related to wind energy is made possible by integrating numerous data sources, including remote sensing and meteorological observations [7]. In addition, planning for infrastructure (deployment and maintenance, and grid connections) is complex, as such infrastructure may not be cohesive with wind farm sites. Furthermore, effective deployment of offshore wind farms depends on country-specific infrastructure (onshore (e.g. ports) and offshore (e.g. appropriate ships) as well as expertise, including subsea cabling and maintenance facilities. Addressing power transmission networks connectivity is also essential to ensure integration with the electrical grid, and any issues that need consideration [14,15].

Spatial siting for offshore wind farms is facilitated by integrated planning and decision support systems, such as Geographic Information Systems (GIS) and multi-criteria decision analysis (MCDA) assessment tools, such as the analytical hierarchy process (AHP), which support wind farm site choice, optimisation, and effect evaluation [15]. Using multi-criteria decision analysis, trade-offs may be systematically assessed, and the best options determined within the conducted analyses. Such approaches will be applied here to determine the offshore wind energy potential around Africa.

Machine learning (ML) utilisation may augment traditional mapping methods by learning directly from real wind farm sites, coupled with spatial data, to predict suitable locations for new projects and their optimal capacities [16]. Developing ML specific tools may unravel the complex, nonlinear mix of factors – such as water depth, grid distance, and fishing activity – that affect siting, while explainable tools make these drivers transparent. For researchers and planners, this means that machine learning, where appropriate data sets are available, offers a scalable and practical approach to guiding offshore wind development while balancing energy needs with environmental and social considerations [17]. A broader review of various offshore wind spatial siting comparisons is available in these comprehensive studies [5,18,19].

Previous studies to assess the offshore wind energy potential in Africa are sparse and have not been applied regionally across the continent. Most of the previous studies focused on one country rather than the whole continent, for example, Egypt [5,20,21], Morocco [3,14,22,23], and South Africa [2,7,24,25]. Out of these, only two considered using the spatial siting of offshore wind energy [5,14]. A study in 2019 used the capacity factor derived from the mean wind speed to determine Africa's wind energy "hotspots" [26]. This study utilised 1000 m depth as the lower limit for the water seabed depth criteria. Other studies in [3,14,21,27] attempted to build on the analyses in [26] for specific countries. The study for Morocco [23] suggested limiting the depth to 800 m, as the technology used to anchor the foundation of the Hywind floating wind farm operating off the coast of Scotland in the UK can be deployed to a depth of 800 m [28].

The African continent is bounded between 38°N and 35°S latitude and 25°W and 64°E longitude, with a spatial extent that includes multiple offshore regions, encompassing the Red Sea, the Gulf of Aden, the Indian Ocean, the Atlantic Ocean, and the Mediterranean Sea. Currently, most African countries rely on fossil fuels as their primary source of electricity supply. Oil, coal, and natural gas represent over 80 % of the electrical power generation in Africa [29], resulting in high carbon emissions and many negative environmental impacts.

In 2023, investment in renewable energy in Africa hit a record of $15 billion, which is more than double that of 2022. This record was fuelled by a rise in small-scale off-grid solar photovoltaic (PV) installations. PV is still the most widely used renewable energy technology on the continent. But this recent development in Africa only represents 2.3 % of the global renewable investment [30]. Most of the investment was focused on Egypt, Morocco and South Africa. This inadequate investment does not reflect the enormous renewable energy potential of the continent, nor is it appropriate for transitioning its current and future energy demand to low-carbon sources. Although Africa has one of the world's best solar resources, and as will be shown here, offshore wind is also very significant, offering additional opportunities for renewable energy in the continent. Furthermore, currently, only a few onshore wind energy farms are installed in Africa, representing less than 3 % of its installed power capacity, and there are no current offshore wind energy installations in Africa [31].

To overcome some of the shortcomings of the current knowledge, this research addressed the core requirement to arrive at estimates of the offshore wind potential around the African shores. The presented research used GIS, MCDA-based AHP with four criteria to characterise the wind resource potential – wind speed, sea depth, grid connection, and coastline distance. The analyses developed the suitability maps of offshore wind potential for the continent, showing physical deployment sites, whilst considering infrastructure proximity (grid and ports) that guide policy for exploiting offshore wind resources for electricity production at a continental scale.

The focus of the research is to quantify offshore wind energy resources and provide country-specific electrical capacity potentials based on appropriate site selection criteria linked to infrastructure and current wind turbine technology designs.

The paper is structured as follows. Following the introduction, the case for quantifying the African offshore wind energy resources was presented. This is followed by methodology, which describes the GIS-based multi-criteria decision analysis (MCDA) framework and the Representative Cost Ratio (RCR) approach used to identify suitable offshore wind sites. The approach validation using offshore wind developments in the UK and China to test the robustness was presented, followed by a detailed data consideration. The results and discussion are then presented, showing the suitability maps and potential capacities for Africa at both continental and national levels. The last section presents the conclusions, which highlights the main findings, their policy relevance, and the contribution of offshore wind to Africa's future energy mix.

Importance of quantifying Africa's wind energy potential

Quantifying the wind energy potential for Africa is important as the continent's population is set to double by 2050, and providing sustainable energy, which is affordable, is not only crucial for such an increase in population but also for development and for addressing the climate goals. Furthermore, there are currently around 600 million people, mostly living in sub-Saharan Africa, who lack access to electricity [32] which can also benefit from exploiting such wind energy resources.

As highlighted above, there is also an African 300 GW renewables target that will need to be achieved by 2030 [30]. In its Green Recovery Action Plan 2021 – 27, the African Union (AU) made a commitment to deploy 300 GW of renewables by 2030, approximately more than four times the continent's 2023 installed capacity of 72 GW [33]. In October 2023, the EU Directorate-General for International Partnerships announced the €150 billion investment called the EU-Africa: Global Gateway Investment Package, which is in partnership with the African Union, with sustainable energy as a cornerstone of the package [34,35]. This commitment was reaffirmed during the November 2024 Rio de Janeiro G20 Summit [34].

The set target and the announced investments are not only essential to delivering the recovery plan but are critical for both energy access and decarbonisation of the energy sector. It is estimated that achieving the 300 GW target will be challenging, as it will require the region to collectively add more than 33 GW of new capacity annually during 2025–2030 [30]. This study is aimed at contributing to this endeavour.

It is therefore important to identify appropriate renewable energy resources that can assist in delivering the set target whilst providing technology deployment pathways based on the current characteristics of African countries. This research will contribute to the needed knowledge by presenting the conduct of resource potential analyses that will be required to guide finance and decision makers to achieve the set-out goals and propel Africa into self-reliance in terms of sustainable electrical power provisions.

Methodology

Spatial planning is a multidimensional process aimed at locating a specific project in the most suitable area. It goes beyond selecting how land is utilised and considers the harmony of numerous elements, which could be challenging to accomplish with traditional planning methods. Such strategies can be equally applied to determine offshore and onshore wind energy potential and sites, as they have common components such as wind speed and distance to the grid. However, the definitions of the components and any restrictions that may arise in these two cases vary. When considering onshore wind, for instance, in addition to appropriate wind speed (power generation is proportional to the cube of the wind speed) [36], the distance from highways and the closeness of wind farms to the national grid (populated centres) are essential in delivering electrical power at an acceptable cost to consumers. However, when considering offshore wind, factors like wind speed, sea depth, grid and deployment infrastructures, and proximity to sites are critical parameters.

AHP methods for wind energy spatial siting

The spatial planning methodology to determine wind farm siting can be summarised as follows:

(a) Utilise AHP or a comparable methodology to identify the geographical features of wind energy extraction sites and associated criteria such as wind speed, grid and infrastructure proximity, water depth, etc.
(b) Standardise the derived criteria parameters using fuzzy membership or "one's criteria derived judgment".
(c) Use pairwise comparison or similar techniques to weigh the relative importance of the individual criteria.
(d) Combine the resultant factors and constraints layers using GIS tools coupled with the relevant weights of the selected parameters, such as using the weighted linear combination (WLC) in the AHP process.

Spatial planning comprises the analysis of a large number of suitable alternatives and multiple criteria that will need to be examined and evaluated. Once the appropriate criteria are selected, they are evaluated and weighted accordingly. This is typically conducted by appraisers consisting of experts, stakeholders, and scholars, where the weights and importance of the criteria are determined based on their knowledge and experience of the case or problem under consideration [37]. In such cases, the Analytic Hierarchy Process (AHP) is used to identify the problem criteria, to weight them according to the expert views, and to then evaluate each of the alternatives [38,39].

The AHP systematic decision-making process was created by Thomas Saaty in the 1970 s [40]. It is a frequently used method that chooses several criteria or options to tackle complex situations by breaking down the issues into a hierarchy of criteria and sub-criteria. The criteria and sub-criteria are assessed and prioritised by experts based on their relative importance, to provide a systematic decision-making process geared to arrive at appropriate solutions. The AHP process can be linked to a geographical information system (GIS) model to efficiently solve the problem of mapping appropriate wind farm sites by considering local aspects and defining relevant criteria. The criteria weights and any conflicts, which are known as factors and constraints, are considered. Establishing suitability maps for appropriate locations of wind energy farms requires the AHP analyses to produce factor (criteria) weights to score and map the available areas of wind energy resource, and rank them numerically, arriving at areas of high and moderate suitability or not suitable. In essence, the AHP analyses create numerical scores for these areas of available wind resources, providing a ranking from the highest to the lowest suitability (i.e. suitability maps). These outcomes are normally used to assist stakeholders in targeting investments by exploiting the most suitable areas first, then the moderate areas and so on.

Fuzzy membership functions are necessary to combine different layers of the GIS modelling into one final map. Such functions overcome the fact that factors have differing magnitudes and units, which cannot be combined. To overcome this, fuzzy membership functions convert these different factors and their units to a comparable scale. For instance, water depth is measured in metres; on the other hand, distance to the shoreline is measured in kilometres. To combine the two components, a standardisation method converts their magnitudes to equivalent scales varying from 0 to 1. This process is carried out using a fuzzy linear function, which is available as a tool in ArcGIS [41].

In addition, factors also have different weights according to their *importance*, so the pairwise comparison method is used to weigh these factors as per the method developed in [40,42]. Such pairwise comparison of factors is undertaken to establish the relative relevance or preference of each factor in a collection of factors under consideration. These comparisons rank options, prioritise possibilities or assess the solutions encountered in engineering, psychology, and economic studies [43]. Each factor is compared to others in the set, using a predetermined scale known as the *Importance Index*. Typically, the degree of importance is expressed using a numerical scale or a series of vocal expressions. The scale may change depending on the setting or issue being addressed.

The Importance Index is an integer with a scale between 1 and 9 and is critical in determining the relationship and importance between factor pairs that govern a project and its cost. In the case under study, the Importance Index addresses the importance of the factors utilised and compares them in pairs and is also crucial in evaluating the link and importance between factor pairs. The degree of importance scales used to represent pairwise comparison values between factor pairs are defined and explained using Saaty's Importance Index scale definitions and explanations [40,44]. For example, a pair receives a score of 1 if both elements are equally important, and a pair gets a score of 9 if the first component is significantly more important than the other. The numbers in between represent the scale for the spectrum of importance, ranging from 1 to 9.

Fig. 1 summarises the methodological steps required to address the above discussion, encompassing steps (a) – (d) above. These steps must be undertaken to map the appropriate offshore wind resource sites in Africa using the combination of MCDA, AHP and GIS. The section below provides additional explanations of the methodology covering the set of concepts contained in Fig. 1. As indicated earlier, the weights and importance of the criteria are determined based on the experience and knowledge of the experts involved in evaluating the proposition under consideration. To find the final weight associated with each factor, one needs to produce two matrices: the pairwise comparison matrix P_w and the normalised matrix N_w. The pairwise comparison matrix P_w contains equal numbers of rows and columns, with the number of rows (columns) equal to the number of factors (see Table 2 and Table 3 for such a matrix).

The three conditions associated with P_w matrix construction:

(i) The matrix-relevant cell will take on the value assigned in the scale of intensity of significant value allocated from Saaty's scale if the factor on the left side of the matrix is more relevant than the component on the top side of the matrix [42].
(ii) In the reverse scenario, the cell equals the inverse of the scale value.
(iii) If the factor is compared to itself, or the two factors have the same importance, the cell value will be 1.

The normalised matrix N_w is obtained by dividing each cell of the P_w matrix by its column sum. The N_w matrix is used to calculate each factor's weight W_i, which equals the average of the row (see Table 2 and Table 3 for such a matrix).

