Introducing site selection flexibility to technical and economic onshore wind potential assessments: New method with application to Indonesia

Langer, J.K.A.; Zaaijer, M B; Quist, J.N.; Blok, K.

DOI
10.1016/j.renene.2022.11.084

Publication date
2022

Document Version
Final published version

Published in
Renewable Energy

Renewable Energy 202 (2023) 320–335

Contents lists available at ScienceDirect

Renewable Energy

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

Introducing site selection flexibility to technical and economic onshore wind potential assessments: New method with application to Indonesia

Jannis Langer [a,*], Michiel Zaaijer [b], Jaco Quist [a], Kornelis Blok [a]

[a] Delft University of Technology, Faculty of Technology, Policy and Management, Department of Engineering Systems and Services, Jaffalaan 5, 2628 BX, Delft, the Netherlands

[b] Delft University of Technology, Faculty of Aerospace Engineering, Kluyverweg 1, 2629 HS, Delft, the Netherlands

ARTICLE INFO

Keywords:
Onshore wind potential
Indonesia
Flexible site selection criteria
Land use
Bias correction
Levelized cost of electricity

ABSTRACT

Onshore wind potentials are commonly mapped with site selection criteria that either fully include or exclude land for wind farms. However, current research rarely addresses the variability of these criteria, possibly resulting in overly conservative or optimistic potentials. This paper proposes a method to account for the variability of site selection criteria in resource assessments. We distinguish between static and flexible, non-binary criteria and assess onshore wind's technical and economic potential with bias-corrected ERA5 data, 28 turbine power curves, and a turbine-specific cost model. For Indonesia, we show that our flexible mapping approach improves the transparency of resource potential assessments and could contribute to more informed and useful recommendations. These recommendations could address the (1) calibration of site exclusion thresholds, (2) dilemmas of preferring one land type over others, (3) location-specific challenges of wind farm deployment, and (4) more direct support schemes for affected stakeholders and wind farm operators.. We report a technical potential of 207–1,994 TWh/year in Indonesia, which could cover more than 50% of 2030 electricity demand on all islands. LCOEs range between 5.8 and 24.5 US¢(2021)/kWh with an economic potential of 16 TWh/year, which improves to 31–212 TWh/year with a carbon tax of 100 US$(2021)/t$CO_2$e.

1. Introduction

The mapping of onshore wind power resources emerged as a popular research field with many studies published so far [1]. Like other renewables, onshore wind potentials can be mapped on a geographical, technical, and economic level [2] with gradually more restrictive site selection criteria excluding unfavourable areas. Knowing about these resources and their location is important. Wind power has a great potential to decarbonise energy systems worldwide [1] but may compete against other land uses like forestry and urban development with its relatively large land footprint [3]. Therefore, available land must be allocated wisely to foster a socially just and acceptable energy transition [4].

The exclusion of unsuitable land is a well-established practice in resource assessment literature [1]. However, current studies mostly take on a binary approach, where certain areas are either fully included or excluded. Regarding the exclusion criteria, Ryberg et al. note that *"there appears to be a lack of knowledge of the abstract geospatial qualities of these constraints, and […] how the application of one or more can impact the result of an [land eligibility] or similar analysis"* [5, p.2]. However, Ryberg et al. [5,6] address this shortcoming only in terms of land area, but not electricity production. Furthermore, McKenna et al. reviewed over 900 articles and reviews on onshore wind energy and found that *"[m]ost often, the set of criteria and their buffers are chosen once"* and that *"up to now, most approaches for the geographical potential are more or less static"* [1, p.664]. Out of the reviewed documents, they only found few studies that assessed the impact of exclusion layers further, e.g. via scenarios. We reviewed these studies [6–10] mentioned by McKenna et al. [1] and further papers [11–13] and, despite their relevance, found three limitations. First, the reviewed studies only report on the results per scenario, but not on the impact of individual land types causing the differences. Second, even if the potentials exceed the local electricity demand by a manifold, it remains unclear which types of land would be used to meet the demand and which stakeholders would be affected the most by the wind farms. Third, only one study [8] compared the costs of onshore wind against local electricity tariffs, but not per land type. Consequently, contemporary studies do not show which land types play a key role in onshore wind power's development, whether there is enough available land per land type to meet future electricity demand,

* Corresponding author.
E-mail address: j.k.a.langer@tudelft.nl (J. Langer).

https://doi.org/10.1016/j.renene.2022.11.084
Received 2 May 2022; Received in revised form 16 November 2022; Accepted 19 November 2022
Available online 25 November 2022

Abbreviations, symbols, and indices

Abbreviation	*Meaning*
GIS	Geographic Information System
GWA	Global wind atlas
NREL	National Renewable Energy Laboratory

Symbol	*Meaning Unit (if applicable)*
α	Shear exponent
η	Efficiency %
a	Availability factor %
A	Area km^2
BPP	Biaya pokok penyediaan (basic costs of electricity provision) US¢(2021)/kWh
C	Wind farm correction factor %
CAPEX	Capital expenses US$(2021)
CRF	Capital recovery factor %
D	Rotor diameter m
E	Electricity production kWh/year
h	Hub height m
H	Number of wind turbines inside wind farm area
i	Discount rate %
LCOE	Levelized cost of electricity US¢(2021)/kWh
N	Lifetime years
OPEX	Operational expenses US$(2021) per year
P	Power kW
S	Spacing factor between turbines
v	Wind speed m/s

Index	*Meaning (excluding cost components)*
±20%	Variation by ±20% of reference value
100m	Hub height at 100 m
50m	Hub height at 50 m
a	Annual
c	Finely subdivided polygon
C	Number of finely subdivided polygons inside wind farm polygon
f	Factor
farm	Meshed wind farm polygon
lat	Latitudinal
long	Longitudinal
rated	Rated
t	Time step t
T	Total number of intervals (175,320 intervals over 20 years)
Wake	Wake losses of the wind farm

and whether there could be economic benefits and disadvantages from preferring certain land types for wind farm deployment over others.

Against this background, this paper proposes a new method to include inconclusive, non-binary site selection criteria in resource assessment studies. The innovation of our paper is the distinction between static and flexible site selection criteria for wind farm siting. Static criteria generally prohibit the deployment of onshore wind farms, like settlement areas. Flexible criteria apply to land which could be considered either via land transfer or co-existence, e.g. as forest-integrated wind farms. We demonstrate our method for Indonesia due to its strongly growing electricity demand and current dependence on fossil fuels [14]. There, onshore wind is considered unattractive by some [15–17], resource potential estimations are few [18–20], and none of these studies address the three limitations above. Therefore, we want to shed more light on Indonesia's wind resources and challenge the common belief that wind power is generally unattractive there.

We calculate the technical potential using 20 years of hourly bias-corrected ERA5 wind speed data and the power curves of 28 currently available wind turbines. The potentials are compared to the present and projected 2030 electricity demand. We calculate the *Levelized Cost of Electricity (LCOE)* using a turbine-specific cost model to determine the economic potential, which is the part of the technical potential with LCOE $\leq$ local electricity tariff. Moreover, we conduct a sensitivity analysis on technical and economic parameters.

The motivation of the article is to address the limitations detected by the leaders of the field and to showcase the usefulness of more flexible exclusion criteria for resource potential studies. Despite the regional focus of our case study, this paper gains a global relevance as it addresses a general shortcoming in literature with methods that can be scaled to other case studies with global, publicly available datasets. Besides researchers, we target Indonesian policymakers and offer them a comprehensive overview of onshore wind's technical and economic potential, based on which wind power could be prioritised in national and regional energy transition strategies.

The paper is structured as follows. Section 2 elaborates on the materials, methods and assumptions used in this paper and their limitations. We report and discuss our results in section 3, and end the paper with conclusions in section 4.

2. Materials and methods

In this section, we elaborate on the methods and assumptions to introduce site selection flexibility to wind potential assessments. We apply them to our case study of Indonesia as a running example to aid understanding. Nonetheless, we note that these methods can be applied at any desired, computationally feasible, regional scope.

2.1. Site selection with static and flexible criteria

First, the *Geographic Information System (GIS)* environment needs to be prepared, starting with a base map of the region's total land area and land use. Next, we distinguish between static and flexible exclusion criteria as shown in Table 1 for Indonesia. Static criteria generally prohibit the deployment of onshore wind power, and respective areas are fully removed from the base map. The criteria are based on technical and economic limitations, like maximum elevation and slope, environmental barriers from wetlands and volcanoes, and social restrictions from built-up infrastructure. We use a settlement buffer of 500 m based on observations on google maps [21] (see Supplementary Fig. 2).

Flexible exclusion criteria cover land that may be available after further scrutiny. The need for further assessment may stem from the (1) site's properties and their impact on the wind farm's technical and economic feasibility, or the (2) affected stakeholders and their acceptance to make land available for wind farm development. For the remainder of the paper, we label these two groups as *site-property-related* and *stakeholder-related* criteria. Regarding (1), local site properties affect the feasibility of a wind farm, but the thresholds determining feasibility may be perceived differently per region and person, and may change with technological progress. Regarding (2), some land types may require a more intensive involvement of affected stakeholders during the wind farm development process to ensure social acceptance. For clarity, and to prioritise assessment of sites with higher potential, we group land types as shown in Table 1 under "Open Land", "Agriculture", "Forestry", and "Rest".

We include conservation zones as some countries, like Indonesia [17], offer a legal basis to use them for renewable energy deployment. We are aware that this could be perceived as controversial given the social and cultural significance of these areas to local communities. Our

Table 1
Exclusion criteria for the mapping of onshore wind farm sites and open land layers. Unless stated otherwise, all thresholds and buffers are taken from the review by McKenna et al. [1], and land use data for Indonesia from 2017 originates from Ref. [22] as shown in Supplementary Fig. 1. The layer "Settlements" also contains former transmigration areas.

Criterion Group	Exclusion layers	Layer type + Resolution	Threshold/Buffer/Remarks
Static exclusion criteria			
Orography	Slope [23]	Raster, 463 m	Slope $\geq$30° No buffer
	Elevation [23]	Raster, 463 m	Elevation $\geq$2,000 m No buffer
Water bodies/wetlands	Water bodies	Vector	1,000 m
	Fish pond	Vector	1,000 m
	Swamp	Vector	1,000 m
	Swamp shrub	Vector	1,000 m
	Coastline	Vector	1,000 m
	Primary mangrove forest	Vector	1,000 m
	Secondary mangrove forest	Vector	1,000 m
	Primary swamp forest	Vector	1,000 m
	Secondary swamp forest	Vector	1,000 m
Natural catastrophes	Volcano [24]	Vector	1,000 m
Built-up infrastructure	Transmission lines	Line	250 m
	Settlements	Vector	500 m
	Airports/harbours [25]	Point + Vector	2,000 m
Flexible stakeholder-related exclusion criteria			
Agriculture	Dryland agriculture	Vector	–
	Estate crop plantation	Vector	–
	Shrub-mixed dryland farm	Vector	–
	Rice field	Vector	–
	Mining	Vector	
Forestry	Plantation forest	Vector	–
	Primary dryland forest	Vector	–
	Secondary dryland forest	Vector	–
Rest	Nature conservation zones [26]	Vector	–
	Earthquake [24]	Vector	No high risk areas (own criterion)
	Landslide [24]	Vector	No high risk areas (own criterion)
Distance to built-up infrastructure	Substations [27]	Point	Within 10 km–∞ (25–500 kV)
	Road [28]	Line	Minimum 0–500 m (classes: motorway, primary, secondary, service, tertiary, trunk, unclassified)
	Settlements	Vector	Minimum 500–2,000 m
Flexible site-property-related exclusion criteria			**Range**
Wind speed	Minimum wind speed	Raster, 463 m	0 and maximum wind speed
Orography	Slope	Raster, 463 m	0–30°
	Elevation	Raster, 463 m	0–2,000 m
Remaining open land (where none of the above exclusion criteria apply)			
Open land	Bare land	Vector	–
	Bush/shrub	Vector	–
	Savannah	Vector	–

intention is to show what would happen if these regulations would be maximally utilised, knowing that this might not be socially acceptable in practice.

