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Reviewing accuracy & reproducibility of large-scale wind resource assessments

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ABSTRACT

The accurate quantification and assessment of available renewable energy resources has emerged as a research topic with high relevance to policymakers and industry. Motivated by the need for a contemporary review on the methodologies and practices prevalent in wind resource assessments, we employ a systematic analysis of 195 articles that describe large-scale wind assessments. Our review reveals significant heterogeneity in global and continental-scale potentials and geographical bias of research towards the Northern Hemisphere, despite electrification needs in regions like Africa and Latin America. A fraction of the literature attempts to explicitly include social and political barriers to wind power development, thereby defining 'feasible' potentials. We delve into advancements in this domain, focusing on innovative methodologies that encapsulate the viewpoints of subject experts and stakeholders in the assessment process. Our analysis underscores pressing challenges relating to data sharing and scientific reproducibility, with our findings revealing a mere 10 % of studies that offer openly available data for download. This highlights a pervasive insufficiency in the reproducibility of wind assessments. Additionally, we tackle notable hurdles concerning wind data and meteorological characterization, including an over-reliance on single-source wind data and a deficit in adequately characterizing temporal wind variability. Relatedly, we uncover a highly heterogenous approach to turbine siting and characterizing wake-related losses. These methods are frequently simplistic, potentially leading to an overestimation of wind potentials by assuming an overly optimistic capacity density. In each of these domains, we discuss the state of the art for modern wind resource assessments, propose best practices, and pinpoint crucial areas warranting future research.

1. Introduction

Global greenhouse gas emissions are largely driven by the power sector, which accounted for almost 40 % of the CO_2 emitted globally in 2022 [1]. Decarbonization of energy systems is a key strategy to limit global warming to well below 2 °C by the end of the century, in line with Intergovernmental Panel on Climate Change (IPCC) goals [2]. Variable renewable energy generation systems, with wind energy a prominent contributor, have a crucial role to play in this transition. Between 2015 and 2019, global wind power capacity grew by 70 % [2] and projections indicate a further growth of 2.4 TW over the next five years [3]. By the end of 2022, wind power held the largest global share of non-hydropower renewable capacity, at 906 GW [4]. Nevertheless, to achieve sustainable development goals, wind energy capacity must continue to grow, requiring focused, international collaboration on policies, business strategies and innovation [5].

The acceptance of ambitious energy transition policies is contingent upon trust in the underlying research and data. Wind resource assessments (WRAs) use computer programs to evaluate the potential wind energy that can be extracted from a given region and are instrumental in determining the feasibility of wind power projects [6,7]. WRAs have developed greatly as research field over the past several decades and play an increasingly important role in the public sphere. As a result, there is increased focus on the **accuracy** of these approaches: i.e., the extent to which they can accurately reflect the real extractable wind energy potential of a given region. The software used to perform these assessments make use of increasingly high-resolution data and

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Nomenclature

Gross national income   GNI
Intergovernmental Panel on Climate Change   IPCC
Levelized cost of electricity   LCOE
Multi-criteria decision analysis   MCDA
Numerical weather prediction   NWP
Preferred Reporting Items for Systematic Reviews and Meta-Analyses   PRISMA
Weather Research and Forecasting model   WRF
Wind resource assessment   WRA

advancements in computing capabilities, while further improvements have been made in the methods used to model atmospheric conditions, to perform land eligibility assessments, and to account for the complexities and uncertainties of real-world wind power projects [7]. Moreover, the use of open data and open-source software has the capacity to strengthen the reliability and real-world relevance of the results by allowing peer researchers to scrutinize and validate methods and results.

Significantly, WRAs are most often undertaken within academic environments, driven by scientific researchers, rather than in industry setting. Therefore, the principles of the scientific method are applicable – with the principle of **reproducibility** being fundamental [8]. Reproducibility, as defined by Gunderson [9] is: "*the ability of independent investigators to draw the same conclusions from an experiment by following the documentation shared by the original investigators.*" In the context of computational science and, by extension, WRAs, this necessitates the sharing of data and code which allows other researchers to not only verify the original results but also replicate the study [10]. As WRAs become increasingly significant in shaping energy policy and directing investment decisions in energy infrastructure, it is imperative that their conclusions are robust and credible, underscoring the importance of reproducibility.

A variety of existing review papers on WRAs cover a wide range of sub-topics, from reviewing the current installed wind energy capacity [6,11-15] and estimated wind potentials [6,7,11,12], to challenges related to the high penetration of wind energy like the economic feasibility [12,13,16], environmental issues [17], technical and social concerns in urban environments [18,19], power system impacts [13], and socio-political barriers to large scale development [20,21]. Further, several review articles analyze the available software, models and tools for WRAs [6,11,22-24] and discuss datasets [7,22] and the application of numerical weather prediction (NWP) models [6]. On a technical level, there is large interest in wind turbine technology [6,7,11,18,25], and the significance of incorporating near-future wind turbine designs in wind assessments [7,26]. There are also ample reviews on the technical methodology contained within the subtasks of a WRA: for example, approaches to the vertical extrapolation of wind [27], approaches to characterizing the probability function of wind speed [28] and estimating Weibull parameters [27,29], methods of turbine siting [7,14], challenges in simulating turbine wake effects [30], and the growing use of artificial neural networks for wind prediction and data mining [31]. Finally, relating to the broader approach of the WRA, few review papers advocate for a standardized framework [22,23], for accurate representation of important social and political factors in turbine siting [7,11,16,24], addressing the challenges of incorporating advanced economic complexities [6,7,11,12,16], and improving the validation and quantification of uncertainty in WRAs [6,7,32].

To the best of our knowledge, there is no systematic review paper on large-scale WRAs with a key focus on the accuracy and reproducibility of the research results. Hence, our literature review addresses the core areas of WRAs where research focus should be directed. The outcome is thus to not only improve the accuracy and relevance of wind assessments, but also to foster public trust in the results, through adherence to the scientific method and scrutiny of the methodologies, data, and models employed in generating those results [33].

In the following sections, we present the results of our systematic review of 195 studies focusing specifically on our key findings. We use a systematic approach, and focus on the implementation of methodology, with respect to reproducible science and accuracy in the field of wind potential assessments. We thereby aim to uncover information on how to standardize the implementation of these assessments in the future, to help automate tasks and reduce the workload for steps that are often repeated, as well as to find key areas for future research focus and highlight knowledge gaps. To avoid redundancy, we avoid discussing findings that have already been reported in previous review papers on the topic of wind potential assessments (e.g. [7,28,30,34,35]).

We present the Methodology for our review in Section 2, outline our Results in Section 3 and then discuss and synthesize the core findings, as well as introduce potential avenues for future research focus in Section 4.

2. Review methodology and scope

Applying a systematic literature review method as per the "Preferred Reporting Items for Systematic review and Meta-Analyses" (PRISMA) [36] guidelines, we screened 1736 records on WRAs from SCOPUS (Elsevier) and Web of Science (WOS) (Clarivate Analytics) databases using the search terms outlined in the Appendix. Initial screening based on the criteria outlined in Fig. 1 excluded studies not focused on generating a wind potential assessment (e.g. [37–39]), lacking a software implementable approach (e.g. [40]), with a geographical extent below 2000 km^2 (e.g. [41,42]) or at least seven observation sites (e.g. [43,44]), and studies concentrated on hybrid VRE systems, rooftop, or urban wind generation (e.g. [45]). Through this methodology, we were able to identify 195 studies performing large-scale wind resource assessments published between 2012 and 2022.

Appendix Table 13 provides further information on the search terms used, while Tables 14 and 15 provide additional bibliometric information). Thus, we present a clear snapshot of the state of WRAs rather than only studies representing the best-practices.

We next performed data extraction from the 195 articles into a Microsoft Excel worksheet, focusing on data related to accuracy and reproducibility. We have made this full worksheet available for download on Jülich Data. In the following sections, whenever we refer to studies, we are referring to our results in the detailed Excel worksheet provided.

3. Results

In following sections, we present the results of our literature review. In Section 3.1, we categorize the various types of wind potentials and discuss challenges in demarcating different potential types (Section 3.1.1). We summarize results of large-scale studies, noting a bias toward Northern-Hemisphere regions (Section 3.1.2). Next, we emphasize the need for holistic methods to determine feasible wind potentials by addressing socio-political concerns and uncertainties in wind farm planning (Section 3.1.3), and examine existing methods Section 3.1.4. Section 3.2 shifts focus to the accuracy of WRAs and inconsistencies in data validation and assumptions (Section 3.1.2). Further sub-sections detail the importance of wind speed extrapolation methods (Section 3.2.2), categorization of the wind resource (Section 3.2.3), and the need for diverse modelling scenarios and sensitivity analyses (Section 3.2.4). We address the current state of wake modelling in WRAs (Section 3.2.5). Finally, in Section 3.3 we critically analyze the current state of open data and open-source software in the literature, highlighting barriers to transparency in the field.

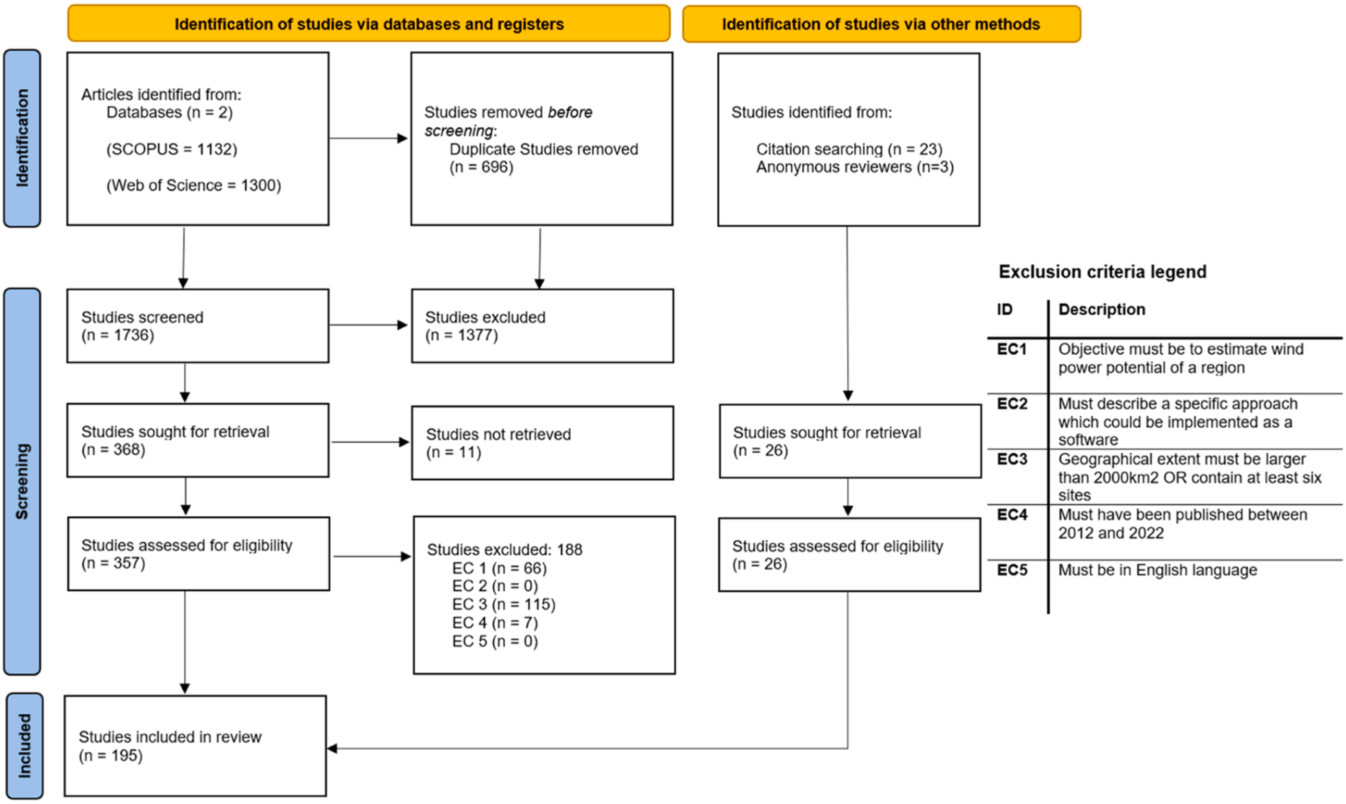


Fig. 1. Flow diagram representing the methodology used in the systematic literature review according to the PRISMA 2020 guidelines [36]. Our analysis included two databases (SCOPUS and Web of Science Core) and the application of our exclusion criteria to an initial 1736 articles screened resulted in 195 articles included in the review. The review process was conducted from October 2022 to June 2023. From: http://www.prisma-statement.org/.

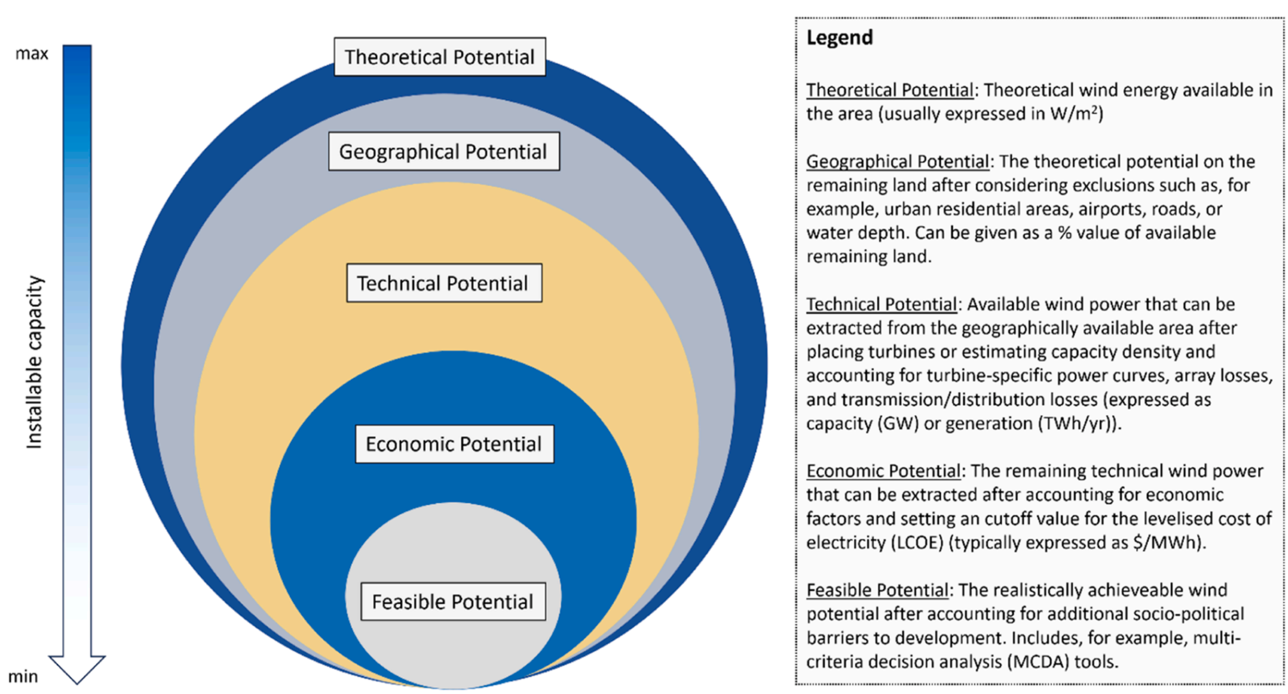


Fig. 2. Hierarchy of wind potentials, from theoretical to feasible. Theoretical potentials reflect a region's total available wind energy, while the geographical potential limits this value by excluding unusable land. The technical potential factors in turbine power curves, array losses, and transmission/distribution losses, further reducing the potential. Economic potentials refer to the available potential after setting a maximum cost of electricity (typically per MWh), while the feasible potential attempts to account for real-world complexities and uncertainties. Adapted from [50].

3.1. Understanding wind power potentials

3.1.1. Defining the different types of wind potentials

Despite the acceleration of wind development globally, significant challenges remain for the large-scale adoption of wind power into national grids. An accurate estimation of the wind potential, considering a realistic set of barriers to development, is essential for project planning and policy work. However, the term "wind potential" can refer to one of five types of potentials. A clear understanding of these potentials and their relevancy is essential in interpreting results of WRAs. Since wind potentials have been defined in detail in the previous literature [7, 46-49], we do not develop the concept further here, but rather provide a brief illustrative description of common definitions for later reference in Fig. 2.

As in McKenna et al. [7], we find that the boundaries between these types of potentials are often not clearly delineated in the reviewed studies. Specifically, the definition of "*feasible*" potential is difficult to apply since the definition often requires a high degree of subjective analysis, such as identifying the types of land exclusions that separate a feasible potential from a techno-economic one [202–204].

Additionally, some studies estimate the technical potential before accounting for relevant land exclusions (e.g. [49,51]). As per the definitions used in this paper, this would mean that the technical potential is estimated before the geographical potential (which therefore has a lower potential and is defined in Archer & Jacobson, [49] as the "practical potential"). While the sequence in which wind resource potentials are estimated remains subject to healthy debate (see, e.g. the definitions in [7] and [49]), the majority of WRAs we reviewed align with our definitions.

Most studies in our review can be classified as "technical" (n = 70, 36 %) (see Table 1), incorporating a land eligibility assessment along with a simulation of wind generation by one or more wind turbine types, and accounting for various losses in the wind farm array (such as wake effects and electrical losses). Note that in this definition, a technical potential also includes a geographical potential – as a percentage of the land that is available for wind development – although this is often not referred to in the studies. Along with theoretical (27 %) and techno-economic (26 %) studies, technical potentials make up the bulk of the literature. We can classify only nine studies as generating a "geographical" potential as the end result (although almost all technical and techno-economic studies implicitly incorporate a geographical potential as a percentage value of available land which is then used for placing turbines and simulating power production).

Table 1
Distribution of the wind resource assessment type through the literature, classified according to onshore, offshore, or both. Note that these refer to the result of the study. A technical assessment would, by definition, also include a geographical assessment although this may not be reported in the study.

Type of assessment	Extent	Count	Refs
Theoretical		**53**	
	Onshore	27	[52–78]
	Offshore	11	[79–89]
	Onshore & Offshore	15	[90–104]
Geographical		**9**	
	Onshore	8	[34,105-111]
	Offshore	0	
	Onshore & offshore	1	[112]
Technical		**70**	
	Onshore	36	[35,113-147]
	Offshore	19	[148–166]
	Onshore & Offshore	15	[14,49,167-179]
Techno-economic		**50**	
	Onshore	37	[48,51,180–214]
	Offshore	9	[215–223]
	Onshore & Offshore	4	[224–227]
Feasible		**13**	
	Onshore	6	[217,228-232]
	Offshore	6	[160,233-237]
	Onshore & Offshore	1	[238]

3.1.2. Results of large-scale wind resource assessments

3.1.2.1. Global and continental-scale studies. Our review considers large geographical regions (national level or greater) of at least 2000 km^2 or using observed data from at least seven sites. Fig. 3 shows that 27 global studies are included, with most focus on China (17), USA (13), Germany (9), India (9), and Pakistan (8). Europe and Asia are the most represented continents, while Australia and South America are the least studied. A total of 24 studies focus on Africa, with six [105,113,114,148, 167,180] continent-wide analyses (although only three provide an estimate of the entire continent's wind potential).

Below, we present the results of selected global and continental-scale wind potential estimates. Table 2 provides insights into global-scale studies, while Table 3 focusses on European and Africa-scale analyses. One key observation is the diverse set of wind data sources employed across the studies, exhibiting marked differences in temporal and spatial resolution. Additionally, differences in technical characteristics of turbines and wind parks (see Section 3.2.3, 3.2.4), including hub height, nameplate capacity, turbine availability, array efficiency, and capacity density, contribute significantly to the disparities in results. Further assumptions surrounding land use availability contribute too, although these are not discussed in detail in this paper as they have already been addressed significantly in recent papers (e.g., [6,7,35]).

At a global scale, our analysis reveals a wide range of estimates for overall wind potential, from 212 PWh [227] to 872 PWh [174] annual generation capacity. Notably, a consensus emerges among these studies, indicating that onshore wind resources exhibit a greater potential (between 23 PWh/yr [145] and 580 PWh/yr [143]) compared to offshore wind (ranging from 69 PWh/yr [227] to 330 PWh/yr [261]). As described in McKenna et al. [7], application of a threshold LCOE value to the technical potential allows the estimation of an economic potential. With a maximum LCOE of 80 USD/MWh, Wu et al. estimate the onshore potential of 140 TW, with an offshore potential of 48 TW [189]. Meanwhile, Zhou et al. estimate the global onshore economic wind potential at 120 PWh/yr at 90 USD/MWh [51], while Silva Herran estimates 29 PWh/yr at 100 USD/MWh [232].

Note that only Archer & Jacobson [57] run global simulations in a climate model to explicitly account for kinetic energy extraction by turbines when calculating the technical wind potential. Marvel et al. [99] also run a similar simulation, but they calculate a theoretical potential, since turbines are simulated over the entire planet and the analysis does not exclude unavailable land. Other studies use a multiplication factor of 80 – 95 % to represent the overall array efficiency and account for losses. The limitations of this approach are discussed in Section 3.2.5.

At a continental scale, the variation in wind potential estimates persists. For Europe, McKenna et al. estimate an onshore technical potential of 20 PWh/yr [211], while Ryberg et al. suggest a higher estimate of 34 PWh/yr [48], with an economic potential of 16 PWh/yr at 60 USD/MWh. In stark contrast, Enevoldsen et al. estimate a much larger technical potential of 138 PWh/yr [238], leading to a discussion on the methodology of the latter paper [262,263]. For Africa, Sterl et al. estimate an onshore potential of 29 TW [105], while Mentis et al. estimate the onshore generation capacity at 31 PWh/yr [113]. Elsner et al. focus on offshore potential, estimating it at 11 PWh/yr [148]. In the following sections of this paper, we explore key reasons for these discrepancies in results and propose methods for improving the accuracy of future large-scale WRAs.