As noted above, in the past, alternatives, criteria, and their weights were often evaluated by several expert individuals (decision-makers, managers, stakeholders, and interest groups) who may have conflicting preferences and objectives in arriving at the required factors and their weights. The expert evaluation requires undertaking a comprehensive survey of such experts to solicit their opinions [15,45–51]. In such a process, errors invariably occur, coupled with the lengthy period needed to arrive at a consensus decision on factors among the experts. In order to circumvent these issues, a new approach called the Representative Cost Ratio (RCR) was developed in [15] is utilised to facilitate the comparison process. In the following sections, the steps undertaken to estimate these relationships and the values for both the RCR and Importance Index are discussed in the following sections.

Representative cost ratio and importance index

The Representative Cost Ratio (RCR) is a new approach developed in [15] to replace the existing, time-consuming, and less reliable techniques for determining the Importance Index and evaluating offshore wind energy projects. The RCR is determined based on the economics (cost ratios) of the various constituents of a wind farm development. The association between AHP and cost ratios was established by the authors

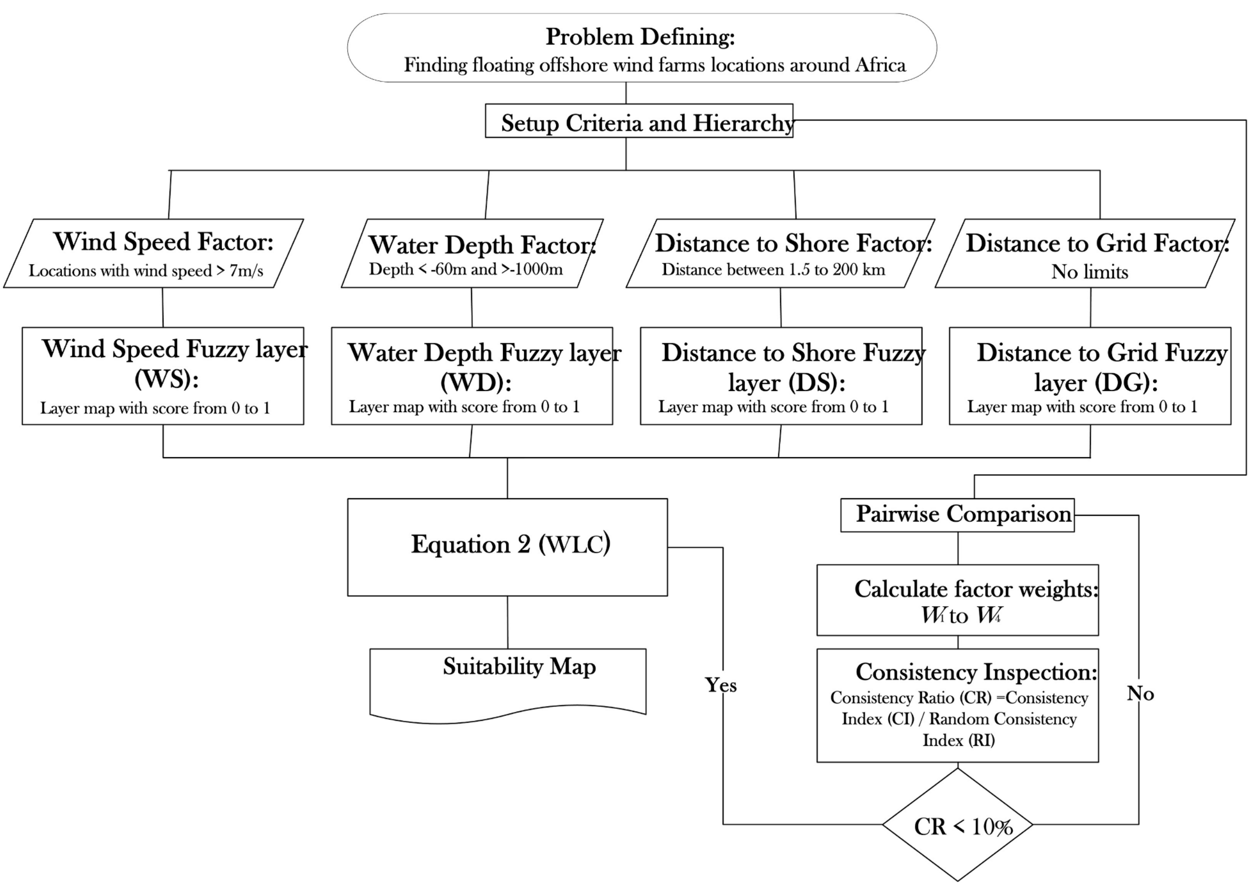

Fig. 1. Methodological steps undertaken to arrive at the suitability map for offshore wind energy resources in Africa. The methodology starts with the problem description, establishing criteria, fuzzy layers, and the necessary processing is done as part of the AHP process to arrive at the most suitable locations for offshore wind.

in [15] through analysis of data in the literature, evaluating the potential for wind energy spatial siting [66–68]. These three studies carried out by different researchers covered the siting of wind energy farms in various regions around the world and at different periods of time. As these studies are not connected in any way, the experts arrived at a similar range of cost ratios for the various sites, which allowed the authors to build on this and establish the Representative Cost Ratio (RCR) concept in [15]. The approach can be applied universally using the RCR developed factors as shown in the following sections. These sections also augment the validity of the approach by capturing newly published data related to the topic and applying it to offshore wind deployment across Africa.

Estimating the Representative cost ratio and the Importance Index

The RCR was established to take into account the underpinning economics of a wind energy project development, considering its various constituents (and their cost ratios), facilitating generalisable applicability across the sector. The RCR values are dependent on contributions brought about by the various project factors (e.g. wind speed) to the Levelised Cost of Energy (LCOE) as compared to the total turbine cost (CAPEX) and how this is influenced by the contribution of the other considered factors (e.g. water depth) to arrive at the final weights of pairs of these factors. Such connections between RCR and LCOE impact the results of the site's suitability maps. In other words, if the LCOE of a factor, e.g. wind speed, is relatively higher than that of other factors, the areas with high wind speeds will dominate, and vice versa. The relationship between the RCR and the economics represented by the LCOE of offshore wind energy is coherent. In Appendix A, Table A1 shows the historical results for these relationships by considering the values of turbines capacities, their CAPEX, the factors contributing to the CAPEX and the cost ratio for these. Table A1 gives the average values of these contributing factors for the period 2017–24 which were used in the analyses of the seabed fixed turbines, whilst the values in the last row of the table are used for the floating turbines case.

The Importance Index is a scale of absolute numbers introduced by Saaty [40] with the aim of finding a number between 1 and 9 to express the importance of two factors numerically. For example, if the two factors have equal importance, the importance index will be one. While if one of the factors is exceptionally more important than the other one, then the index will be nine and so on [40].

The Importance Index (*II*) values related to the RCR factor pairs were determined from published literature for the period 2017 to 2024 [5,6,14,60–65] for the case of seabed-fixed offshore wind energy turbines. Table 1 depicts the RCR factor pairs (e.g. wind speed vs water depth) (Column A), whilst Column B shows the cost ratio values of the various factors gained from the average values in Table A1. The cost ratio is the contribution of a factor to the final LCOE of the project and is determined from the average values (Table A1) of these factors, repeated in column B of Table 1. The RCR associated with a certain factor pair is calculated by dividing the cost ratio of the two factors (F1/F2) shown in Column C. For example, from Table 1, the RCR for the cost ratio of wind speed vs shoreline distance is 54.1:9.6, resulting in a value of 5.6 in Column C of Table 1, and so forth. Column D shows the published *II* values, which were averaged in Column E. These values were used to determine the relevant range (1–9) of RCR for each factor pair in terms of the Importance Index for the case of seabed fixed offshore turbines.

The values from Columns C and E of Table 1 were used to determine the relationship between the RCR and *II*, as shown in Fig. 2. From the figure, this relationship is represented by Equation (1).

$$II = 2.588\ln(RCR) + 0.9467 \tag{1}$$

Fig. 2 also shows the relationship between RCR and *II* using the data for onshore wind from previously conducted studies undertaken between 2001 and 2015 [15]. Both trends representing span the period 2001 to 2024 and as shown in the figure, the trend present similar dependency between RCR and the Importance Index covering the levelised cost of energy (LCOE). This also gives confidence that the proposed RCR concept can be used for the siting of wind farm locations and circumvents the difficulties in assessing the weights of the required criteria [32]. This provides further support to the study in [15], utilising the RCR in offshore wind applications, which has yielded results comparable to those conducted by the UK Crown Estate for feasible offshore wind locations in the UK [13,69,70]. This work also introduced further verification of the appropriateness of the approach, which was applied to the Chinese offshore wind energy projects and correctly predicted their siting (see Section *Validation of the Representative Cost Ratio*).

Generating suitability maps

The final stage in the AHP process is to determine the best locations for offshore wind through applying the Weighted Linear Combination (WLC) (see Fig. 1), which combines the standardised factors after multiplying each factor by its weight. The output maps are then multiplied by a Boolean mask, which is created by multiplying all the constraints to eliminate the considered restricted areas of values of zero, and the unrestricted areas that have values of one. The resulting map is the Suitability Map, derived [38] as follows:

$$Suitability(WLC) = \left(\sum_{i=1}^{n} W_i X_i\right) \times \left(\prod_{j=1}^{l} C_j\right) \tag{2}$$

Table 1
Process of obtaining the RCR range from previous offshore wind studies.

Column A	Column B		Column C	Column D Importance Index (II) determined references, over the period 2017–2024												Column E
RCR pair(F1 vs F2)	F1 (%)	F2 (%)	RCR = F1/F2	2017 [60]	2018 [5]	2019 [61]	2020 [6]	2021 [14]	2021 [62]	2022 [65]	2023 [52]	2023 [53]	2024 [54]	2024 [56]	2024 [55]	Average
Wind speed vs Water depth	54.1	29.4	1.8	3	3	1/3	3	3	3	3	5	3	–	4	3	3
Wind speed vs Shore distance	54.1	9.6	5.6	5	6	4	7	7	6	6	–	–	–	4	4	5
Wind speed vs Grid distance	54.1	6.7	8	5	8	3	9	5	–	–	–	6	6	9	8	7
Water vs Shore distance	29.4	9.6	3.1	3	3	5	5	5	3	2	–	–	–	–	1/3	3
Water depth vs Grid distance	29.4	6.7	4.4	3	4	4	6	3	–	–	–	5	–	–	–	4
Shore distance vs Grid distance	9.6	6.7	1.4	3	3	1/2	3	1/3	–	–	–	–	–	–	–	3

Table 2
Pairwise comparison of Important Index selection using the RCR approach for the floating offshore wind turbine case.

Factors	(Column A) Contribution to LCOE (Table A1)(%)	Factors	(Column B) Contribution to LCOE (Table A1) (%)	RCR (A/B)	Importance Index (II)								
					1	2	3	4	5	6	7	8	9
					RCR Range (Fig. 2, [15])								
					(0 ∼ 1)	(1 ∼ 2)	(2 ∼ 3)	(3 ∼ 4)	(4 ∼ 7)	(7 ∼ 10)	(10 ∼ 13)	(13 ∼ 18)	Over 18
Wind Speed (WS)	45	Water Depth (WD)	35	1.3		x							
		Distance to Shoreline (DS)	15	3.0				x					
		Distance to Grid (DG)	5	9.0						x			
Water Depth (WD)	35	Distance to Shoreline (DS)	15	2.3			x						
		Distance to Grid (DG)	5	7.0					x				
Distance to Shore (DS)	15		5	3.0			x						

Table 3
Shows the values of two matrices for the Pairwise comparison P_w, and the Normalised N_w arrays and the final factor weight value Wi for the floating offshore wind farms case.

	Wind Speed		Water Depth		Distance to Shoreline		Distance to Grid		
	P_w	N_w	P_w	N_w	P_w	N_w	P_w	N_w	W_i
Wind Speed (WS)	1	0.52	2	0.57	4	0.48	6	0.40	0.49
Water Depth (WD)	1/2	0.26	1	0.28	3	0.36	5	0.33	0.31
Distance to Shore (DS)	1/4	0.13	1/3	0.09	1	0.12	3	0.20	0.14
Distance to Grid (DG)	1/6	0.09	1/5	0.06	1/3	0.04	1	0.07	0.06
Sum (Σ)	1.92	1.00	3.53	1.00	8.33	1.00	15	1.00	1.00

Where: W_i is the weight assigned to factor I, X_i is the criterion score (0 ∼ 1) of a factor i [see Figs. 3, 4 and Table C1 in Appendix C], n is the number of factors, C_j is zero or one score of the constraint j (Boolean Mask j), Π is the product of all constraints, and ℓ is the number of constraints.

A Boolean Mask is used to exclude restricted areas or the cells in the map before beginning the suitability analysis. Boolean overlay, where "0" or "1" represents the outcome of using Boolean relationships like (And, OR, or Not) to arrive at a given conclusion. As a result, there are just two tones on the map: one colour designates limited zones, while the other designates available areas [69]. The Boolean overlay is appropriate for making quick and easy geographic judgments, such as determining whether offshore regions are open to wind energy development. The Boolean Mask is produced by multiplying all restriction layers together (ΠC_j) as defined in Equations (3) and (4).