Other stakeholder-related criteria may target project developers and investors, like distance to existing grid infrastructure (i.e. substations) and roads for site access. Expert consultation has indicated that a maximum distance to the electricity grid of 10 km is used in Indonesia. Therefore, we use this value as the most conservative threshold under practical project development conditions.

2.2. *Integration of flexible site selection into geospatial analysis*

After defining the static and flexible site selection criteria above, we present our step-by-step approach in Fig. 1 to integrate them in geospatial analyses. The steps are listed as follows:

1. Apply static exclusion criteria
2. Subdivide resulting wind farm polygon with a grid mesh
3. Subdivide by land type
4. Subdivide by wind speed class
5. Assign location-specific attributes to resulting polygons

After applying all static exclusion criteria in step 1, the resulting shapefile consists of thousands of polygons, each representing land (potentially) suitable for wind farms. We remove polygons smaller than 0.65 km^2 to curb computational efforts, which affected 0.08% of the otherwise suitable area. We acknowledge that the footprint of a single turbine is far smaller than the abovementioned threshold, so even those small areas could host individual turbines. Therefore, our potentials might be slightly too conservative.

Polygons are split along the province borders so that the technical and economic potentials can be attributed to individual provinces. Even then, polygons might stretch over thousands of square kilometres. Averaging properties like wind speed over such large areas might affect the resource assessment negatively, as local landscape details would be disregarded. Hence, we subdivide the wind farm polygons in step 2. We

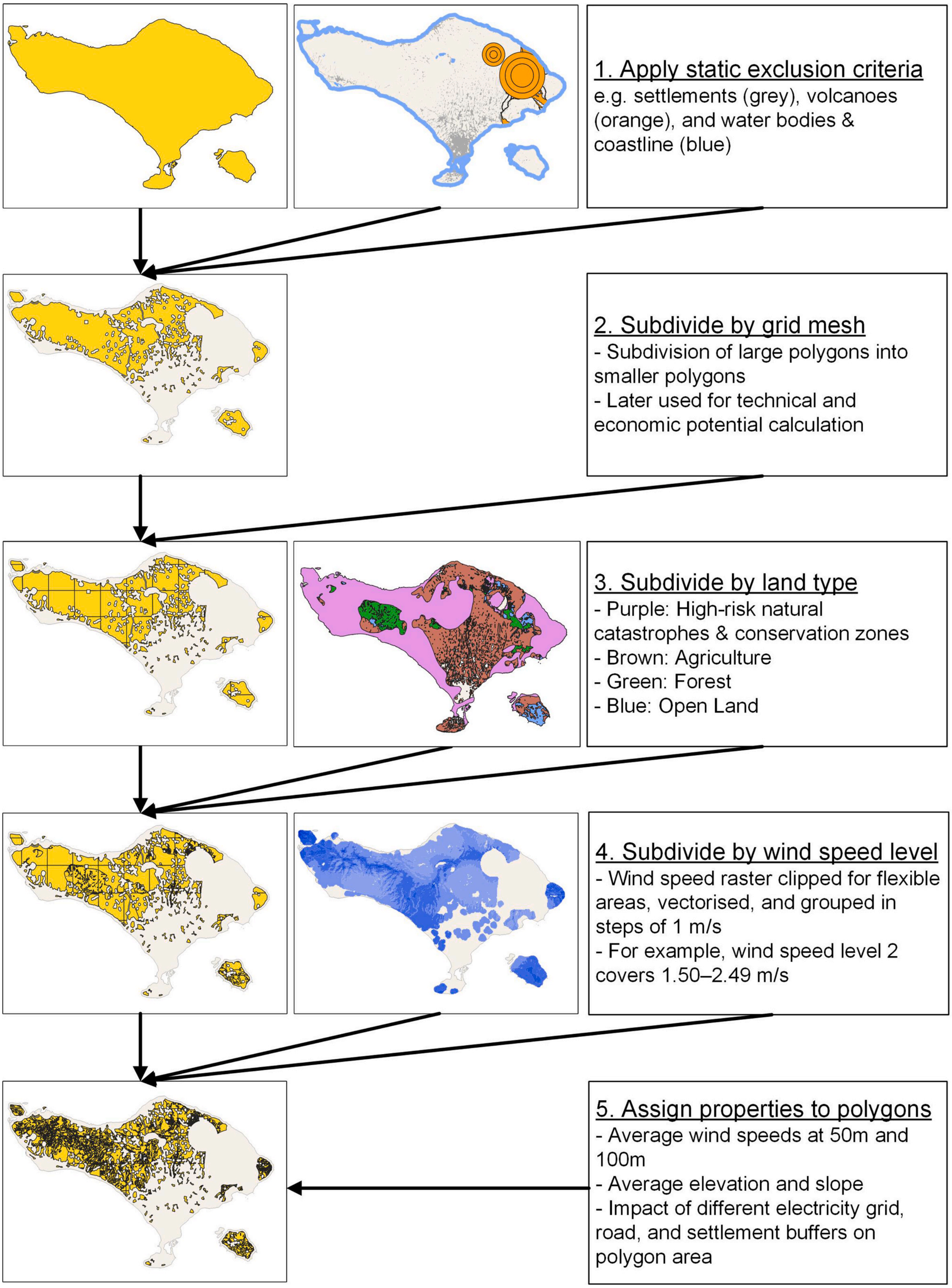

Fig. 1. Overview of polygon subdivision used in this paper as demonstrated for Bali, Indonesia, as an example. The result is a shapefile that contains all areas suitable for onshore wind, their site properties, and distinguishes between different land uses and wind speed levels. This paper mainly reports and discusses the results per meshed polygons (after step 2) and per finely subdivided polygons (after step 5).

lay a 0.125° × 0.125° grid mesh (about 14 km × 14 km) over the wind farm shapefile and intersect the polygons with the mesh. From now on, these polygons are called *meshed polygons*. In steps 3 and 4, we subdivide these polygons further by the land groups listed in section 2.1 and wind speed using data from the *Global Wind Atlas (GWA)* [29]. For the latter, we clip the GWA raster file to the wind farm polygons (after step 1), vectorise it, and group the wind speeds in steps of 1 m/s. The polygons obtained from step 4 are called *finely subdivided polygons* from now on.

After step 4, all wind farm areas consist of several finely subdivided polygons. In step 5, we add location-specific information to them. Besides average wind speed, elevation, and slope inside the polygon area, we also add the impact of varying buffers around substations (electricity grid), roads, and settlements as shown in Table 1. For the latter group, we create duplicate versions of the shapefile from step 4 and remove the areas that overlap with the different buffers. Then, the areas of the new resulting polygons are re-calculated and added as a new data column of the original shapefile.

After step 5, all finely subdivided polygons contain the following information:

- Island (group) and province in Indonesia
- Area of meshed and finely subdivided polygons in [km^2] for different buffers around substations, roads, and settlements
- Land type
- Mean GWA wind speeds at 100 m and 50 m hub height in [m/s]
- Mean elevation and slope in [m] and [°]
- Index of closest ERA5 point (see below)
- Local electricity tariff in [US¢(2021)/kWh] (see section 2.3.3)

One of the attributes is the index of the closest ERA5 point containing 20 years of hourly local wind speed data at 100 m height. We use ERA5 wind speed data to calculate the electricity production of the wind farms. By itself, ERA5 does not yet reflect the detailed local orography given its coarse spatial resolution of 0.25° × 0.25° (28 km × 28 km). Therefore, we complement the ERA5 data with GWA data, which provides average, high-resolution wind speed data (250 m × 250 m). The abovementioned ERA5 index determines which wind profile from the ERA5 dataset should be used per finely subdivided polygon. Then, we compare the average wind speed of the ERA5 wind profile with the mean GWA wind speed assigned in step 5. As done in Refs. [30–34], we compute a time-invariant, constant correction factor from the difference between ERA5 and GWA. The ERA5 profile is then multiplied with the correction factor to match the GWA value. Recent studies indicate that correction factors are close to unity (between 0.8 and 1.2) in far-offshore regions but tend to be higher in (1) near-shore areas due to the complexity at the land-sea interface with factors above 2 [35], and in (2) mountainous terrain with factors above 3 [31]. Such high correction factors might lead to strongly fluctuating wind profiles with large amplitudes. Therefore, we assess what causes high correction factors and whether they lead to disproportional wind speeds. In this study, wind speeds are considered disproportional if they exceed the 50-year return gust of the IEC wind class [36]. For example, if a polygon is situated at a IEC class III location (i.e. with average speeds of up to 7.5 m/s), wind speeds above 52.5 m/s are considered disproportional.

2.3. Technical and economic analysis of onshore wind power

2.3.1. Technical onshore wind potential

The technical onshore wind potential is the aggregated annual electricity production E_a of the wind farms deployed over all suitable areas. We calculate E_a for each finely subdivided polygon with Eq. (1) using turbine-specific power curves *P(v),* the number of wind turbines H inside each polygon, and constant values for wake efficiency η_{Wake} and availability factor a_f (88% and 97%, respectively [23]). With Eq. (1), we calculate the average net electricity production in kWh/year in a computationally inexpensive way. Nevertheless, a shortcoming is the omission of annual fluctuations of electricity generation, which in practice could affect the wind farms' bankability, e.g. for loan repayment [37].

$$E_{a,c} = \frac{\sum_{t=1}^{T} P(v_{c,t})}{T} * H_c * \eta_{Wake} * a_f * 8,760 \frac{hours}{year} \tag{1}$$

Variables	Indices
η: efficiency	*a:* annual
a: availability	*c:* finely subdivided polygon
E: electricity production	*f:* factor
H: number of turbines in a polygon (see Eq. (2))	*t:* time step (hourly)
P: power output of single turbine	*T:* total number of intervals (175,320 intervals over 20 years)
v: wind speed	*Wake*: wake effects of the wind farm

We use the power curves *P(v)* of 28 turbine models (see Supplementary Table 1) from The Wind Power [38] database. We select the wind turbines based on four criteria, namely (1) rated power ≥1,500 kW, (2) cut-in wind speed ≤3 m/s, (3), rated wind speed ≤12 m/s, and (4) current availability on the global market (as of February 2022). We also include the turbine models deployed in Indonesia's only two existing wind farms, Sidrap and Jeneponto, which otherwise would have been excluded for not being available anymore (Sidrap) and a too high rated wind speed (Jeneponto). We present and discuss the results not per turbine, but as median values and 25th and 75th percentiles.