Note that in Tables 2 and 3, we differentiate between onshore and offshore results. However, in the rest of the paper, we generally consider these two together, given that their methodological frameworks are largely the same. Even so, several distinctions can be made which

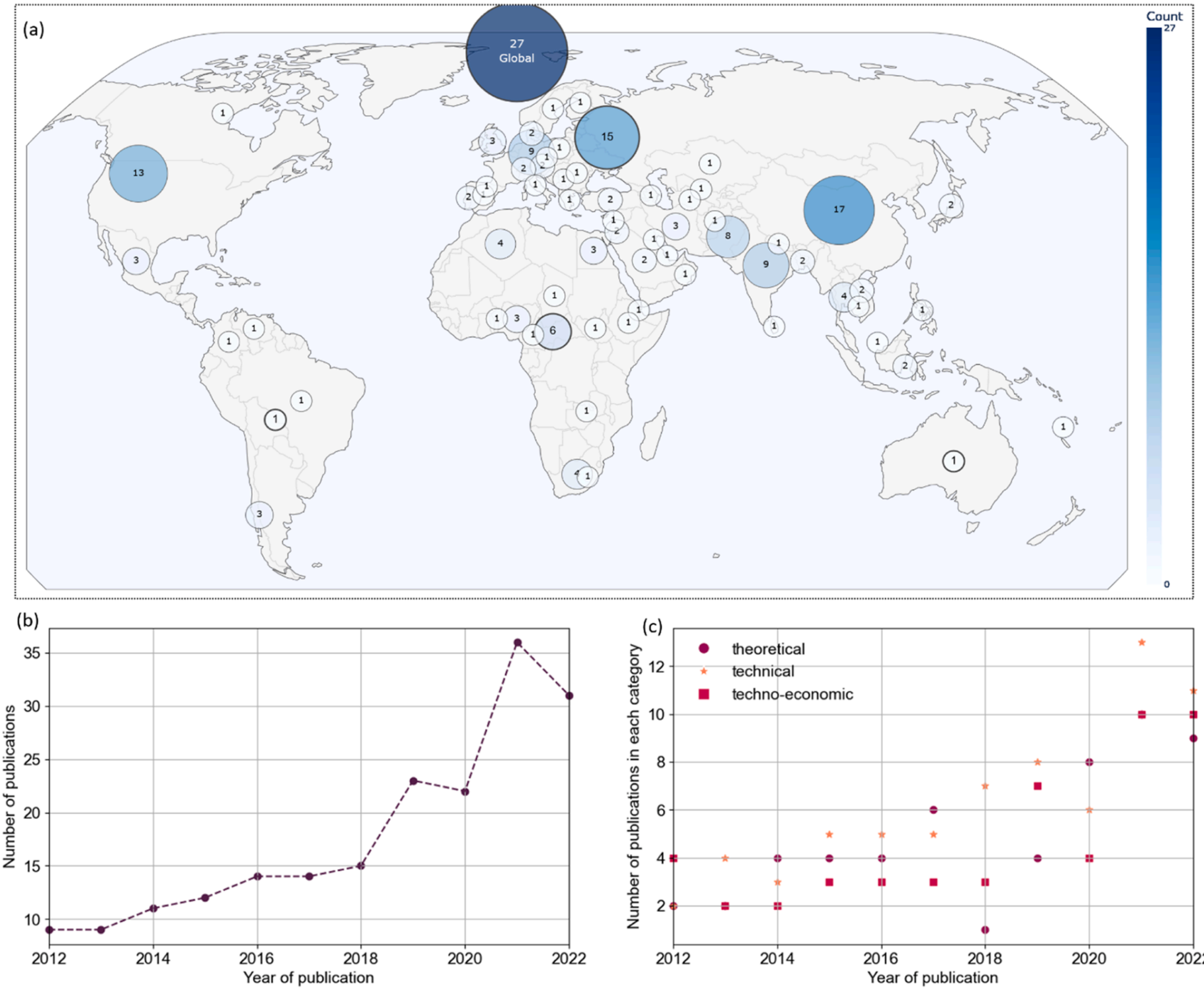


Fig. 3. (a) Geographical distribution of focus of the 195 articles analysed in this literature review. Global and continental-scale studies are illustrated as circles with bold outlines; (b) Total number of publications analysed in this paper per year; (c) Number of publications per year estimating theoretical (circles), technical (stars) and techno-economic (squares) potentials.

warrant specific attention, as follows:

First, the results of our review showed that offshore areas generally exhibit greater wind speed than on land (see, e.g. [94,174,175,179, 238]), while onshore wind is subject to greater variability on small geographical scales, due to differences in topographical features which require high resolution data to accurately model (e.g. [76,95,102,173]). Second, observation wind data sources may diverge: offshore WRAs in predominantly rely on buoys and satellites (e.g. [81,89,155]), while onshore assessments generally utilize existing meteorological stations. Third, there are significant differences in wind turbine characteristics: offshore turbines are significantly larger, both in terms of dimensions and power output, compared to those developed for onshore use. Fourth, land-use evaluations are typically more complex for onshore than offshore WRAs due to a multitude of land-use categories and associated regulations. Conversely, offshore assessments utilize eligibility assessments which usually entail fewer exclusionary parameters, such as distance to shore, proximity to shipping lanes, and the ocean depth, among others. Finally, cost assessments, including LCOEs, differ substantially between onshore and offshore installations owing to differences in infrastructure and regulations.

3.1.2.2. Northern hemisphere bias. As described in Table 4, our review revealed a Northern Hemisphere bias in large-scale wind resource assessments, especially focused on Europe and Asia. Although many studies estimate wind potentials for "Lower middle income" nations, Northern Hemisphere "high income" nations [276] remain dominant. This echoes the observation of scarce literature in energy system modelling in Africa [243,277], despite projected growth of renewable electricity production there over the next decade [278]. Increased research on underrepresented regions, particularly in the Southern Hemisphere, is urgently required.

Seyedhashemi et al. find that over 57 % of Africa's landmass has a capacity factor above 20 %, making it viable for wind energy extraction [114]. Meanwhile, Sterl et al. [105] develop an open-source workflow for generating model supply regions over African, finding a similar "boomerang" distribution of potential (high potentials over Northern and Southern Africa, lower potentials over Central Africa) and an average levelized cost of electricity (LCOE) of \$35 – \$127/MWh (2022 USD). Elsner et al. [148] estimate the continent's *gross* (without deduction of array and transmission losses) annual technical offshore potential at 11.3 PWh when including the full exclusive economic zone (EEZ), and 2.4 PWh for shallow water installations (both using a

Table 2
Overview of selected global studies within the literature review period (2012 – 2022), outlining technical aspects and the estimated technical and (where possible) economic potentials. For studies which include different technical specifications or results for onshore and offshore potentials, the two are separated with a slash "/" and the onshore-relevant value is given first.

Reference	Wind data source	Spatial resolution [° lat-lon]	Turbine capacity [MW]	Hub height [m]	Capacity density [MW/ km^2]	Turbine availability [%]	Array efficiency [%]	Avg. capacity factor [%]	Technical potential	Economic threshold [USD/ MWh]	Economic potential
A – Global onshore & offshore											
Archer & Jacobson, 2013 [49]	GFS reanalysis [264], GATOR-GCMM model [265], Observation data	1.5°	5	100	Varies by grid cell.	n.a.	87.5	28	93 TW	n.a.	n.a.
Lu & McElroy 2012	Goddard Earth Observing System Data Assimilation System (GEOS-5 DAS)	0.63×0.5°	2.5 / 3.6	100	5.8	n.a	n.a	>20	840 PWh/yr (690 / 150 PWh/ yr)	n.a	n.a
Jacobson & Archer, 2012 [179]	GATOR-GCMM model	1.5°	5	100	5.6	n.a.	n.a.	31	80 TW (72 / 8 TW)[1]	n.a.	n.a.
Wu et al., 2022 [189]	Vortex [266]	9 km	3	100	5	n.a.	n.a.	32 / 45	206 TW (150 / 56 TW)	80	184 TW (140 / 48 TW)
Eurek et al., 2017 [174]	NCAR C Four-Dimensional Data Assimilation (CFDDA) [267]	40 km	3.5	90	5	95	90	24 / 36	872 PWh/yr (557 / 315 PWh/ yr)	n.a.	n.a.
Dupont et al., 2018 [227]	ERA-Interim [268]	0.75°	8 / 2	71 / 124	10 / 6.4	96	90	33	212 PWh/yr (143 / 69 PWh/ yr)	Energy return on investment > 12	27.5 PWh/yr (13.6 / 13.9 PWh/yr)
B – Global onshore											
Bosch et al., 2017 [143]	MERRA-2 [269], Global Wind Atlas [270]	0.05°	2.5 - 7	100	6.5	97	n.a.	>15	580 PWh/yr	n.a.	n.a.
Zhou et al., 2012 [51]	NCEP: C Forecast Systems Reanalysis [271]	0.3°	1.5	80	5	97	90	30	400 PWh/yr	90	119.5 PWh/ yr
Silva Herran et al., 2016 [232]	Surface Meteorology and Solar Energy [272]	1°	2	80	9	89	80	22	n.a.	100, 140	29, 110 PWh/yr
Jung, Taubert, & Schindler, 2019 [145]	ERA-20C [273]	0.5°	3.7	100	0.4, 1	97	95	n.a.	23.3 PWh/yr	n.a.	n.a.
C – Global offshore											
Arent et al., 2012 [165]	NOAA Blended Sea Winds [274]	0.25°	3.5	90	5	95	90	>20	192 PWh/yr	n.a.	n.a.
Bosch et al., 2018 [261]	MERRA-2, Global Wind Atlas	0.05°	2.5 - 7	100	6.5	97	n.a.	>15	330 PWh/yr	n.a.	n.a.

[1] Excluding land over Antarctica. When including this land mass, the total installable capacity is 253 TW.

Table 3
Overview of selected continental studies for Europe and Africa within the literature review period (2012 – 2022), outlining technical aspects and the estimated technical and (where possible) economic potentials. For studies which include different technical specifications or results for onshore and offshore potentials, the two are separated with a slash "/" and the onshore-relevant value is given first.

Reference	Wind data source	Spatial resolution [° lat-lon]	Turbine capacity [MW]	Hub height [m]	Capacity density [MW/km^2]	Turbine availability [%]	Array efficiency [%]	Avg. capacity factor [%]	Technical potential	Economic threshold [USD/MWh]	Economic potential
A – European onshore & offshore											
Zappa & van den Broek, 2018 [138]	ERA-Interim [268]	0.75°	n.a.	100 / 150	4.2 - 6	n.a.	87	22 / 38	849 GW (300 / 549 GW)	n.a.	n.a.
European Commission, 2018 [178]	MERRA [275], Global Wind Atlas [270]	0.5×0.65°	0.25, 3	50 – 200 / 100	5	n.a.	85	28 / 40	26 PWh/yr (11.7 / 14.3 PWh/yr)	n.a.	n.a.
B – European onshore											
McKenna et al., 2015 [211]	ERA-Interim	0.75°	3	65 – 149	8.3 – 18.6	95	85	Variable.	20	n.a.	n.a.
Enevoldsen et al., 2019 [238]	Global Wind Atlas	0.01°	4.5	100	4.9	n.a.	n.a.	30	138.0 PWh/yr	n.a.	n.a.
Ryberg et al., 2018 [48]	Global Wind Atlas, MERRA	0.5×0.65°	3 – 5	88 – 120	Explicit placement	n.a.	n.a.	n.a.	34.3 PWh/yr	60 €	22.1 PWh/yr
C – European offshore											
Caglayan et al., 2019 [223]	MERRA	0.5×0.65°	3 – 20	80 – 200	Explicit placement	n.a.	n.a.	n.a.	39.9 PWh/yr	60 €	16.2 PWh/yr
D – African onshore											
Sterl et al., 2022 [105]	ERA-5, Global Wind Atlas	0.25°	n.a.	100	12	n.a.	n.a.	44	29 TW	n.a.	n.a.
Mentis et al., 2015 [113]	VORTEX [266], NASA Climatology Resource for Agroclimatology	6 km	2	80	2 – 5	97	90	>20	31 PWh/yr	n.a.	n.a.
E – African offshore											
Elsner, 2019 [148]	NOAA National Centres for Environmental Information (NCEI)	0.25°	8	100	3	n.a.	70	>37	11.3 PWh/yr	n.a.	n.a.

Table 4
Classification of national-scale wind potential analyses based on the World Bank income classification of 2022–2023 [276] according to Gross National Income (GNI). Note that continental and global studies are excluded from this table, which is why the percentage values do not add up to 100 %. Dollar units are equivalent to 2022 USD.

Classification	Annual GNI / capita	Countries	Share [%]
High income	> $13,205	Australia [54], Austria [181], Canada [90], Chile [80,182,215], China [55,56,79,106,117-119,149, 168,169,183-185,224,225,234], Czechia [120], Denmark [120], Finland [57], France [170], Germany [35,58,107,121-123, 186-189], Greece [81], Italy [150], Japan [91,151], Kuwait [92], Oman [152], Poland [190], Portugal [53, 59], Qatar [171], Romania [153], Saudi Arabia [191,228], Spain [154], Sweden [172], Switzerland [60,172], United Kingdom [115,216, 229], United States of America [61, 82,93,94,124,125,155,173,192,193, 226,230]	34 (n=67)
Upper middle income	$4256 - $13,205	Azerbaijan [214], Brazil [235], Colombia [62], Fiji [95], Jordan [116], Kazakhstan [194], Malaysia [126], Mexico [127,156,157], Serbia [217], South Africa [63,128,129, 158], Thailand [64,159,160,218], Turkey [108,236], Turkmenistan [195]	11 (n=22)
Lower middle income	$1086 - $4255	Algeria [65,96,196,197], Bangladesh [66,130], Benin [83], Cambodia [150], Cameroon [67], Djibouti [198], Egypt [199,200,219, 233], India [68,69,84,97,98,109, 161,201,202], Indonesia [131,203], Iran [132,133,220], Lebanon [85], Lesotho [70], Nepal [204], Nigeria [134,205,206], Pakistan [71,110, 135,146,207-209], Philippines [221], Sri Lanka [110], Uzbekistan [210], Venezuela [136], Vietnam [162,231]	26 (n=51)
Low income	< $1085	Afghanistan [111], Chad [72], Ethiopia [73], S. Sudan [74], Zambia [75]	3 (n=5)

capacity factor threshold of 37.6 %). While national-scale WRAs are well represented by African researchers, only two continental-scale studies [167,180] were conducted by a lead author with an African affiliation.

Only a handful of studies conducted WRAs for South American countries, despite the large potential for wind development. Vinhoza and Schaeffer [235] estimate Brazil's offshore technical wind potential as about 1050 GW (with a feasible potential of 330 GW). Mattar & Borvaran calculate Chile's offshore technical potential with an annual generation of ~30 GWh for an 8 MW turbine [80]. Furthermore, the International Renewable Energy Agency (IRENA) estimates South America's wind potential at around 240 GW for grid-connected projects with further 180 GW available off grid [279]. In 2022, Latin America's installed wind capacity was approximately 45 GW [4], highlighting a significant untapped potential.

Per capita energy consumption is directly linked to human development [280–282]. Despite hosting almost 15 % of the world's population [283], the Southern Hemisphere accounts for only 7 % of the its electricity consumption [284]. Excluding Australia, New Zealand, Brazil and South Africa, the mean per capita energy consumption for this region is 800 kWh/year, which is considerably less than for Germany (7,5 times) or the USA (15 times) [283,284]. To achieve Sustainable Development Goal 7 of "*affordable, reliable and sustainable modern energy for all*" by 2030, urgent expansion of the region's electricity sector is needed.

3.1.3. Holistic, feasible potentials are urgently needed

While technical and techno-economic potential analyses can provide a reasonable estimation of the wind power availability of a given region, and even consider economic constraints, they may overlook key market, technical and socio-political barriers to wind power development [7,20, 239-242]. Explicitly accounting for these barriers would allow wind potential assessments to provide more accurate estimations and serve as valuable resources for energy planning and policy. As such, feasible wind potentials attempt to incorporate a realistic set of barriers to wind development to provide an estimation of the available energy potential that is as close to the actual *achievable real-world potential* as possible. This is achieved by building on technical or techno-economic potential assessments to include further considerations.

We find several innovative methodologies that build upon traditional technical or techno-economic potential analyses which can be used to estimate feasible potentials. We highlight examples of these approaches in Table 5. Importantly, these methods are found separately throughout the literature, and no single study attempts to combine them to provide a fully holistic result.

Additionally, it is essential to consider the perspectives of nations from the Global South in such analyses and to account for important geographical differences in energy markets, socio-political circumstances, and institutions – factors which impact the relevance of results from wind potential analyses [243]. For example, Diógenes et al. [242] find that social barriers (e.g., the absence of community-level acceptance) are reported in 88 % of developed nations, yet in only 12 % of developing nations. Conversely, issues with "poor market infrastructure" are reported in over half of developing nations, but only 8 % of studies from developed countries [242]. In a similar vein, Zwarteveen et al. [20] cluster 259 factors affecting wind energy expansion into eight categories, and discover significant differences based on the income level of the country being considered, thereby highlighting the importance of considering geographical differences in barriers to expansion of wind energy.

Expanding on the approaches to estimating feasible potentials, McKenna et al. [7] outline three methods, which we also elaborate on here. First are *land eligibility studies* which consider a larger set of restrictions than geographical potentials, striving to incorporate non-technical impacts into potential assessments. These could be, for example, exclusions of areas impacting cultural sites [34], landscape protected zones [172], or non-human life, like animal migration routes [186] or coral reefs [221]. We have not categorized such studies as feasible potentials in our review because, while accounting for a wide range of social impacts, they often do not fully reflect the ambiguity and complexity inherent in real-world siting [7,14].

Second are studies which perform welfare analyses: i.e., which attempt to minimize the total *social* cost of wind turbine development. For example, Langer et al. [203] create a flexible model for site selection in Indonesia, allowing a flexible approach for assessing site feasibility based on stakeholder input. Similar to [7], we could not find a study where a full welfare analysis was conducted. Lastly, there are multi-criterion decision analysis (MCDA) approaches, which often overlap with the welfare analyses category.

In assessing the wind potential, local barriers such as setback regulations can vary substantially, not just between countries, but also among provinces within a nation. Public attitudes toward wind park development greatly influence the development of real-world wind farms and thus there needs to be an attempt to include these in WRA models [14,240,242,245,246]. These can include concerns regarding noise [247–250], visual impacts [241,251-253], and environmental effects – for example, obstructing migratory bird routes [254–256], among many others. These factors are typically integrated into assessments as "hard" exclusions; that is, any land meeting the exclusion criteria (for

Table 5
Selected approaches from the literature that build on traditional techno-economic analyses to incorporate complex considerations needed for a feasible potential analysis.

Approach	Region	Details	Reference
A - Additional economic factors			
Grid connectivity	Nepal	Includes grid connectivity, transmission costs to identify project opportunity areas	[204]
Turbine ageing	United Kingdom	Accounts for the economic impacts of wind turbine ageing	[115]
Cradle-to-grave lifecycle	Global	Uses "energy return on investment" to account for cradle-to-grave lifecycle of wind power	[227]
Use of industry standard turbine classes	Global	Use of wind speed classes to select turbine and calculate CAPEX costs and account for extreme gusts	[212]
B - Use of multiple scenarios			
Wind power generation scenarios	China	Calculates the LCOE under three different wind power generation scenarios	[225]
Multiple demand scenarios	Europe	Optimisation algorithm for placing turbines under multiple demand scenarios	[138]
Multi-objective optimisation scenarios	China	Uses three multi-objective optimization scenarios for zonal deployment of wind power in China	[118]
Use of multiple land restriction scenarios	Germany	Employs five land restriction scenarios and conducts a sensitivity analysis	[35]
C - Incorporation of non-technical elements			
Impacts of turbine visibility	Global	Evaluates the impacts of transmission costs and visibility impacts under three scenarios	[232]
Social acceptance criteria	United Kingdom	Defines several social acceptance criteria and incorporates them into a MCDA model	[229]
Policy risk and employment	Egypt	Includes policy risk and employment issues in a MCDA-model	[219]
Climate mitigation benefits	China	Calculates the CO2 savings from wind projects	[224]
Participatory approach	Aegean Sea	Considers expert advice from multiple stakeholders decide on criteria weights in MCDA-analysis	[244]
Nature protected areas	Poland	Performs a sensitivity analysis of the effects of various buffer sizes for natural protected areas on wind potential	[190]
D - Novel machine learning / AI-based approaches			
Intelligent optimization algorithms	China	Uses a genetic algorithm for siting wind farms based on the spatial and temporal variability of wind	[55]
Machine learning methods	Switzerland	Develops an extreme learning machine based on a single layer feedforward neural network for siting turbines	[142]

example, proximity to urban areas, protected lands, or animal migratory routes) is entirely omitted from the available land, often with an additional setback distance added. However, this binary approach does not accurately reflect the complexity of real-world decision-making, particularly when legal guidelines are ambiguous or non-existent [14,35,257]. In such cases, a more dynamic methodology, involving the weighted optimization of multiple land categories, offers a more realistic and flexible assessment framework [189,228,258].

3.1.4. Multi-criteria decision analysis (MCDA) approaches

In the MCDA approach, trade-offs between different objectives are explicitly modelled under various scenarios. This set of methods, growing in use in energy system modelling, allows stakeholders and decision-makers to consider quantitative, technical goals alongside social or non-technical criteria [7,258]. Typically, weights are assigned to various objectives (such as distance to settlements, use of forests, or environmental impacts) to optimize the placement of turbines, considering the multidimensional nature of energy system planning. Despite the considerable difficulties in assigning weights to various criteria [259], MCDA modelling offers a more holistic and balanced approach to siting than a traditional, binary land eligibility analysis. We find several types of MCDA methodologies in the literature, detailed in Table 6.

The most common MCDA method is the Analytic Hierarchy Process (AHP), employed in 11 studies. This is followed by the "Fuzzy-AHP" methodology, incorporating fuzzy numbers into the AHP framework to better account for uncertainty and vagueness in the decision-making process. Other methodologies include Mostafaeipour et al. [111], using the Stepwise Weight Assessment Ratio Analysis (SWARA) method

Table 6
Descriptions of MCDA methods used in at least two studies in the literature, and their application within the context of wind resource assessments.

MCDA method	Description	Pros	Cons	Used in
Analytic Hierarchy Process (AHP)	A structured approach that creates a multi-level hierarchy and uses pairwise comparisons to calculate weights for each criterion and sub-criterion.	Allows for both quantitative and qualitative data. Utilizes a consistency ratio to ensure logical consistency of weights.	Weight assignments can be complex. Vagueness not as well dealt with as other methods.	[109, 110, 149, 150, 158, 218, 231, 235, 236]
Fuzzy AHP	Builds on AHP by incorporating fuzzy set theory to better account for vagueness and uncertainty in weight classification.	Allows for better handling of uncertainty. Incorporates quantitative data into the decision-making process.	Greater complexity than AHP. High computational demands.	[217, 244]
Fuzzy-TOPSIS	Assigns fuzzy numbers to represent criteria for projects locations, based on their distance to the "ideal" and "anti-ideal" solutions and ranks alternatives by "closeness coefficient".	Straightforward ranking of locations by best to worst. Handles uncertainty and vagueness well.	Computationally demanding and highly complex. Assumes independence of ranking criteria.	[106, 108, 208]
PROMTHEE	Conducts a pairwise comparison of locations based on preference functions and ranks alternatives based on net flow scores.	Allows the incorporation of multiple preference functions. Provides a full ranking of alternatives.	Does not handle vagueness and uncertainty as well as other methods. Primarily for quantitative data.	[228, 234]

for calculating weights to the exclusion criteria. Similarly, Harper et al. [229] use a simple weighted sum method (WSM), while Gao et al. [55] employ a genetic optimization algorithm. Although the advancement in MCDA-based wind assessment research is promising, practical implementation is not always possible due to the high computational demands and methodological complexity.

Real-world wind energy project development is a long-term, complex decision-making process that is dependent on multiple factors including the economic viability, license agreements, and community acceptance [14,260]. During the initial feasibility phase, elements analogous to those modelled in WRAs are considered. These include wind characteristics, market considerations, and proximity to infrastructure such as power grids, housing, airports, and transportation networks. However, the *in-situ* complexity of wind farm development surpasses a mere selection of windy sites coupled with a binary land eligibility analysis. This conventional approach fails to mirror the multifaceted nature of actual wind development processes and can only offer limited utility to stakeholders.

The incorporation of socio-political elements, adoption of diversified scenarios, or use of novel approaches, while an enhancement of the conventional approach, also does not inherently ensure a realistic estimation of feasible potentials in WRAs. For example, even if a study accounts for various societal barriers or cultural considerations, presuming a turbine deployment density exceeding real-world deployment would invariably result in overly optimistic potentials. To navigate these complexities and improve WRA accuracy, a more systematized approach should be considered which allows researchers to make use of best practices each time they perform an analysis.