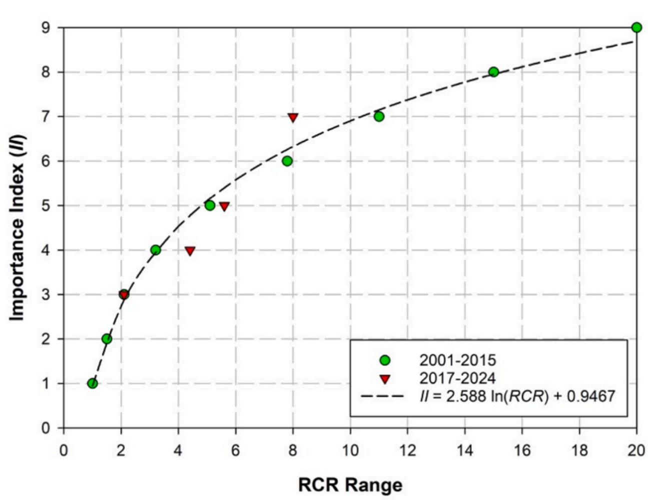

Fig. 2. The interpolation curve estimates the RCR range for the LCOE for the period 2001–2015 (green circles) [15]. The triangles represent the updated RCR data for the period 2017–2024 [5,6,14,52–65].

RCR and factor weights

As indicated earlier, using the RCR to calculate factor weights provides a robust approach (see trends in Fig. 2 and the validation approach in Section *Validation of the Representative Cost Ratio*). The process reduces the time and effort required to rank the criteria in offshore wind spatial siting. This section outlines the methodological analyses undertaken to quantify factor weights for both floating offshore and seabed-fixed turbines, with the same considerations applied for both types.

For floating offshore wind turbines, Table 2 shows the Importance Index, *II*, of each possible factor pair as defined by the scale given in [42] and the RCR range derived from Fig. 2. The selected values for the Importance Index are chosen based on the contribution to the final Levelised Cost of Energy (LCOE) as extracted from Table A1 in Appendix A for the floating offshore wind case shown on the last row and last four columns of the table. The percentage contribution to the LCOE is repeated in columns A and B in Table 2. For a floating wind turbine, the wind speed contributes to the LCOE with 45 %, the water depth with 35 %, the distance to the shoreline with 15 % and the distance to the grid with 5 % (Table 2). To determine the RCR value, the contribution of

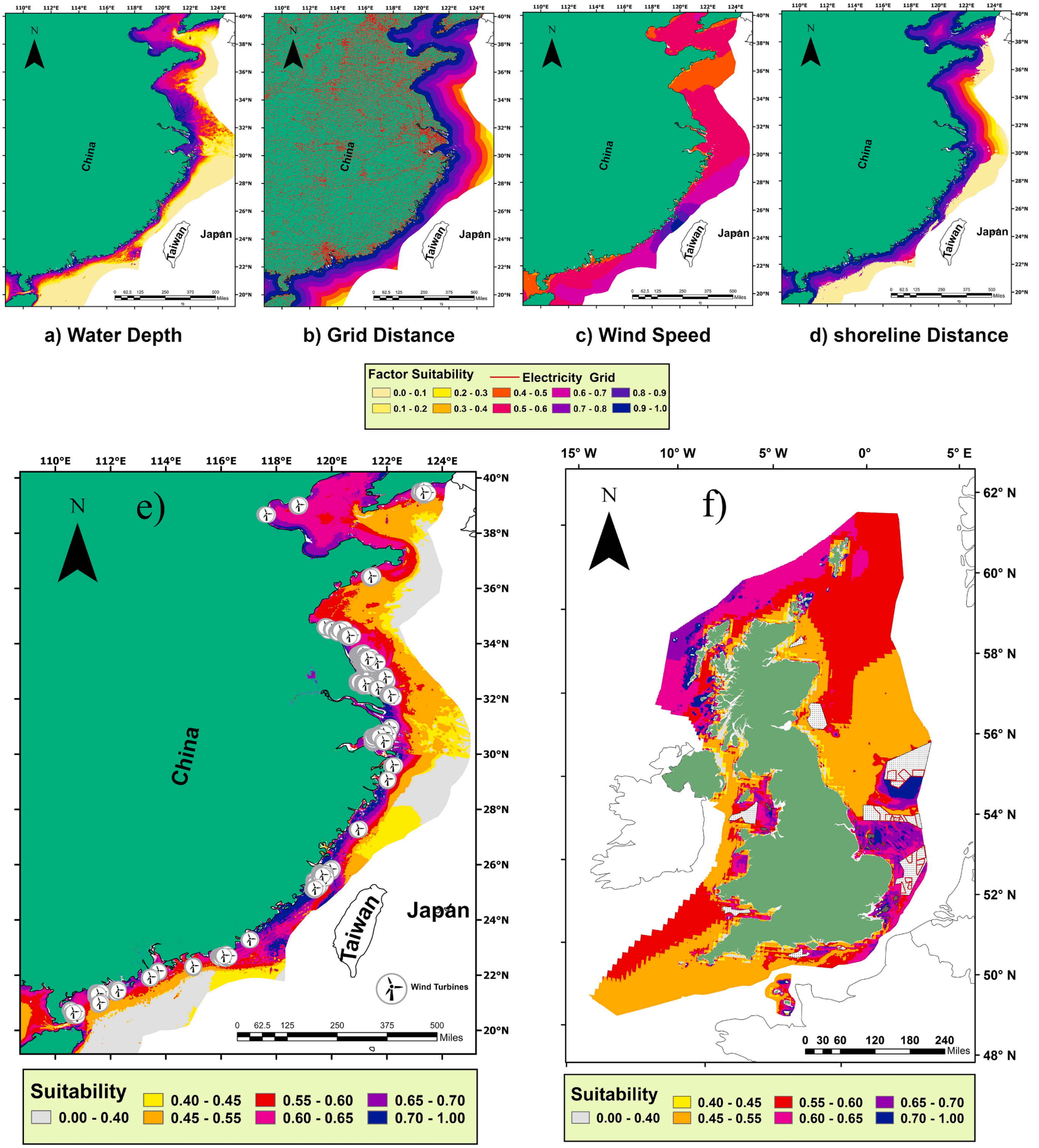

Fig. 3. (a) – (d) shows the suitability maps for the four factors water depth, grid distance, wind speed and shoreline distance (W_1X_1 to W_4X_4, Equation (2) under investigation respectively; (e) shows the offshore wind suitability for fixed turbines around China and the actual locations of their operational offshore wind turbines.; and (f) shows the UK's offshore wind suitability map utilising the PCR relationship with the Important Index [15] predicting the UK 3 funding "Rounds" (Rounds 1, 2, and 3 in doted grey with wind farms being deployed outlined in red. In both cases, the suitability score ranges from 0 (least suitability) to 1 (highest suitability). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

these pairs in relation to each other will need to be established.

To accomplish this, the wind speed (WS) needs to be paired with other factors, such as water depth (WD), distance to shore (DS), and distance to the grid (DG), amongst others. Hence, the Importance Index score will depend on these combined contributions and the range of RCR given in Fig. 2, also shown in Table 2. For instance, the ratio WS:WD = 45 %:35 %=1.3, which occurs within the RCR range of (1 ~ 2) (Fig. 2), which corresponds to a value of 2 for the Important Index *II* in Table 2. Additionally, these values can also be gained using Equation (1), and from Fig. 2, the RCR value is 1.3 (x-axis), so the corresponding *II* value is 1.63 (y-axis). Therefore, the final value of the Importance Index for the WS:WD pair is rounded to the value 2, which corresponds to the nearest integer value in Fig. 2. Similarly, WS:DG = 45 %:5%=9, the RCR range for this value is (7 ~ 10), and as a result, the corresponding Importance Index *II* is 6 [6,15,42], and so on. Using Equation (1), the RCR value will be 9, so the *II* value is 6.3. Therefore, the final value of the Importance Index for the WS:DG pair is 6, that is corresponding to the nearest integer value in (Fig. 2).

The values in Table 2 were then used to establish the pairwise comparison matrix (Table 3), using the three conditions (i) – (iii) discussed under the methodology section. The normalised matrix (Table 3) is determined by dividing each matrix element by its column sum. For instance, in Table 3, the wind speed value in the normalised matrix is determined by $1 \div 1.92 = 0.52$, giving the value for N_w and so on for the other values. The Factor Weight values W_i in Table 3 represent the average values determined for each factor in the corresponding row.

Similar considerations were undertaken for the case of seabed-fixed turbines, including appropriate Pairwise and Normalised tables, which are given in Appendix B.

Validation of the Representative Cost Ratio

The utilisation of the Representative Cost Ratio (RCR) was validated by applying it to existing and future offshore wind farms in both the UK and China.

Starting with the case of China, where the country accounted for 46 % of worldwide offshore wind capacity in 2022 and continued to lead global offshore wind development [70]. By the end of 2021, China had deployed over 5670 offshore wind turbines of the seabed-fixed type, rather than floating. Hence, it has been selected for analysis to provide further verification of the RCR concept with a similar methodology as in [15] which considered the UK case for seabed-fixed offshore wind turbines. Although China has released the location maps for its offshore wind turbines, it has not provided specifics on the process used for the spatial placement of the wind farms in their deployment areas. On the other hand, their reports explain the criteria and scenarios/iterations used when approving their projects.

Using information from the World Bank data repository [71], four suitability factor layers were created in GIS to analyse the Chinese offshore wind farms. The data for the criteria factors of wind speed (m/s), sea depth (meters), distance to shore (km), and distance to the grid (km) and value scales were transformed to a raster format with a pixel size of 400x400 m and a Geographic Coordinate System of "WGS 1984″ [72]. As a result, to reach the Weighted Linear Combination (WLC) step (the final step in Fig. 1), linear fuzzy constraints were used to unify their scales and dimensions to a measure ranging from zero to one. These additional layers, known as factor suitability maps, reflect the above-listed criteria factors. The four maps are processed in ArcGIS Pro using the Fuzzy-membership Tool and are shown in Fig. 3a-d. The figure covers the maps for water depth, grid distance, wind speed, and shoreline distance, providing relative suitability and confidence in low to high desirable locations for these factors.

Using Equation (2), the ArcGIS Pro Raster Calculator Tool combined the four suitability maps. The final China suitability score for each map pixel is calculated as follows: [0.28 × water depth fuzzy layer + 0.08 × distance to grid fuzzy layer + 0.12 × distance to shorelines fuzzy layer + 0.51 × wind speed fuzzy layer]. For the Chinese seabed-fixed turbines consideration, the weights are extracted from calculations, as shown in Tables B1 and B2 in Appendix B. Fig. 3e shows the offshore wind suitability for seabed-fixed offshore wind turbines around China, categorised into three suitability ranges: inappropriate (0.0–0.39), moderate (0.4–0.59), and high (0.6–1.0). According to the results, all of China's active offshore wind turbines are in areas within moderate to high suitability. The most appropriate places are scattered along the Chinese coast, with enormous potential in the Bohai Sea.

As can be seen from the results for the China case, the findings confirmed the siting of the wind turbines supporting the Representative Cost Ratio (RCR) method as being precise, giving 97 % predictions of these farms, which are placed in high suitability areas and the residuals in moderate locations. The utilisation of the RCR concept is also supported by the previous consideration of the UK offshore wind farms case, where the outcome can be seen in Fig. 3f, which displays the final suitability map outcome predictions for the UK offshore wind deployment, including current and future wind farms [15]. This gives confidence that the RCR approach is accurate, as in both cases, all the modelling output cells for these projects are located in either moderate or high suitability categories determined by this study.

The results shown in Fig. 3e-f confirm the appropriateness of using the RCR and the quality of the different assumptions used, which accurately predicted the suitability maps of offshore wind energy sites for both the UK and China. This approach will now be applied in the analyses to predict the potential for offshore wind energy at the continental scale of Africa.

Data and modelling considerations

A systematic approach, building on the considerations presented in previous sections, is presented in the following sections to establish the suitability maps for the offshore wind energy potential of Africa. The approach covers the wind energy resource, its characteristics, infrastructure availability, and the considered restrictions. All modelling codes used are embedded within ArcGIS, as per the practice in the utilisation of ArcGIS. With regard to data sources used in the research, these are summarised in Appendix C, Table C1.

Factors and their suitability maps for floating and seabed fixed turbines

Due to the large continental footprint and the different conditions presented by the considered countries, the analyses used 6 criteria, made up of 4 factors (underlined) and 2 constraints (italics). The four criteria factors are: (i) wind speed in (m/s), (ii) water depth (bathymetry) in (m), (iii) distance to the shoreline in (km), and (iv) distance to the grid infrastructure in (km). The constraints used are (v) *wind speed limits* in (m/s), and (vi) *water depth limits* in (m). These criteria were selected due to their appropriateness for offshore wind energy assessment in the case under study.