We compute the number of turbines inside a polygon H with Eq. (2) as a function of polygon area A, rotor diameter D, and dimensionless turbine spacing factor S (*5D × 10D* [23]). Initially, H is calculated for the finely subdivided polygons, which can lead to $H < 1$, i.e. less than one full turbine. This is to be expected, as the subdivided polygons merely represent a fraction of the entire wind farm area obtained from step 1. The sum of all H would be a float, although in practice it needs to be an integer. Therefore, we calculate a correction factor C with Eq. (3), which uses a floor function to ensure that all H of finely subdivided polygons inside a meshed polygon add up to an integer.

$$H_c = \frac{A_c}{S_{long} * D * S_{lat} * D} * C_{farm} \tag{2}$$

$$C_{farm} = \frac{\left\lfloor \frac{\sum_{c=1}^{C} A_c}{S_{long} * D * S_{lat} * D} \right\rfloor}{\frac{\sum_{c=1}^{C} A_c}{S_{long} * D * S_{lat} * D}} \tag{3}$$

Variables	Indices
A: area of wind farm	*a:* annual
C: correction factor	*c:* finely subdivided polygon
D: rotor diameter	*C:* Number of finely subdivided polygons inside meshed polygon
H: number of turbines in a polygon	*farm:* meshed wind farm polygon
S: dimensionless spacing between turbines in a wind farm	*lat:* latitudinal
	long: longitudinal

One limitation of our approach is the use of time- and space-invariant constants for turbine spacing, wake efficiency η_{Wake}, and availability factor a_f as found in literature [1,30]. It was computationally infeasible to model these parameters for more than 700,000 finely subdivided polygons and 20 years of hourly resource data. The wind farms in Indonesia can have a far denser turbine spacing than *5D×10D* as seen in

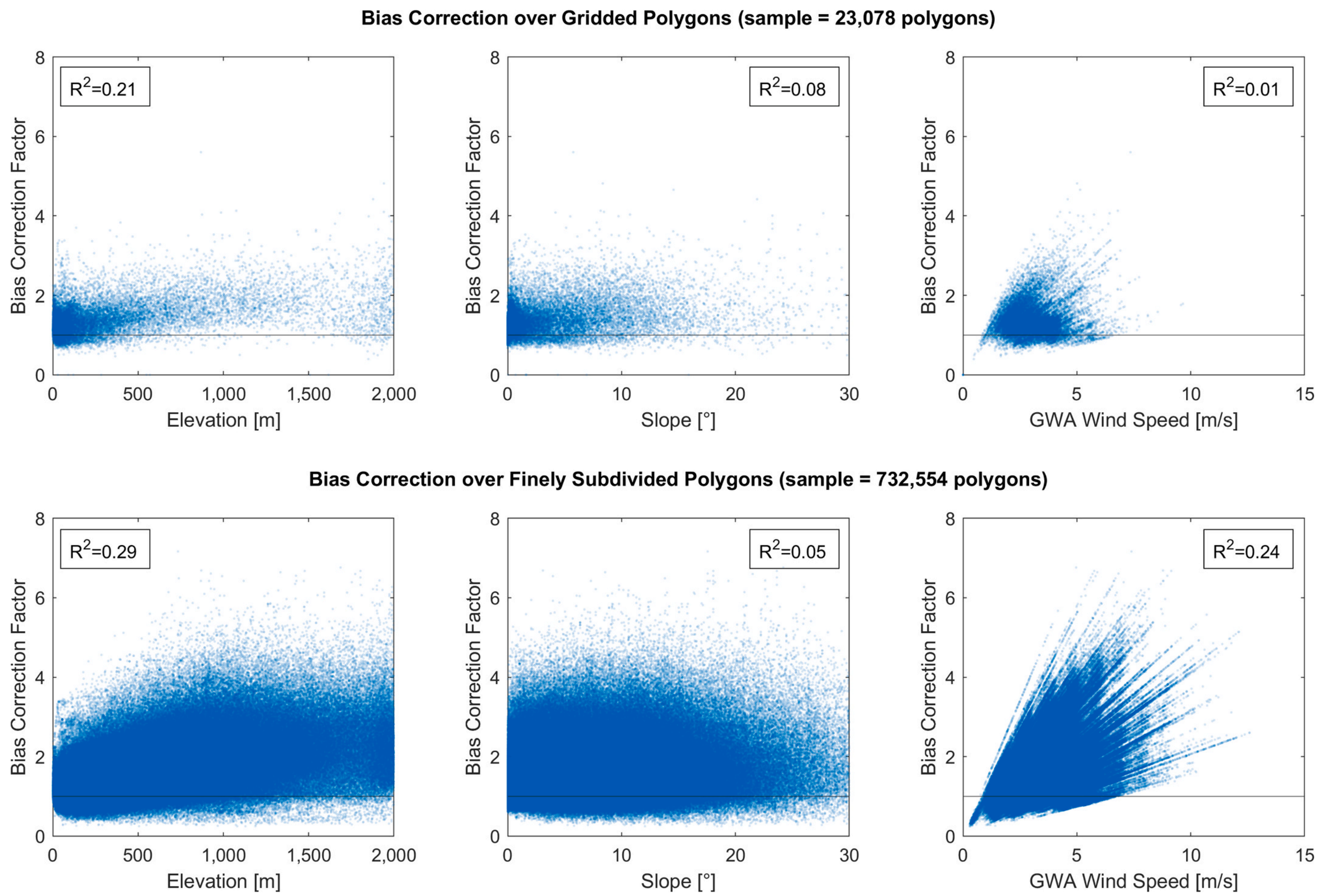

Fig. 2. Impact of elevation, slope, and average GWA wind speed on bias-correction factors for meshed and finely subdivided polygon (i.e. the polygons obtained from step 2 and 4 in Fig. 1, respectively).

Table 2
Comparison of calculated electricity generation values with the recorded generation of Indonesia's two wind farms Jeneponto and Sidrap. For the original CAPEX of Jeneponto, we assume US$(2017) based on the start of construction [55].

		Sidrap	Jeneponto
Coordinates		119.71° E 3.99 °S	119.76° E 5.65 °S
Size [MW]		75 MW	72 MW
Number of turbines		30	20
Hub height [m]		80	133
Rotor diameter		114	130
Average 100m wind speed [m/s]	GWA	7.18	6.16
	ERA5	3.21	4.91
Correction factor		2.24	1.26
Start of commercial operation		5th April 2018	14th May 2019
CAPEX [US$ (2017) million]		150	160
Inflation-corrected CAPEX [US$ (2021) million]		162	173
Calculated CAPEX [US$ (2021) million] and deviation [%]		97 (−40%)	106 (−39%)
Recorded electricity generation 2020 [GWh]		473	
Calculated electricity generation 2020 [GWh] and deviation [%]	Uncorrected	181 (−62%)	
	Bias-corrected	494 (+4%)	

Supplementary Fig. 2. But since we could not check the corresponding wake losses at these wind farms, we use a matching spacing S and wake efficiency η_{Wake} from literature [23]. Another limitation is the omission of air density effects on the turbine power curves, which might be significant in locations with higher altitudes.

Later, we evaluate the accuracy of our simulated power production profiles with Indonesian wind power statistics [39]. As of February 2022, there are two wind farms in Indonesia, Sidrap and Jeneponto [40]. A full year of wind power production from both wind farms is available for the year 2020. For that year, we compare the recorded electricity production with the simulated production of the uncorrected and corrected ERA5 wind profiles. A sample of two wind farms and one production year is far too small to make a final statement about the accuracy of our production profiles. Moreover, we would have preferred to use real-life hourly production data for bias correction via a measure-correlate-predict approach [41]. However, such data is not publicly available for Indonesia's existing wind farms.

To put the technical and economic potentials into perspective, we compare them to the present and future electricity demand. For Indonesia, we use the (expected) electricity generation in 2018 [42] and 2030 [14], respectively. We group Indonesia's 34 provinces (as of February 2022) in "Sumatera", "Java & Bali", "Kalimantan", "Sulawesi", and "Nusa Tenggara, Maluku, and Papua", which is in line with the practices of the country's state utility company [14]. The electricity generation is then aggregated per island group and compared with the calculated electricity generation of our onshore wind farms.

2.3.2. Levelized cost of electricity and turbine-specific cost model

For the economic analysis, we calculate the *Levelized Cost of Electricity (LCOE),* which indicates the electricity tariff needed to break even with all project costs at the end of the project's useful lifetime and is

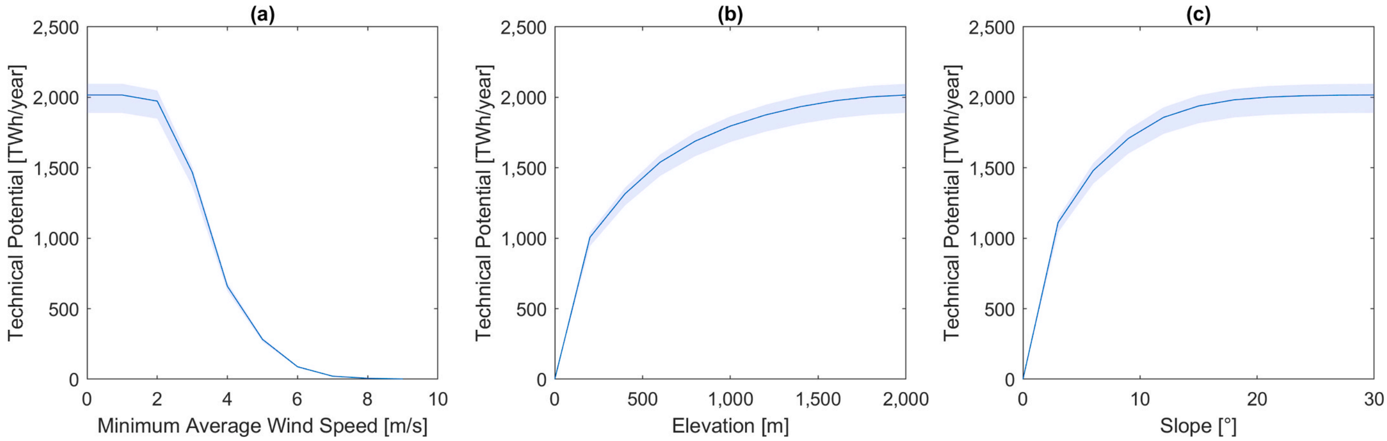

Fig. 3. Impact of (a) minimum average wind speed at hub height, (b) maximum elevation, and (c) maximum slope on the technical onshore wind potential (blue line: median, light-blue field: 25th–75th percentile).

Table 3
Impact of exclusion criteria on land usage and technical potential. The percentage of excluded area is based on the total Indonesian land area of 1,890,077 km^2. The range of excluded technical potential is based on the capacity densities of 2.9–5.3 MW/km^2 in Supplementary Table 1. The excluded area and technical potential of the individual criteria do not add up to the total excluded land because some criteria overlap.

Exclusion Group	Excluded Area [10^3 km^2]	Percentage of total area [%]	Technical potential [GW]
Static criteria			
Maximum slope and elevation	50	3%	147–266
Water bodies/ wetlands	515	27%	1,493–2,729
Volcanoes	36	2%	80–146
Built infrastructure	144	8%	418–764
Total excluded static land (before excluding flexible land)	**687**	**36%**	**1,993–3,642**
Stakeholder-related criteria			
Nature conservation	226	12%	659–1,195
Agriculture & Mining	583	31%	1,692–3,092
Forestry	797	42%	2,319–4,208
Natural-catastrophe-prone areas	351	19%	1,018–1,861
Site-property-related criteria			
Minimum average 100m wind speed (0–2–4 m/s)	0–282–1,654	0–15–88%	0–8,766
Distance from settlements (0.5–1–2 km)	128–203–331	7–11–17%	370–1,752
Minimum distance from roads (0–250–500 m)	0–243–410	0–13–22%	0–2,176
Proximity to substation (∞–100–10 km)	0–118–1,674	0–6–89%	0–8,872
Total excluded static and flexible land	**1,771–1,782–1,889**	**93.7–94.3–99.9**	**9,386–10,012**

calculated with Eqs. (4) and (5), assuming a discount rate *i* of 10% [43,44] and a lifetime *N* of 20 years [30]. The project costs consist of *Capital Expenses (CAPEX)* and *Operational Expenses (OPEX)* as elaborated below.

$$LCOE_{farm} = \frac{CRF * CAPEX_{farm} + OPEX_{farm}}{E_{a,farm}} \tag{4}$$

$$\text{with } CRF = \frac{i * (1+i)^N}{(1+i)^N - 1} \tag{5}$$

Variables	Indices
CAPEX: capital expenses	*a:* annual
CRF: capital recovery factor	*farm:* wind farm (polygon after step 1 in Fig. 1)
E: electricity production	
i: discount rate	
N: lifetime	
OPEX: operational expenses	

We use the mass-based cost model developed by the *National Renewable Energy Laboratory (NREL)* [45] to calculate CAPEX and OPEX. We calibrate the cost model with updated component costs and technology-specific correction factors derived from the most recent cost review report by NREL [46]. The component cost functions and correction factors are listed in Supplementary Table 2. We check the cost model by comparing the calculated CAPEX with the investment costs of the wind farms Sidrap and Jeneponto in Indonesia. Unless stated otherwise, all costs are converted to US$(2021) using the currency conversion rates listed in Supplementary Table 3 [47,48].

