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Abstract

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Keywords

Wind energy, Indonesia, Renewable Resources, Weather Research and Forecasting

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Energy Potential Assessments and Investment Opportunities for Wind Energy in Indonesia

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Indonesia has a target of achieving 23% of renewable energy share in total energy mix in 2025. However, as commonly observed across developing economies, Indonesia also does not have accurate and comprehensive database of renewable energy potentials, especially wind energy. Therefore, this article aims to assess the theoretical potential of wind speed and to visualize the wind speed by province based on wind map using GIS for the entire Indonesia. Our assessment integrates advanced analytical techniques, i.e., Weather Research and Forecasting (WRF) model, method geographic information system (GIS), Newtonian relaxation assimilation technique, and Variational Analysis Method (VAM). The robustness of our analysis is confirmed by using high resolution data from the National Aeronautics and Space Administration (NASA) database and Cross-Calibrated Multi-Platform (CCMP) Reanalysis satellite data. Wind resource measurement data in Jayapura, Bantaeng and Sukabumi sites are used to validate the modelling results. The biases of the modelled data are 0.324, 0.368, and 0.324 in Jayapura, Bantaeng and Sukabumi respectively. This conclusion has two global implications. First, this study shows the WRF method is a feasible option to estimate wind speed data in developing countries commonly lacking meteorological stations to measure the wind energy resources. Second, the yearly wind mapping by province level produces mean wind speed map that is a useful information to indicate the profile of wind energy resource as the input for the wind energy system planning. We then match the wind energy potentials with other factors influencing wind warm feasibility, e.g., renewable energy tariffs, and parameters of power system flexibility.

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1. Introduction

Wind power is one of renewable energy with highest capacity growth worldwide (REN21, 2019). Total global capacity of wind power has been increasing from 121 gigawatts (GW) in 2008 to 591 GW in 2018, making wind power as the second largest renewable energy capacity just after hydropower capacity, i.e., 1,132 GW in 2018. Within the period, 52% of the additional capacity were installed in Asia region, particularly China who has become the country with the largest installed capacity of wind power to approximately 210 GW (REN21, 2019).

Another emerging Asia country in wind energy development is Indonesia who commercially operate its first wind farm 75 megawatts (MW) in 2018. The capacity of wind power in Indonesia is officially expected to grow rapidly reaching 1,800 MW by 2025 (GOI, 2017). Yet, this target is disagreed by the Agency for the Assessment and Application of Technology (BPPT) who forecasts smaller capacity addition of wind power by 2025 (BPPT, 2018). The difference is caused by different data of wind energy potential that GOI (2017) uses 60,647 MW data while BPPT (2018) uses 970 MW data. Moreover, BPPT (2018) eventually predicts that the addition capacity of wind power in 2017 to 2050 will be 2,500 MW, exceeding the used data of wind power potential. Such data conflicts and modelling errors are common problems in renewable energy planning analysis, especially in developing countries (Al Irsyad et al., 2019; Al Irsyad et al., 2017). Such data scarcity causes difficulty to make energy policy based on empirical data (Nepal et al., 2020). Therefore, the development of forecasting models is growing not only for policy analysis, but also for producing reliable data of renewable energy resources (Weekes et al., 2015). ‘

Wind power resource in Indonesia has been measured by various institutions (Martosaputro and Murti, 2014). For instances, Martosaputro and Murti (2014) provided global wind speed by using satellite data from 3TIER and wind resource assessment data in 11 sites. Martosaputro and Murti (2014) concluded that high wind power potentials are located on Java provinces (especially the south coast parts), East Nusa Tenggara, and Molucca. In contrast, Archer and Jacobson (2005) suggested that wind power potential in Indonesia is very low that no site has wind speed higher than 6.9 m/s. Hence, further reliable and high-resolution assessments of wind energy resources are important to provide trusted wind energy potential in Indonesia.

This study proposes an assessment methodology that assimilates two weather data sources (i.e., Cross-Calibrated Multi-Platform/ CCMP and the National Centers for Environmental Prediction – Final/ NCEP-FNL) to produce more accurate and higher-resolution data. NCEP data is a common data resources for wind speed assessment due to its accuracy but has lower resolution than that of CCMP. Meanwhile, CCMP has higher spatial and temporal resolutions but has lower accuracy in high-wind speed (i.e., > 15 m/s) and rainy conditions. Previous studies mostly used data from NCEP only (Beaucage et al., 2014; Carvalho et al., 2014b; Hossain et al., 2011; Jimenez et al., 2007; Lazić et al., 2010). An exception is Hesty and Hadi (2015) who has assimilated CCMP and NCEP-FNL but their wind energy assessment was only for a specific site (microscale). Therefore, the novelty of this study is the assimilation of those two-weather data to estimate wind energy in mesoscale with Indonesia as a case.