The wind speed (m/s) factor is the atmospheric rate value of the moving air measured at a turbine hub height of 150 m (considering the utilisation of current technology of a 15 MW wind turbine) above sea level. A minimum *wind speed restriction* of 7 m/s was selected to ensure economic viability [15]. Seawater depth (bathymetry) factor is expressed in metres and ranges from 5 to 60 m (*water depth constraint*) for the seabed-fixed offshore wind turbines [87]. The chosen *water depth constraint* for floating offshore wind turbines was in the range 60 to 1000 m [7]. The distance to shore factor is the distance between the shoreline and the wind farms locations in the sea. To maintain a realistic cost for underwater cabling, this factor is limited to the range 1.5 to 200 km from the shoreline [88]. The distance to the power grid connections factor determines the cable length required to connect the offshore wind farms to the countries' national unified power network on shore. The distance is variable depending on country specific grid connection characteristics.

Given the multitude of factors influencing the spatial placement of offshore wind energy, the challenge now lies in finding the ideal sites for offshore wind energy across African shores and providing clear details of the needed data for each country, which will address the identified criteria appropriately.

A map layer was created in ArcGIS using readily available and relevant geographical data for each criterion. The British Oceanographic Data Centre serves as the primary source for the bathymetry data for the nearby seas and oceans, ensuring the data's reliability [79]. The dataset was already in raster format to aid input to the GIS. A Boolean mask is used to remove areas with water depths: (i) for seabed-fixed turbines above − 5 m or below 60 m and (ii) for floating wind turbines, above 60 m and below 1000 m. The geographic coordinate system used for this layer is "GCS_WGS_1984″, and the cell size for this layer is (x, y) = (800, 800) m for both cases. For all generated new layers to be compatible with the source data for the bathymetry raster layer, the cell size and coordinate system were adapted to match this layer.

The wind speed data used are derived from the global wind atlas developed by the World Bank and the Department of Wind Energy at the Technical University of Denmark (DTU), available in freely accessible high-resolution global wind maps [81]. The map's grid size is 250x250 meters, and the wind speed data used for the model is at a hub height of 100 m; the wind data was then adjusted to 150 m height to be in line with the 15 MW hub height. As will be shown later, this will need to be transformed to the selected cell sizes considered for both cases.

The "Wind Atlas for Egypt" [11], Global Atlas for Renewable Energy [89], and the DTU Global Wind Atlas were used to gather data on wind speed around Africa [80,81]. The Georeferencing Tool created a map image to represent the wind speed as a layer in the ArcGIS, with four geographic control points considered in this process and subsequent layers. Then, a shape feature containing the wind speed contour map was inserted. With the help of the Vector to Raster Tool, the shape feature was turned into a raster file. The map of Africa's unified power networks was taken from [82–86], which was utilised to find the power grid connection points on shore. The Euclidean Distance Tool was used to compute the distance between each power line. Using the Euclidean Distance Tool, the African coasts were also created to calculate the distance of the wind farm locations to the shoreline.

The source shape files were transformed to a raster format for the selected cell size (800 × 800) m and Geographic Coordinate System of "WGS 1984." Data for several parameters were collected in various dimensions (wind speed, sea depth, distance to shore, and distance to the grid − referred to as layers) and value scales. As a result, to reach the Weighted Linear Combination (WLC) (Equation (2) phase (the final step in Fig. 1), fuzzy linear limits were used to unify their scales and dimensions to a scale ranging from 1 to 0 (see methodology). These additional layers, known as factor suitability maps, reflect the following factors: (a) wind speed, (b) water depth, (c) distance to shoreline, and (d) distance to power grid.

Floating offshore wind case

For the case of floating offshore wind, a Boolean mask with 0 or 1 scores was developed to exclude the limited cells, that is, all the cells with one or more restrictions. For the analyses, two maps were created: one for the wind speed constraints (WSC) and the other for water depth constraints (WDC). These two constraints were combined into a single layer within the GIS. The Raster Calculator tool in ArcGIS was used to sum up all the limitation layers into one layer (overall Boolean Mask); and this new Boolean Mask layer was derived using the following equation:

$$Boolean_{Mask} = WSC \text{ x } WDC1 \text{ x } WDC2 \tag{3}$$

Where WSC is the wind speed constraint, that is, those that are less than 7 m/s; WDC1 is the water depth constraint, that is, those that are less than 60 m; and WDC2 is the water depth constraint, that is, those that are greater than 1000 m.

Fig. 4 shows the outcome of the analyses, depicting the four-factor suitability maps for the four criteria processed in ArcGIS and using the Fuzzy-membership Tool.

Seabed-fixed offshore wind turbines case

For the case of seabed-fixed offshore wind turbines in Africa, the Boolean mask was used as follows:

$$Boolean_{Mask} = WSC \text{ x } WDC3 \text{ x } WDC4 \tag{4}$$

Where WSC is the wind speed constraint, less than 7 m/s; WDC3 is the water depth constraint, less than 5 m; and WDC4 is the water depth constraint, greater than 60 m.

For the case of seabed-fixed offshore wind turbines in Africa, the four factor suitability maps were produced, using a similar approach as that for floating wind turbines and the results are given in Appendix D, Fig. D1.

Building on the previous considerations, and for both floating and seabed-fixed offshore wind turbines, the derived factor suitability maps were used to arrive at the final overall suitability maps and the resultant electrical power capacities that can be deployed around the coast of Africa. The results for both cases are shown in the next section.

Results and discussion

This section reports on the conducted analyses to determine the suitability maps needed to support the deployment of both seabed-fixed and floating offshore wind energy turbines around the continent of Africa using appropriately defined criteria coupled with the AHP approach discussed in the methodology and the data and modelling consideration sections. The analyses covered 38 countries with a combined maritime area of almost 14 million km^2 and over 30,000 km of coastline. This section starts by considering the farm spatial distribution parameters needed to estimate the African offshore wind power potential capacities based on the current technology of a 15 MW wind turbine size and capacity. Then the results for the two types of offshore wind energy turbines (a) floating and (b) seabed-fixed deployment are presented and discussed.

Estimating the potential electrical power capacities for the two types of turbines

Determining the offshore wind energy potential in terms of electrical power capacities for the investigated African offshore regions requires consideration of the spatial distribution of the area occupied (farm footprint) by the turbines and their inter-turbine spacing within a farm or an array. The areas are determined from the suitability maps (see

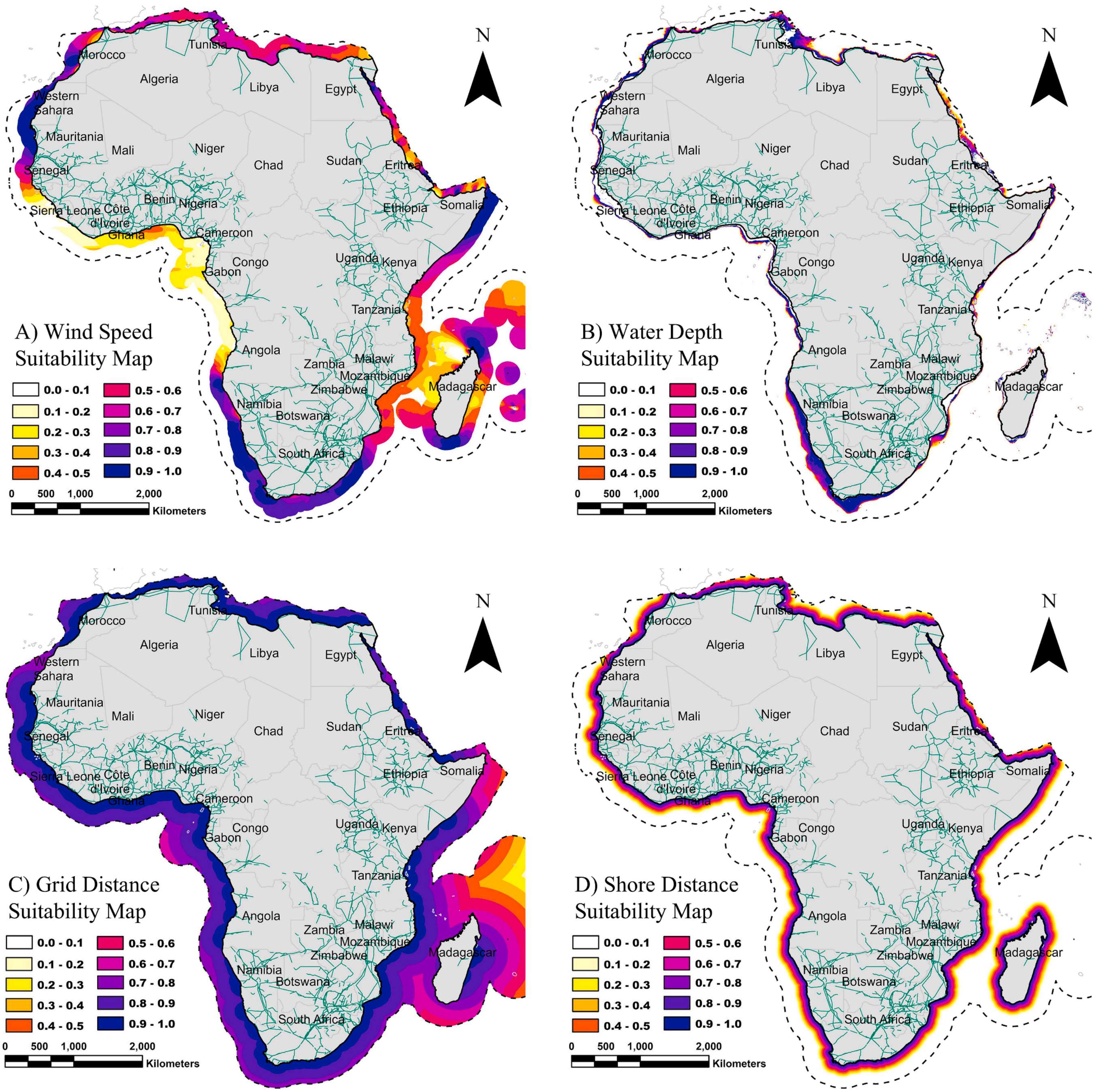

Fig. 4. Floating offshore wind turbine factor suitability maps for the four considered factors: (A) Wind speed factor, (B) Water depth factor, (C) Distance to electricity grid lines, and (D) Distance to shorelines. In Equation (2), these factors are represented by the values $W_1 X_1$ to $W_4 X_4$. The dashed line represents exclusive economic zones (EEZs).

following sections), and the inter-turbine array spacing S is determined following a similar approach presented in [15] and using equation (5) proposed in [90].

$$S = R_d{}^2 L_d L_c \tag{5}$$

Where S is the array spacing giving the footprint for each offshore wind turbine in an array, R_d is the rotor diameter, L_d represents the downwind spacing factor, L_c is the crosswind spacing factor.

To reduce wake-effect interaction between the turbines in a farm, the ideal turbine spacing was considered to be in the range 5——8 times that of the turbine rotor diameter [91]. Hence, in the presented analysis, L_c was given the value 5 and L_d the value 8 and R_d, the rotor diameter, is 236 m [92], giving a wind turbine footprint $S = 5 \times 8 \times 236^2$ for a 15 MW turbine.