The cost model and surrounding assumptions come with three limitations. First, we did not consider land type specific cost components, like compensation payments to farmers. Second, we did not include system integration costs covering grid connection and management. Third, we do not consider cost developments from economies of scale and technological learning as two wind farms are too few to make tangible statements about the latter's effects on wind farm costs in Indonesia. However, we recommend the consideration of the above-mentioned aspects in future research once wind power progressed further in Indonesia.

2.3.3. Economic onshore wind potential with and without carbon tax

The LCOE itself is already useful for comparing onshore wind's economic performance against other power generation technologies. However, it does not reveal the economic feasibility against the local electricity tariff. As of February 2022, the receivable tariff in Indonesia is based on and capped by the *Biaya Pokok Penyediaan (BPP – Basic cost of electricity provision)*. Based on a simplification of regulation MEMR Nr.

Table 4
Available land, technical potential, and share of present and future electricity demand of onshore wind power per island (group) in Indonesia depending on whether all land types or only open land are used. For distance to settlements, roads, and electricity grid, we assume the most lenient thresholds, i.e. 500 m to settlements, 0 m to roads, and no maximum distance to the next substation. Note that all island groups combined represent Indonesia as a country.

Island (Group)	Maximum available land for onshore wind [km^2]	Percentage of regional land area [%]	Median technical potential [TWh/year]	Coverage of (projected) demand in 2018 and 2030 [times]	
All land types considered					
Sumatera	309,633	65.0%	509	12	6.0
Jawa + Bali	64,371	46.6%	223	1.1	0.8
Kalimantan	372,390	69.6%	408	35	15
Sulawesi	139,718	75.3%	241	21	10
Nusa Tenggara, Maluku, and Papua	316,623	57.1%	613	102	38
Indonesia	**1,202,735**	**63.6%**	**1,994**	**7.2**	**4.5**
Only open land					
Sumatera	26,193	5.5%	45.5	1.1	0.5
Jawa + Bali	502	0.4%	1.8	0.009	0.006
Kalimantan	61,259	11.4%	74.9	6.5	2.8
Sulawesi	12,476	6.7%	25.1	2.1	1.0
Nusa Tenggara, Maluku, and Papua	18,423	3.3%	60.6	10.1	3.8
Indonesia	**118,851**	**6.3%**	**207.2**	**0.7**	**0.5**

169/2021 [49], we assume that all wind farms receive 85% of the regional BPP, resulting in a tariff range of 5.37–16.59 US¢(2021)/kWh.

With these tariffs, it is possible to calculate the economic onshore wind potential. In this paper, the economic potential is the part of the technical potential for which $LCOE \leq$ local electricity tariff. We want to stress that the receivable tariffs may differ in practice from the tariffs assumed here since we use cap values. Moreover, renewable energy support schemes frequently change in Indonesia [50], so it is unclear how renewable energy producers will be remunerated in the future.

One criticism of the current BPP-based scheme is that external costs from pollution are not considered [51]. Therefore, we investigate the impact of a carbon tax on the economic onshore wind potential. We calculated the electricity tariffs with carbon tax via the back-of-the-envelope calculation in Supplementary File 1 based on general emission factors [52] and the 2018 primary energy consumption and generation mix in Indonesia [53].

2.4. Sensitivity analysis

To address the limitations elaborated in section 2.3, we conduct a sensitivity analysis to understand their impact on the results better. We vary the CAPEX, OPEX, discount rate, wind speed, hub height, and BPP by ±20% to show the change of median LCOE, technical potential, and economic potential. For the hub height h, the wind speed v is adjusted with Eqs. (6) and (7). The local shear exponent α is calculated with GWA data at 50 and 100 m height [54].

$$v_{\pm 20\%,c,t} = v_{100m,c,t} * \left(\frac{h_{\pm 20\%}}{h_{100m}}\right)^{\alpha_c} \tag{6}$$

$$\alpha_c = \frac{\ln\left(\frac{v_{100m,c}}{v_{50m,c}}\right)}{\ln\left(\frac{h_{100m}}{h_{50m}}\right)} \tag{7}$$

Variables	Indices
α: shear exponent	±20%: variation by ±20%
h: height	50m: hub height at 50 m
v: wind speed	100m: hub height at 100 m
	c: finely subdivided polygon
	t: time step (hourly)

3. Results and discussion

3.1. Evaluation of bias-correction factors and cost model

Before presenting the results of the technical and economic analysis, we assess the bias-correction factors, their impact on the wind profiles, and the accuracy of our wind farm and cost model. Fig. 2 shows the impact of elevation, slope and GWA wind speeds on the bias-correction factors across Indonesia.

Three insights can be drawn from Fig. 2. First, most correction factors are above 1, indicating that ERA5 mostly underestimates wind speeds on land compared to GWA data. Second, a more detailed subdivision of suitable wind farm areas enables a more comprehensive analysis of local site conditions. For example, the maximum averaged GWA wind speed in Indonesia increases from 9.7 m/s to 12.6 m/s if polygons are finely subdivided. Third, due to the more detailed representation of local site conditions, correction factors tend to increase with further subdivision, with the maximum correction factor increasing from 5.6 to 7.2.

These insights show that ERA5, as well as other reanalysis datasets, cannot fully capture the local orography and its impact on local wind resources. This is in line with Gruber et al. [31], who found high correction factors above 2 in mountainous terrain in Brazil, USA, South Africa, and New Zealand. Indonesia's complex, archipelagic geography might be a reason why our correction factors are higher. Then again, factors above 5 are exceptional even for Indonesia, as more than 95% of our factors range between 0.33 and 3.

The correction factors presented above mostly do not lead to disproportional wind speeds as per our definition in section 2.2. Only 84 polygons (or 0.01% of all finely subdivided polygons) showed peak wind speeds higher than the 50-year return gust of the IEC wind class to which the site belongs. Their correction factors range between 1.3 and 3.4 and almost all of them are on East Java, indicating that the ERA5 profile there already contains unusual spikes. The bias-corrected peak wind speeds rarely exceed 30 m/s (see Supplementary Fig. 3), even for extreme correction factors above 5.

Table 2 shows a comparison of recorded and calculated electricity generation with and without bias correction. Bias correction

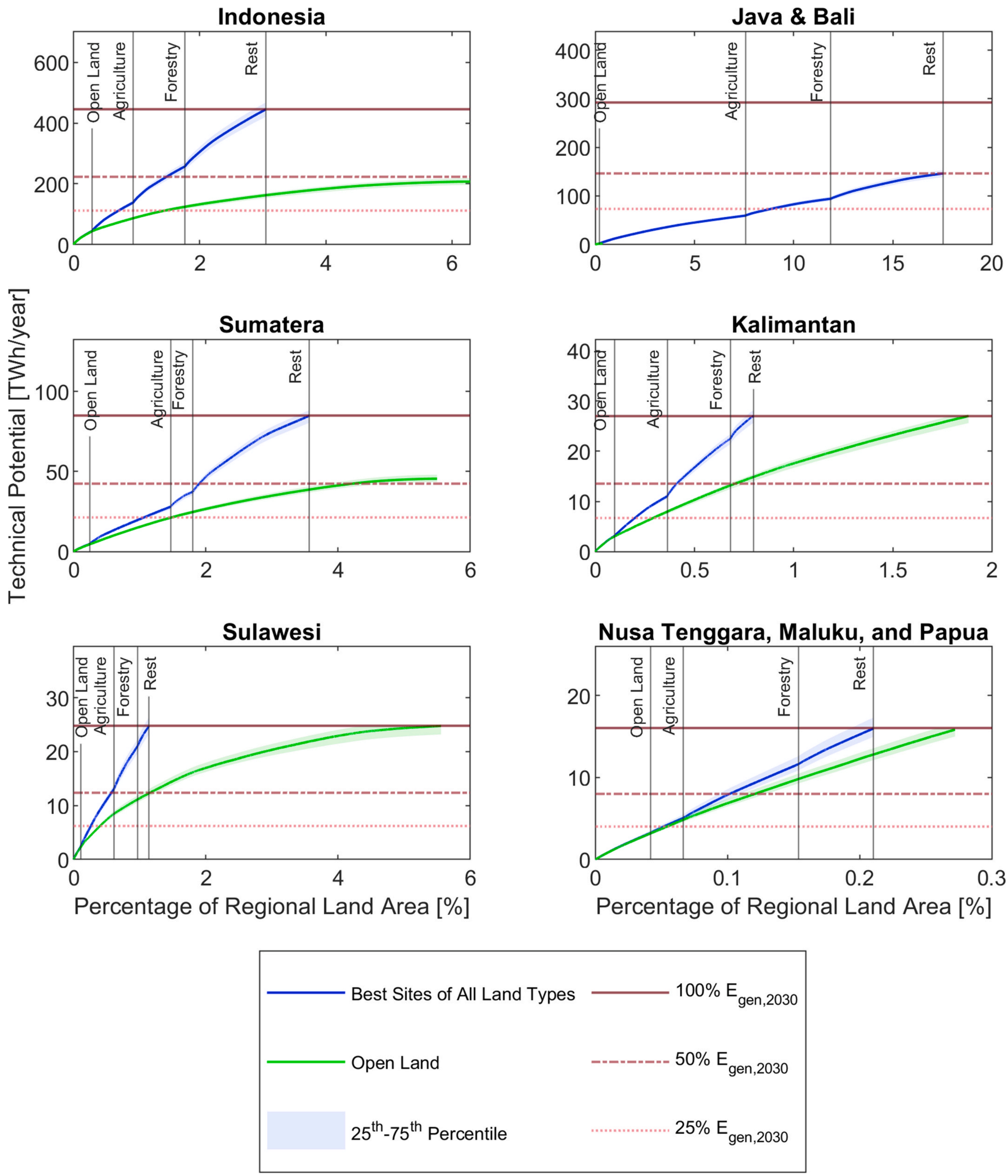

Fig. 4. Land area and land type requirements to meet certain shares of 2030 electricity demand in Indonesia and its island groups. For Java & Bali, 50% demand coverage is illustrated as there are not sufficient resources to cover 100% demand. The sites are ranked by 100m GWA wind speed to ensure that technically favourable sites are selected for demand coverage. Mining areas are included in "Agriculture". "Rest" refers to conservation zones and areas with high risk of earthquakes or landslides. The labels of the x- and y-axes apply to all subplots. Note that the land impact shown here refers to the area spanned by the wind farms. The footprint of the individual turbines (e.g. turbine tower) is much smaller.