Consequently, we recommend the adoption of a standardized workflow which permits the incorporation of multiple facets of feasible potentials (for example, from Table 5). Such an approach would allow WRAs to align with existing best practices and removes the necessity of researchers to develop the full process of trying to include as many aspects as possible of feasible potentials on each iteration – a task that inevitably grows in complexity over time.

3.2. Approaches to enhancing the accuracy of wind resource assessments

3.2.1. The critical role of wind data validation and multiple wind datasets

In recent studies, the reliability of wind data used in WRAs, and the associated implications, have come under scrutiny. Davidson & Millstein [61] and Langer et al. [203] highlight a key challenge inherent in reanalysis data, identifying significant discrepancies between SCADA data and both MERRA-2 and ERA-5 reanalysis datasets, particularly at an hourly temporal resolution. These inconsistencies are further corroborated by Staffell & Pfenninger [52], who reveal that NASA's flagship reanalysis datasets may overestimate wind speeds by as much as 50 % in northwest Europe, while underestimating them by 30 % in the Mediterranean. Building on this, Soukissian & Papadopoulos [81] argue for the utilization of blended sea satellite data, which they posit as a more accurate alternative to NWP models, particularly for offshore studies in the Mediterranean area. The implication is that, since wind interactions with complex terrain manifest at both *meso* and micro scales, the use of a single wind dataset typically falls short in providing adequate results in WRAs.

To address these discrepancies, three approaches are suggested in the literature. The first entails using high-resolution wind atlas data to downscale relatively coarse reanalysis data (e.g. [48,105,178,203]). Wind atlases, such as the Global Wind Atlas [270], provide static wind speed data at a very high resolution (~250 m^2) and can effectively enhance the accuracy of reanalysis data at the local level through various interpolation techniques.

The second approach relies on the validation of reanalysis data using meteorological station observations (e.g. [62,65,75,98]) or data from numerical weather prediction models (e.g. [155]). This allows researchers to quantify the reanalysis data bias and generate correction factors that can improve the overall data quality.

The third approach involves using reanalysis data to set the initial boundary conditions for NWP models (e.g. [80,101,160]). This allows for the nesting of domains within the NWP model, providing enhanced boundary conditions. Several studies use more complex approaches, integrating a mix of data types for more comprehensive analyses (e.g. [53,75,81,89,100,103]).

Despite the identified need for multi-source data and verification, our analysis reveals a prevalence of relying on a single source of wind data (67 % of studies). Only 10 % of studies used more than two data types and just 21 % performed a validation of the input data prior to the analysis (please refer to the Supplementary Materials for a full list of these studies). A selection of studies performing validation of input wind data is shown in Table 7. These results point to a significant gap in the current research methodology, emphasizing the need for more rigorous data validation and multiple sources of data.

3.2.2. Adopting recent advancements in vertical wind speed extrapolation methods

Between 1999 and 2021, the average onshore wind turbine hub height in the United States increased by approximately 66 %, from 57 m to 94 m [285]. In Europe, the average hub height for turbines installed in 2020 was 104 m [286]. Wind velocity data are typically provided at 10 –

Table 7
Overview of selected studies where wind speed data is validated against observation data (meteorological masts or wind turbine data) and the root mean square error (RMSE) is quantified in m/s.

Reference	Data source	Region	No. stations	RMSE [m/s]	Wind height [m]
A - Climate models					
Geyer et al. 2015 [89]	COSMO-CLM	North Sea	7	2.59	10
Akhtar et al. 2021 [163]	COSMO-CLM	North Sea		2.7	90
Libanda and Paeth 2023 [75]	CMIP6 (11 models)	Zambia	38	0.6	10
B - Reanalysis datasets					
Onea et al. 2016 [86]	ERA-Interim	Mediterranean Sea	N.A.	2.24	10
Satyanarayana Gubbala, Dodla, and Desamsetti 2021 [98]	ERA-Interim	India	N.A.	0.57	20
Fekih, Abdelouahab, and Marif 2023 [65]	ERA-5	Algeria	3	1.49	10
Gil Ruiz, Barriga, and Martínez 2021 [62]	ERA-5	Colombia	13	2.55	10
Rabbani and Zeeshan 2020 [135]	MERRA-2	Pakistan	-	11.95	10
C - NWP models					
D'Isidoro et al. 2020 [70]	WRF	Lesotho	2	2.3	10
Dayal et al. 2021 [95]	WRF	Fiji	24	2.24	10
Mattar and Borvarán 2016 [80]	WRF v3.6 *Era-5*	Chile	1	2.2	20, 30, 40
Dvorak et al. 2013 [155]	WRF	USA – East Coast	32	2.24	5, 45
Carvalho et al. 2014 [53]	WRF v3.4.1 *Era-Interim*	Portugal	13	2.1	Various

50 m above ground. Since velocity increases with height mostly due to reduced effects of surface roughness and drag, a suitable method for extrapolating the wind speed to hub height is required. The three most common methods of vertical wind extrapolation in the literature, to estimate wind speed at hub height (z_2) from a given lower wind speed (z_1) are described in Table 8. These include logarithmic law (*Log law*), the power law, and linear (spline) interpolation between two known wind speeds at different heights.

Gualtieri [27] reviews 332 applications of theoretical and empirical methods of vertical extrapolation of wind speeds. He finds that the logarithmic models are no longer suitable for extrapolation of wind speed to hub heights because of their limited range (median, 10 – 50 m) and high sensitivity to ground roughness. Eurek et al. [174] find that the normalized root mean square deviation (NRMSD) increases with height for all three methods, but that linear interpolation provides the most accurate wind speed extrapolation at 90 m hub height. In some cases, however, the power law provided similar results up to 115 m. Similarly, Soares et al. [87] find that both the log and power laws provided poor estimations of wind power density WPD at 100 m compared to linear interpolation, described as likely due to the complexities of accurately representing the atmospheric stabilities conditions. The choice of method for extrapolating wind speed to hub height may, therefore, introduce unexpected error into the result and thus, it is important that the rationale for selecting a particular method is documented.

Previous work has been done to address the limitations of these common approaches. For example, Archer & Jacobson [290,291] developed a least squares fitting approach, which allows the extrapolation of wind speeds to hub height by fitting a wind speed profile to sounding station data and then extrapolating surface measurements to hub height using a nearby sounding profile. The extent to which these methodological developments have been used in recent WRAs is low despite the apparent benefits, which may be due to a lack of high-quality data availability over large geographical scales.

Our analysis revealed that 40 studies employed the logarithmic law, while another 44 utilized the power law. Five others use linear spline interpolation to determine the wind speed at hub height based on two wind speeds [80,87,89,151,174], while 103 did not note the method used for extrapolating the wind speed. In concurrence with Gualtieri [27], the power law is the most used method in the literature, likely due to its relative reliability and ease-of-use. Nevertheless, as wind turbine design increases the rotor swept area, interactions with the atmospheric boundary layer, and the size of the swept rotor area, may necessitate using interpolation between two heights as a preferred method.

3.2.3. Addressing gaps in variability, intermittency, and turbulence characterization in wind assessments

A defining characteristic of wind is its variable nature. For an accurate assessment of this variability, several meteorological elements must be considered. Two key areas of concern are: first, the phenomenon of 'wind droughts', extended periods of low winds that can significantly impact wind power generation [292]; and second, extreme wind conditions [7] such as cyclones [221] or hurricanes [155], which are projected to worsen with climate change [293] and are difficult to model due to ongoing spatio-temporal challenges, known as the "spectral gap" [294]. Interestingly, few studies delved into an explicit examination of the variability or intermittency of wind over extended time frames. Jung et al. [145] discerned through trend analysis that wind park expansion is increasingly influencing wind resource variability. Similarly, Hallgren et al. [54] assessed wind speed intermittency in various Australian regions, focusing on periods under the cut-in threshold for wind generation.

The fact that the wind does not blow at a constant rate introduces additional complexities. Wind turbulence and gusts, along with high frequency fluctuations in wind speed, have a pronounced effect on the stability of wind power generation [295]. These were not adequately accounted for in the literature, possibly introducing a positive bias in the results. Best practice examples include G. Gualtieri [137], who quantified turbulence intensity (*I*) and gust factor (*G*) for Tuscany, and Gil Ruiz et al. [62], who calculated temporally-correlated turbulence intensity over the Caribbean region of Colombia.

It is equally important to note the temporal variability of wind speed and direction across different timescales: inter-annually, intra-annually, and daily. We found that temporal variability was only accounted for in about 23 % of the studies analyzed. Several studies did perform an analysis on intra-annual cycles: for example, Staffell & Pfenninger [52] found that capacity factors decrease across the EU by around 44 % from winter to summer. A handful also evaluated the diurnal wind cycle: for example, Kruyt et al. [60] found that most Swiss weather stations exhibited decreased wind speeds in the afternoon due to changes in boundary layer conditions.

Lastly, the length of data used in most studies was insufficient to account for longer-term climate effects. Climate is evaluated over a 30-year period [296]; however, the median length of wind data used was only 13 years. Out of the 114 studies that provided a date range for their wind data, only 30 % used data spanning at least 30 years. Consequently, longer-term climatic oscillations cannot be identified in most of the data.

3.2.4. Emphasizing the use of diverse scenarios for wind turbine characterization and siting

Turbine characteristics: Regarding specific turbine characteristics, the median nominal capacity for all onshore turbines in the literature over 2012–2022 was 2.4 MW, with a median hub height of 80 m and a rotor diameter of 90 m. Offshore turbines exhibit superior characteristics, with a median capacity of 4.8 MW within the same period and median hub height and rotor diameters of 100 m and 126 m, respectively. These features are graphically represented in Fig. 4 (panels *a* and *b*) juxtaposed with projections for near-future turbine dimensions in 2035, according to Wiser et al. [26]. Additionally, it is worth noting that the turbine capacity, hub height, and rotor diameters used in the literature generally align with empirical data for operational wind farms for each corresponding year [285,297] (see Fig. 4 (panels *c* and *d*)).

Interestingly, the turbine specifications applied in the literature are markedly smaller than the projected near-future designs. Given the substantial lead time, typically ranging from five to ten years [260], between the initial feasibility study and a wind farm's commissioning, using currently valid turbine characteristics in an WRA could lead to significant underestimation of the generation capacity for the study area. In this context, employing near-future turbine characteristic projections, as seen in Ryberg et al. [48], can be considered as the best

Table 8
Common methods of vertical wind extrapolation in the literature, their standard formula, and required inputs.

Name	Formula	Requires	Reference
Logarithmic law	$v(z_2) = v(z_1)\frac{\ln(z_2/z_0)}{\ln(z_1/z_0)}$	z_0 , roughness length	[27,287]
Power law	$v(z_2) = v(z_1)\left(\frac{z_2}{z_1}\right)^{\alpha}$	α, Hellman's wind shear exponent	[27,288]
Spline Interpolation	$v(z) = a(z - z_1)^3 + b(z - z_2)^2 + c(z - z_1) + d$, for $z_1 \le z \le z_2$ *and* $z_2 \le z \le z_3$	a, b, c, d, coeffcients such that $v(z)$ and its 1st and 2nd derivatives are continuous at $z = z_2$	[289]

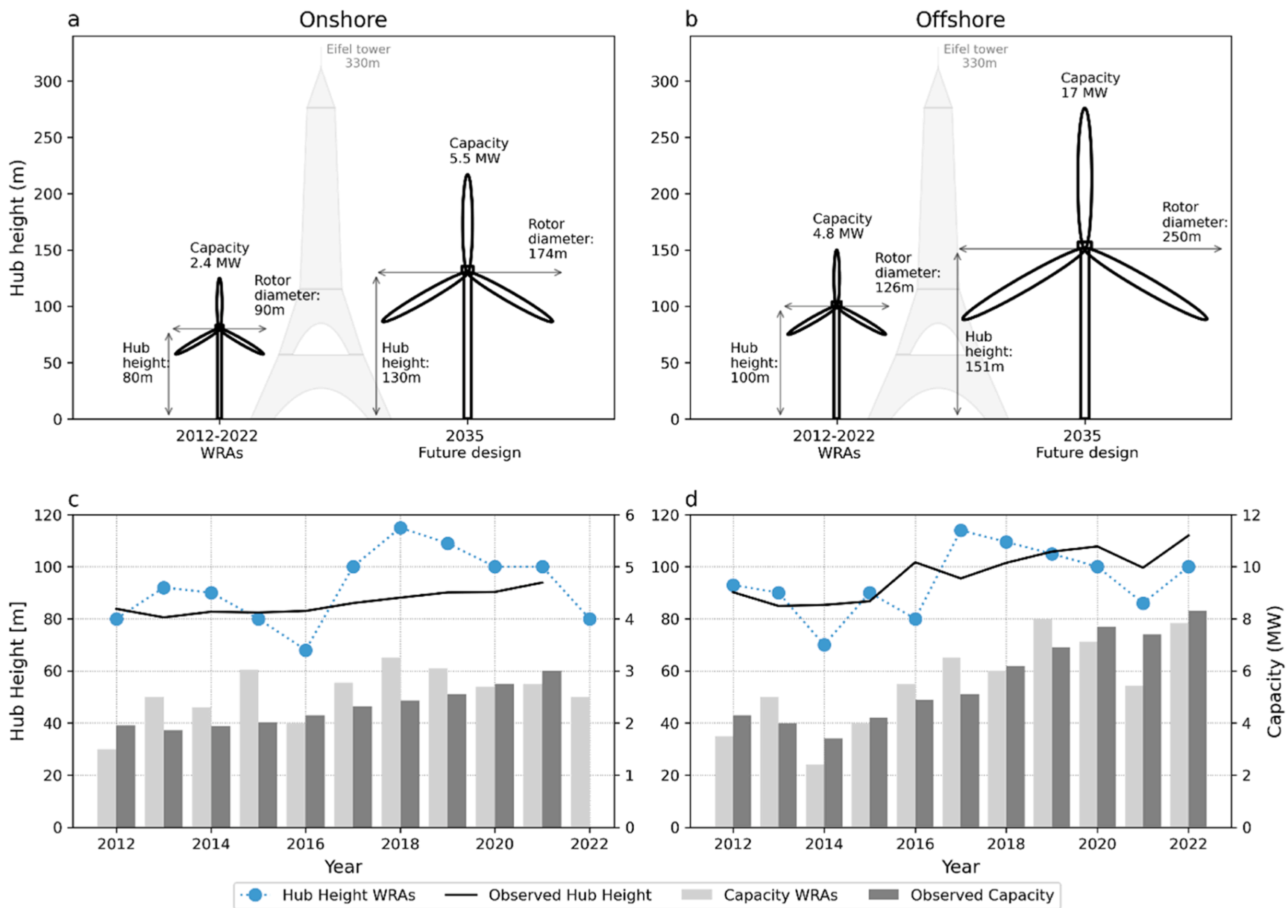


Fig. 4. Panel detailing the median characteristics of a) onshore and b) offshore wind turbines as presented in the literature versus near-future (2035) designs [26], including hub height, turbine capacity, and rotor diameter. Panels c) and d) compare the nominal capacity and hub heights for onshore and offshore turbines, respectively, from the literature against the US Department of Energy (DOE)'s data [285,297] for turbine installations in the corresponding years.

practice. Despite the potential overestimations in generation capacity for the current turbine set, by the time of the farm's construction, turbines with significantly improved performance are likely to be available [26].

It is important that the selected turbine used in a WRA correspond to the characteristic wind speeds and intensities of the study area, as capital expenditures are influenced by hub height. Choosing an inappropriate turbine model would lead to results with limited practical applicability [212]. Thus, the use of International Electrotechnical Commission (IEC) standards (see Table 9) for turbine selection can be considered a best practice. Additionally, our analysis revealed that 45 % of the studies employed a single turbine model in their analysis, while only 27 % considered a broader scope of more than five turbine models. Adopting a variety of turbine models can be considered a best practice, as it yields a more diverse and dynamic set of results rather than a single, static result which may be over- or underestimated if the incorrect turbine model was selected.

Table 9
The International Electrotechnical Commission (IEC) Standard 611,400–1:2019 [298] for Wind Turbine Classes. The standard categorizes turbines into three classes based on operable wind speeds and turbulence intensity. The table below describes the reference wind speed and average wind speed as well as turbulence intensity for Class I, II and III turbines. These are suited to a specific average wind speed (V_{ave}) and a maximum 50-year extreme speed (V_{ref}). Class S is designed for site-specific conditions. I_{ref} denotes the reference turbulence intensity in% at the site.

Wind Class		I	II	III	S
$\mathbf{V_{ave}}$	(m/s)	10	8,5	7,5	Site-specific
$\mathbf{V_{ref}}$	(m/s)	50	42,5	37,5	
	tropical (m/s)	57	57	57	
$\mathbf{I_{ref}}$	A+	18%			
	A	16 %			
	B	14 %			
	C	12 %			

Best practice examples include Pryor and Berthelmie [104], who developed a global atlas of extreme winds, finding that almost 4 % of grid cells excluded Class III turbines. Islam et al. [130] classified two sites on the Bangladeshi coast as wind class S, which then guided their selection of turbine models to employ in the technical analysis. Satymov et al. [212] employed power curves of six turbines from all three classes to estimate capital expenditures, finding Class III as the most economically viable for most land, while Class II was optimal along coastlines. Additionally, their study indicated that the full load hours of turbines could be increased by up to 20 % in most regions by optimizing turbine selection using IEC wind classes. Finally, Rodriguez et al. [127] proposed a novel method for estimating wind resource errors, aligning with the IEC 61,400–12–1 standard.

Turbine siting: Turbine placement is typically quantified as *deployment density*, defined as the total MW potential wind power capacity divided by the total size of the wind farm or region, usually expressed in MW per km^2. The mean capacity density reported in the literature is 5.6 MW/km^2, with a median of 4.95 MW/km^2. Corroborating the findings of Hedenus et al. [14], our review also reveals an overestimation of deployment density in WRAs, considering that the average deployment density in real-world municipalities seldom surpasses 0.5 MW/km^2, with infrequent exceptions exceeding 1.5 MW/km^2

[14]. In fact, Hedenus et al. [14] find a median deployment density of only 0.077 MW/km^2 for onshore municipalities, indicating that the median density in current WRAs is significantly greater than in real-life. In contrast, Enevoldsen & Jacobson, in contrast, report a much higher mean installed density for European wind farms: 19.8 MW/km^2 onshore and 7.2 MW/km^2 offshore [15]. However, these larger figures are inside the wind farm itself, rather than for the entire study region. Further, such high deployment density values greatly reduce the overall efficiency of the wind farm [173]. Occasionally, deployment density is conveyed as the number of turbines per square kilometer. The turbine density exhibited greater variation in offshore wind farms (0.05 to 2 turbines per km^2) compared to onshore installations (1 to 2 turbines per km^2).

In WRA simulation software, there are two methodologies utilized for turbine siting. Most studies implement a simple deployment density value across the available land area, typically estimated by assuming an even distribution of turbines over the available land based on with spacings ranging from 4 – 16 rotor diameters (median 10) in the prevailing wind direction and 3 – 16 rotor diameters (median 5) in the crosswind direction. This staggered placement of turbines aims to mitigate the impact of turbulence and wake effects on wind power generation. The remainder either simulate a turbine at sites where wind observations have been taken, or use more complex software to parameterize turbines, accounting for the prevailing wind and rotor diameter of the selected turbine model. It is worth mentioning that the approach to parameterize turbines is significantly more computationally demanding, hence only a handful of studies employ this method (e.g. [35,48,101,173,175,218,223]).

Despite being computationally straightforward and more reliable than the use of a simplistic deployment density value, this method remains somewhat rudimentary as it does not fully account for the complexity of wake effects, which are significantly influenced by wind speed, turbine characteristics and wind farm size (see Section 3.2.5). A minority of studies deployed an optimization solver for determining the optimum distance between turbines [141,181,190], while some others explored various spacing scenarios [93,101]. Nevertheless, as with the selection of land exclusions and turbine characteristics, most studies employed a static approach to turbine siting, rather than using multiple scenarios.

3.2.5. *Integrating wake effects and tropospheric kinetic energy loss in large-scale wind farm simulations*

Wake effects within wind farms have been extensively studied, given their significant impact on energy production efficiency [299,300]. These phenomena, primarily characterized by downwind velocity deficits and enhanced turbulence, are highly dependent on atmospheric conditions such as wind speed, temperature, and atmospheric stability. Traditional approaches to modelling wake effects include the Jensen model [301] and eddy viscosity models [302]. In recent years, a variety of modelling methodologies have been employed, including fluid dynamics simulations within NWP models like the WRF-ARW [303,304], as well as modern machine learning applications [305]. Moreover, the development of open-source software like PyWake [306] offers easy-to-use implementations of wake simulations within WRA workflows.

The pronounced rise in computing power, particularly through the application of advanced GPUs [307], has made it feasible to simulate wake effects in greater detail and over larger domains. However, our analysis showed that the majority of WRAs still employ a simplified process by applying a flat reduction factor to account for wake losses within wind farms. Typically, this is referred to as array efficiency, and accounts for additional losses such as electrical loss over the whole wind farm. In the literature, the median value for array efficiency was 0.88, which underrepresents the actual losses from wakes, which vary temporally in a range of around 10 % [308] -to 40 % [309]. While computationally expedient, the use of such a simplistic loss factor overlooks important interactions within the wind farm and implies that a significant portion of WRAs in the literature may provide overestimated potentials. Hence, the adoption of more comprehensive wake modelling approaches is important for improving the accuracy of WRAs.

The development of large wind farms, particularly those exceeding 100 km^2 [175], has revealed unique complexities in wind energy dynamics, characterized by large-scale wake effects, which can extend up to 70 km downwind from a large wind farm [163]. These dynamics are especially apparent in WRAs examining a study area of national scale or greater, or when employing a relatively high capacity density above around 1 MW/km^2 [173].

The complexities of these dynamics stem from the interplay between horizontal and vertical kinetic energy influx, which drives the electricity generation of a wind farm. At small scales, the available energy for the turbine is horizontal kinetic energy, which is converted to heat, mechanical energy, and turbulent kinetic energy. At larger scales, however, the wind farm depletes this horizontal energy, and thus kinetic energy must be replenished by vertical downflux from the lower levels of the troposphere above the hub height, as well as inflow from below the hub height [179]. The efficiency of this replenishment is intrinsically linked to meteorological aspects including atmospheric stability, prevailing weather conditions, and changes in wind speed and direction [76,163, 173].

Further, surface drag – attributable to local geographical features – similarly converts kinetic energy to heat and turbulent kinetic energy, reducing the available energy for downwind turbines. This large-scale extraction of kinetic energy from the lower levels of the planetary boundary layer (PBL), illustrated in Fig. 5, can result in considerable reductions in wind speeds at higher levels, increasing mechanical mixing and increasing local temperatures [175]. At sufficient scales, these effects extend to the global scale, prompting changes in circulation patterns such as a poleward shift of the Hadley Cell [99].

Finally, these effects have implications both for turbines located within a large wind farm and for turbines in nearby, downwind farms. Within a wind farm, a loss of wind speed up to 2.5 m/s downwind is possible [163] and at a high capacity density of 2.8 MW/km^2 or above, the internal turbine capacity factor is halved with a wind farm length of 82 km [93]. The concept of 'transitional scales' [76] refers to the scale of wind farms at which the turbine performance is affected more by upstream wind farms than by other local turbines. The transitional length is dependent on the stability of the planetary boundary layer but can result in significant capacity factor loss in nearby farms [163].