Offshore wind energy potential using floating turbines

Floating offshore wind turbines provide technical innovations that

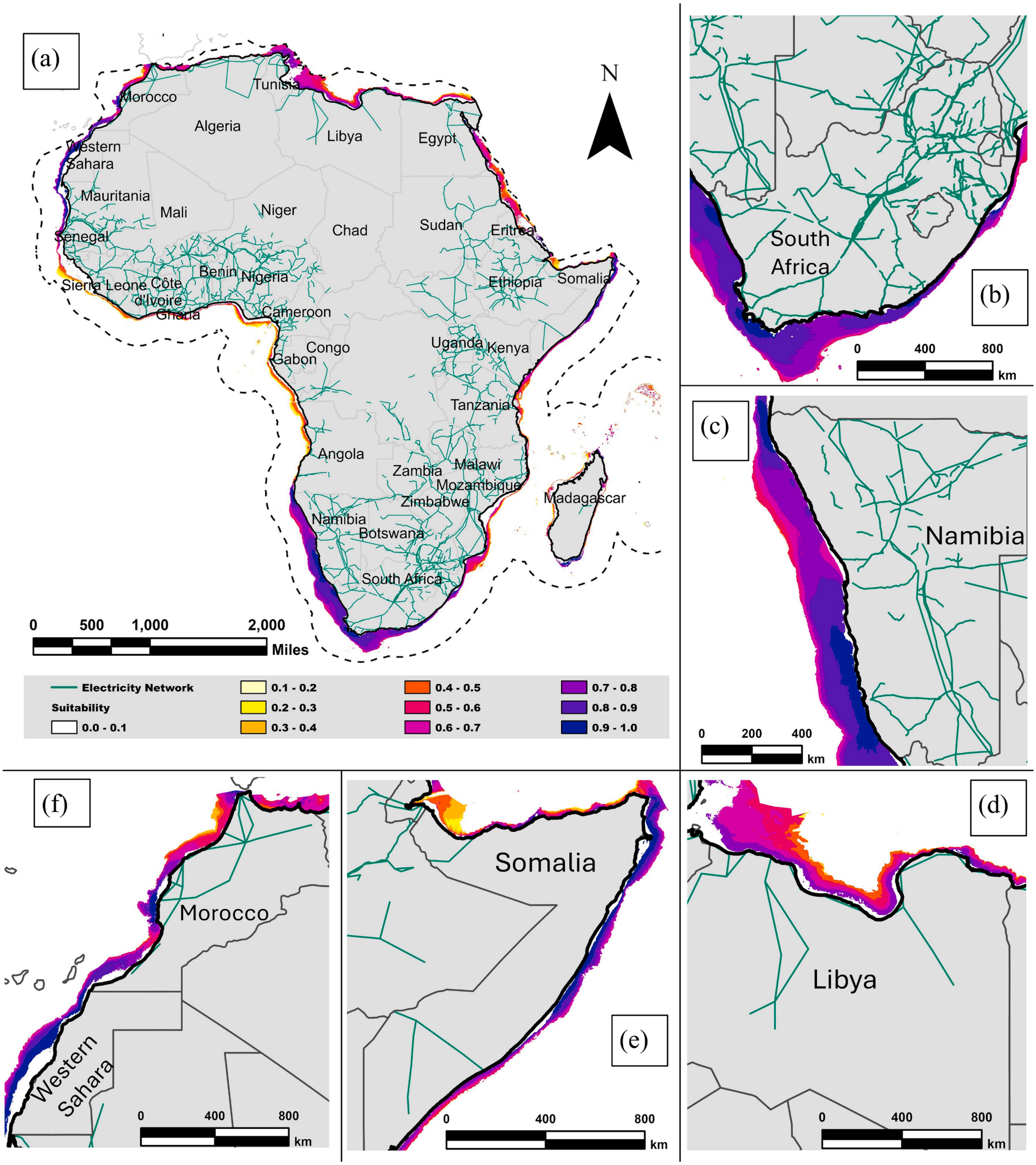

Fig. 5. Floating offshore wind resources map for Africa: (a) the overall resources map and (b) to (f) represent the top five countries with the highest potential for floating offshore wind energy. The dashed line represents exclusive economic zones (EEZs).

Table 4
Offshore wind potential utilising both floating and seabed-fixed 15 MW turbine for the top 10 African countries.

Country	Country Population in 2023 [Million]	Current National Power Capacity [GW]	Floating Turbines Identified Suitable Offshore Wind Areas [1000 km^2]	Potential Capacity using 15 MW Turbines [GW]	Seabed-Fixed Turbines Identified Suitable Offshore Wind Areas [1000 km^2]	Potential Capacity using 15 MW Turbines [GW]	Country Electricity Access [%]
South Africa	60.61	64.50	240.2	1617.3	2.2	14.5	84.4
Namibia	2.86	0.50	187.0	1259.1	0.0	0	56.3
Libya	6.90	0.16	86.9	585.1	0.0	0	69.7
Somalia	17.60	0.11	65.3	439.7	1.1	7.3	49.7
Morocco	38.32	14.45	56.7	381.8	0.0	0	100.0
West Sahara	0.64	0.06	51.8	348.8	2.3	15.4	48.2
Tunisia	12.24	6.58	50.4	339.3	0.0	0	100.0
Mauritius	1.30	0.88	49.4	332.6	0.0	0	99.7
Mozambique	31.30	2.75	40.6	273.4	0.0	0	30.6
Egypt	102.30	58.8	40.2	270.7	5.0	33.5	100.0
Total		**148.7**	**868.5**	**5847.4**	**10.6**	**70.7**	

allow them to be used in areas of high wind resources available in deep water, resulting in high energy yields as compared to those of seabed-fixed offshore wind turbines.

For the floating turbine case, the modelling used an 800 x 800 m square cell size, restricted to the bathymetry map's source file, which spans a water depth range of −60 to −1000 m. Four factors (wind speed, water depth, distance to shore and distance to grid – Fig. 4) and three restrictions (two for the depth restricted in the range 60 and 1000 m and wind speed to be < 7 m/s) as per Equation (3) were used to analyse the alternatives of cells on the African continent.

The four criteria and two constraints were used to optimise the spatial selection process to create a suitability map for floating turbines for offshore wind energy around Africa. The suitability is calculated as [0.31 x water depth score + 0.06 x grid score + 0.14 x distance to shorelines score + 0.49 x wind speed score], where the numerical scores (values) are those for Factor Weight values W_i as shown in the last column in Table 3. To establish the restricted cells (value = zero) and unrestricted cells (value = one) a Boolean mask was created using the Raster Calculator tool in ArcGIS by removing restricted cells that have: (a) wind speed less than 7 m/s, (b) are located inland, and (c) with water depth less than 60 m, or greater than 1000 m.

All used criteria were combined using the Weighted Linear Combination (WLC), as per Equation (2) and Fig. 1. The four factor suitability maps with suitability scores in the range 0 to 1, as shown in Fig. 4, were multiplied by their Factor Weights W_i using the suitability as given by Equation (2) and then summed using the Raster Calculator tool in ArcGIS. As mentioned above, the Boolean Mask layer removed restricted cells from the WLC layer. The suitability map was divided into areas ranked according to the scores, their levels of energy yields, and their economic prowess as per the RCR evaluation. The final scores and associated areas are ranked as follows:

(i) 0.0 < Cell Score < 0.39 – **not suitable**, representing 40 % or 972 thousand km^2 of the continental regions (note, the zero-score assigned by the factors Boolean Mask is not accounted for in this area).
(ii) 0.4 < Cell Score < 0.59 – **moderately suitable**, representing 19 % or 452 thousand km^2 of the region.
(iii) Cell Score > 0.6 – **highly suitable**, representing around 41 % or 990 thousand km^2 of the studied regions.

Fig. 5 shows the floating offshore wind resources map for Africa, where Fig. 5 (a) shows the overall suitability map for offshore wind energy potential in Africa. The major available wind capacities are concentrated in the higher suitability tier, with values exceeding 0.6, while the moderate suitability ranges from 0.4 to 0.6, representing slightly less than half of the higher range tier, indicating a significant potential for offshore wind using floating offshore wind turbines. Fig. 5 (b) – (f) show a high-resolution suitability map of the top five countries. The results show that the model efficiently handled the geographic siting problem for offshore wind farms by coping with the specified conflicting elements and restrictions.

Offshore wind energy potential using seabed-fixed turbines

Seabed-fixed offshore wind turbines are structures anchored to the seabed, and due to technology limitations and cost, their deployment is water-depth dependent to around 60 m in depth. At lower depths, the turbines' foundations (mainly monopiles) become extravagant in terms of size and economics. These limitations restrict the use of such turbines to locations where the wind resources are acceptable; however, much higher energy yields can be gained in deeper waters, where the best wind resources are normally encountered.

For this case of seabed-fixed offshore wind turbines to be situated on African shores, the four-factor suitability maps were produced by the research and are given in Appendix D in Fig. D1. These were integrated using the ArcGIS Raster Calculator Tool, applying Equation (2) (Weighted Linear Combination (WLC) method). The suitability score equals [0.28 x water depth suitability + 0.08 x grid suitability proximity + 0.12 x shorelines proximity suitability + 0.51 x wind speed suitability], where the numerical scores (values) are those for Factor Weight values derived from Table B1 and B2 in Appendix B.

The overall suitability map for Africa for the seabed-fixed offshore wind turbines' case is shown in Appendix D in Fig. D2, with suitability scores ranging from 0 (least suitability) to 1 (highest suitability).

Estimated power potential for both floating and seabed-fixed offshore wind turbines

For floating offshore wind turbines, the results provided are for those high suitability maps covering areas (score > 0.6). For the seabed-fixed wind turbines, the major available capacities are concentrated in the moderate suitability score range of 0.4 to 0.6, indicating that other areas are unlikely to be economical using seabed-fixed turbines.

Table 4 provides the estimated power capacities using floating and seabed-fixed offshore wind turbines, depicting the potential for the 10 countries with the highest capacities based on a wind turbine having a nameplate capacity of 15 MW. Estimates for all the 38 countries studied are given in Appendix E, Table E1. In Table 4, the country capacity was estimated by dividing the Suitable Area (km^2) (Column 4 in Table 4 for floating turbines and Column 6 for seabed-fixed turbines) by the inter-turbine array spacing S estimated from Equation (4). Table 4 and Table E1 (in Appendix E) also include some characteristics of the African countries, such as current population, current installed power capacities, and current energy access.

Discussion

The results in Table 4 (top ten countries) and the full results in Table E1 (Appendix E) only considered the high suitability areas (score > 0.6), representing around 990,000 km^2 for the floating offshore wind case (Fig. 5) and 126,000 km^2 for the seabed-fixed (Appendix D, Fig. D2) of the studied regions. As depicted in Table 4 and Fig. 5, the highest potential for floating offshore wind in the top 10 African countries is around 5848 GW, whilst for the whole 38 coastal countries in Africa, this was found to be around 6665 GW (Table E1, Appendix E). South Africa has the lion's share, followed by Namibia. In terms of the seabed-fixed offshore turbines, Egypt has the lion's share, followed by Western Sahara and Morocco combined. All the high potential exists in deeper water, which would necessitate the use of floating offshore wind turbines rather than the seabed-fixed turbines. This potential far exceeds the current installed power capacities of 148.7 GW of the African countries (Table 4).

It is also clear from the results (Appendix D, Fig. D2, Table 4 and Table E1) that close to shore and at depths < 60 m, the available potential based of seabed-fixed turbines is not substantial and was estimated to be around 84.5 GW, mainly occurring in seven countries (Table E1) where around 40 % of this is situated in Egypt especially around the Gulf of Suez (Table 4) followed by Western Sahara and Morocco combined.

It should be noted that for floating offshore wind, considering the moderately suitable areas also ($0.4 <$ Cell Score < 0.59, Fig. 5) would result in an additional 452,000 km^2 of the region and would substantially increase the available wind energy potential. It is also anticipated that the development of such potentials will take time, and one would start with areas of high potential first. Furthermore, the development of various available zones will also require further in-depth detailed studies to address local issues and to take into account future turbine developments that are likely to have higher capacities than the 15 MW used here.

In summary, this research has considered and provided results encompassing the following:

- Covered the use of a Geographical Information System (GIS) and a multi-criteria decision analysis (MCDA) technique coupled with the use of the Representative Cost Ratio (RCR) method to provide stakeholders with more accurate information that can be used to exploit the identified wind energy resources around African shores.
- The research covers 38 coastal countries with a maritime area of nearly 14 million km^2 and over 30,000 km of coastline. The overall results showed an 85 GW of shallow water depth potential that can be exploited using seabed-fixed turbines. In contrast, floating offshore wind has the potential to deliver over 6665 GW, which is roughly 28 times the current installed power capacity of Africa
- The utilisation of the validated RCR ties the siting criteria weights to project economics and reduces subjectivity in the evaluation process.
- The presented outcomes consist of appropriate results which provided graded suitability scales, identifying the most suitable locations where early wind energy exploitation opportunities can be established.

The research linked potential offshore wind energy sites to grid infrastructure and deployment logistics, providing policy-relevant insights to inform large-scale energy planning.

Conclusions

The research presented thorough analyses of the offshore wind energy potential in Africa, covering the utilisation of both seabed-fixed and floating offshore wind turbine technologies. The GIS/MCDA analyses used four criteria of sea depth, grid connection, wind speed, and coastline distance, with some restrictions on depth and wind speed to develop the suitability map. The added advantage in these analyses is the links to current infrastructure, such as the availability of connections to the grid and the distance to shore, to address deployment locations. The utilisation of the RCR was shown to have the appropriate applicability in such studies, augmenting the authors' previous work [15], which covered offshore wind energy potential in locations in the UK [13,69,70] with further verification of the RCR approach when applied to the Chinese offshore wind energy projects (Section *Validation of the Representative Cost Ratio*).

The results show that:

(i) Close to shore at shallow depths less than 60 m covering the exploitable resource in Africa resides within the moderate suitability area of $\sim$ 126,000 km^2, with an estimated offshore wind energy potential of around 84.5 GW using a 15 MW turbine. This shallow water resource is not substantial and can be exploited using depth-dependent seabed-fixed turbines.