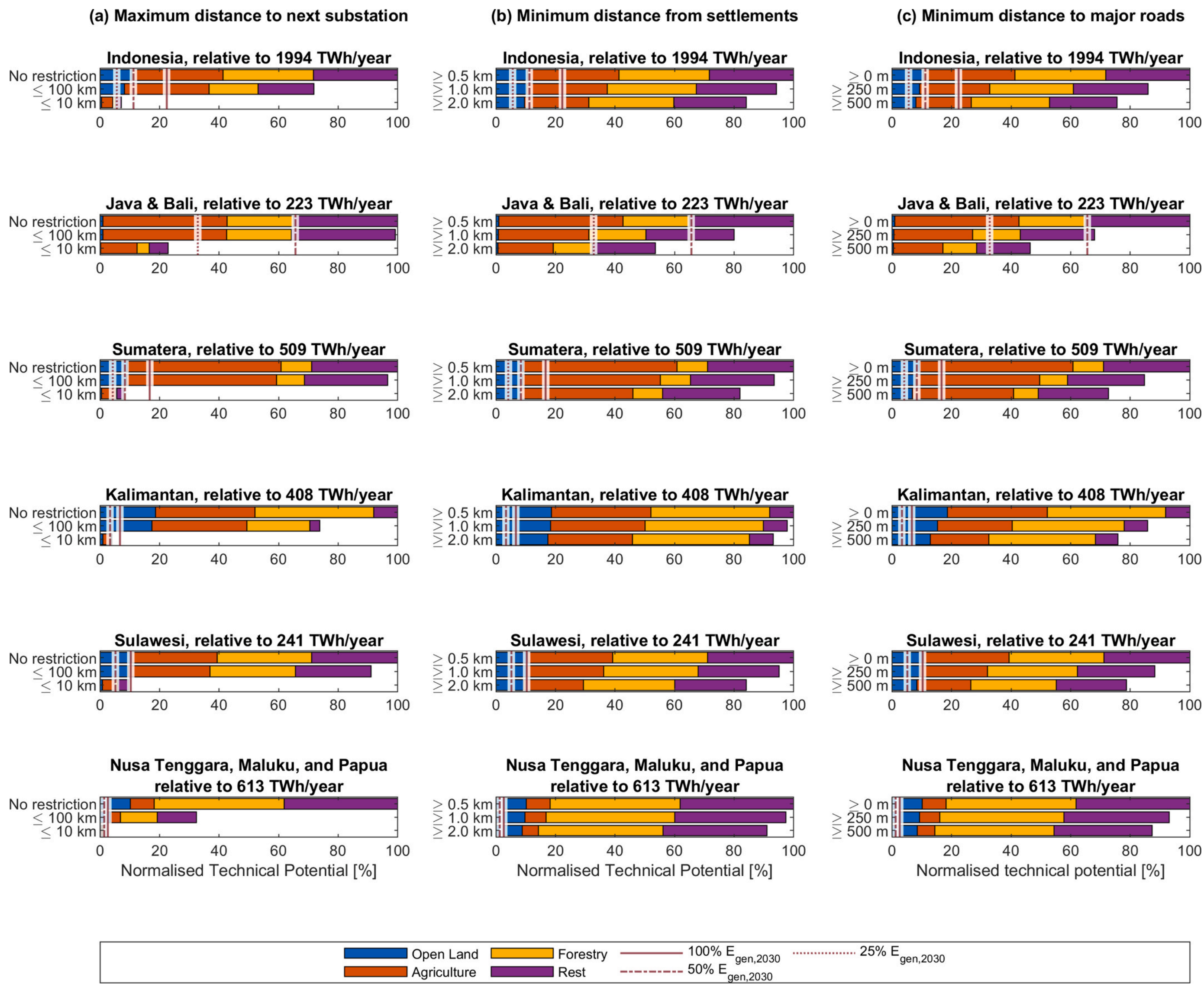

Fig. 5. Impact of distance to the (a) closest substation, (b) settlements, and (c) roads on the median technical onshore wind potential on different land types in Indonesia and per island (group). Mining areas are included in "Agriculture". "Rest" refers to conservation zones and areas with high risk of earthquakes or landslides. The labels of the x-axis apply to all subplots.

significantly improves the accuracy of electricity generation estimations, from a deviation of −62% without correction to +4% with bias correction. This underlines that re-analysis data should not be used for electricity production estimations without prior bias correction, especially for onshore sites in complex terrain.

Our CAPEX estimations in Table 2 are roughly 40% lower than the reported investment costs [56,57]. The cost model and calibration data originate from the US [45,46], so the different development stages of onshore wind in the USA and Indonesia could explain the deviations. In the USA, wind power is a mature technology with 118 GW of installed capacity in 2021 [58], while Sidrap and Jeneponto are the first two large wind farms in Indonesia. These wind farms might be more expensive due to first-of-its-kind costs, and hence not representative once wind power progresses further. Therefore, we continue to use the cost model with the US data to provide an outlook to onshore wind's future economic potential in Indonesia.

3.2. The technical potential and impact of static and flexible site selection criteria

In this section, we report and discuss the technical onshore wind potential in Indonesia and the impact of static and flexible site selection criteria. Fig. 3 reveals that flexible criteria can help determining suitable thresholds for site exclusion. Most notably, the technical potential already declines sharply at a minimum average wind speed of 2 m/s. In literature, more stringent thresholds at 4.5 m/s and higher are used due to economic infeasibility [59,60]. From a technical perspective, such thresholds may exclude considerable resources from further analysis, in Fig. 3(a) almost 1,500 TWh/year. These resources might become economically feasible if low-wind-speed turbines are further developed and their costs gradually decline. The static elevation and slope thresholds of 2,000 m and 30° from Table 1 seem adequate and do not exclude noticeable technical resources.

If only static criteria are used, 63.6% of Indonesia's land area would be suitable for onshore wind as shown in Table 3. The most limiting static criterion are wetlands given Indonesia's vast mangrove and swamp forests as well as more than 50,000 km of coastline [61].

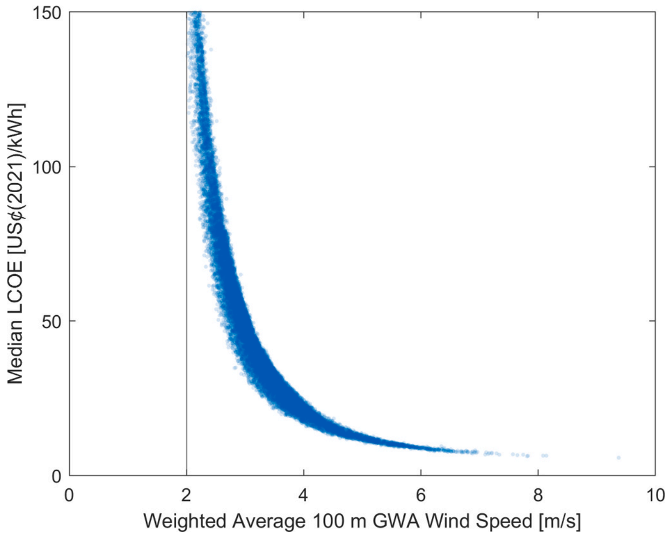

Fig. 6. Median levelized cost of electricity vs. weighted average 100 m GWA wind speed per meshed polygon. For clarity, the graph is limited to wind speeds ≥2 m/s and LCOE ≤150 US¢(2021)/kWh as the LCOE move towards infinity at smaller wind speeds.

Moreover, Table 3 not only demonstrates the impact of flexible criteria, but also how their selection affects the results. For example, if conservative thresholds from literature [1] and practice in Indonesia apply, the share of suitable land declines drastically to 0.08%. However, the resulting potentials may be overly conservative as seen for a maximum distance to the next substation of 10 km. This threshold may reflect the practical perspective of Indonesia's state utility company, project developers, and lending institutions, but it also disregards the possible extension of the public grid and off-grid solutions, which could make the removed sites feasible again. Therefore, a critical assessment of exclusion criteria and their development over time may yield more than a snapshot of renewable resources.

Furthermore, flexible site selection criteria could provide a more useful and transparent set of options for decision makers to allocate renewable capacity. In Table 4, Indonesia's median technical onshore wind potential ranges between 207 and 1,994 TWh/year depending on the available land types. Both sides of the range come with benefits and limitations.

The lower end limits onshore wind to open land, which might improve the social acceptance of the technology as no land is transferred from agriculture and forestry, and conservation zones remain unaffected. But again, this option might be overly conservative, as wind farms can be integrated into forests and agricultural land for shared use. Such integrated solutions could be especially interesting for islands where open land is scarce, like Java and Bali. Moreover, some farmers

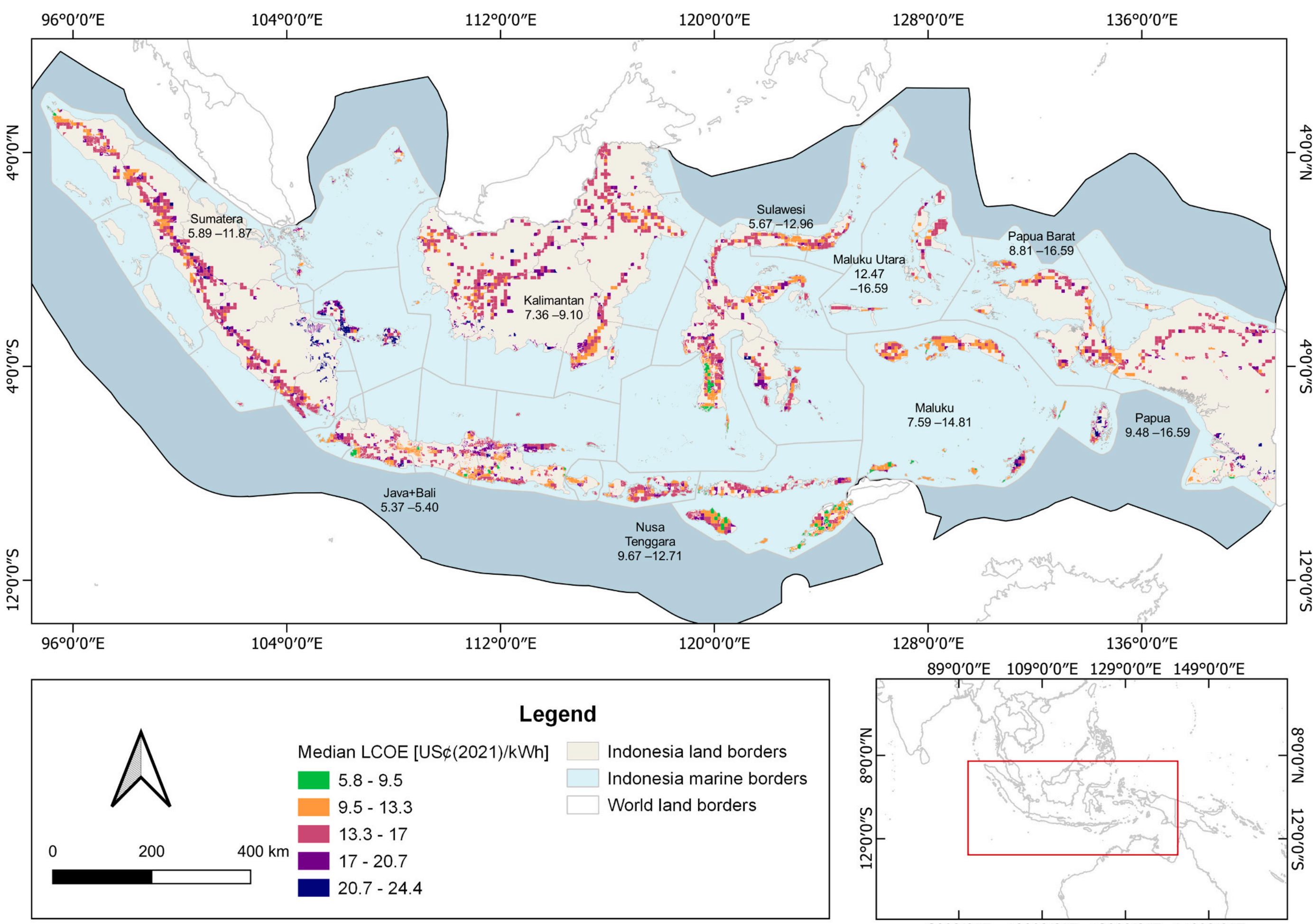

Fig. 7. Median LCOEs of onshore wind farms in Indonesia with average 100 m GWA wind speeds ≥4 m/s. For each island (group), the range of minimum and maximum received electricity tariffs are shown. The tariffs are based on the BPP scheme and inflation corrected as described in section 2.3.3.