In addition, we juxtapose the resulted wind energy potentials with investment opportunities and risks. For this purpose, we review regional tariffs for wind energy, the power plant expansion plan of the State-owned Electricity Company (PLN), and the flexibility of regional electricity systems. Such systematic analysis is essential to understand actual feasible wind energy potentials. This is the first study to estimate wind energy potentials in Indonesia by integrating various modelling approaches supported by observation data from three meteorological masts.

The rest of paper is structured as follows. Chapter 2 reviews literatures related to wind energy potential assessment and Chapter 3 explains the methodology used in this study. Chapter 4 presents the results of wind energy assessment and the summary of wind energy potentials in Indonesia. Chapter 5 discusses regional wind farm plan, electricity tariffs, and flexibility of regional electricity systems and Chapter 6 discusses the conclusions and recommendations.

2. Literature Review

Wind energy assessments involve the determination of wind speed probability distribution, wind energy yield, capacity factor, wind farm layout, and finally the levelized cost of wind generated electricity (Mentis et al., 2016). The assessment can use various methods as used by studies in Table 1. Appropriately selecting numerical methods and physical configuration as well as using high resolution terrain data is the key to minimize error in the wind simulation (Carvalho et al., 2012; Carvalho et al., 2014b). Selecting an analytical tool for wind resource assessment depends on the analysis level, i.e., micro and meso levels.

The improvement of the wind energy assessment would not have been as successful without the use of numerical weather prediction (NWP) model. Micro-level analysis commonly uses models of MM5, Wind Atlas Analysis and Application Program (WAsP) and WindSIM (Hwang et al., 2010; Jimenez et al., 2007). MM5 and WAsP may produce comparable results, but MM5 has a critical advantage that it only needs reanalysis data without requiring wind measurement data (Jimenez et al., 2007). Reanalysis data is useful for wind resource assessments in a case when observational data is not available. NWP model, a software to describe atmospheric processes and changes, along with reanalysis is the main tool to construct historical climate data in a regional grid by integrating various past observation and measurement systems years (Al-Yahyai et al., 2010; Carta et al., 2013). NWP models can be used to downscale reanalysis data sets while adding physical phenomena, due to their smaller spatial and temporal time scales, including the consideration of local topographical features. The most widely used reanalysis data is generated from the National Centre for Environmental Prediction (NCEP) and the National Centre for Atmospheric Research (NCAR) (Carta et al., 2013). Yet, NCEP/NCAR reanalysis data is not suitable for use in the measure-correlate-predict (MCP) method with a purpose estimating energy production of a wind farm (Brower, 2006). The most accurate data for the wind energy simulation is ERA-Interim reanalysis for onshore area and NCEP-R2 reanalysis for offshore area (Carvalho et al., 2014a; Carvalho et al., 2014b). Hesty and Hadi (2015) assimilated CCMP and NCEP-FNL to increase data resolution from 27 km into 3 km for wind speed assessment in West Java coast, Indonesia.

Table 1 Studies on wind energy potentials

Study	Country	Methods	Data source
Al-Yahyai et al. (2012)	Oman	Nested ensemble NWP	
Archer and Jacobson (2005)	Global including Indonesia	Least square extrapolation	Kennedy Space Center Network
Beaucage et al. (2014)	US	Jackson-Hunt model, CFD/RANS, coupled NWP and mass-consistent model, coupled NWP and LES	NCAR, NCEP
Carvalho et al. (2012)	Portugal	WRF	NCAR, NCEP
Carvalho et al. (2014a)	Iberian Peninsula region	WRF	NCEP-R2, ERA-Interim, NCEP-CFSR, NASA-MERRA, NCEP-FNL and NCEP-GFS
Carvalho et al. (2014b)	Portugal	WRF	ERA-Interim, NASA-MERRA, NCEP-CFSR, NCEP-GFS and NCEP-FNL
Hesty and Hadi (2015)	Indonesia	WRF, FFDA	NCEP-FNL, CCMP
He and Kammen (2014)	China	GIS	3TIER
Hossain et al. (2011)	India	GIS	NCEP/NCAR
Hwang et al. (2010)	Korea	WinSIM, RANS	
Jimenez et al. (2007)	Germany	WAsP, MM5, GIS	NCEP
Jung et al. (2013)	South Korea	Weibull distribution, Bayesian approach	
Jung and Kwon (2013)	South Korea	ANN	
Kwon (2010)	South Korea	MCP, Weibull distribution, Monte-Carlo analysis	
Lazić et al. (2010)	Sweden	Eta model	NCEP
Latinopoulos and Kechagia (2015)	Greece	GIS, MCDA	
Santos-Alamillos et al. (2013)	Spain	WRF	
Weekes and Tomlin (2014a)	UK	Weibull distribution, LR, MCP	
Weekes and Tomlin (2014b)	UK	MCP, LR, LR2, VR	
Weekes et al. (2015)	UK	Linear MCP algorithm	MIDAS