With these complex interactions, increased research focus is aimed at exploring the impacts of large-scale kinetic energy extraction on the maximum geophysical potential for wind energy production [99-101, 173,175,179]. Jacobson & Archer refer to this concept as the "saturation wind power potential" [179] and employ a global circulation model to calculate the maximum extractable wind power at 100 m. By parameterising wind turbines under various power density scenarios, simulating wind generation over numerous wind farms, and accounting for electricity and kinetic energy losses, they calculate a maximum global potential wind power of 253 TW, with 72 TW over land, excluding Antarctica and a further 8 TW over the near-shore ocean.

Further studies have estimated the maximum energy that can be extracted from the atmosphere by wind farms at expansive geographical scales. These studies employ atmospheric models, notably the WRF model [310] and the CESM v3.5 model [311] to parameterize wind turbines and account for the complex interactions with atmospheric circulation discussed above. The studies suggest relatively low limits, ranging from 1 to 3 W/m2 [101,175] for onshore, and up to 6.7 W/m2 for very large offshore wind farm installations [100]. However, these studies do not consider additional technical considerations (like array losses and transport/distribution losses), land eligibility assessments, and do not provide an overall estimate of installable capacity or potential generation (as in Archer & Jacobson [57]). Further, the scale of the wind farms is exceedingly high, far larger than what would be

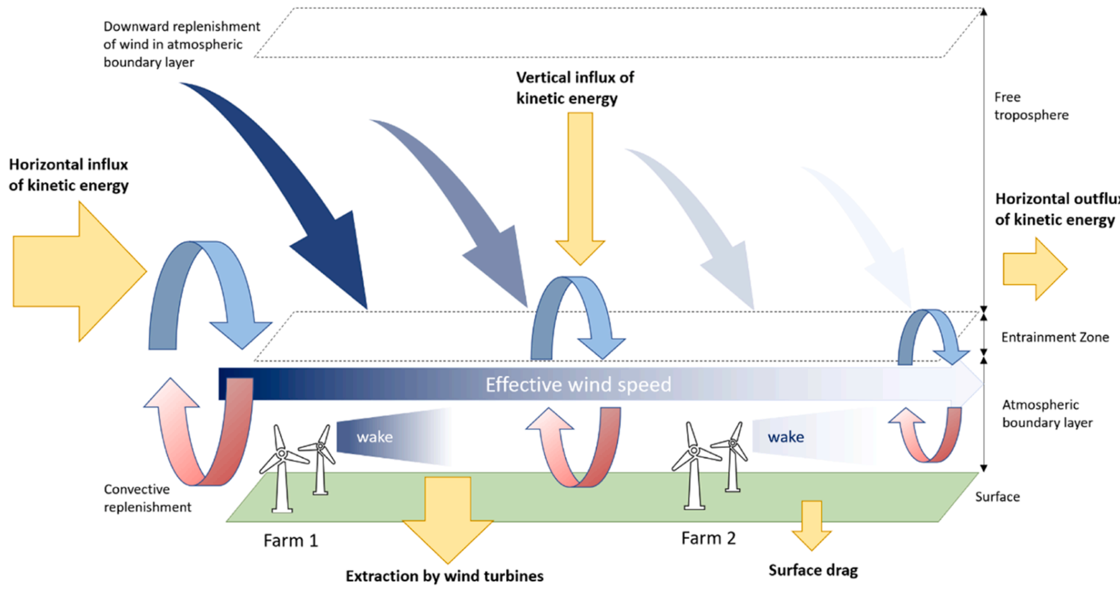
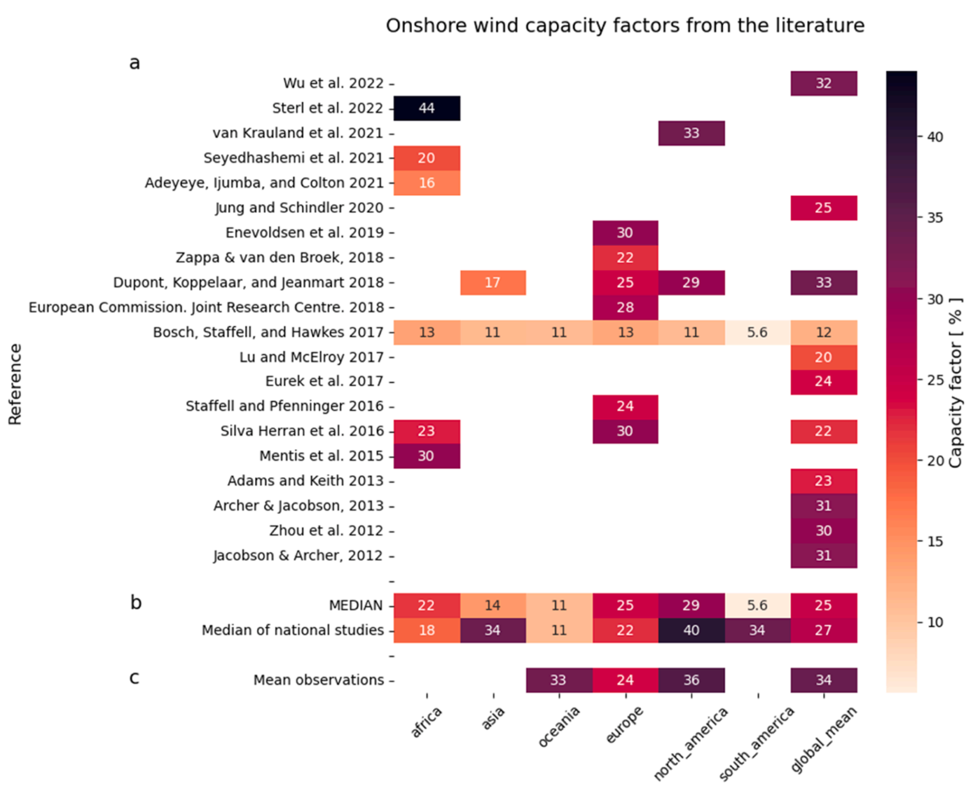


Fig. 5. Schematic diagram illustrating the energy flows and changes in effective wind speed over large areas including mulitple wind farms, and the diminishing effect on kinetic energy replenishment from the free troposphere. High wind speed is illustrated in dark blue, with lighter shades indicated reduced velocity. Energy flow is illustrated in yellow.Adapted from Kleidon & Miller [93].

constructed in the foreseeable future. Analysis of real-world data from wind operators in Europe [15] indicate that the mean output power density from currently installed onshore wind farms is much higher (6.64 W/m^2) for onshore farms, and within the estimated range (2.94 W/m^2) for offshore farms.

Given these complexities and the substantial effects on potential power generation at large scales, there is a pressing need for the increased adoption of advanced simulation methods that account for wake effects and kinetic energy extraction. As such, and considering the heterogenous approach to WRAs in general, the use of various datasets, differences in turbine characteristics and siting procedures, and additional factors outlined above, the results of the studies we analyzed show a high degree of variability, as illustrated in Fig. 6.



Reference	africa	asia	oceania	europe	north_america	south_america	global_mean
Wu et al. 2022							32
Sterl et al. 2022	44						
van Krauland et al. 2021					33		
Seyedhashemi et al. 2021	20						
Adeyeye, Ijumba, and Colton 2021	16						
Jung and Schindler 2020							25
Enevoldsen et al. 2019				30			
Zappa & van den Broek, 2018				22			
Dupont, Koppelaar, and Jeanmart 2018		17		25	29		33
European Commission. Joint Research Centre. 2018				28			
Bosch, Staffell, and Hawkes 2017	13	11	11	13	11	5.6	12
Lu and McElroy 2017							20
Eurek et al. 2017							24
Staffell and Pfenninger 2016				24			
Silva Herran et al. 2016	23			30			22
Mentis et al. 2015	30						
Adams and Keith 2013							23
Archer & Jacobson, 2013							31
Zhou et al. 2012							30
Jacobson & Archer, 2012							31
MEDIAN	22	14	11	25	29	5.6	25
Median of national studies	18	34	11	22	40	34	27
Mean observations			33	24	36		34

Fig. 6. Heatmap showing capacity factors calculated for 6 continental regions (onshore wind generation) from the literature (a), compared to the median values for national-scale studies in each region (b) and data from actual wind farms (c) for Australia [312], Europe [313], the USA [285] and global mean [314,315]. The figure highlights the heterogeneity of results arising from use of different datasets and methodologies.

3.3. Encouraging reproducibility in WRAs through open data and code sharing

3.3.1. Open data is essential for reproducibility

WRAs are multi-dimensional and complex, requiring multiple data inputs, including: wind, climate, topographic, environmental, economic, and land exclusion data, to name only a few [35]. Of all the data types, wind data is arguably the most consequential for WRA outcomes due to the cubic relationship between wind speed and power. Major sources for wind data are illustrated in Table 10. These data include: reanalysis datasets (e.g. ERA-5 [316] or MERRA-2 [206]), which combine multiple data sources such as observations from weather stations with numerical weather models meteorological data; observation data from weather stations, satellites, LiDAR, buoys, and weather balloons; aggregated wind atlases (e.g. Global Wind Atlas [205]), and numerical weather prediction (NWP) models (e.g. Weather Research & Forecasting Model [303]), which mathematically model the atmosphere using empirical equations to describe fluid flows, thermodynamics and radiative transfers [317]. Rarely, climate models such as the COSMO—CLM [318] or the CMIP6 model ensemble [319] are utilized.

In WRAs targeting current or imminent future conditions, reanalysis data are generally favoured over climate data as the latter often exhibit diminished accuracy [320,321] and a coarser spatial resolution [319]. Notably, while high-resolution climate datasets are available (e.g. HighResMIP [322]), we did not encounter any WRA using them for the analysis.

Although 80 % of the studies use open wind data, the methodology for processing the data (e.g., handling missing data, selecting the appropriate coordinate reference system) is documented in full by only 5 % of the articles ([52,125,130,173,175,182,186,206,207,221]). As an example, the methodology for vertical extrapolation of wind speed is commonly described, but details on the horizontal interpolation processes are sparse. Around a third of the studies provide a visual flowchart of the methodology, which often includes several data processing steps. Few studies disclose the version of the data used, a crucial element for reproducibility. Historically, access to certain types of wind data (for example, SCADA data) has been limited due to costs and proprietary rights. Recently, more open-source SCADA datasets have become available [327], adding valuable inputs for comprehensive open-source analysis Fig. 7.

The scarcity of studies which make their data downloadable is another area of concern, as illustrated in Fig. 7. Of the studies analyzed, only 16 % provide a statement on data availability in the article; 10 % make the output data available for download, and another 7 % offer the data on request (refer to the Excel file in the Supplementary Materials for the exact studies). The FAIR principles for scientific data stewardship and management [328] call for data that is findable, accessible, interoperable and reusable. Thus, over 83 % of the studies do not provide data that is findable and accessible, and therefore violate the FAIR principles.

3.3.2. Advocating the use of open-source software

All WRAs utilize geographical information software (GIS) for land eligibility assessments and simulation software to simulate wind power generation. In many instances, a combination of programs is employed. However, only 43 % of the studies provide an explicit description of the software used in the analysis. Some do reference a software program but do not mention the program's name. We identify several common software tools used in the literature, summarized in Table 11 and Table 12. Specific references to each program can be found in the supplementary Excel table and therefore, in the following tables, we only reference the number of mentions for each software program.

Our analysis reveals two categories of proprietary software used in WRAs: GIS software, such as ArcGIS [329], QGIS [330] and PostGIS [331], and wind simulation tools (see Table 11). GIS software is predominantly used for applying land category exclusions and identifying

Table 10
Overview of widely cited data sources in WRA literature including developers, open-source availability, and spatial-temporal resolutions.

Name	Developer	Open-source	Mentions in 192 WRA studies	Spatial resolution	
A - Reanalysis data					
ERA-5 [316]	ECMWF / Copernicus Climate Change Service	Yes	23 [61,62,65,73,75,77,85,87,89,98,104,139,150,152-154,157,158,161,164,198,203,224]	0.25	1
ERA-Interim [268]	ECMWF / Copernicus Climate Change Service	Yes	16 [53,57,80,82,86,88,96,98,103,122,138,166,211,215,227,323]	~0.7	6
MERRA [275]	NASA Global Modelling and Assimilation Office (GMAO)	Yes	15 [48,52-54,58,64,94,101,115,124,136,176-178,223]	0.5 × 0.625	1
MERRA-2 [206]	NASA Global Modelling and Assimilation Office (GMAO)	Yes	11 [52,55,61,74,77,129,135,143,157,183,202]	0.5 × 0.625	1
NCEP models, (e.g. NCEP-NCAR [324])	National Centers for Environmental Prediction (NCEP)	Yes	8 [51,53,86,90,117,155,160,174]	2.5 × 2.5	6
B - Meteorological stations					
Meteorological stations, satellites, and remote-sensing data	Government data or meteorological offices.	No	68 [53,56,59,60,62,65,66,68,69,71,72,75,77,81,82,84,92,95-98,102,107,109,116,119,125,130,131,134-136,142,144,148-150,155,162,163,168-172,176,184-186,188,191,194-196,198,200,205-207,209,210,213,213,218,219,221,236,325]	NA	Varied
C - Numerical weather prediction (NWP) models					
Weather Research Forecasting (WRF) model [310]	NCAR, NOAA, AFWA	Yes	15 [53,70,76,80,82,95,101,102,137,150,155,160,162,173,175]	Varied	Varied – 10 s to 1hr
Wind atlases					
Global Wind Atlas [205]	Technical University of Denmark (DTU)	Yes	17 [34,48,105,112,118,143,167,177,178,180,203,204,225,231,238,244]	~0.003	NA
National / industry wind atlases	Public or private sector research departments	Some	12 [57,63,69,85,133,181,187,190,216,217,233,235]	Varied	NA
D - Climate models					
Climate models (e.g. COSMO—CLM [326])	Public or private sector research departments	Some	13 [61,75,78,89,99,100,103,121,141,156,163,166,170]	Varied	Varied

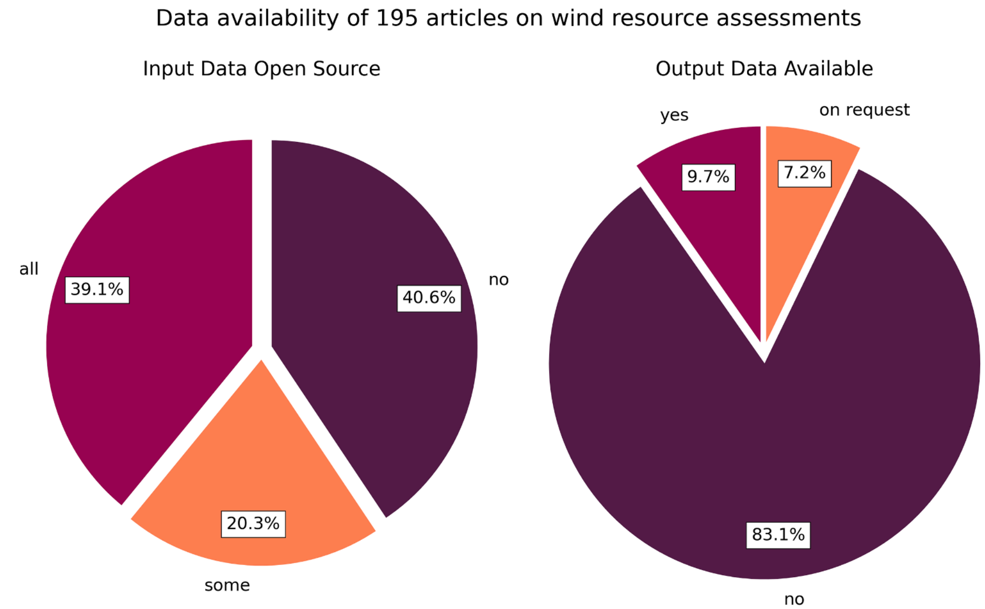


Fig. 7. Data availability for 195 articles which used data in their analyses. a) shows the proportion of open data used in the analyses, while b) shows the proportion of studies which made their calculated data available for download.

Table 11
Named proprietary software in the publications analysed for this literature review.

Program name	Developer	Mentions in 192 WRA studies	Open source	Programming language
A - GIS software for spatial analysis				
ArcGIS [329]	ESRI	21 [64,109,112,113,138,145,150,151,159,168,172,176,183,186,187,199,211,216,224,233,244]	No	Multiple
QGIS [330]	QGIS Development Team	2 [217,238]	Yes	C++, python
PostGIS [331]	Multiple	1 [168]	Yes	C
B - Wind resource simulation software				
WaSP [332]	DTU Wind Energy	13 [46,86,95,102,130,133,136,137,143,160,185,196,218]	No	Not available
WindSim [333]	WindSim AS	2 [64,160]	No	Not available
Meteodyn WT [334]	Meteodyn	1 [136]	No	Not available
WindPRO [335]	EMD International A/S	1 [136]	No	Not available
FirstLook [336]	3Tier	1 [72]	No	Not available
RIAM-COMPACT [337]	RIAM Computational Fluid Dynamics	1 [72]	No	Not available
C - Programming environments				
MATLAB [338]	MathWorks	6 [67,122,135,138,145,236]	MATLAB	Not available

suitable locations for siting. Wind simulation tools cater to a variety of applications within wind farm power generation simulation. For example, predicting wind power production based on wind turbine specifications and wind data and calculation of wind farm efficiency [332], or using computational fluid dynamics to simulate wind flow over complex terrains [333].

Issues relating to the use of proprietary, paid software in research have been apparent at least since 2012 [344], mainly due to its limitations in allowing for reproducibility in scientific research. Comparatively, open-source software offers a broad range of benefits. Typically, these are smaller-scale programs developed by a research institution, aiming to execute at least one key process within the WRA. They are free to use, although a hidden cost may be associated with learning the software, particularly if documentation is insufficient. Moreover, open-source software encourages community development and innovation, fostering a network of researchers and in some instances, furthering the development of standards and benchmarks.

However, a mere eight of the 195 articles [76,93,102,104,105,139,141,226] provide downloadable code, implying that the majority (96 %) of studies do not meet the requirements for scientific reproducibility. Despite the advantages of open-source software, their usage must be more transparent and accessible to improve transparency and reproducibility in WRAs.

4. Discussion and future recommendations

4.1. Summary of key findings

The term “wind potential” may refer to one of five definitions which are often inconsistently interpreted in the literature, making cross-study comparisons challenging. Most studies focus on technical potentials, which include land eligibility assessments and wind generation simulations. While these estimates are useful, they, along with techno-economic potentials, neglect important market, social, and political barriers to wind power development. Global and continental-scale technical potential estimates vary widely due to differences in data

Table 12
Open-source software developed by research institutes used in the literature analysed in the literature review. Where the model was used only once, the reference is included in the "Model name" column. Where the model is used more than once, or is not developed in study that employs it, the additional associated references can be found in the "Mentions" column.

Model name	Developer	Mentions in 192 studies	Programming language	Description
aiRthermo [339]	AI4CEE Lab of the National Technical University of Athens	1	R	A package for computing thermodynamics of atmospheric processes.
atlite [139]	PyPSA / atlite Team	1	Python	A package for calculating technical renewable power potentials and time series.
GATOR-GCMM [265]	Jacobson, M.	2 [179]	Unavailable	Global air pollution and weather forecast model built at University of Stanford
Geospatial Land Availability for Energy Systems (GLAES) [34]	Ryberg, S., Robinus, M., & Stolten, D.	4 [35,48,223]	Python	A package for conducting land eligibility assessments for energy system analyses.
GlobalEnergyGIS [340]	Mattsson, N.	1	Julia	A package for generating input data to use in energy system models.
KEBA model of the atmosphere [93]	Kleidon, A, & Miller, L.	1	Microsoft Excel	A simulation tool for calculating the effect of large wind farms on kinetic energy in the troposphere.
Renewable Energy Potential (reV) Model [226]	National Renewable Energy Laboratory (NREL)	3 [192,232]	Python	A toolkit for simulating renewable energy generation, LCOEs, energy supply curves and geospatial analysis.
RESKit [48]	Ryberg, et al.	1	Python	A toolkit to help generate renewable energy generation time-series for energy systems analysis
RETscreen Clean Energy Management Software [341]	Government of Canada	2 [111,127]	Unavailable	Management software for assessing the viability of clean energy projects and investments.
Systems Advisor Model (SAM) [342]	National Renewable Energy Laboratory (NREL)	1 [192]	C++	Performance and financial model for facilitating decision making in renewable energy projects.
Virtual Wind Farm Model / Renewables.Ninja [52]	Staffell, I., & Pfenninger, S.	1	Python, MATLAB	A simulation tool for turbine power output based on MERRA data.
WindCurves [343]	Bokde, N. & Feijoo, A.	1 [142]	R	A tool to fit and compare wind turbine power curves with successful fitting techniques.

sources, assumptions surrounding technical characteristics of turbines and wind farm layouts, and methods for assessing land-use eligibility. Onshore wind generally shows a higher overall potential than offshore, despite the greater offshore wind speeds. Yet, large-scale WRA studies show a bias toward the Northern Hemisphere, overlooking regions with significant potential such as Southern and Northern Africa, and South America.

Innovative methods for capturing non-technical aspects and estimating feasible potentials, include multi-criteria decision analysis (MCDA) methods, such as analytical hierarchy process (AHP) and fuzzy-TOPSIS, which offer promising results. However, practical challenges remain, including computational demands and complexities regarding assignment of weights to various criteria.

High quality wind data is essential for the accuracy of WRAs. While reanalysis data is favored, there is significant variability in wind data sources in the literature. All available wind datasets have limitations, with significant discrepancies observed across common datasets. Despite the clear benefit of using multiple sources, most studies continue to rely on a single wind dataset and only a fifth of studies performed validation on the input data.

In terms of methodological gaps, as turbine hub heights continue to increase, the choice of wind speed extrapolation methods gain importance. While the power law remains the most popular, its limitations become more apparent at higher hub heights. Advanced methods, such as least squares fitting, remain rare in the literature, despite their benefits. Additionally, the variability of wind poses challenges for accurate WRAs. Despite the importance of phenomena such as wind droughts, turbulence, and extreme conditions, these aspects are often underrepresented, and most studies employ data over periods too short to capture the region's climatology and identify long-term trends.

A further point of concern is that the literature tends to use turbine characteristics that do not fully reflect the ongoing improvements in performance. Best practices suggest modelling near-future turbines and considering a range of models, while almost half the studies employ a single turbine model and employ optimistic power density factors to model turbine placement, which may lead to overestimated potentials. Finally, modelling the effects of wakes and kinetic energy extraction are crucial for accurate estimates in large-scale WRAs, especially for farms exceeding $100km^2$ or with high turbine densities. At large scales, the use of simple loss factors is not sufficient to capture the complex dynamics of wind flow within the wind farm. However, there are significant computational barriers to performing such simulations at high resolutions.

Regarding reproducibility of results, while most studies employ open data sources, only a small fraction fully document their processing methodology. This lack of transparency extends to the principles of FAIR data management, as over 83 % of studies do not make their output data available. While GIS and simulation software are integral to WRAs, only 43 % of the studies in our review mention the software they employed. Furthermore, the ongoing use of proprietary software poses challenges to reproducibility, and open-source alternatives exist. Alarmingly, only 4 % of studies provide downloadable code, hindering the capacity for scientific reproducibility.