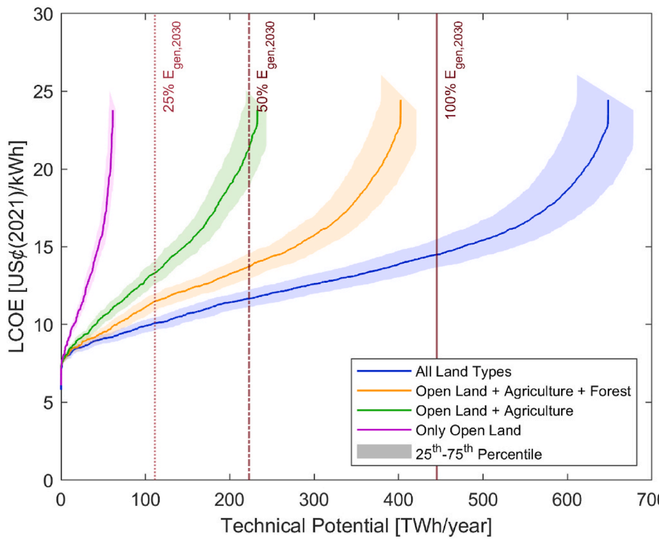

Fig. 8. Cost supply curves of onshore wind power in Indonesia at sites with 100 m GWA wind speeds ≥4 m/s for different land use restrictions against various shares of the projected electricity generation $E_{gen,2030}$ in 2030. The LCOEs do not include the costs of local grid connection and extension.

and forest owners might be willing to share or even sell their land. Regarding earthquake risk, wind farms can be designed to withstand seismic stresses, e.g. by following DNV's recommended practice [62].

The upper end of the potential assumes that all flexible land is considered for wind farms, which boosts onshore wind's impact for Indonesia's energy transition but might also create fierce social resistance. Furthermore, too optimistic resource potentials may raise skewed expectations about their practical feasibility. Only 2.2% of all finely subdivided polygons have a median capacity factor above the global wind industry's average of 34% [63], with values above 40% mainly in South Sulawesi, Maluku, and East Nusa Tenggara. In contrast, more than 70% of the polygons have capacity factors below 10%. Lastly, the potentials do not reflect the actual regional electricity demand. For example, a technical onshore wind potential of up to 613 TWh/year in Nusa Tenggara, Maluku, and Papua is opposed by an expected combined 2030 demand of 16 TWh [14]. Even without considering the economics of onshore wind there, only a small fraction of the technical potential can be materialised in practice, unless the local demand exceeds current expectations significantly.

With these contemplations, more specific energy transition goals could be proposed with more adequate support schemes for affected stakeholders. Fig. 4 shows the electricity demand coverage and land use of onshore wind for Indonesia and its island groups. In one case, we only use open land; in the other we use all land types ranked by average 100m GWA wind speed. Considering all land types, onshore wind could supply 100% of 2030 electricity demand everywhere except for Java and Bali, where 50% of demand could be covered.

Fig. 4 illustrates the drawbacks of only considering open land for wind farm deployment, as more land is required to produce the same amount of electricity. Considering the subsequent surplus cost, this insight harmonises with Wehrle et al. [64], who found that leaving landscapes undisturbed could lead to considerable opportunity cost. Furthermore, our findings may raise a moral question about what is preferred: to use open, less socially controversial land with suboptimal wind resources and thus higher land requirements, or to resort to used and conserved land with better wind resources and lower environmental impact from land conversion, but with potentially negative implications for local communities and wildlife? Although we cannot provide an answer to this complex question here, we believe that flexible site selection may at least create an awareness of such dilemmas.

However, flexible site selection also reveals the local challenges of onshore wind from built-up infrastructure and a lack thereof, as shown in Fig. 5. Urbanised islands like Java and Bali have an extended electricity grid, but also a dense network of roads and settlements. Thus, onshore wind's potential decreases significantly if a minimum distance from roads and settlements is introduced. The proximity to substations is less impactful in Java and Bali compared to other islands, but still significant with a reduction to roughly 20% of the original technical potential with a maximum distance to substation of 10 km.

On the one hand, distance to roads and settlements is far less impactful on rural, less-developed islands. On the other hand, proximity to existing grid infrastructure wipes out most of the otherwise available technical potential, e.g. to as little as 2% of the original potential on Nusa Tenggara, Maluku, and Papua. These observations underline that there is no one-size-fits-all solution for the energy transition. On islands like Java and Bali, renewables that can be integrated into urban infrastructure, like rooftop solar PV, might be preferable over onshore wind, which could take a complimentary role at less built-up sites. On rural, less-connected islands, considerable investments in electricity grid and road infrastructure would be required to materialise the above-mentioned potentials. Especially in East Indonesia, many wind farm sites are situated hundreds of kilometres from the next substation, e.g. on remote islands. There, a solution could be small-scale wind farms integrated via micro-grid systems.

3.3. The economic potential of onshore wind power

In this section, we discuss the economic onshore wind potential in Indonesia, influence of flexible site selection criteria, and impact of a carbon tax. We start with the LCOE, which we calculate per meshed wind farm polygon.

Fig. 6 shows the usefulness of minimum wind speed thresholds when mapping economic wind resources, but also potential pitfalls currently unaddressed in literature. There is an exponential relationship between LCOE and wind speed, and 4 m/s appears to be a reasonable threshold beyond which LCOE might reach competitive levels. At average wind speeds between 4 and 10 m/s, the LCOEs range between 5.8 and 24.5 US ¢(2021)/kWh. The lower end of the range is on par with the industry's average of 6 US¢(2018)/kWh [63], and shows that Indonesia could produce cheap renewable electricity if costs reach current US levels. However, Fig. 6 shows the complexity of choosing the "right" threshold. If too low, uneconomic sites are not filtered out and thus potentially lead to an overestimation of economic potential. If too high, economic sites may be excluded and the economic potential becomes too conservative. This dilemma underlines the benefits of flexible site selection criteria, as thresholds be determined transparently and evaluated critically.

Our LCOE range of 5.8–24.5 US¢(2021)/kWh is wider than the 14.6–14.9 US¢(2020)/kWh by Ref. [65] and 7.4–16.1 US¢(2019)/kWh by Ref. [43], which stems from differences in technical and economic assumptions, like CAPEX, as well as thresholds, e.g. for capacity factors and minimum wind speed. But since the ranges above are in the same order of magnitude, we see our results in line with existing work.

Fig. 7 shows the median LCOE of onshore wind farms across Indonesia at sites with average 100 m wind speeds ≥4 m/s, as well as the ranges of local electricity tariffs. Most of the low-LCOE sites are situated in the high-capacity-factor areas in East Nusa Tenggara, Maluku, Java, South Sulawesi, and at the southern part of Papua. On Kalimantan and Bali, LCOEs are not as low, but still below 13 US¢(2021)/kWh. With LCOE below 9.5 US¢(2021)/kWh, onshore wind would be cost competitive against all other currently deployed power generation technologies in Indonesia, including subsidised fossil-fuelled plants [43].

The cost supply curves of onshore wind in Indonesia are depicted in Fig. 8. Using all flexible land, more than 50% of Indonesia's 2030 electricity generation could be provided at LCOEs of roughly 12.5 US¢ (2021)/kWh. With more restrictions on land types, the supply curves become much shorter and steeper as gradually more sites with

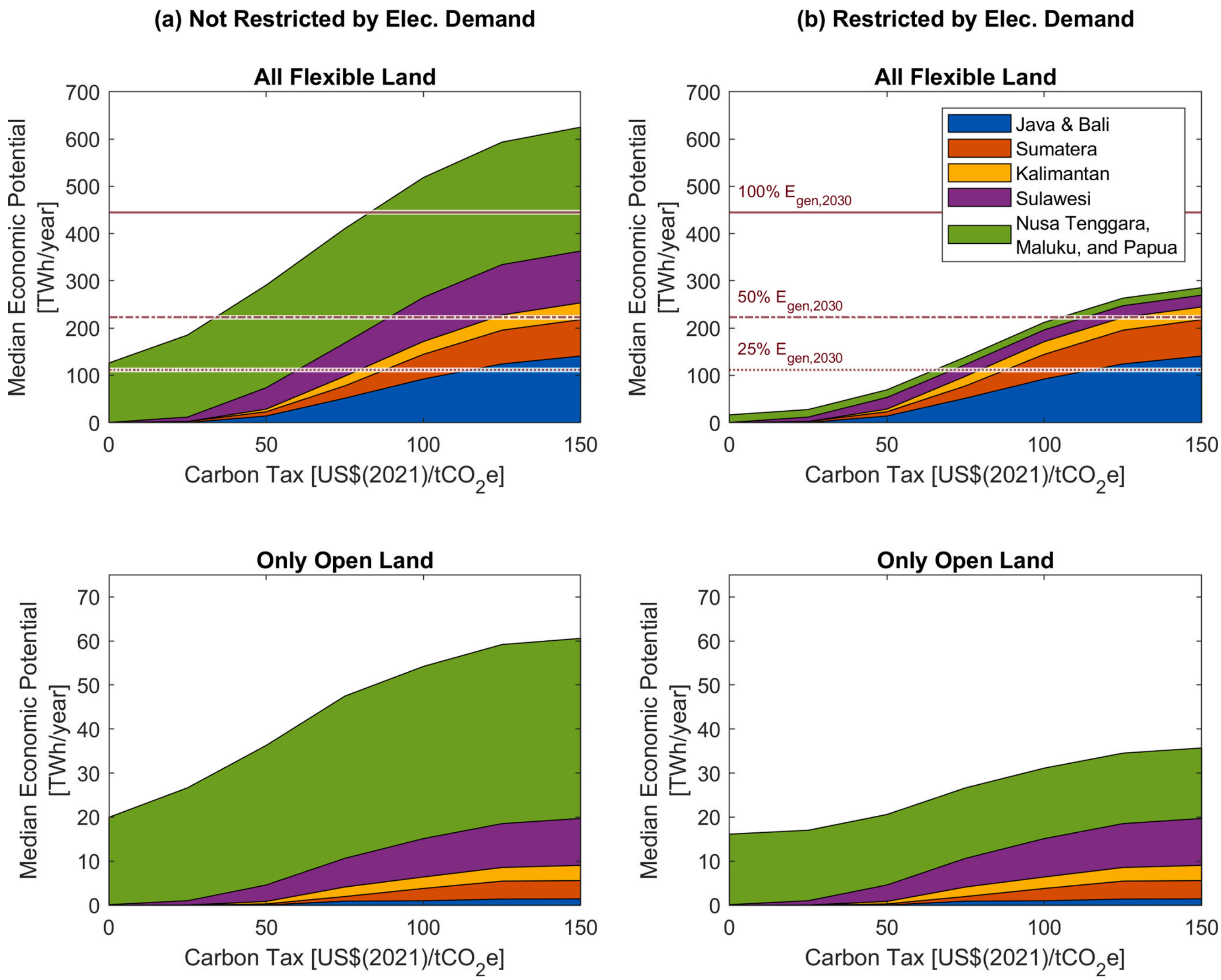

Fig. 9. Median economic potential of onshore wind per island (group) for different carbon taxes. The wind farms are situated on open and all flexible land. The potentials in (a) comprise all wind farms with LCOE ≤ local electricity tariff plus carbon tax without considering regional electricity demand, while the potentials in (b) are capped at the projected local electricity generation in 2030. The economic potentials are shown for wind farms on any flexible land (top row) and only open land (bottom row). The legend as well as electricity demand lines apply to all subplots.

potentially high wind resources are filtered out. With open land, only 31 TWh/year could be produced at 12.5 US¢(2021)/kWh.

Note that the costs of system integration, e.g. transmission and distribution lines, are not adequately reflected here. We agree with McKenna et al. [1] that a more integrated approach should be taken when calculating the LCOE. This paper is part of an effort to catalogue Indonesia's renewable energy resources and their rough technical and economic potential. We plan to study the integration of these resources into existing and future grid infrastructure in follow-up work.