Note: ANN = artificial neural network; CCMP = Cross-Calibrated Multi-Platform; CFD = computational fluid dynamics; FFDA = Four Dimension Data Assimilation; FNL = Final Global Data Assimilation System; GIS = geographic information system; LES = large-eddy simulations; LR = linear regression; LR2 = linear regression with Gaussian scatter; MCDA = Multi-criteria decision analysis; MCP = measure—correlate-predict; MIDAS = Met office integrated data archive system; NCAR = National Centre for Atmospheric Research; NCEP = National Centres for Environmental Prediction; RAMS = Regional Atmospheric Modeling System; RANS = Reynolds-averaged Navier–Stokes; VR = Variance ratio regression; WAsP = Wind Atlas Analysis and Application Program; WRF = Weather Research and Forecasting.

The MCP method involves short-term measurements in a specific site and, then, the measured data is correlated to long-term data records from reference surface stations. After that, the resulting data from the correlation process become basis data for making a long-term prediction. MCP is relatively accurate to perform long-term hindcasting of the wind conditions by using short-term data in a complex terrain compared to physical models (Carta et al., 2013). Weekes et al. (2015) used MCP to compare the data of the 4 km resolution, operational forecast model (UK4) and meteorological observations. As a result, the UK4 provide forecast the weather better than nearby meteorological stations. Among MCP methods, the regression MCP technique outperforms the bivariate Weibull (BW)-based MCP especially for analysis in short measurement periods (Weekes and Tomlin, 2014a). Moreover, linear regression with Gaussian scatter provide less bias and percentage error than standard linear regression and variance ratio regression (Weekes and Tomlin, 2014b). Kwon (2010) applied data from MCP to Wiebull probability distribution that was then used for Monte-Carlo based simulation procedure to estimate uncertainty of wind energy potentials in Kwangyang Bay, South Korea.

Recently, the MCP method also uses long-term reference data derived from the NWP model and the atmospheric reanalysis data set (Brower, 2006; Kalnay et al., 1996; Weekes et al., 2015). One of the most widely used NWP models is the Weather Research and Forecasting (WRF) model, which provides relatively accurate wind estimates for analysis on flat and homogenous flat terrain (Santos-Alamillos et al., 2013). For higher terrain complexity, WRF requires more detailed terrain data (Carvalho et al., 2012; Carvalho et al., 2014a). As a mesoscale model, NWP models are commonly coupled to microscale wind flow model to obtain a higher spatial resolution and accuracy (Beaucage et al., 2014). Another NWP model is Eta model, a regional atmospheric NWP that could produce accurate forecast of wind speeds (Lazić et al., 2010).

Studies estimating wind energy potential continuously develop new methodologies. Jung et al. (2013) offered a new Bayesian approach that has better accuracy than the conventional deterministic approach. Jung and Kwon (2013) proposed artificial neural network (ANN) considering wind speed frequency and power performance curve to develop weighted error function. The function improves the estimation accuracy for 8 to 12% compared to the conventional ANN. Studies for wind energy assessment also commonly uses geographic information system (GIS). It then can be integrated with the simulation of capacity factor (CF) of wind turbine and plant load factor (PLF) to determine the locations of wind farm potentials and electricity production potential from the wind farms (He and Kammen, 2014; Hossain et al., 2011). Moreover, Latinopoulos and Kechagia (2015) combined GIS and multi-criteria decision analysis (MCDA) to find the most proper sites for wind farms.