(ii) At deeper water, the wind energy resource was found to be very substantial. The high suitability areas alone (score > 0.6), represent around 990,000 km^2 with an estimated capacity of around 6665 GW using a 15 MW turbine. At such water depths, exploitation would necessitate the use of floating offshore wind turbines. This potential alone is approximately 28 times that of Africa's total installed power capacity in 2022.

This enormous potential of green renewable energy could help overcome energy access in the continent of Africa, where 50 % of its population has no access to electricity, whilst opening other opportunities for power export to other world regions and the development of clean hydrogen production. For example, it would contribute to the EU-Africa €150 billion investment, having a 2030 target of deploying at least an additional 300 GW of renewable power capacity and 40 Gigawatts of electrolyser capacity and help develop the renewable hydrogen sector by unlocking business opportunities in both the supply and demand side for energy-intensive industries [34]. With a well-coordinated policy and capacity building, this energy potential could also reduce fossil fuel imports, helping Africa's GDP and foreign exchange balances.

Lastly, the primary task of this work was to answer the following questions: *Where are the offshore wind energy resources, their most suitable locations and their power potential in Africa? How can this energy potential be linked to the current infrastructure* (e.g. *grid connections, ports to support deployment to distant locations)?* In the view of the authors, the work has succeeded in answering these questions, coupled with addressing the knowledge gap in estimating African offshore wind energy potential for both floating and seabed-fixed wind turbine technologies. To the best of the authors' knowledge, these results reflect a comprehensive evaluation of the African offshore wind energy potential, and the approach undertaken has been implemented for the first time at such a broad continental scale.

CRediT authorship contribution statement

AbuBakr S. Bahaj: Conceived of the study, Obtained funding, Participated in the design of the study, Coordinated the study, analyses and outputs, Drafted the manuscript, Carried out sequence alignments, Responded to the reviewers comments and Carried out the final editing and proofs of the manuscript. **Mostafa Mahdy:** Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization.

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.

Acknowledgements

This work is part of the activities of the Energy and Climate Change Division and the Sustainable Energy Research Group in the Faculty of Engineering and Physical Sciences at the University of Southampton (www.energy.soton.ac.uk), UK. It is also supported by EPSRC grants, including EP/K012347/1, the International Centre for Infrastructure Futures (ICIF), Saudi Ministry of Education scheme -Implementation of International Collaboration Projects in Research and Development –Grand Challenge -No. (714), and EP/R030391/1 Fortis Unum: Clustering Mini-Grid Networks to Widen Energy Access and Enhance Utility Network Resilience.

Appendix A

Historical Turbine Capacities and their CAPEX.

As mentioned in the main paper, the relationship between the RCR and the economics represented by the LCOE of offshore wind energy is coherent. In Appendix A, Table A1 shows the historical results for these relationships by considering the values of turbines capacities, their CAPEX, the factors contributing to the CAPEX and the cost ratio for these. Table A1 gives the average values of these contributing factors for the period 2017–24 which were used in the analyses of the seabed fixed turbines, whilst the values in the last row of the table are used for the floating turbines case.

Table A1
Historical turbine capacities and their CAPEX, factors contributing to CAPEX, and the relative value of factors.

Year, [source]	Turbine Capacity [MW]	Total Capex [US $/kW]	(Cost Ratio) affecting offshore wind projects. Factors contributing to the Total CAPEX of the project [US$/kW]				Cost ratio = (Factor contribution to the Total CAPEX /Total Cost), [%]			
			Wind Speed	Water Depth	Shore Distance	Grid Distance	Wind Speed	Water Depth	Shore Distance	Grid Distance
2017 [64]	5.64	4536	2434	1166	637	299	53.7	25.7	14	6.6
2018 [65]	5.5	5355	2318	2241	624	172	43.3	41.8	11.7	3.2
2019 [66]	6.06	4077	2120	1460	238	258	52	35.8	5.8	6.3
2020 [67]	8	3756	2313	997	171	275	61.6	26.5	4.6	7.3
2021 [68]	8	3871	2349	1052	180	290	60.7	27.2	4.7	7.5
2022 [69]	12	4640	2655	1107	581	297	57.2	23.8	12.5	6.4
2023 [70]	12	5411	2847	1452	722	390	52.6	26.8	13.3	7.2
2024 [54]	12	4536	2434	1166	637	299	51.4	27.9	10.3	9.4
						Average	**54.1**	**29.4**	**9.6**	**6.7**
2024 Floating [54]		**7348**				**Average**	**45**	**35**	**15**	**5**

Appendix B

Analyses of Factor Weights of Seabed-fixed Offshore Wind Turbines Covering China and Africa.

Appendix B discusses the considerations and analyses of factor weights for seabed-fixed offshore wind turbines, specifically in China and Africa, as outlined in the article's main body. The following section provides the data (Tables B1 and B2) used to: (i) validate the development of factor weights for the African seabed-fixed turbine case similarly to the offshore floating wind turbines discussed in the main text (Section 5), and (ii) validate the Representative cost ratio (RCR) for the Chinese offshore seabed-fixed turbines (Fig. 3e main text), leading to the factor suitability maps shown in Fig. D1 in Appendix D.

Factor weights.

Table B1 shows the Importance Index (II) for each possible factor pair, as defined by the scale given in [42] and the RCR range, which is shown in Fig. 2. The selected values for the Importance Index are based on their contribution to the final Levelised Cost of Energy (LCOE), as outlined in the values presented in Table A1 in the main text of this article. The Levelised Cost of Energy (LCOE) is provided in columns A and B of Table B1. For the seabed-fixed wind turbine, the wind speed contribution to the LCOE is 51.4 %, while the contributions for water depth, distance to shoreline, and distance to the grid are 27.9 %, 10.3 %, and 9.4 %, respectively (Table B1). The RCR values associated with the contribution of these pairs in relation to each other are established as described below.

The wind speed (WS) must be paired with several factors, including water depth (WD), distance to shore (DS), and distance to the grid (DG). Therefore, the Importance Index score will rely on these combined contributions and the range of RCR shown in Fig. 2, also shown in Table B1. For instance, the ratio WS:WD = 51.4 %:27.9 % = 1.84, which falls within the RCR range of 1 to 2 (Fig. 2), corresponds to a value of 2 for the Importance Index *II* (Table B1) and so on.

Table B1
Pairwise comparison of Important Index selection using the RCR approach for the seabed-fixed offshore wind turbine case.

Factors	(Column A) Contribution to LCOE (Table A1) (%)	Factors	(Column B) Contribution to LCOE (Table A1) (%)	RCR (A/B)	Importance Intensity (II)								
					1	2	3	4	5	6	7	8	9
					RCR Range (Fig. 2, [15])								
					(0 ~ 1)	(1 ~ 2)	(2 ~ 3)	(3 ~ 4)	(4 ~ 7)	(7 ~ 10)	(10 ~ 13)	(13 ~ 18)	Over 18
Wind Speed (WS)	51.4	Water Depth (WD)	27.9	1.8		x							
		Distance to Shoreline (DS)	10.3	5.0					x				
		Distance to Grid (DG)	9.4	5.5					x				
Water Depth (WD)	27.9	Distance to Shoreline (DS)	10.3	2.7			x						
		Distance to Grid (DG)	9.4	2.9			x						
Distance to Shore (DS)	10.3		9.4	1.1		x							

The values in Table B1 were then used to establish the pairwise comparison matrix (Table B2), as discussed in the methodology section, using the three conditions (i)–(iii).

The normalised matrix (Table B2) is determined by dividing each matrix element by its column sum. For instance, in Table B2, the wind speed value in the normalised matrix is calculated by $1 \div 1.9 = 0.53$, giving the value for N_w, and so on, for the other values. The Factor Weight values W_i in Table B2 represent the average values determined for each factor in the corresponding row.

Table B2
Shows the values of two matrices for the Pairwise comparison P_w, and the Normalised N_w arrays and the final factor weight value W_i for the seabed-fixed offshore wind farms case, Where WS = Wind Speed, WD = Water Depth, DS = Distance to Shore, DG - Distance to Grid and (Σ) = Sum of values.

	Wind Speed		Water Depth		Distance to Shoreline		Distance to Grid		
	P_w	N_w	P_w	N_w	P_w	N_w	P_w	N_w	W_i
WS	1.00	0.53	2.00	0.55	5.00	0.53	5.00	0.45	0.51
WD	1/2	0.26	1.00	0.27	3.00	0.32	3.00	0.27	0.28
DS	1/5	0.11	1/3	0.09	1.00	0.11	2.00	0.18	0.12
DG	1/5	0.11	1/3	0.09	1/2	0.05	1.00	0.09	0.08
(Σ)	1.90	1.00	3.70	1.00	9.5	1.00	11.00	1.00	1.00

Appendix C

Data Sources

Table C1
Data sources and available links.

Data set	Source Reference or Link
CAPEX data of offshore projects and studies	2017 [73], 2018 [74], 2019 [75], 2020 [76], 2021 [63], 2022 [77], 2023 [78], 2024 [59]
China's four criteria data	World Bank data repository [72]
Bathymetry	British Oceanographic Data Centre [79]
Wind data	Department of Wind Energy at the Technical University of Denmark (DTU) [80], Wind Atlas for Egypt" [11], Global Atlas for Renewable Energy [81]
Africa's unified power networks	[82–86]

Appendix D

Four Factor Suitability Maps for the Case of Seabed-fixed Offshore Wind Turbines in Africa.

For the case of seabed-fixed offshore wind turbines in Africa, the four-factor suitability maps were produced in the same fashion as the case for floating offshore wind turbines covered in Section 4.1 in the main text. Fig. D1 shows the four-factor suitability maps representing the fuzzy layers in the Fuzzy Membership Tool in ArcGIS, used to convert the original factor layers into standardised layers with a score range of 0 to 1. The four factors considered were: (a) Wind speed factor, (b) Water depth factor, (c) Distance to electricity grid line, and (d) Distance to shorelines (X_1 to X_4, Equation (2).

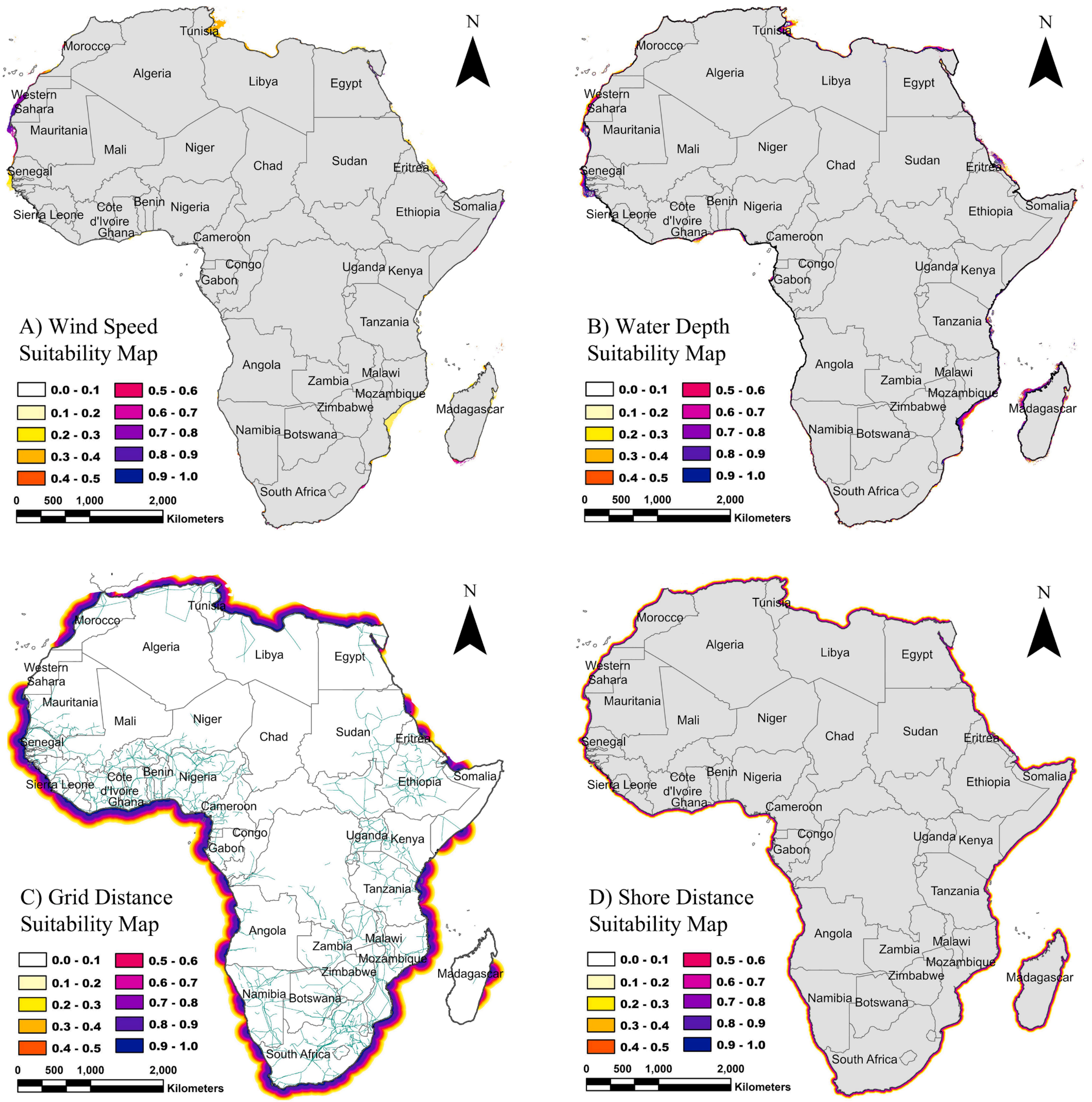

Fig. D1. Seabed-fixed turbine factor suitability maps for the four considered factors: (A) Wind speed factor, (B) Water depth factor, (C) Distance to electricity grid lines, and (D) Distance to shorelines. In Equation , these factors are represented by the values W_1X_1 to W_4X_4.