4.2. Limitations

We can, however, note several limitations to our study. While the systematic approach was designed to capture the full breadth of the field, it is possible that we overlooked significant studies that were not captured by our literature search, or that were outside of the evaluation period (e.g. [290,291,345]). The databases we searched (see Appendix Table 13), SCOPUS and Web of Science, though extensive, have their own indexing criteria, which may introduce a selection bias. We opted to avoid performing a rigorous quality assessment of the papers before including them in our review, to present a clear picture of the field that is not limited to the papers illustrating best practices. However, this could affect the reliability of the results. Furthermore, results from conference papers, unpublished studies and grey literature were not included in our analysis. Finally, our paper only encompasses literature published between 2012 and 2022, necessitating periodic future updates to remain current. Nonetheless, despite these constraints, we are confident that our review offers a thorough evaluation of the current state of wind resource assessment research, and that the results can be applied across the field.

4.3. Discussion and future recommendations

Our review highlights the heterogeneity in the methodologies used across WRAs. The absence of an explicitly defined workflow and standardized processes is a significant issue in the reliability of outcomes. The consideration of geographically- and income-dependent socio-political barriers to development in WRAs, as opposed to merely assessing the technical or economic potential, is essential for providing results that can spur informed discussion in the energy field. In this regard, nations in the Northern Hemisphere dominate the literature focus and there is an urgent need to include a wider geographical extend, especially considering the high potential for renewables in lower-income countries. However, even the incorporation of complex, ambiguous concerns in WRAs does not guarantee results that have relevance outside the academic sphere. As an example, despite the progressive adoption of tools such as multi-criteria decision analysis models and neural networks, most studies still employ simplistic methods for assuming the placement of turbines, with significantly higher capacity densities than seen in real-life – thereby producing overly optimistic results.

The reproducibility issues in WRAs also demands immediate attention. While the utilization of open data is promising, the literature often lacks comprehensive documentation of processing methodologies, hampering its potential to serve as a beneficial resource. Furthermore, the minor percentage of studies providing downloadable data and code starkly contrasts with the scientific community's push towards open access and reproducibility. Addressing these deficiencies will enhance scientific credibility and foster trust and collaboration in the broader community.

In this review, we define accuracy as the ability of a WRA to capture the actual or true wind generation potential of a region. The methodology involves progressively limiting the available land for development by performing land category exclusions, applying a capacity density value, or using a software program to place wind turbines with specific characteristics in the remaining area, and then simulating the wind and other meteorological conditions, thereby ascertaining the turbines' capacity factor and full load hours. While improvements have been made in terms of both land exclusions and simulations, the accuracy of WRAs can be further improved by employing multiple scenarios for turbine characteristics and siting regimes, validating both input data and results, employing sensitivity analyses, and better accounting for complex phenomena such as the effects of large-scale wakes on downwind farms. With wind energy's promising trajectory, ensuring high-quality WRAs is essential to set the stage for informed decision-making and to provide actionable insights.

Based on our findings and the above discussion, we can outline the following suggestions for improvements in state-of-the-art WRAs:

- **Feasible wind potential assessments** attempt to account for socio-political barriers to development in addition to technical and economic aspects, to produce results that are as close to real-world wind potentials as possible. The complexity of this modelling increases when weighing different objectives, which involves subjective considerations. The adoption of novel methods including machine learning algorithms and multi-criteria decision analysis tools are promising paths, but more focus is needed in this area. WRAs should shift away from technical and techno-economic assessments to better incorporate socio-political barriers which show significant geographical disparities.
- The use of **multiple scenarios, sensitivity analyses, and validation of both input data and results** against real-world observations is essential, given the heterogeneity of data and approaches used in WRAs. By acknowledging and explicitly addressing ambiguity and uncertainties, WRAs can produce outputs that are more robust and actionable in the real world. Especially important is the use of multiple siting scenarios since the literature shows a significantly greater capacity density than in real-world wind farms. Validation of results must be extended the costs and impacts of wind development, not solely the potential output.
- The is an **urgent need to promote the open access to research resources** such as processed data and code used in the WRA, to ensure accessibility and reproducibility of the results in accordance with good scientific practices. It is concerning that only 10 % of the studies provided accessible data, and only 4 % offer downloadable code. Adhering to the FAIR principles of data management and stewardship is essential for upholding scientific rigor.
- **Turbine model characterization and siting techniques** can more accurately represent real-world conditions when a selection of near-future turbine models is used, and more detailed justifications for turbine siting methods are given.
- Given the increasingly important role of **large-scale wake effects for large wind farms,** advanced simulations of complex phenomena, within and between wind farms, will be indispensable for enhancing the accuracy of WRAs. Our analysis reveals that current methods for accounting for wake effects at large scales may be oversimplified, leading to potential overestimations.
- **Resource assessments must better address underrepresented regions, particularly in the Southern Hemisphere**, where there is currently a dearth of research. Notably, only 9 % of the 195 studies focused specifically on Southern Hemisphere nations. There were an additional six continent-scale African analyses, only two of which were led by authors with African affiliations.
- Finally, we advocate for a **standardized workflow approach** to manage the tasks contained within WRAs. Since all WRAs perform a general sequence of tasks in a specific order, there is room for developing an open-source workflow management system, to help manage the heterogeneity of approaches, and ensure standards and best-practices are upheld.

CRediT (contributor roles taxonomy) author statement

The following abbreviations are used: Conceptualization (C), Methodology (M), Formal Analysis (FA), Writing - original draft (WO), Writing - review & editing (WR), Supervision (S), Project administration (PA), Funding acquisition (FU), Visualization (V). **TP:** C, M, FA, WO, WR, V. **JW:** C, WR, S, PA, V. **PK**: C, WR, S. **RM**: WR. **JL**: WR. **DS**: FU.

Research data statement

The accompanying research data is provided as an Open Access Excel Table and hosted on Jülich Data repository.

Declaration of generative AI and AI-assisted technologies in the writing process

Statement: During the preparation of this work the author used the tool "ChatGPT" by OpenAI in order to check grammar and spelling in a few places, and to make minor improvements to readability and style. After using this tool, the author reviewed and edited the content as needed, and takes full responsibility for the content of the publication.

Declaration of competing interest

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

Data availability

The data is shared on an open source repository at Jülich Data, and there is a link to the data in the manuscript.

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Appendix

Table 13
Search terms employed for the literature review search on SCOPUS and Web of Science Core. We include all "article" type publications between 2012 and 2022.

SCOPUS		Web of Science Core	
Search term	Results	Search term	Results
TITLE-ABS-KEY (wind AND (power OR generation OR energy) AND (evaluat* OR assess* OR analy* OR pot* OR plan* OR simul* OR optimi* OR model*)	200′783	TS=(wind AND (power OR generation OR energy) AND (evaluat* OR assess* OR analy* OR pot* OR plan* OR simul* OR optimi* OR model*))	161′491
AND TITLE ("wind power" OR "wind energy" OR "wind resource" AND (evaluat* OR assess* OR analy* OR pot* OR plan* OR simul* OR optimi* OR model))	11′427	AND TI = ("wind power" OR "wind energy" OR "wind resource" AND (evaluat* OR assess* OR analy* OR pot* OR plan* OR simul* OR optimi* OR model))	16′968
AND TITLE-ABS-KEY (potential OR locat*) AND (generation OR cost OR lcoe OR econom*))	1′859	AND TS=(potential OR locat*) AND (generation OR cost OR lcoe OR econom*))	2′458
AND SRCTYPE (j) AND PUBYEAR > 2012 AND (LIMIT-TO (DOCTYPE, "ar"))	1′132	AND DT=(Article) + *Timespan: 2012–01–01 to 2022–10–01 (Index Date)*	1′300
TOTAL	**1′132**		**1′300**

Table 14
Distribution of the 195 reviewed papers by journal, including the 2022–2023 journal impact factor and the share of total studies. Only those journals with five or more studies are included in this table.

Journal	Impact Factor (2022–2023)	Studies	Share of total 195 studies [%]
Renewable Energy	8.634	24	12
Energy	8.857	18	9
Renewable & Sustainable Energy Reviews	16.799	13	7
Energies	3.252	13	7
Applied Energy	11.446	10	5
Energy Policy	7.576	8	4
Journal of Cleaner Production	11.072	5	3
Sustainable Energy Technologies and Assessments	7.632	5	3

Table 15
The 20 most relevant studies by global citations in the field of large-scale wind resource potential estimations (06.06.2023).

Reference	Title	Journal	Cited by[2]
Staffell I., Pfenninger S., 2016 [52]	Using bias-corrected reanalysis to simulate current and future wind power output	*Energy*	657
Staffell I., Green R., 2014 [115]	How does wind farm performance decline with age?	*Renewable Energy*	313
Carvalho D., et al., 2014 [53]	WRF wind simulation and wind energy production estimates forced by different reanalyses: Comparison with observed data for Portugal	*Applied Energy*	191
Zheng C.-W., Pan J., Li J.-X., 2013 [79]	Assessing the China Sea wind energy and wave energy resources from 1988 to 2009	*Ocean Engineering*	183
He G., Kammen D.M., 2014 [168]	Where, when and how much wind is available? A provincial-scale wind resource assessment for China	*Energy Policy*	135
Mentis D., et al., 2015 [113]	Assessing the technical wind energy potential in Africa a GIS-based approach	*Renewable Energy*	126
Mahdy M., Bahaj A.S., 2018 [233]	Multi criteria decision analysis for offshore wind energy potential in Egypt	*Renewable Energy*	113
Cavazzi S., Dutton A.G., 2016 [216]	An Offshore Wind Energy Geographic Information System (OWE-GIS) for assessment of the UK's offshore wind energy potential	*Renewable Energy*	107
Grassi S., Chokani N., Abhari R.S., 2012 [193]	Large scale technical and economical assessment of wind energy potential with a GIS tool: Case study Iowa	*Energy Policy*	101
Dupont, E., Koppelaar, R., Jeanmart, H., 2018 [227]	Global available wind energy with physical and energy return on investment constraints	*Applied Energy*	99
Marvel, K., Kravitz, B., Caldeira, K., 2013 [99]	Geophysical limits to global wind power	*Nature Climate Change*	96
Eurek, K., et al., 2017 [174]	An improved global wind resource estimate for integrated assessment models	*Energy Economics*	94
Wu, Y., et al., 2020 [234]	A decision framework of offshore wind power station site selection using a PROMETHEE method under intuitionistic fuzzy environment: A case in China	*Ocean and Coastal Management*	89
McKenna, R., Hollnaicher, S., Fichtner, W., 2014 [186]	Cost-potential curves for onshore wind energy: A high-resolution analysis for Germany	*Applied Energy*	88
Mattar, C., Borvarán, D., 2016 [80]	Offshore wind power simulation by using WRF in the central coast of Chile	*Renewable Energy*	86
Siyal, S.H., et al., 2015 [172]	Wind energy assessment considering geographic and environmental restrictions in Sweden: A GIS-based approach	*Energy*	79
Zhang, J., et al., 2015 [124]	Comparison of numerical weather prediction based deterministic and probabilistic wind resource assessment methods	*Applied Energy*	79
Adams, A.S., Keith, D.W., 2013 [175]	Are global wind power resource estimates overstated?	*Environmental Research Letters*	79

(*continued on next page*)

Table 15 (*continued*)

Reference	Title	Journal	Cited by[2]
Mohsin, M., et al., 2019 [208]	Economic assessment and ranking of wind power potential using fuzzy-TOPSIS approach	*Environmental Science and Pollution Research*	78
Khaled M. Bataineh, Doraid Dalalah [116]	Assessment of wind energy potential for selected areas in Jordan	*Renewable Energy*	77

S According to SCOPUS bibliometric information, June 2023.

The first step in any wind potential analysis is to conduct a land eligibility assessment, such that the available land area for the development of wind power projects is made available for the computer model. Aligning to the findings of Risch et al. [35], we found that this process generally proceeded according to a "greenfield" approach, whereby all the land in the region is first assumed to be available, and then land is progressively excluded according to the criteria set for the land eligibility assessment. The only other method that we encountered, were cases where the "available land area" referred to several sites where wind speed measurements were performed, and thus the final wind power potential was "site-specific" instead of an estimate for the entire geographical region (e.g. [125,129,144,205,218]). In contrast, MCDA methods, as illustrated in studies such as [75,111,218,227], often diverge from the greenfield approach in that their siting method is not based on a systematic removal of ineligible land. Rather, they utilize soft (< 100 %) weightings to evaluate various site selection criteria, to explicitly encapsulate the ambiguity and potential trade-offs that are prevalent in real-world siting projects. It is noteworthy that many studies incorporate a hybrid approach by applying "hard" or absolute exclusions to certain land categories, and then proceeding with the MCDA approach for the remaining available land area. This approach reflects a departure from traditional blanket exclusions to a more comprehensive decision-making paradigm.

The selection of appropriate exclusion criteria, buffer sizes and the associated datasets is important for accurately quantifying the available land area to develop wind projects. These have been reviewed in previous studies (e.g. [7,34,35]), and we therefore do not explore this topic in detail. Nevertheless, it is important to mention that there is currently no standardised approach to performing land exclusion analyses – with regards to which exclusions to apply, which datasets to use, and what size of buffer to apply around various exclusion criteria. For example, in the literature for onshore potentials we reviewed, the maximum height above sea level for excluding turbine construction ranged from 1500 m [202,217] to 4000 m [189,204], the buffer around urban and residential areas ranged from 0 m (e.g. [51,117,118,142,192,201]) to 5000 m [202]; and the slope exclusion ranged from 2,41° [168] to 30° [203,224]. Similarly, for offshore assessments, the maximum depth of water for constructing wind projects ranged from 20 m [168] to 100 m [161], for fixed monopiles, and 150 m [189] and 1000 m [87,174,227,235] for floating constructions. The minimum distance from the shoreline ranged from 1 km [218] to 22 km [178,222]; and the setback around oil and gas platforms ranged from 0 m [221] to 7,5 km [235].

It is also noteworthy that there exist national and, in some cases like Germany subnational regulations regarding various setback distances – which means that a one-size-fits-all approach is not possible for assigning exclusion criteria and setback distances. Often, when buffer regulations are not available, proxies are used (e.g. [238]). However, we identified a noticeable lack of clarity in many studies for justifying the selection criteria for exclusions, as well as the basis for determining which setback distances to use. In certain cases, the rationale was not communicated at all.

Complimenting this, as McKenna et al. [7] highlighted, there was a noteworthy scarcity of studies employing sensitivity analyses for various land exclusions and setback distances (as seen in, for example, Risch et al. [35]). While a few studies did incorporate different exclusion scenarios, they typically did not extend this approach so far as to include a sensitivity analysis. The majority of studies thus relied on a single set of exclusion criteria and setback distances, leading to a static set of results. Such results offer limited utility in guiding policy or industry, particularly in light of recent results from Hedenus et al. [14], indicating substantial discrepancies between modelled exclusions and those employed in real-world wind farm projects.

References

[1] International Energy Agency (IEA), 'CO2 emissions in 2022′, International Energy Agency (IEA), 2023. [Online]. Available: https://www.iea.org/reports/co2-emissions-in-2022.

[2] L. Clarke et al., 'Chapter 6: energy systems', in In IPCC, 2022: climate change 2022: mitigation of climate change. Contribution of working group iii to the sixth assessment report of the intergovernmental panel on climate change., Cambridge, UK and New York, NY, USA: Cambridge University Press, pp. 613–746. [Online]. Available: doi:10.1017/9781009157926.008.

[3] IEA, 'Renewables 2022′, IEA, Paris, 2022. [Online]. Available: https://www.iea.org/reports/renewables-2022.

[4] Global Wind Energy Council (GWEC), 'Global wind report 2023′, GWEC, Brussels, Belgium, Mar. 2023. [Online]. Available: GWEC.NET.

[5] International Energy Agency (IEA), 'World energy outlook 2022′, International Energy Agency (IEA), Paris. [Online]. Available: https://www.iea.org/reports/world-energy-outlook-2022.

[6] Murthy KSR, Rahi OP. A comprehensive review of wind resource assessment. Renew Sustain Energy Rev 2017;72:1320–42. https://doi.org/10.1016/j.rser.2016.10.038.

[7] McKenna R, et al. High-resolution large-scale onshore wind energy assessments: a review of potential definitions, methodologies and future research needs. Renew Energy 2022;182:659–84. https://doi.org/10.1016/j.renene.2021.10.027.

[8] Diaba-Nuhoho P, Amponsah-Offeh M. Reproducibility and research integrity: the role of scientists and institutions. BMC Res Notes 2021;14(1):451. https://doi.org/10.1186/s13104-021-05875-3.

[9] Gundersen OE. The fundamental principles of reproducibility. Philos Trans R Soc A 2021;379(2197):20200210. https://doi.org/10.1098/rsta.2020.0210.

[10] Understanding reproducibility and replicability. Reproducibility and replicability in science. Washington, D.C.: National Academies Press; 2019. p. 39–55. https://doi.org/10.17226/25303.

[11] Keivanpour S, Ramudhin A, Kadi DAit. The sustainable worldwide offshore wind energy potential: a systematic review. J Renew Sustain Energy 2017;9(6):065902. https://doi.org/10.1063/1.5009948.

[12] Wimalaratna YP, Afrouzi HN, Mehranzamir K, Siddique MBM, Liew SC, Ahmed J. Analysing wind power penetration in hybrid energy systems based on techno-economic assessments. Sustain Energy Technol Assess 2022;53:102538. https://doi.org/10.1016/j.seta.2022.102538.

[13] Shafiullah GM, Oo AMT, Shawkat Ali ABM, Wolfs P. Potential challenges of integrating large-scale wind energy into the power grid—a review. Renew Sustain Energy Rev 2013;20:306–21. https://doi.org/10.1016/j.rser.2012.11.057.

[14] Hedenus F, Jakobsson N, Reichenberg L, Mattsson N. Historical wind deployment and implications for energy system models. Renew Sustain Energy Rev 2022;168:112813. https://doi.org/10.1016/j.rser.2022.112813.

[15] Enevoldsen P, Jacobson MZ. Data investigation of installed and output power densities of onshore and offshore wind turbines worldwide. Energy Sustain Dev 2021;60:40–51. https://doi.org/10.1016/j.esd.2020.11.004.

[16] Azevêdo R, Rotela Junior P, Chicco G, Aquila G, Rocha LC, Peruchi R. Identification and analysis of impact factors on the economic feasibility of wind energy investments. Int J Energy Res 2021;45(3):3671–97. https://doi.org/10.1002/er.6109.

[17] Nazir MS, Ali N, Bilal M, Iqbal HMN. Potential environmental impacts of wind energy development: a global perspective. Curr Opin Environ Sci Health 2020;13:85–90. https://doi.org/10.1016/j.coesh.2020.01.002.

[18] Tasneem Z, et al. An analytical review on the evaluation of wind resource and wind turbine for urban application: prospect and challenges. Dev Built Environ 2020;4:100033. https://doi.org/10.1016/j.dibe.2020.100033.

[19] Reja RK, et al. A review of the evaluation of urban wind resources: challenges and perspectives. Energy Build 2022;257:111781. https://doi.org/10.1016/j.enbuild.2021.111781.

[20] Zwarteveen JW, Figueira C, Zawwar I, Angus A. Barriers and drivers of the global imbalance of wind energy diffusion: a meta-analysis from a wind power Original Equipment Manufacturer perspective. J Clean Prod 2021;290:125636. https://doi.org/10.1016/j.jclepro.2020.125636.

[21] Brown TW, Bischof-Niemz T, Blok K, Breyer C, Lund H, Mathiesen BV. Response to "Burden of proof: a comprehensive review of the feasibility of 100% renewable-electricity systems. Renew Sustain Energy Rev 2018;92:834–47. https://doi.org/10.1016/j.rser.2018.04.113.

[22] Sánchez-del Rey A, Gil-García IC, García-Cascales MS, Molina-García Á. Online Wind-Atlas Databases and GIS tool integration for wind resource assessment: a Spanish case study. Energies 2022;15(3):852. https://doi.org/10.3390/en15030852.

[23] Lopez G, et al. Impacts of model structure, framework, and flexibility on perspectives of 100% renewable energy transition decision-making. Renew Sustain Energy Rev 2022;164:112452. https://doi.org/10.1016/j.rser.2022.112452.

[24] Christidis T, Law J. Review: the use of geographic information systems in wind turbine and wind energy research. J Renew Sustain Energy 2012;4(1):012701. https://doi.org/10.1063/1.3673565.

[25] Kaldellis JK, Kapsali M. Shifting towards offshore wind energy—recent activity and future development. Energy Policy 2013;53:136–48. https://doi.org/10.1016/j.enpol.2012.10.032.

[26] Wiser R, et al. Expert elicitation survey predicts 37% to 49% declines in wind energy costs by 2050. Nat Energy 2021;6(5):555–65. https://doi.org/10.1038/s41560-021-00810-z.

[27] Gualtieri G. A comprehensive review on wind resource extrapolation models applied in wind energy. Renew Sustain Energy Rev 2019;102:215–33. https://doi.org/10.1016/j.rser.2018.12.015.

[28] Shi H, Dong Z, Xiao N, Huang Q. Wind speed distributions used in wind energy assessment: a review. Front Energy Res 2021;9:769920. https://doi.org/10.3389/fenrg.2021.769920.

[29] Jiang H, Wang J, Wu J, Geng W. Comparison of numerical methods and metaheuristic optimization algorithms for estimating parameters for wind energy potential assessment in low wind regions. Renew Sustain Energy Rev 2017;69:1199–217. https://doi.org/10.1016/j.rser.2016.11.241.

[30] Archer CL, et al. Review and evaluation of wake loss models for wind energy applications. Appl Energy 2018;226:1187–207. https://doi.org/10.1016/j.apenergy.2018.05.085.

[31] Bermejo JFerrero, Gómez Fernández JF, Polo FOlivencia, Crespo Márquez A. A review of the use of artificial neural network models for energy and reliability prediction. A study of the solar PV, hydraulic and wind energy sources. Appl Sci 2019;9(9):1844. https://doi.org/10.3390/app9091844.

[32] Rediske G, Burin HP, Rigo PD, Rosa CB, Michels L, Siluk JCM. Wind power plant site selection: a systematic review. Renew Sustain Energy Rev 2021;148:111293. https://doi.org/10.1016/j.rser.2021.111293.

[33] Baker M. 1,500 scientists lift the lid on reproducibility. Nature 2016;533(7604):452–4. https://doi.org/10.1038/533452a.

[34] Ryberg DS, Robinius M, Stolten D. Evaluating land eligibility constraints of renewable energy sources in Europe. Energies 2018;11(5). https://doi.org/10.3390/en11051246.

[35] Risch S, et al. Potentials of renewable energy sources in germany and the influence of land use datasets. Energies 2022;15(15). https://doi.org/10.3390/en15155536.

[36] Page MJ, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372. https://doi.org/10.1136/bmj.n71.

[37] Kong F, Dong C, Liu X, Zeng H. Quantity versus quality: optimal harvesting wind power for the smart grid. Proc IEEE 2014;102(11):1762–76. https://doi.org/10.1109/JPROC.2014.2359448.

[38] Castorrini A, Gentile S, Geraldi E, Bonfiglioli A. Increasing spatial resolution of wind resource prediction using NWP and RANS simulation. J Wind Eng Ind Aerodyn 2021;210:104499. https://doi.org/10.1016/j.jweia.2020.104499.

[39] Ghimire S, Alizadeh SM. Developing a decision tree algorithm for wind power plants siting and sizing in distribution networks. Energies 2021;14(8):2293. https://doi.org/10.3390/en14082293.