Fig. 9 shows the economic potential of onshore wind on all flexible land and only open land for different carbon tax rates. Without considering a carbon tax and local electricity demand, the economic potential ranges between 20 and 126 TWh/year (only open land and all flexible land, respectively), and decreases to a demand-restricted potential of 16 TWh/year, or 4% of national 2030 demand. This is because all of the economic potential is situated in East Indonesia (Nusa Tenggara, Maluku, and Papua), where resources are plentiful but electricity demand is low. A carbon tax of roughly 100 US$/t$CO_2$e could help spreading the economic potential to high-demand regions, like Java and Bali, with an electricity-demand-restricted range of 31–212 TWh/year, or 7–48% of 2030 demand. Such a carbon tax would be much higher than the current Indonesian carbon tax of 2.1 US$(2021)/t$CO_2$e [66], but lower than the ones in Sweden, Switzerland, and Liechtenstein [67]. Furthermore, such a tax rate would be similar to the price of EU Emission Allowances, which temporarily traded for 105 US$/t$CO_2$e (96 €/t$CO_2$e) in February 2022 [68]. However, such a high carbon tax might not be socially accepted as the increases in conventional power production costs could be passed down to consumers via increased electricity prices. Therefore, we recommend more research on how a socially acceptable carbon tax could be implemented without disadvantaging vulnerable groups in Indonesia.

3.4. Sensitivity analysis

Fig. 10 visualises how our results are affected by (1) uncertainties in input data (wind speed, CAPEX, OPEX, discount rate, BPP), (2) development of input data (CAPEX, OPEX, discount rate, BPP), and (3) design choices (hub height). Our results are the most sensitive to the wind speed. Therefore, we recommend to validate our results with measured long-term data, which was not possible for this research. There have been previous measurement campaigns in Indonesia, but, to our knowledge, only at heights between 30 and 50 m [69]. Future campaigns could take place at heights between 80 and 130 m at technically and economically attractive locations as suggested in this paper. The

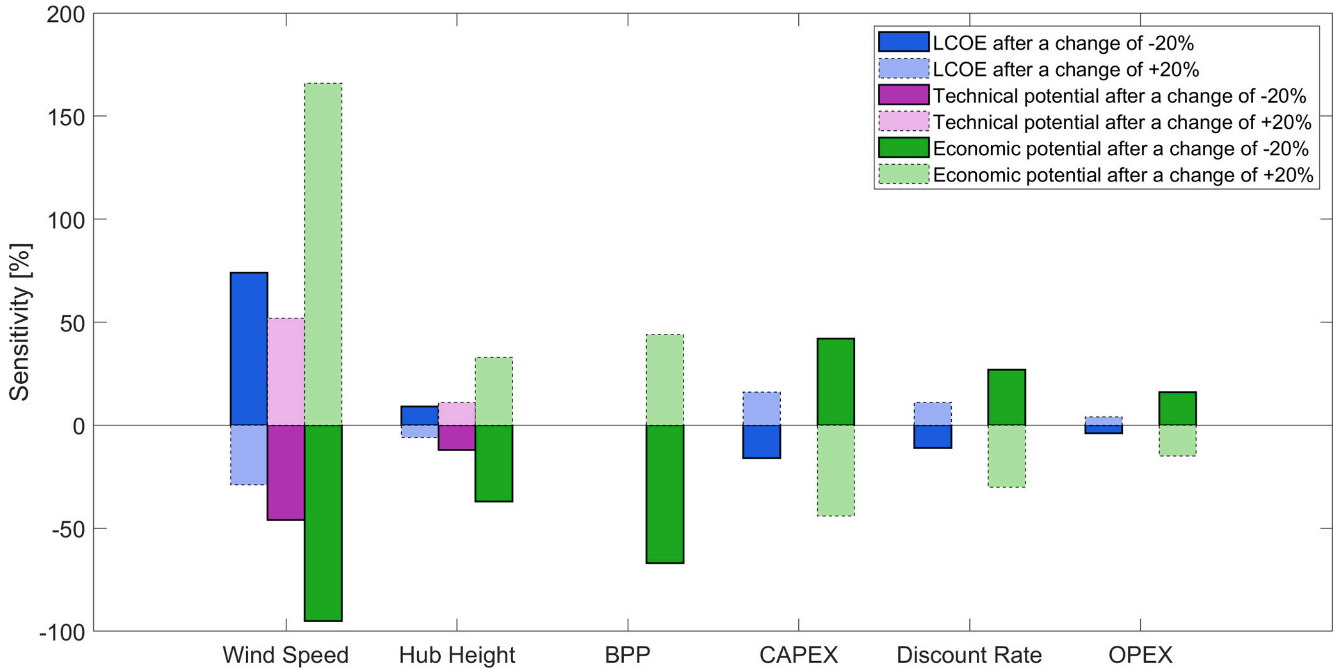

Fig. 10. Sensitivity of median LCOE, technical potential, and economic potential to changes in model parameters by ±20%. LCOEs and potentials are calculated per meshed polygon with weighted average 100 m GWA wind speed of ≥4 m/s (sample size: 5,242 polygons). The economic potential refers to original electricity tariffs without carbon tax.

CAPEX and discount rate also considerably affect the economic outputs of this research. This indicates that onshore wind's economic potential in Indonesia might not be as high as projected here while experience with the technology is still limited. Then again, the industry expects the technology's costs to decrease further in the future [63]. Once onshore wind gains traction in Indonesia, costs might decline below the costs assumed here and higher economic potentials might be possible. Out of all outputs, the economic potential is by far the most sensitive, which is in agreement with previous research [9]. Therefore, we suggest to re-assess Indonesia's economic onshore wind potential once the technology progressed further, a better understanding of investment and financing costs has been gained, or if new tariff and support schemes are introduced.

4. Conclusions

This paper proposes a method to account for the variability of site selection criteria when mapping onshore wind potentials. Our motivation stems from the shortcomings in current literature, where site exclusion criteria are often used in a binary, in-or-out fashion. We distinguish between static site selection criteria, which always apply, and flexible criteria, which may require further scrutiny due to site-specific properties like wind speed and elevation and the impact on stakeholders from agriculture and forestry, amongst others. To assess the technical and economic performance of onshore wind, we use 20 years of bias-corrected ERA5 wind speed data, 28 power curves, and a turbine-specific cost model. We demonstrate our method for Indonesia, a country with rising electricity demand and currently high fossil fuel dependency.

We find that flexible exclusion criteria can increase the transparency and usefulness of resource mapping analyses. The impact of individual criteria can be measured and thresholds for site exclusion fine-tuned accordingly, for example the economic minimum average wind speed at hub height of 4 m/s. Furthermore, our approach shows how much land per land type would be required to cover certain shares of present and future demand, which enables more informed recommendations for policymakers and capacity planners. Flexible criteria from built-up infrastructure reveal the individual, regional challenges of the energy transition in urbanised and rural areas. Minimum distance to road and settlements are significantly more impactful in urbanised regions, like Java and Bali, while maximum distance to next substation is most effective in rural areas with less-developed grid infrastructure. With these insights, more direct policies can be developed addressing stakeholders affected by wind farm deployment and their (potentially conflicting) interests. Of course, policy recommendations could already be deduced from the previous, binary resource mapping method, but we believe that our flexibility-based method can add considerable depth to them.

For our Indonesian case study, we report a technical potential of 207–1,994 TWh/year. The high end of the range could cover more than 50% of 2030 electricity demand on all islands. LCOEs range between 5.8 and 24.5 US¢(2021)/kWh with an electricity-demand-restricted economic potential of 16 TWh/year, which improves to 31–212 TWh/year with a carbon tax of 100 US$(2021)/t$CO_2$e. We conclude that onshore wind may not be suitable for Indonesia's national energy transition. However, with sufficient policy support, it could become an important complimentary technology in regions with sufficient wind resources.

The methods presented here could be improved further by addressing the limitations of our study, namely (1) limited site adaptation of wind farm design and assessment via constant turbine spacing, wake efficiencies, and availability factors, (2) omission of system integration cost and land-type-specific cost, and (3) omission of economies of scale and technological learning.

Data availability

The dataset related to this article can be found under the DOI 10.4121/19625385, hosted at the repository 4TU.ResearchData [70].

CRediT authorship contribution statement

Jannis Langer: Conceptualization, Data curation, Formal analysis, Investigation, Methods & Materials, Writing – original draft. **Michiel Zaaijer:** Contributions, Methodology, Supervision, Validation, Writing –

review & editing. **Jaco Quist:** Supervision, Writing – review & editing. **Kornelis Blok:** Contributions, Methodology, Supervision, Validation, Writing – review & editing.

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.

Acknowledgement

The work reported in this paper is funded by a grant from the Dutch research council NWO for the project entitled "Regional Development Planning and Ideal Lifestyle of Future Indonesia", under the NWO Merian Fund call on collaboration with Indonesia. Map data copyrighted OpenStreetMap contributors and available from https://www.openstreetmap.org. Many thanks to Sergio Simanjuntak, whose excellent master thesis inspired this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.renene.2022.11.084.