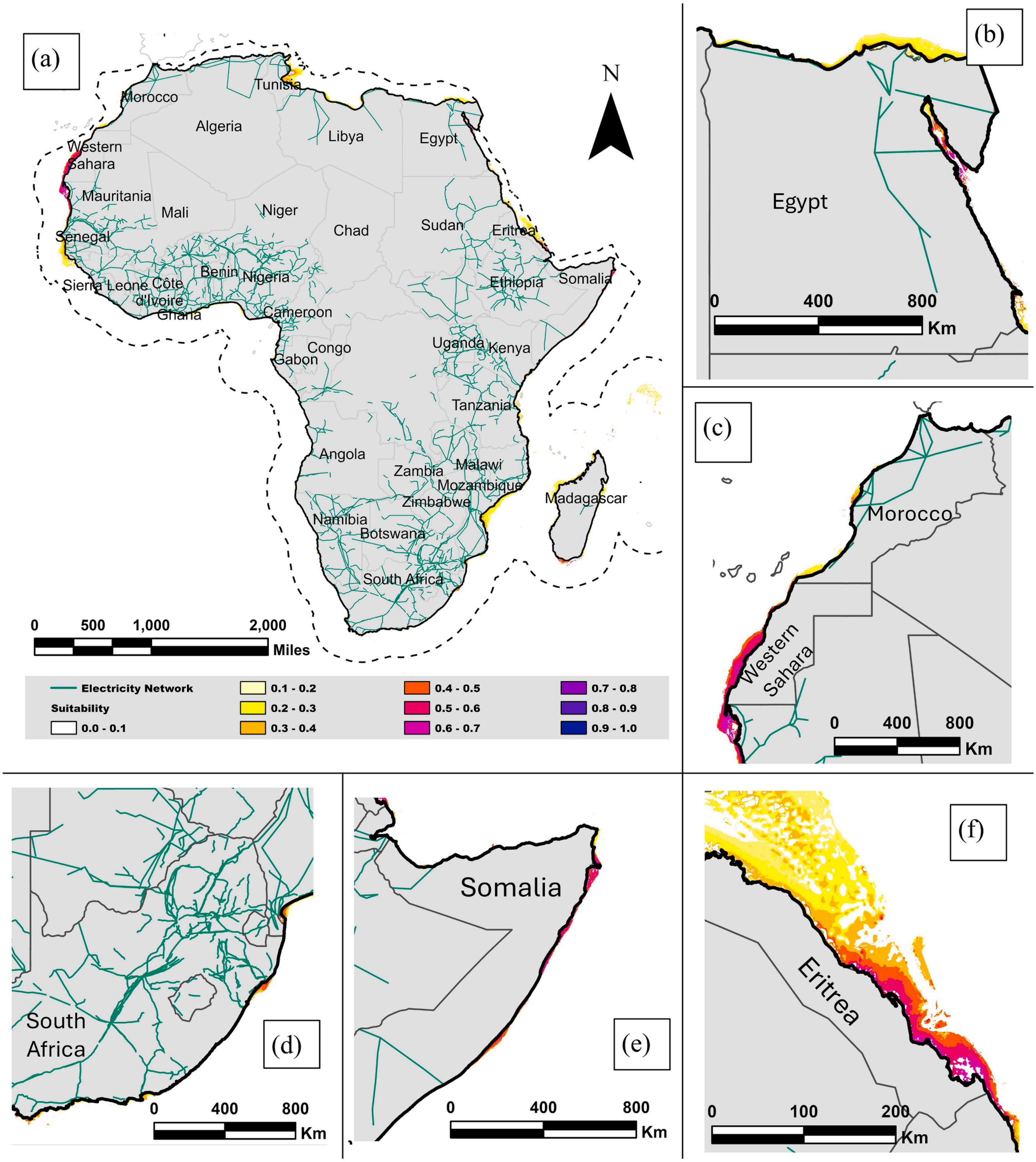

Fig. D2. Seabed-fixed offshore wind resources map for Africa (a) and (b) to (f) represent the top five countries with high potential for seabed-fixed offshore wind turbines. The dashed line represents exclusive economic zones (EEZs).

Appendix E

Overall Estimated Results of Both Floating and Seabed-Fixed Wind Turbine Energy Potential for All Coastal African Countries.

Table E1 presents the full data, extending the information in Table 4 to cover 38 countries addressed in the research. The data in the table provides the estimated wind energy potential for all African coastal countries, based on a wind turbine nameplate capacity of 15 MW, for both floating and seabed-fixed turbine configurations. The considerations are the same as those in Table 4, where the country capacity was estimated by dividing the suitable area in km^2 (Column 4 in Table E1 for floating turbines and Column 6 for seabed-fixed turbines) by the inter-turbine array spacing (S) estimated from Equation (4). Table E1 also provides some characteristics of the African countries, including current population, current installed power capacities, and current energy access. Table E2 shows the accumulated results divided into the six main African regions.

Table E1
Offshore wind potential utilising both floating and seabed-fixed 15 MW turbine arrays of the African countries.

Country	Country Population in 2023 [Million]	Current National Power Capacity [GW]	Floating Turbines Identified Suitable Offshore Wind Areas [1000 km^2]	Potential Capacity using 15 MW Turbines [GW]	Seabed-Fixed Turbines Identified Suitable Offshore Wind Areas [1000 km^2]	Potential Capacity using 15 MW Turbines [GW]	Country Electricity Access [%]
South Africa	60.61	64.5	240.2	1617.3	2.2	14.5	84.4
Namibia	2.86	0.5	187	1259.1	0.0	0	56.3
Libya	6.9	0.16	86.9	585.1	0.0	0	69.7
Somalia	17.6	0.11	65.3	439.7	1.1	7.3	49.7
Morocco	38.32	14.45	56.7	381.8	0.0	0	100
West Sahara	0.64	0	51.8	348.8	2.3	15.4	48.2
Tunisia	12.24	6.58	50.4	339.3	0.0	0	100
Mauritius	1.3	0.88	49.4	332.6	0.0	0	99.7
Mozambique	31.3	2.75	40.6	273.4	0.0	0	30.6
Egypt	102.3	58.8	40.2	270.7	5.0	33.5	100
Madagascar	27.7	0.69	34.6	233	0.2	1.1	33.7
Mauritania	4.6	0.63	20.7	139.4	0.0	0	47.3
Sudan	43.8	3.95	11.5	77.4	0.0	0	55.4
Eritrea	3.5	0.25	10.3	69.3	1.6	10.9	52.2
Kenya	53.8	3.18	10.1	68	0.0	0	71.4
Algeria	43.9	21.65	9.6	64.6	0.0	0	99.8
Senegal	16.7	1.64	9	60.6	0.0	0	70.4
Angola	32.9	8.17	5.3	35.7	0.0	0	46.9
Cabo Verde	0.6	0.18	3.6	24.2	0.0	0	94.2
Seychelles	0.1	0.15	3.2	21.5	0.0	0	100
Djibouti	1	0.13	2.2	14.8	0.3	1.8	61.8
Gambia	2.4	0.14	1.4	9.4	0.0	0	62.3
Benin	12.1	0.01	0	0	0.0	0	41.4
Cameroon	26.5	1.76	0	0	0.0	0	64.7
Congo	5.5	0.83	0	0	0.0	0	49.5
Côte d'Ivoire	26.4	2.28	0	0	0.0	0	69.7
DR Congo	89.6	3.2	0	0	0.0	0	19.1
Equatorial Guinea	1.4	0.55	0	0	0.0	0	66.7
Gabon	2.2	0.78	0	0	0.0	0	91.6
Ghana	31.1	5.45	0	0	0.0	0	85.9
Guinea	13.1	0.96	0	0	0.0	0	44.7
Guinea-Bissau	2	0.03	0	0	0.0	0	33.3
Liberia	5.1	10.52	0	0	0.0	0	27.5
Nigeria	206.1	16.4	0	0	0.0	0	55.4
Sierra Leone	8	0.1	0	0	0.0	0	26.2
Tanzania	59.7	1.82	0	0	0.0	0	39.9
Togo	8.3	0.28	0	0	0.0	0	100
Zimbabwe	14.9	1.11	0	0	0.0	0	52.7
Total		**235.57**	**990**	**6665.7**	**12.7**	**84.5**	

Table E2
Offshore wind potential utilising both floating and seabed-fixed 15 MW turbine arrays of the African countries' regions.

Region	Country Population in 2023 [Million]	Current National Power Capacity [GW]	Floating Turbines Identified Suitable Offshore Wind Areas [1000 km^2]	Potential Capacity using 15 MW Turbines [GW]	Seabed-Fixed Turbines Identified Suitable Offshore Wind Areas [1000 km^2]	Potential Capacity using 15 MW Turbines [GW]	Country Electricity Access [%]
North Africa	92.3	106.22	327.8	2207.1	7.3	48.9	620.4
Western Africa	318.8	37.03	14	94.2	0	0	666.3
Eastern Africa	145.7	8.93	163.1	1098.2	3.2	21.1	339.3
Southern Africa	14.9	66.11	427.2	2876.4	2.2	14.5	193.4
Indian Ocean Islands	0.1	0.15	3.2	21.5	0	0	100
Central Africa	171.2	16.25	5.3	35.7	0	0	383.2
Total		**235.57**	**990**	**6665.7**	**12.7**	**84.5**	