[40] Geißler G, Köppel J, Gunther P. Wind energy and environmental assessments—a hard look at two forerunners' approaches: Germany and the United States. Renew Energy 2013;51:71–8. https://doi.org/10.1016/j.renene.2012.08.083.

[41] Chen X, Foley A, Zhang Z, Wang K, O'Driscoll K. An assessment of wind energy potential in the Beibu Gulf considering the energy demands of the Beibu Gulf Economic Rim. Renew Sustain Energy Rev 2020;119:109605. https://doi.org/10.1016/j.rser.2019.109605.

[42] Badawi ASA, et al. Evaluation of wind power for electrical energy generation in the Mediterranean coast of Palestine for 14 years. IJECE 2019;9(4):2212. https://doi.org/10.11591/ijece.v9i4.pp2212-2219.

[43] Almutairi K, Hosseini Dehshiri SS, Hosseini Dehshiri SJ, Mostafaeipour A, Jahangiri M, Techato K. Technical, economic, carbon footprint assessment, and prioritizing stations for hydrogen production using wind energy: a case study. Energy Strategy Rev 2021;36:100684. https://doi.org/10.1016/j.esr.2021.100684.

[44] Khraiwish Dalabeeh AS. Techno-economic analysis of wind power generation for selected locations in Jordan. Renew Energy 2017;101:1369–78. https://doi.org/10.1016/j.renene.2016.10.003.

[45] Karthikeya BR, Negi PS, Srikanth N. Wind resource assessment for urban renewable energy application in Singapore. Renew Energy 2016;87:403–14. https://doi.org/10.1016/j.renene.2015.10.010.

[46] Jäger T, McKenna R, Fichtner W. The feasible onshore wind energy potential in Baden-Württemberg: a bottom-up methodology considering socio-economic constraints. Renew Energy 2016;96:662–75. https://doi.org/10.1016/j.renene.2016.05.013.

[47] Hoogwijk M, de Vries B, Turkenburg W. Assessment of the global and regional geographical, technical and economic potential of onshore wind energy. Energy Econ 2004;26(5):889–919. https://doi.org/10.1016/j.eneco.2004.04.016.

[48] Ryberg DS, Caglayan DG, Schmitt S, Linßen J, Stolten D, Robinius M. The future of European onshore wind energy potential: detailed distribution and simulation of advanced turbine designs. Energy 2019;182:1222–38. https://doi.org/10.1016/j.energy.2019.06.052.

[49] Archer CL, Jacobson MZ. Geographical and seasonal variability of the global "practical" wind resources. Appl Geogr 2013;45:119–30. https://doi.org/10.1016/j.apgeog.2013.07.006.

[50] Caglayan DG, et al. Technical potential of salt caverns for hydrogen storage in Europe. Int J Hydrogen Energy 2020;45(11):6793–805. https://doi.org/10.1016/j.ijhydene.2019.12.161.

[51] Zhou Y, Luckow P, Smith SJ, Clarke L. Evaluation of global onshore wind energy potential and generation costs. Environ Sci Technol 2012;46(14):7857–64. https://doi.org/10.1021/es204706m.

[52] Staffell I, Pfenninger S. Using bias-corrected reanalysis to simulate current and future wind power output. Energy 2016;114:1224–39. https://doi.org/10.1016/j.energy.2016.08.068.

[53] Carvalho D, Rocha A, Gómez-Gesteira M, Santos CSilva. WRF wind simulation and wind energy production estimates forced by different reanalyses: comparison with observed data for Portugal. Appl Energy 2014;117:116–26. https://doi.org/10.1016/j.apenergy.2013.12.001.

[54] Hallgren W, Gunturu UB, Schlosser A. The potential wind power resource in Australia: a new perspective. PLoS One 2014;9(7). https://doi.org/10.1371/journal.pone.0099608.

[55] Gao Y, Ma S, Wang T, Miao C, Yang F. Distributed onshore wind farm siting using intelligent optimization algorithm based on spatial and temporal variability of wind energy. Energy 2022;258. https://doi.org/10.1016/j.energy.2022.124816.

[56] Liang Y, et al. Statistical modelling of the joint probability density function of air density and wind speed for wind resource assessment: a case study from China. Energy Convers Manage 2022;268. https://doi.org/10.1016/j.enconman.2022.116054.

[57] Ekström J, Koivisto M, Mellin I, Millar J, Saarijärvi E, Haarla L. Assessment of large scale wind power generation with new generation locations without measurement data. Renew Energy 2015;83:362–74. https://doi.org/10.1016/j.renene.2015.04.050.

[58] Ritter M, Shen Z, López Cabrera B, Odening M, Deckert L. Designing an index for assessing wind energy potential. Renew Energy 2015;83:416–24. https://doi.org/10.1016/j.renene.2015.04.038.

[59] Correia JM, Bastos A, Brito MC, Trigo RM. The influence of the main large-scale circulation patterns on wind power production in Portugal. Renew Energy 2017;102:214–23. https://doi.org/10.1016/j.renene.2016.10.002.

[60] Kruyt B, Lehning M, Kahl A. Potential contributions of wind power to a stable and highly renewable Swiss power supply. Appl Energy 2017;192:1–11. https://doi.org/10.1016/j.apenergy.2017.01.085.

[61] Davidson MR, Millstein D. Limitations of reanalysis data for wind power applications. Wind Energy 2022;25(9):1646–53. https://doi.org/10.1002/we.2759.

[62] Gil Ruiz SA, Barriga JEC, Martínez JA. Wind power assessment in the Caribbean region of Colombia, using ten-minute wind observations and ERA5 data. Renew Energy 2021;172:158–76. https://doi.org/10.1016/j.renene.2021.03.033.

[63] Ayodele TR, Jimoh AA, Munda JL, Agee JT. A statistical analysis of wind distribution and wind power potential in the coastal region of South Africa. Int J Green Energy 2013;10(8):814–34. https://doi.org/10.1080/15435075.2012.727112.

[64] Niyomtham L, Lertsathittanakorn C, Waewsak J, Gagnon Y. Mesoscale/microscale and CFD modeling for wind resource assessment: application to the Andaman Coast of Southern Thailand. Energies 2022;15(9). https://doi.org/10.3390/en15093025.

[65] Fekih A, Abdelouahab M, Marif Y. Evaluation of wind resource and mapping during 2009–2018 based on ERA5 reanalysis data: a case study over Algeria. Int J Energy Environ Eng 2023;14(1):15–34. https://doi.org/10.1007/s40095-022-00500-w.

[66] Mondal Mithun, Djamal Hissein Didane Alhadj, Hisseine Issaka Ali, Manshoor Bukhari. Technical assessment of wind energy potentials in Bangladesh. ARFMTS 2022;96(2):10–21. https://doi.org/10.37934/arfmts.96.2.1021.

[67] Tonsie Djiela RH, Tiam Kapen P, Tchuen G. Wind energy of Cameroon by determining Weibull parameters: potential of a environmentally friendly energy. Int J Environ Sci Technol 2021;18(8):2251–70. https://doi.org/10.1007/s13762-020-02962-z.

[68] Boopathi K, Kushwaha R, Balaraman K, Bastin J, Kanagavel P, Reddy Prasad DM. Assessment of wind power potential in the coastal region of Tamil Nadu, India. Ocean Eng 2021;219. https://doi.org/10.1016/j.oceaneng.2020.108356.

[69] Chandel SS, Ramasamy P, Murthy KSR. Wind power potential assessment of 12 locations in western Himalayan region of India. Renew Sustain Energy Rev 2014;39:530–45. https://doi.org/10.1016/j.rser.2014.07.050.

[70] D'Isidoro M, et al. Estimation of solar and wind energy resources over Lesotho and their complementarity by means of WRF yearly simulation at high resolution. Renew Energy 2020;158:114–29. https://doi.org/10.1016/j.renene.2020.05.106.

[71] Sumair M, Aized T, Gardezi SAR, Bhutta MMA, Ubaid ur Rehman S, Sohail Rehman SM. Weibull parameters estimation using combined energy pattern and power density method for wind resource assessment. Energy Explor Exploit 2021;39(5):1817–34. https://doi.org/10.1177/0144598720947483.

[72] Didane DH, Rosly N, Zulkafli MF, Shamsudin SS. Evaluation of wind energy potential as a power generation source in Chad. Int J Rotating Mach 2017;2017. https://doi.org/10.1155/2017/3121875.
[73] Nefabas KL, Söder L, Mamo M, Olauson J. Modeling of ethiopian wind power production using era5 reanalysis data. Energies 2021;14(9). https://doi.org/10.3390/en14092573.
[74] Ayik A, Ijumba N, Kabiri C, Goffin P. Preliminary wind resource assessment in South Sudan using reanalysis data and statistical methods. Renew Sustain Energy Rev 2021;138. https://doi.org/10.1016/j.rser.2020.110621.
[75] Libanda B, Paeth H. Modelling wind speed across Zambia: implications for wind energy. Int J Climatol 2023;43(2):772–86. https://doi.org/10.1002/joc.7826.
[76] Antonini EGA, Caldeira K. Spatial constraints in large-scale expansion of wind power plants. Proc Natl Acad Sci USA 2021;118(27). https://doi.org/10.1073/pnas.2103875118.
[77] Gruber K, Regner P, Wehrle S, Zeyringer M, Schmidt J. Towards global validation of wind power simulations: a multi-country assessment of wind power simulation from MERRA-2 and ERA-5 reanalyses bias-corrected with the global wind atlas. Energy 2022;238. https://doi.org/10.1016/j.energy.2021.121520.
[78] Yang Y, Javanroodi K, Nik VM. Climate change and renewable energy generation in Europe—long-term impact assessment on solar and wind energy using high-resolution future climate data and considering climate uncertainties. Energies 2022;15(1):302. https://doi.org/10.3390/en15010302.
[79] Zheng CW, Pan J, Li JX. Assessing the China Sea wind energy and wave energy resources from 1988 to 2009. Ocean Eng 2013;65:39–48. https://doi.org/10.1016/j.oceaneng.2013.03.006.
[80] Mattar C, Borvarán D. Offshore wind power simulation by using WRF in the central coast of Chile. Renew Energy 2016;94:22–31. https://doi.org/10.1016/j.renene.2016.03.005.
[81] Soukissian TH, Papadopoulos A. Effects of different wind data sources in offshore wind power assessment. Renew Energy 2015;77:101–14. https://doi.org/10.1016/j.renene.2014.12.009.
[82] Lee JA, Doubrawa P, Xue L, Newman AJ, Draxl C, Scott G. Wind resource assessment for Alaska's offshore regions: validation of a 14-year high-resolution WRF data set. Energies 2019;12(14). https://doi.org/10.3390/en12142780.
[83] Aza-Gnandji MR, Fifatin FX, Dubas F, Nounangnonhou TC, Espanet C, Vianou A. Investigation on offshore wind energy potential in Benin Republic. Wind Engineering 2021;45(1):63–73. https://doi.org/10.1177/0309524×19872768.
[84] Varghese J, Christy F, Venkattaramana K. Offshore wind energy potential along Indian Coast. IJCIET 2018;9(7):1480–6.
[85] Ibarra-Berastegi G, Ulazia A, Saénz J, González-Rojí SJ. Evaluation of Lebanon's offshore-wind-energy potential. J Mar Sci Eng 2019;7(10). https://doi.org/10.3390/jmse7100361.
[86] Onea F, Deleanu L, Rusu L, Georgescu C. Evaluation of the wind energy potential along the Mediterranean Sea coasts. Energy Explor Exploit 2016;34(5):766–92. https://doi.org/10.1177/0144598716659592.
[87] Soares PMM, Lima DCA, Nogueira M. Global offshore wind energy resources using the new ERA-5 reanalysis. Environ Res Lett 2020;15(10). https://doi.org/10.1088/1748-9326/abb10d.
[88] Aydoğan B. Offshore wind power atlas of the Black Sea Region. J Renew Sustain Energy 2017;9(1). https://doi.org/10.1063/1.4976968.
[89] Geyer B, Weisse R, Bisling P, Winterfeldt J. Climatology of North Sea wind energy derived from a model hindcast for 1958–2012. J Wind Eng Ind Aerodyn 2015;147:18–29. https://doi.org/10.1016/j.jweia.2015.09.005.
[90] Ashtine M, Bello R, Higuchi K. Assessment of wind energy potential over Ontario and Great Lakes using the NARR data: 1980-2012. Renew Sustain Energy Rev 2016;56:272–82. https://doi.org/10.1016/j.rser.2015.11.019.
[91] Delage R, Matsuoka T, Nakata T. Spatial–temporal estimation and analysis of japan onshore and offshore wind energy potential. Energies 2021;14(8):2168. https://doi.org/10.3390/en14082168.
[92] Alkhalidi MA, Al-Dabbous SK, Neelamani S, Aldashti HA. Wind energy potential at coastal and offshore locations in the state of Kuwait. Renew Energy 2019;135:529–39. https://doi.org/10.1016/j.renene.2018.12.039.
[93] Kleidon A, Miller LM. The Kinetic Energy Budget of the Atmosphere (KEBA) model 1.0: a simple yet physical approach for estimating regional wind energy resource potentials that includes the kinetic energy removal effect by wind turbines. Geosci Model Dev 2020;13(10):4993–5005. https://doi.org/10.5194/gmd-13-4993-2020.
[94] Gunturu UB, Schlosser CA. Characterization of wind power resource in the United States. Atmos Chem Phys 2012;12(20):9687–702. https://doi.org/10.5194/acp-12-9687-2012.
[95] Dayal KK, Bellon G, Cater JE, Kingan MJ, Sharma RN. High-resolution mesoscale wind-resource assessment of Fiji using the Weather Research and Forecasting (WRF) model. Energy 2021;232. https://doi.org/10.1016/j.energy.2021.121047.
[96] Boudia SM, Santos JA. Assessment of large-scale wind resource features in Algeria. Energy 2019;189. https://doi.org/10.1016/j.energy.2019.116299.
[97] Deep S, Sarkar A, Ghawat M, Rajak MK. Estimation of the wind energy potential for coastal locations in India using the Weibull model. Renew Energy 2020;161:319–39. https://doi.org/10.1016/j.renene.2020.07.054.
[98] Satyanarayana Gubbala C, Dodla VBR, Desamsetti S. Assessment of wind energy potential over India using high-resolution global reanalysis data. J Earth Syst Sci 2021;130(2). https://doi.org/10.1007/s12040-021-01557-7.
[99] Marvel K, Kravitz B, Caldeira K. Geophysical limits to global wind power. Nat Clim Change 2013;3(2):118–21. https://doi.org/10.1038/nclimate1683.
[100] Possner A, Caldeira K. Geophysical potential for wind energy over the open oceans. Proc Natl Acad Sci USA 2017;114(43):11338–43. https://doi.org/10.1073/pnas.1705710114.
[101] Volker PJH, Hahmann AN, Badger J, Jrgensen HE. Prospects for generating electricity by large onshore and offshore wind farms. Environ Res Lett 2017;12(3). https://doi.org/10.1088/1748-9326/aa5d86.
[102] Dörenkämper M, et al. The making of the new European Wind Atlas - Part 2: production and evaluation. Geosci Model Dev 2020;13(10):5079–102. https://doi.org/10.5194/gmd-13-5079-2020.
[103] Moemken J, Reyers M, Buldmann B, Pinto JG. Decadal predictability of regional scale wind speed and wind energy potentials over Central Europe. Tellus A 2016;68(1):29199. https://doi.org/10.3402/tellusa.v68.29199.
[104] Pryor SC, Barthelmie RJ. A global assessment of extreme wind speeds for wind energy applications. Nat Energy 2021;6(3):268–76. https://doi.org/10.1038/s41560-020-00773-7.
[105] Sterl S, et al. An all-Africa dataset of energy model "supply regions" for solar photovoltaic and wind power. Sci Data 2022;9(1). https://doi.org/10.1038/s41597-022-01786-5.
[106] Shafiee M. Wind energy development site selection using an integrated fuzzy ANP-TOPSIS decision model. Energies 2022;15(12). https://doi.org/10.3390/en15124289.
[107] Blankenhorn V, Resch B. Determination of suitable areas for the generation of wind energy in Germany: potential areas of the present and future. ISPRS Int J Geoinf 2014;3(3):942–67. https://doi.org/10.3390/ijgi3030942.
[108] Daneshvar Rouyendegh B, Yildizbasi A, Arikan ÜZB. Using intuitionistic fuzzy TOPSIS in site selection of wind power plants in Turkey. Adv Fuzzy Syst 2018;2018. https://doi.org/10.1155/2018/6703798.
[109] Jangid J, et al. Potential zones identification for harvesting wind energy resources in desert region of India—a multi criteria evaluation approach using remote sensing and GIS. Renew Sustain Energy Rev 2016;65:1–10. https://doi.org/10.1016/j.rser.2016.06.078.
[110] Amarasinghe AG, Perera ENC. Modeling predictive suitability to determine potential areas for establishing wind power plants in Sri Lanka. Model Earth Syst Environ 2021;7(1):443–54. https://doi.org/10.1007/s40808-020-00868-w.
[111] Mostafaeipour A, Dehshiri SJH, Dehshiri SSH, Jahangiri M. Prioritization of potential locations for harnessing wind energy to produce hydrogen in Afghanistan. Int J Hydrogen Energy 2020;45(58):33169–84. https://doi.org/10.1016/j.ijhydene.2020.09.135.
[112] Bandoc G, Prăvălie R, Patriche C, Degeratu M. Spatial assessment of wind power potential at global scale. A geographical approach. J Clean Prod 2018;200:1065–86. https://doi.org/10.1016/j.jclepro.2018.07.288.
[113] Mentis D, Hermann S, Howells M, Welsch M, Siyal SH. Assessing the technical wind energy potential in africa a GIS-based approach. Renew Energy 2015;83:110–25. https://doi.org/10.1016/j.renene.2015.03.072.
[114] Seyedhashemi H, Hingray B, Lavaysse C, Chamarande T. The impact of low-resource periods on the reliability of wind power systems for rural electrification in Africa. Energies 2021;14(11):2978. https://doi.org/10.3390/en14112978.
[115] Staffell I, Green R. How does wind farm performance decline with age? Renew Energy 2014;66:775–86. https://doi.org/10.1016/j.renene.2013.10.041.
[116] Bataineh KM, Dalalah D. Assessment of wind energy potential for selected areas in Jordan. Renew Energy 2013;59:75–81. https://doi.org/10.1016/j.renene.2013.03.034.
[117] Feng J, Feng L, Wang J, King CW. Evaluation of the onshore wind energy potential in mainland China—based on GIS modeling and EROI analysis. Resour Conserv Recycl 2020;152. https://doi.org/10.1016/j.resconrec.2019.104484.
[118] Zhang C, et al. Optimal allocation of onshore wind power in China based on cluster analysis. Appl Energy 2021;285. https://doi.org/10.1016/j.apenergy.2021.116482.
[119] Li L, Wang X, Luo L, Zhao Y, Zong X, Bachagha N. Mapping of wind energy potential over the Gobi Desert in Northwest China based on multiple sources of data. Front Earth Sci 2018;12(2):264–79. https://doi.org/10.1007/s11707-017-0663-y.
[120] Nitsch F, Turkovska O, Schmidt J. Observation-based estimates of land availability for wind power: a case study for Czechia. Energy Sustain Soc 2019;9(1). https://doi.org/10.1186/s13705-019-0234-z.
[121] Drücke J, et al. Climatological analysis of solar and wind energy in Germany using the Grosswetterlagen classification. Renew Energy 2021;164:1254–66. https://doi.org/10.1016/j.renene.2020.10.102.
[122] Jung C, Schindler D. On the inter-annual variability of wind energy generation—a case study from Germany. Appl Energy 2018;230:845–54. https://doi.org/10.1016/j.apenergy.2018.09.019.
[123] Eichhorn M, Masurowski F, Becker R, Thrän D. Wind energy expansion scenarios—a spatial sustainability assessment. Energy 2019;180:367–75. https://doi.org/10.1016/j.energy.2019.05.054.
[124] Zhang J, Draxl C, Hopson T, Monache LD, Vanvyve E, Hodge BM. Comparison of numerical weather prediction based deterministic and probabilistic wind resource assessment methods. Appl Energy 2015;156:528–41. https://doi.org/10.1016/j.apenergy.2015.07.059.
[125] Cai B, Vo P, Sritharan S, Takle ES. Wind Energy Potential at Elevated Hub Heights in the US Midwest Region. J Energy Eng 2021;147(4):04021023. https://doi.org/10.1061/(ASCE)EY.1943-7897.0000760.
[126] Ali Kadhem A, Abdul Wahab NI, Abdalla AN. Wind energy generation assessment at specific sites in a Peninsula in Malaysia based on reliability indices. Processes 2019;7(7):399. https://doi.org/10.3390/pr7070399.
[127] Rodríguez O, Del Río JA, Jaramillo OA, Martínez M. Wind power error estimation in resource assessments. PLoS One 2015;10(5). https://doi.org/10.1371/journal.pone.0124830.