References

[1] R. McKenna, S. Pfenninger, H. Heinrichs, J. Schmidt, I. Staffell, C. Bauer, K. Gruber, A.N. Hahmann, M. Jansen, M. Klingler, N. Landwehr, X.G. Larsén, J. Lilliestam, B. Pickering, M. Robinius, T. Tröndle, O. Turkovska, S. Wehrle, J.M. Weinand, J. Wohland, High-resolution large-scale onshore wind energy assessments: a review of potential definitions, methodologies and future research needs, Renew. Energy 182 (2022) 659–684, https://doi.org/10.1016/j.renene.2021.10.027.
[2] M. Hoogwijk, B. de Vries, W. Turkenburg, Assessment of the global and regional geographical, technical and economic potential of onshore wind energy, Energy Econ. 26 (2004) 889–919, https://doi.org/10.1016/j.eneco.2004.04.016.
[3] J.M. Kiesecker, J.S. Evans, J. Fargione, K. Doherty, K.R. Foresman, T.H. Kunz, D. Naugle, N.P. Nibbelink, N.D. Niemuth, Win-win for wind and wildlife: a vision to facilitate sustainable development, PLoS One 6 (2011) 1–8, https://doi.org/10.1371/journal.pone.0017566.
[4] J. Wiehe, J. Thiele, A. Walter, A. Hashemifarzad, J. Zum Hingst, C. von Haaren, Nothing to regret: reconciling renewable energies with human wellbeing and nature in the German Energy Transition, Int. J. Energy Res. 45 (2021) 745–758, https://doi.org/10.1002/er.5870.
[5] D.S. Ryberg, M. Robinius, D. Stolten, Evaluating land eligibility constraints of renewable energy sources in Europe, Energies 11 (2018) 1–19, https://doi.org/10.3390/en11051246.
[6] D.S. Ryberg, Z. Tulemat, D. Stolten, M. Robinius, Uniformly constrained land eligibility for onshore European wind power, Renew. Energy 146 (2020) 921–931, https://doi.org/10.1016/j.renene.2019.06.127.
[7] M. Eichhorn, F. Masurowski, R. Becker, D. Thrän, Wind energy expansion scenarios – a spatial sustainability assessment, Energy 180 (2019) 367–375, https://doi.org/10.1016/j.energy.2019.05.054.
[8] C.D. Yue, M.H. Yang, Exploring the potential of wind energy for a coastal state, Energy Pol. 37 (2009) 3925–3940, https://doi.org/10.1016/j.enpol.2009.04.055.
[9] E. Rinne, H. Holttinen, J. Kiviluoma, S. Rissanen, Effects of turbine technology and land use on wind power resource potential, Nat. Energy 3 (2018) 494–500, https://doi.org/10.1038/s41560-018-0137-9.
[10] Y. Zhou, P. Luckow, S.J. Smith, L. Clarke, Evaluation of global onshore wind energy potential and generation costs, Environ. Sci. Technol. 46 (2012) 7857–7864, https://doi.org/10.1021/es204706m.
[11] B. Sliz-Szkliniarz, J. Eberbach, B. Hoffmann, M. Fortin, 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. 109 (2019) 514–531, https://doi.org/10.1016/j.rser.2019.04.039.
[12] A. Lopez, T. Mai, E. Lantz, D. Harrison-Atlas, T. Williams, G. Maclaurin, Land use and turbine technology influences on wind potential in the United States, Energy 223 (2021), https://doi.org/10.1016/j.energy.2021.120044, 120044.
[13] S.R. Santos Da Silva, G. Iyer, T.B. Wild, M.I. Hejazi, C.R. Vernon, M. Binsted, F. Miralles-Wilhelm, The implications of uncertain renewable resource potentials for global wind and solar electricity projections, Environ. Res. Lett. 16 (2021), 124060, https://doi.org/10.1088/1748-9326/ac3c6b.
[14] P.T.P.L.N. Persero), Rencana Usaha Penyediaan Tenaga Listrik (RUPTL) 2021-2030, 2021. Jakarta.
[15] W.G. Santika, T. Urmee, Y. Simsek, P.A. Bahri, M. Anisuzzaman, An assessment of energy policy impacts on achieving Sustainable Development Goal 7 in Indonesia, Energy Sustain. Dev. 59 (2020) 33–48, https://doi.org/10.1016/j.esd.2020.08.011.
[16] N. Reyseliani, W.W. Purwanto, Pathway towards 100% renewable energy in Indonesia power system by 2050, Renew. Energy 176 (2021) 305–321, https://doi.org/10.1016/j.renene.2021.05.118.
[17] PricewaterhouseCoopers, Power in Indonesia, Jakarta. https://www.pwc.com/id/en/energy-utilities-mining/assets/power/power-guide-2017.pdf, 2018.
[18] J. Langer, J. Quist, K. Blok, Review of renewable energy potentials in Indonesia and their contribution to a 100% renewable electricity system, Energies 14 (2021), https://doi.org/10.3390/en14217033.
[19] Royal Dutch shell, global energy resources database. https://www.shell.com/energy-and-innovation/the-energy-future/scenarios/shell-scenarios-energy-models/energy-resource-database.html#iframe=L3dlYmFwcHMvRW5lcmd5UmVzb3VyY2VEYXRhYmFzZS8, 2020. (Accessed 2 December 2020).
[20] J. Bosch, I. Staffell, A.D. Hawkes, Temporally-explicit and spatially-resolved global onshore wind energy potentials, Energy 131 (2017) 207–217, https://doi.org/10.1016/j.energy.2017.05.052.
[21] Google Maps, P.L.T.B. Jeneponto. https://www.google.com/maps/search/pltb+jeneponto/@-5.6363191,119.7614588,4402m/data=!3m2!1e3!4b1!5m1!1e4, 2022. (Accessed 7 February 2022).
[22] Ministry of Environment and Forestry, Land cover Indonesia. https://www.arcgis.com/sharing/rest/content/items/b1126d52d6c5416496339aeb250d9b39/info/metadata/metadata.xml?format=default&output=html, 2017. (Accessed 13 September 2021).
[23] GEBCO Compilation Group, GEBCO 2020 Grid, 2020, https://doi.org/10.5285/a29c5465-b138-234d-e053-6c86abc040b9.
[24] Ministry of energy and mineral resources, Kebencanaan Geologi. https://geoportal.esdm.go.id/monaresia/rest/services/4.GEOLOGI/Kebencanaan_Geologi/MapServer. (Accessed 4 April 2021).
[25] World port source, satellite map of ports Indonesia, accessed March 9, 2022), http://www.worldportsource.com/ports/IDN.php, 2022.
[26] Ministry of environment and forestry, ArcGIS REST services of MoEF Geoportal. https://geoportal.menlhk.go.id/arcgis/rest/services/KLHK_EN, 2017. (Accessed 4 April 2021).
[27] Ministry of energy and mineral resources, Lokasi Gardu Induk (accessed April 20, 2022), https://geoportal.esdm.go.id/gis2/rest/services/djk_dpm/DJK_DPM_Sebaran_Lokasi_Gardu_Induk/MapServer, 2022.
[28] Geofabrik, OpenStreetMap, GEOFABRIK downloads (accessed April 22, 2022), http://download.geofabrik.de/asia/indonesia.html, 2021.
[29] DTU Wind Energy, The World bank group, Vortex, energy sector management assistance program, Data obtained from the Global Wind Atlas, 3.0, https://globalwindatlas.info/. (Accessed 13 September 2021).
[30] J. Bosch, Spatially-Resolved and temporally-explicit global wind energy potentials as inputs to assessment models, Imperial College London (2018). https://spiral.imperial.ac.uk/handle/10044/1/73112.
[31] K. Gruber, P. Regner, S. Wehrle, M. Zeyringer, J. Schmidt, 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 238 (2022), 121520, https://doi.org/10.1016/j.energy.2021.121520.
[32] D.S. Ryberg, D.G. Caglayan, S. Schmitt, J. Linßen, D. Stolten, M. Robinius, The future of European onshore wind energy potential: detailed distribution and simulation of advanced turbine designs, Energy 182 (2019) 1222–1238, https://doi.org/10.1016/j.energy.2019.06.052.
[33] C.T. Chu, A.D. Hawkes, A geographic information system-based global variable renewable potential assessment using spatially resolved simulation, Energy 193 (2020), 116630, https://doi.org/10.1016/j.energy.2019.116630.
[34] I. González-Aparicio, F. Monforti, P. Volker, A. Zucker, F. Careri, T. Huld, J. Badger, Simulating European wind power generation applying statistical downscaling to reanalysis data, Appl. Energy 199 (2017) 155–168, https://doi.org/10.1016/j.apenergy.2017.04.066.
[35] J. Langer, S. Simanjuntak, S. Pfenninger, A.J. Laguna, G. Lavidas, H. Polinder, J. Quist, H.P. Rahayu, K. Blok, How offshore wind could become economically attractive in low-resource regions like Indonesia, iScience 25 (2022), https://doi.org/10.1016/j.isci.2022.104945, 104945.
[36] International Electrotechnical Commission, IEC 61400, 2009.
[37] S. Raikar, S. Adamson, Renewable Energy Finance, First, Academic Press, London, 2019.
[38] The wind power, manufacturer and turbines - online access - the wind power. https://www.thewindpower.net/turbines_manufacturers_en.php, 2021. (Accessed 29 September 2021).
[39] Ministry of Energy and Mineral Resources, Handbook of Energy & Economic Statistics of Indonesia, 2021. Jakarta.
[40] The wind power, Indonesia - wind farms - countries - online access - the wind power. https://www.thewindpower.net/country_windfarms_en_67_indonesia.php, 2021. (Accessed 28 September 2021).
[41] I. Staffell, S. Pfenninger, Using bias-corrected reanalysis to simulate current and future wind power output, Energy 114 (2016) 1224–1239, https://doi.org/10.1016/j.energy.2016.08.068.
[42] Badan Pusat Statistik, Statistik Indonesia 2020, 2020, https://doi.org/10.3389/fpsyg.2015.00002. Jakarta.
[43] IESR, Levelized Cost of Electricity in Indonesia, 2019. Jakarta.
[44] KPMG, Lombok - Prefeasibility Studies on RE Solutions, 2019.
[45] L. Fingersh, M. Hand, A. Laxson, Wind Turbine Design Cost and Scaling Model, 2006 mendeley.com/research/wind-turbine-design-cost-and-scaling-model/.
[46] T. Stehly, P. Beiter, P. Duffy, 2019 Cost of Wind Energy Review, 2020. NREL/TP-5000-78471.

[47] Macrotrends, EUR USD - Historical Annual Data, 2021. https://www.macrotrends.net/2548/euro-dollar-exchange-rate-historical-chart. (Accessed 16 September 2021).
[48] Bureau of Labour Statistics, CPI Inflation Calculator, 2021. https://data.bls.gov/cgi-bin/cpicalc.pl?cost1=1.00&year1=201801&year2=202101. (Accessed 19 May 2021).
[49] Ministry of Energy and Mineral Resources, Besaran Biaya Pokok Penyediaan Pembangkitan PT Perusahaan Listrik Negara (Persero) Tahun 2020, 2021.
[50] P.J. Burke, J. Widnyana, Z. Anjum, E. Aisbett, B. Resosudarmo, K.G.H. Baldwin, Overcoming barriers to solar and wind energy adoption in two Asian giants: India and Indonesia, Energy Pol. 132 (2019) 1216–1228, https://doi.org/10.1016/j.enpol.2019.05.055.
[51] Asian Development Bank, Renewable Energy Tariffs and Incentives in Indonesia: Review and Recommendations, Mandaluyong City, 2020.
[52] K. Blok, E. Nieuwlaar, Introduction to Energy Analysis, third ed., Taylor and Francis, Abingdon, 2021.
[53] BPS Statistics Indonesia, Statistik Listrik 2013-2018, 2019. Jakarta.
[54] K.L. Nefabas, L. Söder, M. Mamo, J. Olauson, Modeling of ethiopian wind power production using era5 reanalysis data, Energies 14 (2021) 1–17, https://doi.org/10.3390/en14092573.
[55] Vena Energy, Vena energy nears completion of 72 MW first phase of tolo wind farm, ready to begin construction on 72 MW second phase. https://www.venaenergy.com/all_news/vena-energy-nears-completion-of-72-mw-first-phase-of-tolo-wind-farm-ready-to-begin-construction-on-72-mw-second-phase/, 2018. (Accessed 8 February 2022).
[56] The World Bank Group, Sidrap wind farm. https://ppi.worldbank.org/en/snapshots/project/Sidrap-Wind-Farm-8848, 2017. (Accessed 8 February 2022).
[57] The Jakarta Post, Second Sulawesi wind farm project near completion. https://www.thejakartapost.com/news/2018/11/07/second-sulawesi-wind-farm-project-near-completion.html, 2018. (Accessed 8 February 2022).
[58] U.S. Energy Information Administration, The United States installed more wind turbine capacity in 2020 than in any other year. https://www.eia.gov/todayinenergy/detail.php?id=46976, 2021. (Accessed 8 February 2022).
[59] D. Latinopoulos, K. Kechagia, A GIS-based multi-criteria evaluation for wind farm site selection. A regional scale application in Greece, Renew. Energy 78 (2015) 550–560, https://doi.org/10.1016/j.renene.2015.01.041.
[60] J. Schallenberg-Rodríguez, J. Notario-del Pino, Evaluation of on-shore wind techno-economical potential in regions and islands, Appl. Energy 124 (2014) 117–129, https://doi.org/10.1016/j.apenergy.2014.02.050.
[61] Embassy of the republik of Indonesia, facts & figures, n.d. https://www.embassyofindonesia.org/basic-facts/. (Accessed 15 April 2022).
[62] DNV, DNV-RP-0585 Seismic Design of Wind Power Plants, Høvik, 2021.
[63] International Renewable Energy Agency, FUTURE of WIND Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects, (Abu Dhabi, n.d).
[64] S. Wehrle, K. Gruber, J. Schmidt, The cost of undisturbed landscapes, Energy Pol. 159 (2021), 112617, https://doi.org/10.1016/j.enpol.2021.112617.
[65] N. Lee, F. Flores-Espino, R. Oliveira, B. Roberts, T. Bowen, J. Katz, Exploring renewable energy opportunities in select southeast asian countries: a geospatial analysis of the Levelized cost of energy of utility-scale wind and solar photovoltaics, Denver, www.nrel.gov/publications, 2020.
[66] G. Suroyo, B.C. Munthe, Indonesia Introduces Carbon Trading Policy to Reduce Emissions, 2021. https://www.reuters.com/business/cop/indonesia-introduces-carbon-trading-policy-reduce-emission-2021-11-15/. (Accessed 8 December 2021).
[67] The World Bank, State and Trends of Carbon Pricing 2021, 2021, https://doi.org/10.1596/978-1-4648-1728-1. Washington, D.C.
[68] Trading Economics, EU carbon permits. https://tradingeconomics.com/commodity/carbon, 2022. (Accessed 4 April 2022).
[69] Directorate General of Renewable Energy and Energy Conservation, Rencana Strategis, Jakarta, 2020-2024, 2020.
[70] J. Langer, M. Zaaijer, J. Quist, K. Blok, Data underlying the paper "Introducing site selection flexibility to techno-economic onshore wind potential assessments: new method and application to Indonesia. https://doi.org/10.4121/19625385, 2022.