Determining feasible locations of wind farm should consider technical issues (e.g., wind energy potentials, grid infrastructure, electricity demand, and grid flexibility), economic issues (e.g., incentive, and tariffs) as well as social and institutional issues (e.g., bureaucratic constraint, public opinions, protected environments, historical and archaeological sites, tourism facilities, and residential settlements) (Babatunde et al., 2020; Latinopoulos and Kechagia, 2015). One of significant factors determining the feasibility of wind farm is power system flexibility (Papaefthymiou et al., 2018). The power system flexibility is the ability of power system to balance power supply and consumption rapidly in order to preserve the system stability (Heggarty et al., 2020). Therefore, factors influencing the power system flexibility could be from supply, demand, grid, storage, and market sides (Babatunde et al., 2020; Heggarty et al., 2020; IRENA, 2018; Papaefthymiou et al., 2018).

A measure in supply side to improve the flexibility is to limit the share of variable renewable energy (VRE) in a power system. For an instance, Zakeri et al. (2015) suggested the maximum VRE share on total electricity production is 19%. Al Irsyad et al. (2020) assessed the impact of VRE share limit on Indonesia power plant expansions under emission reduction targets. As results, wind energy is a cost-effective power plant to substitute coal-fired power plants. It is clear from Table 1 that no study has specifically assessed wind energy potentials from two different perspectives, i.e., resources potentials, and financial feasibility. Moreover, Our resource assessment lays on an assessment model built from WRF Four-Dimensional Data Assimilation System (WRF-FDDA) and FNL and CCMP dataset. These two approaches could provide more accurate and higher resolution data without requiring huge computation resources (Lorenc, 1986). The finding of this study calls for more discussions about opportunities of wind energy investments in Indonesia as detailed out in section 5 of the paper.

3. Methodology

We estimated wind energy potentials in RUEN by constructing an atmospheric mesoscale model resulting from a regional wind map. MEMR improved the model by experimental wind resource assessments coupled with a data assimilation technique. For this purpose, we used the atmospheric mesoscale WRF model with a spatial resolution of 5 x 5 km to map wind resources at 50 meters (m) above ground level (agl). Figure 1 shows the setup of WRF with two 2-way nested model domains. The outer domain has a horizontal resolution of 27 km and the resolution for the inner domain is 5 km. It has 35 vertical levels and the lowest crucial levels are at around 10, 30, 52 and 97 m agl. Initial and boundary conditions is from FNL datasets with a spatial resolution of 1 x 1º.