[128] Adefarati T, Obikoya GD. Evaluation of wind resources potential and economic analysis of wind power generation in South Africa. Int J Eng Res Afr 2019;44:150–81. https://doi.org/10.4028/www.scientific.net/JERA.44.150.
[129] Rehman S, Natarajan N, Mohandes MA, Meyer JP, Alam MM, Alhems LM. Wind and wind power characteristics of the eastern and southern coastal and northern inland regions, South Africa. Environ Sci Pollut Res 2022;29(57):85842–54. https://doi.org/10.1007/s11356-021-14276-9.
[130] Islam KD, et al. Wind energy analysis in the coastal region of Bangladesh. Energies 2021;14(18). https://doi.org/10.3390/en14185628.
[131] Ismail I, Ismail AH, Nur Rahayu GHN. Wind energy feasibility study of seven potential locations in Indonesia. Int J Adv Sci Eng Inf Technol 2020;10(5):1970–8. https://doi.org/10.18517/ijaseit.10.5.10389.
[132] Filom S, Radfar S, Panahi R, Amini E, Neshat M. Exploring wind energy potential as a driver of sustainable development in the southern coasts of iran: the importance of wind speed statistical distribution model. Sustainability 2021;13(14). https://doi.org/10.3390/su13147702.
[133] Zahedi R, Ghorbani M, Daneshgar S, Gitifar S, Qezelbigloo S. Potential measurement of Iran's western regional wind energy using GIS. J Clean Prod 2022;330. https://doi.org/10.1016/j.jclepro.2021.129883.
[134] Ayodele TR, Ogunjuyigbe ASO, Amusan TO. Wind power utilization assessment and economic analysis of wind turbines across fifteen locations in the six geographical zones of Nigeria. J Clean Prod 2016;129:341–9. https://doi.org/10.1016/j.jclepro.2016.04.060.
[135] Rabbani R, Zeeshan M. Exploring the suitability of MERRA-2 reanalysis data for wind energy estimation, analysis of wind characteristics and energy potential assessment for selected sites in Pakistan. Renew Energy 2020;154:1240–51. https://doi.org/10.1016/j.renene.2020.03.100.
[136] Contreras-Vielma M. Technical evaluation of the wind resource in Venezuela. J Eng Appl Sci 2016;11(7):4399–403.
[137] Gualtieri G. An integrated wind resource assessment tool for wind farm planning: system's upgrades and applications. Int J Renew Energy Res 2016;6(4):1464–75.
[138] Zappa W, van den Broek M. Analysing the potential of integrating wind and solar power in Europe using spatial optimisation under various scenarios. Renew Sustain Energy Rev 2018;94:1192–216. https://doi.org/10.1016/j.rser.2018.05.071.
[139] Hofmann F, Hampp J, Neumann F, Brown T, Hörsch J. atlite: a lightweight python package for calculating renewable power potentials and time series. JOSS 2021;6(62):3294. https://doi.org/10.21105/joss.03294.
[140] Lu X, McElroy MB. Global potential for wind-generated electricity. Elsevier Inc.; 2017. https://doi.org/10.1016/B978-0-12-809451-8.00004-7.
[141] Jensen TV, Pinson P. RE-Europe, a large-scale dataset for modeling a highly renewable European electricity system. Sci Data 2017;4(1):170175. https://doi.org/10.1038/sdata.2017.175.
[142] Amato F, Guignard F, Walch A, Mohajeri N, Scartezzini JL, Kanevski M. Spatio-temporal estimation of wind speed and wind power using extreme learning machines: predictions, uncertainty and technical potential. Stoch Environ Res Risk Assess 2022;36(8):2049–69. https://doi.org/10.1007/s00477-022-02219-w.
[143] Bosch J, Staffell I, Hawkes AD. Temporally-explicit and spatially-resolved global onshore wind energy potentials. Energy 2017;131:207–17. https://doi.org/10.1016/j.energy.2017.05.052.
[144] Jung C, Schindler D. The annual cycle and intra-annual variability of the global wind power distribution estimated by the system of wind speed distributions. Sustain Energy Technol Assess 2020;42. https://doi.org/10.1016/j.seta.2020.100852.
[145] Jung C, Taubert D, Schindler D. The temporal variability of global wind energy—long-term trends and inter-annual variability. Energy Convers Manage 2019;188:462–72. https://doi.org/10.1016/j.enconman.2019.03.072.
[146] Shami SH, Ahmad J, Zafar R, Haris M, Bashir S. Evaluating wind energy potential in Pakistan's three provinces, with proposal for integration into national power grid. Renew Sustain Energy Rev 2016;53:408–21. https://doi.org/10.1016/j.rser.2015.08.052.
[147] von Krauland AK, Permien FH, Enevoldsen P, Jacobson MZ. Onshore wind energy atlas for the United States accounting for land use restrictions and wind speed thresholds. Smart Energy 2021;3:100046. https://doi.org/10.1016/j.segy.2021.100046.
[148] 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. https://doi.org/10.1016/j.rser.2019.01.034.
[149] Wen Y, Kamranzad B, Lin P. Assessment of long-term offshore wind energy potential in the south and southeast coasts of China based on a 55-year dataset. Energy 2021;224. https://doi.org/10.1016/j.energy.2021.120225.
[150] Tuy S, Lee HS, Chreng K. Integrated assessment of offshore wind power potential using Weather Research and Forecast (WRF) downscaling with Sentinel-1 satellite imagery, optimal sites, annual energy production and equivalent CO2 reduction. Renew Sustain Energy Rev 2022;163. https://doi.org/10.1016/j.rser.2022.112501.
[151] Yamaguchi A, Ishihara T. Assessment of offshore wind energy potential using mesoscale model and geographic information system. Renew Energy 2014;69:506–15. https://doi.org/10.1016/j.renene.2014.02.024.
[152] Al-Hinai A, Charabi Y, Aghay Kaboli SH. Offshore wind energy resource assessment across the territory of Oman: a spatial-temporal data analysis. Sustainability 2021;13(5):1–18. https://doi.org/10.3390/su13052862.
[153] Onea F, Rusu E, Rusu L. Assessment of the offshore wind energy potential in the Romanian exclusive economic zone. J Mar Sci Eng 2021;9(5). https://doi.org/10.3390/jmse9050531.
[154] Onea F, Ruiz A, Rusu E. An evaluation of the wind energy resources along the Spanish continental nearshore. Energies 2020;13(15). https://doi.org/10.3390/en13153986.
[155] Dvorak MJ, Corcoran BA, Ten Hoeve JE, McIntyre NG, Jacobson MZ. US East Coast offshore wind energy resources and their relationship to peak-time electricity demand. Wind Energy 2013;16(7):977–97. https://doi.org/10.1002/we.1524.
[156] Magar V, Gross MS, González-García L. Offshore wind energy resource assessment under techno-economic and social-ecological constraints. Ocean Coast Manage 2018;152:77–87. https://doi.org/10.1016/j.ocecoaman.2017.10.007.
[157] Canul-Reyes DA, Rodríguez-Hernández O, Jarquin-Laguna A. Potential zones for offshore wind power development in the Gulf of Mexico using reanalyses data and capacity factor seasonal analysis. Energy Sustain Dev 2022;68:211–9. https://doi.org/10.1016/j.esd.2022.03.008.
[158] Rae G, Erfort G. Offshore wind energy – South Africa's untapped resource. J Energy South Afr 2020;31(4):26–42. https://doi.org/10.17159/2413-3051/2020/v31i4a7940.
[159] Waewsak J, Landry M, Gagnon Y. Offshore wind power potential of the Gulf of Thailand. Renew Energy 2015;81:609–26. https://doi.org/10.1016/j.renene.2015.03.069.
[160] Chancham C, Waewsak J, Gagnon Y. Offshore wind resource assessment and wind power plant optimization in the Gulf of Thailand. Energy 2017;139:706–31. https://doi.org/10.1016/j.energy.2017.08.026.
[161] Patel RP, Nagababu G, Kachhwaha SS, Surisetty VVAK. A revised offshore wind resource assessment and site selection along the Indian coast using ERA5 near-hub-height wind products. Ocean Eng 2022;254. https://doi.org/10.1016/j.oceaneng.2022.111341.
[162] Doan VQ, et al. Usability and challenges of offshore wind energy in Vietnam revealed by the regional climate model simulation. Sci Online Lett Atmos 2019;15:113–8. https://doi.org/10.2151/SOLA.2019-021.
[163] Akhtar N, Geyer B, Rockel B, Sommer PS, Schrum C. Accelerating deployment of offshore wind energy alter wind climate and reduce future power generation potentials. Sci Rep 2021;11(1):11826. https://doi.org/10.1038/s41598-021-91283-3.
[164] Grothe O, Kächele F, Watermeyer M. Analyzing Europe's biggest offshore wind farms: a data set with 40 years of hourly wind speeds and electricity production. Energies 2022;15(5). https://doi.org/10.3390/en15051700.
[165] D. Arent et al., 'Improved offshore wind resource assessment in global climate stabilization scenarios', NREL/TP-6A20-55049, 1055364, Oct. 2012. doi:10.2172/1055364.
[166] Diaconita A, Andrei G, Rusu L. New insights into the wind energy potential of the west Black Sea area based on the North Sea wind farms model. Energy Rep 2021;7:112–8. https://doi.org/10.1016/j.egyr.2021.06.018.
[167] Adeyeye K, Ijumba N, Colton J. A preliminary feasibility study on wind resource and assessment of a novel low speed wind turbine for application in Africa. Energy Eng 2022;119(3):997–1015. https://doi.org/10.32604/ee.2022.018677.
[168] He G, Kammen DM. Where, when and how much wind is available? A provincial-scale wind resource assessment for China. Energy Policy 2014;74(C):116–22. https://doi.org/10.1016/j.enpol.2014.07.003.
[169] Wei X, Duan Y, Liu Y, Jin S, Sun C. Onshore-offshore wind energy resource evaluation based on synergetic use of multiple satellite data and meteorological stations in Jiangsu Province, China. Front Earth Sci 2019;13(1):132–50. https://doi.org/10.1007/s11707-018-0699-7.
[170] Cai Y, Bréon FM. Wind power potential and intermittency issues in the context of climate change. Energy Convers Manage 2021;240:114276. https://doi.org/10.1016/j.enconman.2021.114276.
[171] Méndez C, Bicer Y. Assessment of wind energy potential and characteristics in Qatar for clean electricity generation. Wind Eng 2022;46(2):598–614. https://doi.org/10.1177/0309524×211043855.
[172] Siyal SH, Mörtberg U, Mentis D, Welsch M, Babelon I, Howells M. Wind energy assessment considering geographic and environmental restrictions in Sweden: a GIS-based approach. Energy 2015;83:447–61. https://doi.org/10.1016/j.energy.2015.02.044.
[173] Miller LM, et al. Two methods for estimating limits to large-scale wind power generation. Proc Natl Acad Sci USA 2015;112(36):11169–74. https://doi.org/10.1073/pnas.1408251112.
[174] Eurek K, Sullivan P, Gleason M, Hettinger D, Heimiller D, Lopez A. An improved global wind resource estimate for integrated assessment models. Energy Econ 2017;64:552–67. https://doi.org/10.1016/j.eneco.2016.11.015.
[175] Adams AS, Keith DW. Are global wind power resource estimates overstated? Environ Res Lett 2013;8(1). https://doi.org/10.1088/1748-9326/8/1/015021.
[176] European Commission. Joint Research Centre.. EMHIRES dataset. Part I, wind power generation. LU: Publications Office; 2016. Accessed: Jun. 01, 2023 [Online]. Available: https://data.europa.eu/doi/10.2790/831549.
[177] Ruiz P, et al. ENSPRESO - an open, EU-28 wide, transparent and coherent database of wind, solar and biomass energy potentials. Energy Strategy Rev 2019;26. https://doi.org/10.1016/j.esr.2019.100379.
[178] European Commission. Joint Research Centre.. Wind potentials for EU and neighbouring countries: input datasets for the JRC EU times model. LU: Publications Office; 2018. Accessed: Jun. 01, 2023. [Online]. Available: https://data.europa.eu/doi/10.2760/041705.
[179] Jacobson MZ, Archer CL. Saturation wind power potential and its implications for wind energy. Proc Natl Acad Sci 2012;109(39):15679–84. https://doi.org/10.1073/pnas.1208993109.

[180] Adeyeye KA, Ijumba N, Colton JS. A techno-economic model for wind energy costs analysis for low wind speed areas. Processes 2021;9(8). https://doi.org/10.3390/pr9081463.

[181] Gass V, Schmidt J, Strauss F, Schmid E. Assessing the economic wind power potential in Austria. Energy Policy 2013;53:323–30. https://doi.org/10.1016/j.enpol.2012.10.079.

[182] Watts D, Oses N, Pérez R. Assessment of wind energy potential in Chile: a project-based regional wind supply function approach. Renew Energy 2016;96:738–55. https://doi.org/10.1016/j.renene.2016.05.038.

[183] Gao Y, et al. Assessing the wind energy potential of China in considering its variability/intermittency. Energy Convers Manage 2020;226. https://doi.org/10.1016/j.enconman.2020.113580.

[184] Li Y, Wu XP, Li QS, Tee KF. Assessment of onshore wind energy potential under different geographical climate conditions in China. Energy 2018;152:498–511. https://doi.org/10.1016/j.energy.2018.03.172.

[185] Wan J, et al. Assessment of wind energy resources in the urat area using optimized weibull distribution. Sustain Energy Technol Assess 2021;47. https://doi.org/10.1016/j.seta.2021.101351.

[186] McKenna R, Hollnaicher S, Fichtner W. Cost-potential curves for onshore wind energy: a high-resolution analysis for Germany. Appl Energy 2014;115:103–15. https://doi.org/10.1016/j.apenergy.2013.10.030.

[187] McKenna R, Gantenbein S, Fichtner W. Determination of cost-potential-curves for wind energy in the German federal state of Baden-Württemberg. Energy Policy 2013;57:194–203. https://doi.org/10.1016/j.enpol.2013.01.043.

[188] Hennecke D. Spatial-economic potential analysis of wind power plants in Germany [Räumlich-wirtschaftliche Potenzialanalyse von Windkraftanlagen in Deutschland]. AGIT 2021;7:46–56. https://doi.org/10.14627/537707006.

[189] Wu J, Xiao J, Hou J, Sun W, Li P, Lyu X. A multi-criteria methodology for wind energy resource assessment and development at an intercontinental level: facing low-carbon energy transition. IET Renew Power Gener 2023;17(2):480–94. https://doi.org/10.1049/rpg2.12590.

[190] Sliz-Szkliniarz B, Eberbach J, Hoffmann B, Fortin M. Assessing the cost of onshore wind development scenarios: modelling of spatial and temporal distribution of wind power for the case of Poland. Renew Sustain Energy Rev 2019;109:514–31. https://doi.org/10.1016/j.rser.2019.04.039.

[191] Rehman S. Wind power resources assessment at 10 different locations using wind measurements at five heights. Environ Prog Sustain Energy 2022;41(5). https://doi.org/10.1002/ep.13853.

[192] Lopez A, Mai T, Lantz E, Harrison-Atlas D, Williams T, Maclaurin G. Land use and turbine technology influences on wind potential in the United States. Energy 2021;223. https://doi.org/10.1016/j.energy.2021.120044.

[193] Grassi S, Chokani N, Abhari RS. Large scale technical and economical assessment of wind energy potential with a GIS tool: case study Iowa. Energy Policy 2012;45:73–85. https://doi.org/10.1016/j.enpol.2012.01.061.

[194] Pourasl HH, Khojastehnezhad VM. Techno-economic analysis of wind energy potential in Kazakhstan. Proc Inst Mech Eng A J Power Energy 2021;235(6):1563–76. https://doi.org/10.1177/09576509211001598.

[195] Bahrami A, Teimourian A, Okoye CO, Khosravi N. Assessing the feasibility of wind energy as a power source in Turkmenistan; a major opportunity for Central Asia's energy market. Energy 2019;183:415–27. https://doi.org/10.1016/j.energy.2019.06.108.

[196] Belabes B, Youcefi A, Guerri O, Djamai M, Kaabeche A. Evaluation of wind energy potential and estimation of cost using wind energy turbines for electricity generation in north of Algeria. Renew Sustain Energy Rev 2015;51:1245–55. https://doi.org/10.1016/j.rser.2015.07.043.

[197] Boudia SM, Benmansour A, Tabet Hellal MA. Wind resource assessment in Algeria. Sustainable Cities and Society 2016;22:171–83. https://doi.org/10.1016/j.scs.2016.02.010.

[198] Dabar OA, Awaleh MO, Waberi MM, Adan A-BI. Wind resource assessment and techno-economic analysis of wind energy and green hydrogen production in the Republic of Djibouti. Energy Rep 2022;8:8996–9016. https://doi.org/10.1016/j.egyr.2022.07.013.

[199] Elkadeem MR, et al. Geospatial-assisted multi-criterion analysis of solar and wind power geographical-technical-economic potential assessment. Appl Energy 2022;322. https://doi.org/10.1016/j.apenergy.2022.119532.

[200] El Satta MA, Hafez WA, Elbaset AA, Alaboudy AHK. Economic valuation of electrical wind energy in Egypt based on levelized cost of energy. IJRER 2020;(v10i4). https://doi.org/10.20508/ijrer.v10i4.11463.g8079.

[201] Mentis D, Siyal SH, Korkovelos A, Howells M. A geospatial assessment of the techno-economic wind power potential in India using geographical restrictions. Renew Energy 2016;97:77–88. https://doi.org/10.1016/j.renene.2016.05.057.

[202] Jain A, Das P, Yamujala S, Bhakar R, Mathur J. Resource potential and variability assessment of solar and wind energy in India. Energy 2020;211. https://doi.org/10.1016/j.energy.2020.118993.

[203] Langer J, Zaaijer M, Quist J, Blok K. Introducing site selection flexibility to technical and economic onshore wind potential assessments: new method with application to Indonesia. Renew Energy 2023;202:320–35. https://doi.org/10.1016/j.renene.2022.11.084.

[204] Neupane D, Kafle S, Karki KR, Kim DH, Pradhan P. Solar and wind energy potential assessment at provincial level in Nepal: geospatial and economic analysis. Renew Energy 2022;181:278–91. https://doi.org/10.1016/j.renene.2021.09.027.

[205] Adaramola MS, Oyewola OM, Ohunakin OS, Dinrifo RR. Techno-economic evaluation of wind energy in southwest Nigeria. Front Energy 2012;6(4):366–78. https://doi.org/10.1007/s11708-012-0205-y.

[206] Ajayi O, Fagbenle R, Katende J, Ndambuki J, Omole D, Badejo A. Wind energy study and energy cost of wind electricity generation in Nigeria: past and recent results and a case study for South West Nigeria. Energies 2014;7(12):8508–34. https://doi.org/10.3390/en7128508.

[207] Saeed MA, Ahmed Z, Yang J, Zhang W. An optimal approach of wind power assessment using Chebyshev metric for determining the Weibull distribution parameters. Sustain Energy Technol Assess 2020;37. https://doi.org/10.1016/j.seta.2019.100612.

[208] Mohsin M, Zhang J, Saidur R, Sun H, Sait SM. Economic assessment and ranking of wind power potential using fuzzy-TOPSIS approach. Environ Sci Pollut Res 2019;26(22):22494–511. https://doi.org/10.1007/s11356-019-05564-6.

[209] Saeed MA, Ahmed Z, Zhang W. Optimal approach for wind resource assessment using Kolmogorov–Smirnov statistic: a case study for large-scale wind farm in Pakistan. Renew Energy 2021;168:1229–48. https://doi.org/10.1016/j.renene.2021.01.008.

[210] Bahrami A, Teimourian A, Okoye CO, Shiri H. Technical and economic analysis of wind energy potential in Uzbekistan. J Clean Prod 2019;223:801–14. https://doi.org/10.1016/j.jclepro.2019.03.140.

[211] McKenna R, Hollnaicher S, Ostman v. d. Leye P, Fichtner W. Cost-potentials for large onshore wind turbines in Europe. Energy 2015;83:217–29. https://doi.org/10.1016/j.energy.2015.02.016.

[212] Satymov R, Bogdanov D, Breyer C. Global-local analysis of cost-optimal onshore wind turbine configurations considering wind classes and hub heights. Energy 2022;256. https://doi.org/10.1016/j.energy.2022.124629.

[213] Khan MA, Çamur H, Kassem Y. Modeling predictive assessment of wind energy potential as a power generation sources at some selected locations in Pakistan. Model Earth Syst Environ 2019;5(2):555–69. https://doi.org/10.1007/s40808-018-0546-6.

[214] Shorabeh SN, Firozjaei HK, Firozjaei MK, Jelokhani-Niaraki M, Homaee M, Nematollahi O. The site selection of wind energy power plant using GIS-multi-criteria evaluation from economic perspectives. Renew Sustain Energy Rev 2022;168:112778. https://doi.org/10.1016/j.rser.2022.112778.

[215] Mattar C, Guzmán-Ibarra MC. A techno-economic assessment of offshore wind energy in Chile. Energy 2017;133:191–205. https://doi.org/10.1016/j.energy.2017.05.099.

[216] Cavazzi S, Dutton AG. An Offshore Wind Energy Geographic Information System (OWE-GIS) for assessment of the UK's offshore wind energy potential. Renew Energy 2016;87:212–28. https://doi.org/10.1016/j.renene.2015.09.021.

[217] Doljak D, Stanojević G, Miljanović D. A GIS-MCDA based assessment for siting wind farms and estimation of the technical generation potential for wind power in Serbia. Int J Green Energy 2021;18(4):363–80. https://doi.org/10.1080/15435075.2020.1865363.

[218] Sawasklin P, Saeung S, Taweekun J. Study on offshore wind energy potential in the Gulf of Thailand. IJRER 2021. https://doi.org/10.20508/ijrer.v11i4.12213.g8347.

[219] 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. https://doi.org/10.1177/0309524×17706846.

[220] Amirinia G, Mafi S, Mazaheri S. Offshore wind resource assessment of Persian Gulf using uncertainty analysis and GIS. Renew Energy 2017;113:915–29. https://doi.org/10.1016/j.renene.2017.06.070.

[221] Maandal GLD, Tamayao-Kieke M-AM, Danao LAM. Techno-economic assessment of offshore wind energy in the philippines. J Mar Sci Eng 2021;9(7). https://doi.org/10.3390/jmse9070758.

[222] Schillings C, Wanderer T, Cameron L, van der Wal JT, Jacquemin J, Veum K. A decision support system for assessing offshore wind energy potential in the North Sea. Energy Policy 2012;49:541–51. https://doi.org/10.1016/j.enpol.2012.06.056.

[223] Caglayan DG, Ryberg DS, Heinrichs H, Linßen J, Stolten D, Robinius M. The techno-economic potential of offshore wind energy with optimized future turbine designs in Europe. Appl Energy 2019;255. https://doi.org/10.1016/j.apenergy.2019.113794.

[224] Yu S, Gui H, Yang J. China's provincial wind power potential assessment and its potential contributions to the "dual carbon" targets. Environ Sci Pollut Res 2023;30(5):13094–117. https://doi.org/10.1007/s11356-022-23021-9.

[225] Wang Y, et al. Where is the most feasible, economical, and green wind energy? Evidence from high-resolution potential mapping in China. J Clean Prod 2022;376. https://doi.org/10.1016/j.jclepro.2022.134287.

[226] G. Maclaurin et al., 'The renewable energy potential (reV) model: a geospatial platform for technical potential and supply curve modeling', NREL/TP-6A20-73067, 1563140, MainId:13369, Sep. 2019. doi:10.2172/1563140.

[227] Dupont E, Koppelaar R, Jeanmart H. Global available wind energy with physical and energy return on investment constraints. Appl Energy 2018;209:322–38. https://doi.org/10.1016/j.apenergy.2017.09.085.

[228] Rehman AU, Abidi MH, Umer U, Usmani YS. Multi-criteria decision-making approach for selecting wind energy power plant locations. Sustainability 2019;11(21). https://doi.org/10.3390/su11216112.

[229] Harper M, Anderson B, James P, Bahaj A. Assessing socially acceptable locations for onshore wind energy using a GIS-MCDA approach. Int J Low Carbon Technol 2019;14(2):160–9. https://doi.org/10.1093/ijlct/ctz006.

[230] Martinez-Cesena EA, Mutale J. Wind power projects planning considering real options for the wind resource assessment. IEEE Trans Sustain Energy 2012;3(1):158–66. https://doi.org/10.1109/TSTE.2011.2164102.

[231] Wang C, Nguyen H, Wang J. A two-stage approach of DEA and AHP in selecting optimal wind power plants. IEEE Trans Eng Manage 2021. https://doi.org/10.1109/TEM.2021.3110519.