Data availability

The sources of data used are referenced in the article

References

[1] Council GWE, Global offshore wind report. GWEC: Brussels. Belgium 2023;2023(19):10–2.
[2] Lima DC, et al. *The present and future offshore wind resource in the Southwestern african region*. Clim Dyn 2021;56(5):1371–88.
[3] Laaouidi H, et al. *Assessment of offshore wind potential in Morocco*. International Journal of Energy Technology and Policy 2021;17(5):423–41.
[4] Ren G, et al. *Quantitative insights into the differences of variability and intermittency between wind and solar resources on spatial and temporal scales in China*. J Renewable Sustainable Energy 2021;13(4).
[5] Mahdy M, Bahaj AS. *Multi criteria decision analysis for offshore wind energy potential in Egypt*. Renew Energy 2018;118:278–89.
[6] Mahdy, M.Y.M., *Assessment of offshore wind energy potential in the Middle East: Case studies Egypt, Arabian Peninsula*. 2020, University of Southampton.
[7] Umoh K, Lemon M. *Drivers for and barriers to the take up of floating offshore wind technology: a comparison of Scotland and South Africa*. Energies 2020;13(21):5618.
[8] Allianz Commercial, *A turning point for offshore wind: Global opportunities and risk trends*. 2023.
[9] Essa KS, Embaby M, Marrouf A. *Feasibility study of electrical generation by wind energy on the Red-Sea Coast in Egypt*. Wind Eng 2007;31(4):293–301.
[10] Shata AA, Hanitsch R. *The potential of electricity generation on the east coast of Red Sea in Egypt*. Renew Energy 2006;31(10):1597–615.
[11] Mortensen NG, Said US, Badger J, Atlas of Egypt W. RISO National Laboratory. Egyptian Meteorological Authority: New and Renewable Energy Authority; 2006.
[12] Wind Europe. *New UK Government plans big push on wind*. 2024 14/01/2025]; Available from: https://windeurope.org/newsroom/news/new-uk-government-plans-big-push-on-wind.
[13] The Crowne State. *Floating Offshore Wind Leasing Round 5*. 2024 14/01/2024]; Available from: https://www.thecrownestate.co.uk/our-business/marine/round-5.
[14] Taoufik M, Fekri A. *GIS-based multi-criteria analysis of offshore wind farm development in Morocco*. Energy Convers Manage: X 2021;11:100103.
[15] Bahaj AS, et al. *New approach to determine the Importance Index for developing offshore wind energy potential sites: Supported by UK and Arabian Peninsula case studies*. Renew Energy 2020;152:441–57.
[16] Sun Y, et al. *Data-driven large-scale spatial planning framework for determining size and location of offshore wind energy development: a case study of China*. Appl Energy 2024;367:123388.
[17] Masoumi M. *Machine learning solutions for offshore wind farms: a review of applications and impacts*. Journal of Marine Science and Engineering 2023;11(10):1855.
[18] Gkeka-Serpetsidaki P, et al. *A review of the sustainable siting of offshore wind farms*. Sustainability 2024;16(14):6036.
[19] Spyridonidou S, Vagiona DG. *Systematic review of site-selection processes in onshore and offshore wind energy research*. Energies 2020;13(22):5906.
[20] Abdelhady S, Borello D, Shaban A. *Assessment of levelized cost of electricity of offshore wind energy in Egypt*. Wind Eng 2017;41(3):160–73.
[21] Amin I, et al. *Numerical hydrodynamics-based design of an offshore platform to support a desalination plant and a wind turbine in Egypt*. Ocean Eng 2021;229:108598.
[22] Benazzouz A, et al. *Offshore wind energy resource in the Kingdom of Morocco: Assessment of the seasonal potential variability based on satellite data*. Journal of Marine Science and Engineering 2020;9(1):31.
[23] Alaoui C. *Review and assessment of offshore renewable energy resources in morocco'coastline*. Cogent Eng 2019;6(1):1654659.
[24] Rae G, Erfort G. *Offshore wind energy-South Africa's untapped resource*. Journal of Energy in Southern Africa 2020;31(4):26–42.
[25] Inambao L, Cunden FK. *Offshore wind resource assessment off the south african coastline*. International Journal of Mechanical. Eng Technol 2019;10(6).
[26] Elsner P. *Continental-scale assessment of the african offshore wind energy potential: Spatial analysis of an under-appreciated renewable energy resource*. Renew Sustain Energy Rev 2019;104:394–407.
[27] Chen J, et al. *Green development strategy of offshore wind farm in China guided by life cycle assessment*. Resour Conserv Recycl 2023;188:106652.
[28] Jacobsen A, Godvik M. *Influence of wakes and atmospheric stability on the floater responses of the Hywind Scotland wind turbines*. Wind Energy 2021;24(2):149–61.
[29] Amir M, Khan SZ. *Assessment of renewable energy: Status, challenges, COVID-19 impacts, opportunities, and sustainable energy solutions in Africa*. Energy Built Environ 2021.
[30] Nef, b.,. Africa Power Transition Factbook 2024. 2023..
[31] Irena, a.,. *Renewable Energy market analysis: Africa and its regions*. International Renewable Energy Agency and African Development Bank. Abu Dhabi and Abidjan; 2022.
[32] Global Gateway AU. *A prosperous and sustainable Africa and Europe*. 2024.
[33] African Union, *Green Recovery Action Plan*. 2021.
[34] European Commission. *Scaling up Renewables in Africa*. 2024 21/01/2025]; Available from: https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/stronger-europe-world/global-gateway/energy-africa_en.
[35] European Commission. *EU-Africa: Global Gateway Investment Package*. 2024 21/01/2025]; Available from: https://international-partnerships.ec.europa.eu/policies/global-gateway/initiatives-sub-saharan-africa/eu-africa-global-gateway-investment-package_en.
[36] Burton, T., et al., *Wind energy handbook*. 2011: John Wiley & Sons.
[37] Estoque C. *GIS-based multi-criteria decision analysis,(in natural resource management)*. Ronald, D1–Division of spatial information science. University of tsukuba; 2011.
[38] Eastman JR, Jiang H, Toledano J. *Multi-criteria and multi-objective decision making for land allocation using GIS*. In: *Multicriteria analysis for land-use management*. Springer; 1998. p. 227–51.
[39] Eastman J. *Multi-criteria evaluation and GIS*. Geographical information systems 1999;1:493–502.
[40] Saaty TL. *A scaling method for priorities in hierarchical structures*. J Math Psychol 1977;15(3):234–81.
[41] esri. *The ArcGIS Help Library*. 2012 [cited 2016/07 /14]; Available from: http://help.arcgis.com/en/arcgisdesktop/10.0/help/.
[42] Saaty TL. *Decision making with the analytic hierarchy process*. International journal of services sciences 2008;1(1):83–98.
[43] Ramík J. *Pairwise comparison matrices in decision-making*. Pairwise comparisons method: Theory and applications in decision making; 2020. p. 17–65.
[44] Saaty, T.L., *Decision making with the analytic hierarchy process*. 2002.
[45] Akbari N, et al. *A multi-criteria port suitability assessment for developments in the offshore wind industry*. Renew Energy 2017;102:118–33.
[46] Lozano-Minguez E, Kolios A, Brennan FP. *Multi-criteria assessment of offshore wind turbine support structures*. Renew Energy 2011;36(11):2831–7.
[47] Martin H, et al. *Application and extension of the TOPSIS method for the assessment of floating offshore wind turbine support structures*. Ships Offshore Struct 2013;8(5):477–87.
[48] Lirn T-C, et al. *An application of AHP on transhipment port selection: a global perspective*. Maritime Economics & Logistics 2004;6:70–91.
[49] Dalalah D, Hayajneh M, Batieha F. *A fuzzy multi-criteria decision making model for supplier selection*. Expert Syst Appl 2011;38(7):8384–91.
[50] Aruldoss M, Lakshmi TM, Venkatesan VP. *A survey on multi criteria decision making methods and its applications*. American Journal of Information Systems 2013;1(1):31–43.
[51] Stević Ž, et al. *The selection of the logistics center location using AHP method*. in *2nd logistics international conference*. 2015.
[52] Castro AO, et al. *Feasibility analysis of offshore wind power projects in the Caribbean region of Colombia: a case study using FAHP–GIS*. Sustainability 2023;15(24):16620.
[53] Racetin I, et al. *Fuzzy Multi-Criteria Decision for Geoinformation System-based Offshore Wind Farm Positioning in Croatia*. Energies 2023;16(13):4886.
[54] Albraheem L, Almutlaq F. *A Geographic Information System-based Model and Analytic Hierarchy Process for Wind Farm Site selection in the Red Sea*. ISPRS Int J Geo Inf 2024;13(11):416.
[55] Barzehkar M, et al. *Offshore wind power plant site selection in the Baltic Sea*. Reg Stud Mar Sci 2024;73:103469.
[56] Przewoźniak M, et al. *Conducting a Geographical Information System-based Multi-Criteria Analysis to Assess the potential and Location for Offshore Wind Farms in Poland*. Energies 2024;17(2):283.
[57] Song Z, et al. *Mapping the Unheard: Analyzing Tradeoffs between Fisheries and Offshore Wind Farms using Multicriteria Decision Analysis*. Ann Am Assoc Geogr 2024;114(3):536–54.
[58] Johnston B, et al. *Offshore wind potential in Northern Ireland using GIS multi-criteria assessment*. Appl Energy 2025;378:124764.
[59] Stehly T, Duffy P, Mulas Hernando D. Cost of Wind Energy Review: 2024 Edition National Renewable Energy Laboratory (NREL). CO (United States): Golden; 2024.
[60] Vasileiou M, Loukogeorgaki E, Vagiona DG. *GIS-based multi-criteria decision analysis for site selection of hybrid offshore wind and wave energy systems in Greece*. Renew Sustain Energy Rev 2017;73:745–57.
[61] Gavériaux L, et al. *GIS-based multi-criteria analysis for offshore wind turbine deployment in Hong Kong*. Ann GIS 2019;25(3):207–18.
[62] Elgabiri M, et al. *Offshore wind energy potential for Bahrain via multi-criteria evaluation*. Wind Eng 2021;45(4):838–56.
[63] Stehly, T. and P. Duffy, *2020 cost of wind energy review*. 2021, National Renewable Energy Laboratory (NREL), Golden, CO (United States).
[64] Díaz H, Soares CG. *A novel multi-criteria decision-making model to evaluate floating wind farm locations*. Renew Energy 2022;185:431–54.
[65] Li Z, Tian G, El-Shafay A. *Statistical-analytical study on world development trend in offshore wind energy production capacity focusing on Great Britain with the aim of MCDA based offshore wind farm siting*. J Clean Prod 2022;363:132326.
[66] Latinopoulos D, Kechagia K, A,. *GIS-based multi-criteria evaluation for wind farm site selection. a regional scale application in Greece*. Renew Energy 2015;78:550–60.
[67] Baban SM, Parry T. *Developing and applying a GIS-assisted approach to locating wind farms in the UK*. Renew Energy 2001;24(1):59–71.
[68] Watson JJ, Hudson MD. *Regional Scale wind farm and solar farm suitability assessment using GIS-assisted multi-criteria evaluation*. Landsc Urban Plan 2015;138:20–31.
[69] Mahdy M, Bahaj AS, Alghamdi AS. *Offshore Wind Energy potential around the East Coast of the Red Sea, KSA*, in *Solar World Congress 2017*. UAE: Abu Dhabi; 2017.
[70] Estate TC. Offshore wind operational report 2022:2023.
[71] World Bank, *World development indicators*. 2018: World Bank.
[72] World Bank. *World Bank Maps*. 2025 [cited 21/05/2025]; Available from: https://maps.worldbank.org/maps.
[73] Stehly T, Duffy P, Mulas Hernando D. Cost of Wind Energy Review: 2017 Edition. National Renewable Energy Laboratory (NREL). CO (United States): Golden; 2017.
[74] Stehly T, Duffy P, Mulas Hernando D. Cost of Wind Energy Review: 2018 Edition. National Renewable Energy Laboratory (NREL). CO (United States): Golden; 2018.

[75] Stehly T, Duffy P, Mulas Hernando D. Cost of Wind Energy Review: 2019 Edition National Renewable Energy Laboratory (NREL). CO (United States): Golden; 2019.

[76] Stehly T, Duffy P, Mulas Hernando D. Cost of Wind Energy Review: 2020 Edition National Renewable Energy Laboratory (NREL). CO (United States): Golden; 2020.

[77] Stehly T, Duffy P, Mulas Hernando D. Cost of Wind Energy Review: 2022 Edition National Renewable Energy Laboratory (NREL). CO (United States): Golden; 2022.

[78] Stehly T, Duffy P, Mulas Hernando D. Cost of Wind Energy Review: 2023 Edition National Renewable Energy Laboratory (NREL). CO (United States): Golden; 2023.

[79] The British Oceanographic Data Centre. *The GEBCO_2014 Grid* 2014 [cited 25/03/2025]; Available from: www.gebco.net.

[80] DTU Wind Energy. *Wind Resources for Wind Turbine Production (WAsP)*. [cited 30/03/2025]; Available from: https://www.wasp.dk/wasp.

[81] Gruber K, et al. *Assessing the Global Wind Atlas and local measurements for bias correction of wind power generation simulated from MERRA-2 in Brazil*. Energy 2019; 189:116212.

[82] Network 2025 [cited 27/03/2025]; Available from: http://www.moee.gov.eg/english_new/.

[83] Bissiri M, et al. *A geospatial approach towards defining cost-optimal electrification pathways in West Africa*. Energy 2020;200:117471.

[84] Fattouh B, El-Katiri L. *Energy subsidies in the middle East and North Africa*. Energ Strat Rev 2013;2(1):108–15.

[85] Gaugl R, et al. *GridTool: an open-source tool to convert electricity grid data*. SoftwareX 2023;21:101314.

[86] Eberhard A, et al. *Africa Infrastructure Country Diagnostic (AICD)*. Underpowered: the State of the Power Sector in Sub-Saharan Africa". World Bank 2008.

[87] The Crown Estate's Offshore Wind Cost Reduction Pathways Study (2012) [cited 27/03/2025]; Available from: https://assets.publishing.service.gov.uk/media/5a79990fe5274a684690ab74/5584-offshore-wind-cost-reduction-task-force-report.pdf.

[88] Schillings C, et al. *A decision support system for assessing offshore wind energy potential in the North Sea*. Energy Policy 2012;49:541–51.

[89] Kieffer G, Couture T. Renewable energy target setting. Masdar: IRENA; 2015.

[90] Sheridan B, et al. *Calculating the offshore wind power resource: Robust assessment methods applied to the US Atlantic Coast*. Renew Energy 2012;43:224–33.

[91] E.on,. *Offshore Wind Energy Factbook*. E ON Climate & Renewables GmbH 2012.

[92] Ali S, Park H, Lee D. *Investigating the Structural and Power Performance of a 15 MW Class Wind Energy Generation System under Experimental Wind and Marine Loading*. Journal of Marine Science and Engineering 2024;12(9):1485.