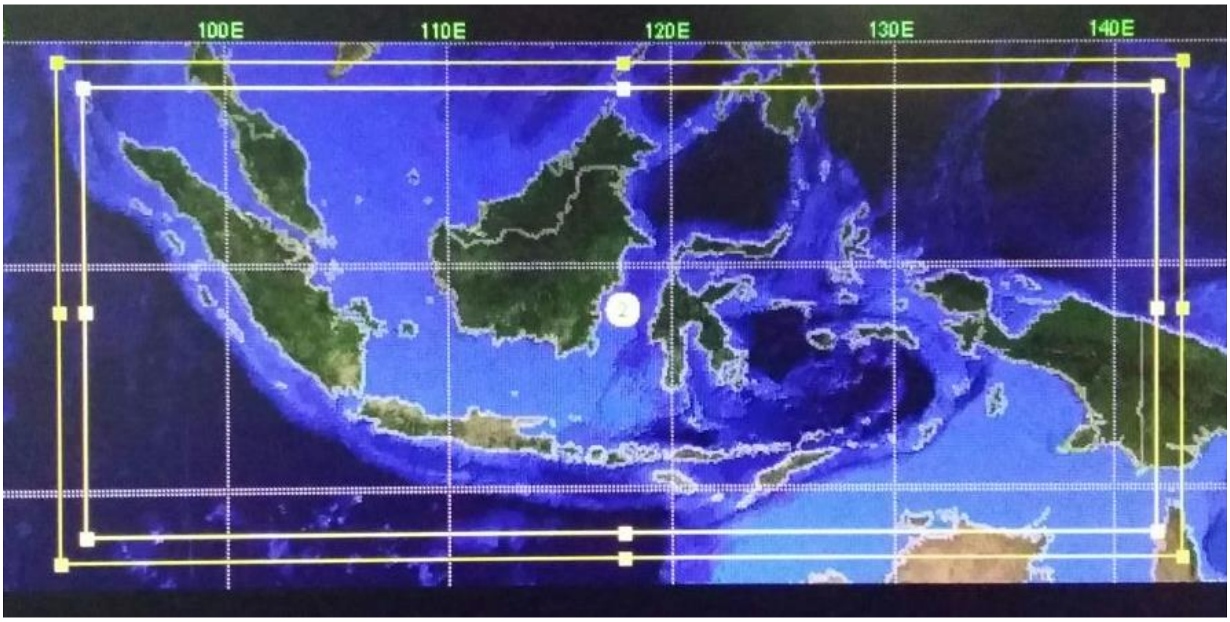


Figure 1. Model domain

We assimilated ocean surface wind data provided from the CCMP satellite data by coupling numerical model with the Newtonian relaxation technique. The CCMP data contains high-resolution wind data generated from the integrations of wind measurements from Remote Sensing Systems (REMSS) satellites and Variational Analysis Method (VAM). The CCMP surface winds dataset contains 0.25º gridded ocean surface wind or about 25 km in the region near the equator. We then added prognostic equations nudging the predicted variables toward available observations (interpolated in each model grid). Nudging the Four-Dimensional Data Assimilation System (FDDA) is an effective and efficient way to reduce model errors. The nudging technique improves lateral boundary condition and relaxation of model forecast towards observed conditions. The nudging equation is given by:

$$\frac{\partial \emptyset_m}{\partial t} = \frac{(\emptyset_{obs} - \emptyset_m)}{\tau} \tag{1}$$

where $\emptyset_m$ is the variable of prognostic model, $\emptyset_{obs}s$ is the measured variable, and τ is the time scale of a relaxation. The spatial variation of nudging is:

$$f(r) = e^{-r/r_0} \tag{2}$$

where r is the distance from the measuring point, and $r0$ is a reference distance representing the nudging range. The weight of the nudging is obtained by multiplying Equations (1) and (2). As results, the selected optimal relaxation time scale is one hour and the selected nudging radius is 25 km. We then convert the estimated wind speed data into wind energy potentials by assuming that a 1 MW wind turbine is for one hectare of land with wind speed above 6 m/s and a 100 kW wind turbine is for one hectare of land with wind speed between 4 – 6 m/s.

4. Results

Figure 2 shows the modelled annual mean wind speed at 50 m agl by using the Geographic Information System (GIS). We classified the wind speed into eight speed classes between the lowest wind speed (< 3 m/s) represented by green color to the highest wind speed (> 9m/s) represented by red color. Wind resources in coastal areas are extremely high exceeding 5 m/s, which is the average cut-in wind speed of many typical commercial wind turbines (Akour et al., 2018; Li and Chen, 2008). Furthermore, Figure 2 shows that the wind speed along the west part of Indonesian offshore areas is often over 7 m/s, which is very attractive wind resources for wind farms.

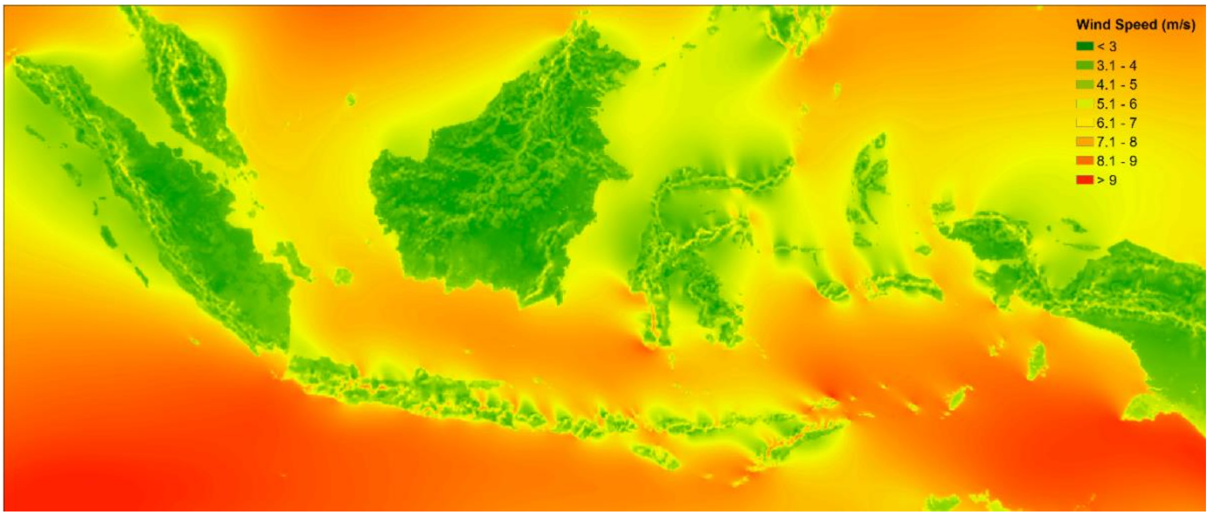
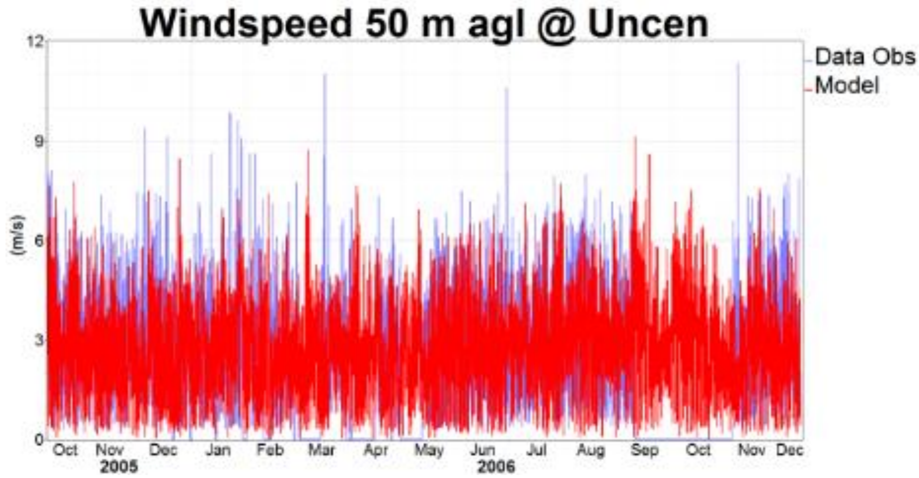