[232] Silva Herran D, Dai H, Fujimori S, Masui T. Global assessment of onshore wind power resources considering the distance to urban areas. Energy Policy 2016;91: 75–86. https://doi.org/10.1016/j.enpol.2015.12.024.
[233] Mahdy M, Bahaj AS. Multi criteria decision analysis for offshore wind energy potential in Egypt. Renew Energy 2018;118:278–89. https://doi.org/10.1016/j.renene.2017.11.021.
[234] Wu Y, Tao Y, Zhang B, Wang S, Xu C, Zhou J. A decision framework of offshore wind power station site selection using a PROMETHEE method under intuitionistic fuzzy environment: a case in China. Ocean Coast Manage 2020;184. https://doi.org/10.1016/j.ocecoaman.2019.105016.
[235] Vinhoza A, Schaeffer R. Brazil's offshore wind energy potential assessment based on a Spatial Multi-Criteria Decision Analysis. Renew Sustain Energy Rev 2021; 146. https://doi.org/10.1016/j.rser.2021.111185.
[236] Emeksiz C, Demirci B. The determination of offshore wind energy potential of Turkey by using novelty hybrid site selection method. Sustain Energy Technol Assess 2019;36. https://doi.org/10.1016/j.seta.2019.100562.
[237] Makridis C. Offshore wind power resource availability and prospects: a global approach. Environ Sci Policy 2013;33:28–40. https://doi.org/10.1016/j.envsci.2013.05.001.
[238] Enevoldsen P, et al. How much wind power potential does europe have? Examining european wind power potential with an enhanced socio-technical atlas. Energy Policy 2019;132:1092–100. https://doi.org/10.1016/j.enpol.2019.06.064.
[239] Weinand JM, Naber E, McKenna R, Lehmann P, Kotzur L, Stolten D. Historic drivers of onshore wind power siting and inevitable future trade-offs. Environ Res Lett 2022;17(7):074018. https://doi.org/10.1088/1748-9326/ac7603.
[240] European Commission. Joint Research Centre.. The social acceptance of wind energy: where we stand and the path ahead. LU: Publications Office; 2016. Accessed: Oct. 26, 2023. [Online]. Available: https://data.europa.eu/doi/10.2789/696070.
[241] McKenna R, et al. Exploring trade-offs between landscape impact, land use and resource quality for onshore variable renewable energy: an application to Great Britain. Energy 2022;250:123754. https://doi.org/10.1016/j.energy.2022.123754.
[242] Diógenes JRF, Claro J, Rodrigues JC, Loureiro MV. Barriers to onshore wind energy implementation: a systematic review. Energy Res Soc Sci 2020;60:101337. https://doi.org/10.1016/j.erss.2019.101337.
[243] Mutiso RM. Net-zero plans exclude Africa. Nature 2022;611(7934):10. https://doi.org/10.1038/d41586-022-03475-0.
[244] Tercan E, Tapkın S, Latinopoulos D, Dereli MA, Tsiropoulos A, Ak MF. A GIS-based multi-criteria model for offshore wind energy power plants site selection in both sides of the Aegean Sea. Environ Monit Assess 2020;192(10). https://doi.org/10.1007/s10661-020-08603-9.
[245] Enevoldsen P, Sovacool BK. Examining the social acceptance of wind energy: practical guidelines for onshore wind project development in France. Renew Sustain Energy Rev 2016;53:178–84. https://doi.org/10.1016/j.rser.2015.08.041.
[246] Weinand JM, McKenna R, Kleinebrahm M, Scheller F, Fichtner W. The impact of public acceptance on cost efficiency and environmental sustainability in decentralized energy systems. Patterns 2021;2(7):100301. https://doi.org/10.1016/j.patter.2021.100301.
[247] Deshmukh S, Bhattacharya S, Jain A, Paul AR. Wind turbine noise and its mitigation techniques: a review. Energy Procedia 2019;160:633–40. https://doi.org/10.1016/j.egypro.2019.02.215.
[248] Teff-Seker Y, Berger-Tal O, Lehnardt Y, Teschner N. Noise pollution from wind turbines and its effects on wildlife: a cross-national analysis of current policies and planning regulations. Renew Sustain Energy Rev 2022;168:112801. https://doi.org/10.1016/j.rser.2022.112801.
[249] Poulsen AH, et al. Short-term nighttime wind turbine noise and cardiovascular events: a nationwide case-crossover study from Denmark. Environ Int 2018;114: 160–6. https://doi.org/10.1016/j.envint.2018.02.030.
[250] Poulsen AH, et al. Long-term exposure to wind turbine noise and redemption of antihypertensive medication: a nationwide cohort study. Environ Int 2018;121: 207–15. https://doi.org/10.1016/j.envint.2018.08.054.
[251] Weinand JM, McKenna R, Heinrichs H, Roth M, Stolten D, Fichtner W. Exploring the trilemma of cost-efficiency, landscape impact and regional equality in onshore wind expansion planning. Adv Appl Energy 2022;7:100102. https://doi.org/10.1016/j.adapen.2022.100102.
[252] Gibbons S. Gone with the wind: valuing the visual impacts of wind turbines through house prices. J Environ Econ Manage 2015;72:177–96. https://doi.org/10.1016/j.jeem.2015.04.006.
[253] McKenna R, et al. Scenicness assessment of onshore wind sites with geotagged photographs and impacts on approval and cost-efficiency. Nat Energy 2021;6(6): 663–72. https://doi.org/10.1038/s41560-021-00842-5.
[254] Wang S, Wang S, Smith P. Ecological impacts of wind farms on birds: questions, hypotheses, and research needs. Renew Sustain Energy Rev 2015;44:599–607. https://doi.org/10.1016/j.rser.2015.01.031.
[255] Desholm M. Avian sensitivity to mortality: prioritising migratory bird species for assessment at proposed wind farms. J Environ Manage 2009;90(8):2672–9. https://doi.org/10.1016/j.jenvman.2009.02.005.
[256] Marques AT, et al. Wind turbines cause functional habitat loss for migratory soaring birds. J Anim Ecol 2020;89(1):93–103. https://doi.org/10.1111/1365-2656.12961.
[257] Ioannidis R, Koutsoyiannis D. A review of land use, visibility and public perception of renewable energy in the context of landscape impact. Appl Energy 2020;276:115367. https://doi.org/10.1016/j.apenergy.2020.115367.
[258] Kumar A, et al. A review of multi criteria decision making (MCDM) towards sustainable renewable energy development. Renew Sustain Energy Rev 2017;69: 596–609. https://doi.org/10.1016/j.rser.2016.11.191.
[259] Lehmann P, et al. Managing spatial sustainability trade-offs: the case of wind power. Ecol Econ 2021;185:107029. https://doi.org/10.1016/j.ecolecon.2021.107029.
[260] Heneghan B, Boyne K, Consulting Ionic. Life-cycle of an onshore wind farm. Ireland: Ionic Consulting, IWEA Irish Wind Energy Association; 2019 [Online]. Available: https://windenergyireland.com/images/files/iwea-onshore-wind-farm-report.pdf.
[261] Bosch J, Staffell I, Hawkes AD. Temporally explicit and spatially resolved global offshore wind energy potentials. Energy 2018;163:766–81. https://doi.org/10.1016/j.energy.2018.08.153.
[262] R. McKenna et al., 'On the socio-technical potential for onshore wind in Europe: a response to Enevoldsen et al. (2019), Energy Policy, 132, 1092-1100′, Energy Policy, vol. 145, p. 111693, Oct. 2020, doi:10.1016/j.enpol.2020.111693.
[263] Enevoldsen P, et al. On the socio-technical potential for onshore wind in Europe: a response to critics. Energy Policy 2021;151:112147. https://doi.org/10.1016/j.enpol.2021.112147.
[264] GFS, 'Global forecast system - 1° x 1° reanalysis fields.' [Online]. Available: http://nomads.ncdc.noaa.gov/data/gfs-avn-hi.
[265] Jacobson MZ. GATOR-GCMM: a global- through urban-scale air pollution and weather forecast model: 1. Model design and treatment of subgrid soil, vegetation, roads, rooftops, water, sea ice, and snow. J Geophys Res 2001;106 (D6):5385–401. https://doi.org/10.1029/2000JD900560.
[266] Vortex, 'Vortex Wind & Site'. 2023. [Online]. Available: https://vortexfdc.com/.
[267] D.L. Rife, J.O. Pinto, A.J. Monaghan, C.A. Davis, and J.R. Hannan, 'NCAR global climate four-dimensional data assimilation (CFDDA) hourly 40km reanalysis'. UCAR/NCAR, p. 26.975TB, 2014. doi:10.5065/D6M32STK.
[268] Dee DP, et al. The ERA-Interim reanalysis: configuration and performance of the data assimilation system. QJR Meteorol Soc 2011;137(656):553–97. https://doi.org/10.1002/qj.828.
[269] Global Modeling And Assimilation Office and Pawson, Steven, MERRA-2 tavg1_2d_slv_Nx: 2d,1-hourly,time-averaged,single-level,assimilation,single-level diagnostics V5.12.4. NASA Goddard Earth Sciences Data and Information Services Center, 2015. doi:10.5067/VJAFPLI1CSIV.
[270] Davis N, et al. Global wind atlas v3. Technical University of Denmark; 2019. https://doi.org/10.11583/DTU.9420803.V1. 316432340369 Bytes.
[271] Saha S, et al. The NCEP climate forecast system reanalysis. Bull Am Meteorol Soc 2010;91(8):1015–58. https://doi.org/10.1175/2010BAMS3001.1.
[272] Stackhouse PW. Surface meteorology and solar energy (SSE). NASA NTRS 2013 [Online]. Available: https://ntrs.nasa.gov/citations/20080012200.
[273] European Centre For Medium-Range Weather Forecasts, 'ERA-20C Project (ECMWF Atmospheric Reanalysis of the 20th Century)'. UCAR/NCAR - Research Data Archive, p. 80.239TB, 2014. doi:10.5065/D6VQ30QG.
[274] Saha K, Zhang HM. Hurricane and typhoon storm wind resolving NOAA NCEI blended sea surface wind (NBS) product. Front Mar Sci 2022;9:935549. https://doi.org/10.3389/fmars.2022.935549.
[275] Rienecker MM, et al. MERRA: NASA's modern-era retrospective analysis for research and applications. J Clim 2011;24(14):3624–48. https://doi.org/10.1175/JCLI-D-11-00015.1.
[276] The World Bank. World bank country and lending groups. worldbank.org; 2023. Accessed: Jun. 26[Online]. Available: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.
[277] Oyewo AS, Sterl S, Khalili S, Breyer C. Highly renewable energy systems in Africa: rationale, research, and recommendations. Joule 2023. https://doi.org/10.1016/j.joule.2023.06.004. S2542435123002271.
[278] International Energy Agency (IEA), Africa energy outlook 2019, International Energy Agency (IEA), 2019. [Online]. Available: http://www.iea.org/africa2019.
[279] Ali AO, Estima J, Fichaux N. Investment opportunities in Latin America. Masdar City, United Arab Emirates: International Renewable Energy Agency (IRENA); 2016.
[280] Ferguson R, Wilkinson W, Hill R. Electricity use and economic development. Energy Policy 2000;28(13):923–34. https://doi.org/10.1016/S0301-4215(00)00081-1.
[281] Niu S, Jia Y, Wang W, He R, Hu L, Liu Y. Electricity consumption and human development level: a comparative analysis based on panel data for 50 countries. Int J Electr Power Energy Syst 2013;53:338–47. https://doi.org/10.1016/j.ijepes.2013.05.024.
[282] Tran BL, Chen CC, Tseng WC. Causality between energy consumption and economic growth in the presence of GDP threshold effect: evidence from OECD countries. Energy 2022;251:123902. https://doi.org/10.1016/j.energy.2022.123902.
[283] The World Bank. Population, total. worldbank.org; 2023. Accessed: Jun. 24 [Online]. Available: https://data.worldbank.org/indicator/SP.POP.TOTL.
[284] U.S. Energy Information Administration (EIA). Electricity consumption. EIA.gov; 2023. Accessed: Jun. 24[Online]. Available: https://www.eia.gov/international/data/world/electricity/electricity-consumption.
[285] R. Wiser et al., 'Land-Based Wind Market Report: 2022 Edition', None, 1882594, ark:/13030/qt48j7s9v1, Aug. 2022. doi:10.2172/1882594.
[286] Bilgili M, Alphan H, Ilhan A. Potential visibility, growth, and technological innovation in offshore wind turbines installed in Europe. Environ Sci Pollut Res 2022;30(10):27208–26. https://doi.org/10.1007/s11356-022-24142-x.
[287] Garratt JR. Surface influence upon vertical profiles in the atmospheric near-surface layer. Q J R Meteorol Soc 1980;106(450):803–19. https://doi.org/10.1002/qj.49710645011.

[288] Justus CG, Hargraves WR, Mikhail A, Graber D. Methods for estimating wind speed frequency distributions. J Appl Meteor 1978;17(3):350–3. https://doi.org/10.1175/1520-0450(1978)017<0350:MFEWSF>2.0.CO;2.
[289] Schoenberg IJ. Spline functions and the problem of graduation. Proc Natl Acad Sci USA 1964;52(4):947–50. https://doi.org/10.1073/pnas.52.4.947.
[290] Archer CL, Jacobson MZ. Evaluation of global wind power. J Geophys Res 2005;110(D12):2004JD005462. https://doi.org/10.1029/2004JD005462.
[291] Archer CL, Jacobson MZ. Spatial and temporal distributions of U.S. winds and wind power at 80m derived from measurements. J Geophys Res 2003;108(D9):2002JD002076. https://doi.org/10.1029/2002JD002076.
[292] Copernicus Climate Change Service (C3S). European state of the climate 2021 summary. 2022. https://doi.org/10.21957/9D7G-HN83.
[293] Intergovernmental Panel on Climate Change. Weather and climate extreme events in a changing climate. In: Climate Change 2021 – The physical science basis: Working Group I contribution to the sixth assessment report of the intergovernmental panel on climate change. 1st ed. Cambridge University Press; 2021. https://doi.org/10.1017/9781009157896.
[294] Lopez-Villalobos CA, Rodriguez-Hernandez O, Martínez-Alvarado O, Hernandez-Yepes JG. Effects of wind power spectrum analysis over resource assessment. Renew Energy 2021;167:761–73. https://doi.org/10.1016/j.renene.2020.11.147.
[295] Milan P, Wächter M, Peinke J. Turbulent character of wind energy. Phys Rev Lett 2013;110(13):138701. https://doi.org/10.1103/PhysRevLett.110.138701.
[296] World Meteorological Organisation, 'WMO guidelines on the calculation of climate normals: 2017 edition', Geneva, WMO-No. 1203, 2017. [Online]. Available: https://library.wmo.int/doc_num.php?explnum_id=4166.
[297] W. Musial, P. Spitsen, P. Beiter, M. Marquis, R. Hammond, and M. Shields, 'Offshore wind market report: 2022 edition', DOE/GO-102022-5765, 1893268, 8923, Oct. 2022. doi:10.2172/1893268.
[298] [IEC] International Electrotechnical Commission. IEC-61400-1:2019. Geneva: International Electrotechnical Commission; 2019 [Online]. Available: https://webstore.iec.ch/publication/26423.
[299] Göçmen T, Laan PVD, Réthoré PE, Diaz AP, Larsen GC, Ott Sø. Wind turbine wake models developed at the technical university of Denmark: a review. Renew Sustain Energy Rev 2016;60:752–69. https://doi.org/10.1016/j.rser.2016.01.113.
[300] Davis NN, Pinson P, Hahmann AN, Clausen NE, Žagar M. Identifying and characterizing the impact of turbine icing on wind farm power generation: impact of turbine icing on wind farm production. Wind Energy 2016;19(8):1503–18. https://doi.org/10.1002/we.1933.
[301] Jensen N.O. A note on wind generator interaction. Risø Natl Lab 1983;2411. Available: https://backend.orbit.dtu.dk/ws/portalfiles/portal/55857682/ris_m_2411.pdf.
[302] Launder BE, Spalding DB. The numerical computation of turbulent flows. Comput Methods Appl Mech Eng 1974;3(2):269–89. https://doi.org/10.1016/0045-7825(74)90029-2.
[303] W.C. Skamarock et al., 'A Description of the Advanced Research WRF Model Version 4′, UCAR/NCAR, Mar. 2019. doi:10.5065/1DFH-6P97.
[304] Tomaszewski JM, Lundquist JK. Simulated wind farm wake sensitivity to configuration choices in the Weather Research and Forecasting model version 3.8.1. Geosci Model Dev 2020;13(6):2645–62. https://doi.org/10.5194/gmd-13-2645-2020.
[305] S.A. Renganathan, R. Maulik, S. Letizia, and G.V. Iungo, 'Data-Driven Wind Turbine Wake Modeling via Probabilistic Machine Learning', 2021, doi:10.48550/ARXIV.2109.02411.
[306] Pedersen M, et al. PyWake 2.5.0: an open-source wind farm simulation tool. Denmark: Technical University of Denmark; 2023. DTU Wind.
[307] Schalkwijk J, Jonker HJJ, Siebesma AP, Van Meijgaard E. Weather forecasting using GPU-based large-eddy simulations. Bull Am Meteorol Soc 2015;96(5):715–23. https://doi.org/10.1175/BAMS-D-14-00114.1.
[308] Hasager CB, et al. Offshore wind resource estimation from satellite SAR wind field maps. Wind Energy 2005;8(4):403–19. https://doi.org/10.1002/we.150.
[309] Dong G, Li Z, Qin J, Yang X. How far the wake of a wind farm can persist for? Theor Appl Mech Lett 2022;12(1):100314. https://doi.org/10.1016/j.taml.2021.100314.
[310] Powers JG, et al. The weather research and forecasting model: overview, system efforts, and future directions. Bull Am Meteorol Soc 2017;98(8):1717–37. https://doi.org/10.1175/BAMS-D-15-00308.1.
[311] Danabasoglu G, et al. The community earth system model version 2 (CESM2). J Adv Model Earth Syst 2020;12(2). https://doi.org/10.1029/2019MS001916. e2019MS001916.
[312] Aneroid Energy, 'Wind Energy: wind power in the Australian Energy Market', anero.id. [Online]. Available: https://anero.id/energy/wind-energy/2023/june/.
[313] G. Costanzo, G. Brindley, P. Cole, R. O'Sullivan, and L. Miro, Wind energy in Europe: 2022 statistics and the outlook for 2023-2027, WindEurope, Brussels, Belgium, Feb. 2023.
[314] IRENA. Future of wind: deployment, investment, technology, grid integration and socio-economic aspects (A global energy transformation paper) 2019.
[315] Miller LM, Keith DW. Observation-based solar and wind power capacity factors and power densities. Environ Res Lett 2018;13(10):104008. https://doi.org/10.1088/1748-9326/aae102.
[316] H. Hersbach et al., 'ERA5 hourly data on single levels from 1940 to present.' Copernicus Climate Change Service (C3S) Climate Data Store (CDS)., 2023. [Online]. Available: doi:10.24381/cds.adbb2d47.
[317] Ross BB. An Overview of Numerical Weather Prediction. In: Ray PS, editor. Mesoscale meteorology and forecasting. Boston, MA: American Meteorological Society; 1986. p. 720–51. https://doi.org/10.1007/978-1-935704-20-1_30. editor.
[318] Sørland SL, et al. COSMO-CLM regional climate simulations in the coordinated regional climate downscaling experiment (CORDEX) framework: a review. Geosci Model Dev 2021;14(8):5125–54. https://doi.org/10.5194/gmd-14-5125-2021.
[319] Eyring V, et al. Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. Geosci Model Dev 2016;9(5):1937–58. https://doi.org/10.5194/gmd-9-1937-2016.
[320] Long Y, Xu C, Liu F, Liu Y, Yin G. Evaluation and projection of wind speed in the arid region of Northwest China based on CMIP6. Remote Sens 2021;13(20):4076. https://doi.org/10.3390/rs13204076.
[321] Bloom A, Kotroni V, Lagouvardos K. Climate change impact of wind energy availability in the Eastern Mediterranean using the regional climate model PRECIS. Nat Hazards Earth Syst Sci 2008;8(6):1249–57. https://doi.org/10.5194/nhess-8-1249-2008.
[322] Haarsma RJ, et al. High resolution model intercomparison project (HighResMIP v1.0) for CMIP6. Geosci Model Dev 2016;9(11):4185–208. https://doi.org/10.5194/gmd-9-4185-2016.
[323] Onea F, Rusu E. An assessment of wind energy potential in the Caspian Sea. Energies 2019;12(13). https://doi.org/10.3390/en12132525.
[324] Kalnay E, et al. The NCEP/NCAR 40-year reanalysis project. Bull Am Meteorol Soc 1996;77(3):437–71. https://doi.org/10.1175/1520-0477(1996)077<0437:TNYRP>2.0.CO;2.
[325] Kardooni R, Yusoff SB, Kari FB. Renewable energy technology acceptance in Peninsular Malaysia. Energy Policy 2016;88:1–10. https://doi.org/10.1016/j.enpol.2015.10.005.
[326] Rockel B, Will A, Hense A. The regional climate model COSMO-CLM (CCLM). Metz 2008;17(4):347–8. https://doi.org/10.1127/0941-2948/2008/0309.
[327] Effenberger N, Ludwig N. A collection and categorization of open-source wind and wind power datasets. Wind Energy 2022. https://doi.org/10.1002/we.2766.
[328] Wilkinson MD, et al. The FAIR guiding principles for scientific data management and stewardship. Sci Data 2016;3(1):160018. https://doi.org/10.1038/sdata.2016.18.
[329] ESRI, 'ArcGIS'. Redlands, CA, 2023. [Online]. Available: https://www.arcgis.com.
[330] QGIS.org, 'QGIS geographic information system'. QGIS Association. [Online]. Available: http://www.qgis.org.
[331] PostGIS Team, 'PostGIS'. 2023. [Online]. Available: http://postgis.net/.
[332] DTU Wind and Energy Systems, 'WAsP - Wind resources for wind turbine production'. 2023. [Online]. Available: https://www.wasp.dk/wasp.
[333] WindSim A.S., 'WindSim'. 2023. [Online]. Available: https://windsim.com/.
[334] Meteodyn. Meteodyn wt. Saint Herblain, France: Meteodyn; 2023 [Online]. Available: https://meteodyn.com/business-sectors/renewable-energy/meteodyn-universe/meteodyn-wt/.
[335] EMD International. WindPRO. Aalborg, Denmark: EMD International; 2023 [Online]. Available: https://www.emd-international.com/windpro/.
[336] 3Tier, 'FirstLook'. Vaisala, 2023. [Online]. Available: https://firstlook.3tier.com.
[337] RIAM Computational Fluid Dynamics. RIAM-Compact 2023 [Online]. Available: http://riam-compact.com/.
[338] The MathWorks Inc, 'MATLAB'. 2022. [Online]. Available: https://www.mathworks.com.
[339] Sáenz J, González-Rojí SJ, Carreno-Madinabeitia S, Ibarra-Berastegi G. Analysis of atmospheric thermodynamics using the R package aiRthermo. Comput Geosci 2019;122:113–9. https://doi.org/10.1016/j.cageo.2018.10.007.
[340] Mattsson N, Verendel V, Hedenus F, Reichenberg L. An autopilot for energy models—automatic generation of renewable supply curves, hourly capacity factors and hourly synthetic electricity demand for arbitrary world regions. Energy Strategy Rev 2021;33:100606. https://doi.org/10.1016/j.esr.2020.100606.
[341] Government of Canada, 'RETScreen Clean Energy Management Software'. 2023. [Online]. Available: https://natural-resources.canada.ca/maps-tools-and-publications/tools/modelling-tools/retscreen/7465.
[342] N. Blair et al., 'System advisor model (SAM) general description (Version 2017.9.5)', National Renewable Energy Laboratory (NREL), NREL/TP-6A20-70414, 2018. [Online]. Available: https://www.nrel.gov/docs/fy18osti/70414.pdf.
[343] Bokde N, Feijóo A, Villanueva D. Wind Turbine Power Curves Based on the Weibull Cumulative Distribution Function. Applied Sciences 2018;8(10):1757. https://doi.org/10.3390/app8101757.
[344] Ince DC, Hatton L, Graham-Cumming J. The case for open computer programs. Nature 2012;482(7386):485–8. https://doi.org/10.1038/nature10836.
[345] von Krauland AK, Long Q, Enevoldsen P, Jacobson MZ. United States offshore wind energy atlas: availability, potential, and economic insights based on wind speeds at different altitudes and thresholds and policy-informed exclusions. Energy Convers Manag X 2023;20:100410. https://doi.org/10.1016/j.ecmx.2023.100410.