Figure 2. Indonesia global wind speed at 50 m height - resolution 5 km

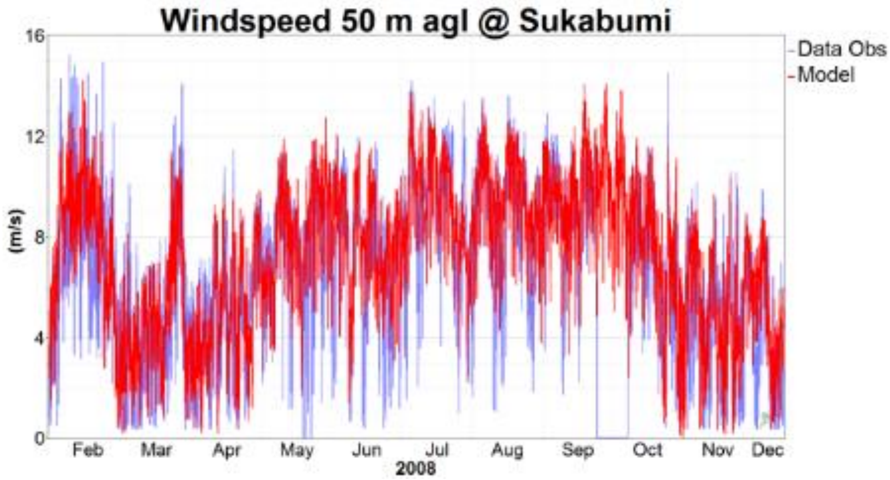
We evaluated the model by using wind measurement data at a height of 50 m agl at University of Cendrawasih (Uncen) - Jayapura, Tamanjaya - West Java, and Bantaeng - South Sulawesi. The three meteorological masts (met masts) in Jayapura, Sukabumi, and Bantaeng observed climatological and weather conditions. The sites of met mast and the measuring period are summarized in Table 2. The time series data obtained from the model is hourly average values at the physical site. The time series data from the three sites at 50m agl is shown in Figure 3. The blue and red lines are the measurement data and the modelling result with nudging respectively. The average wind speeds in Jayapura based on the measurement is 2.33 m/s while the model result is 2.78 m/s. Meanwhile, the average measured wind speed in Sukabumi is 6.70 m/s while wind speed from the model is 7.20 m/s. For Bantaeng, the actual average wind speed is 4.66 m/s, while modelled wind speed is 5.44 m/s. In general, the modelling slightly overestimates the wind speed and the deviations are related to local topographical feature and at low- high wind speed. This analysis emphasizes that the model outputs have realistic meteorological patterns.

Table 2. The coordinate of met mast and measuring periods

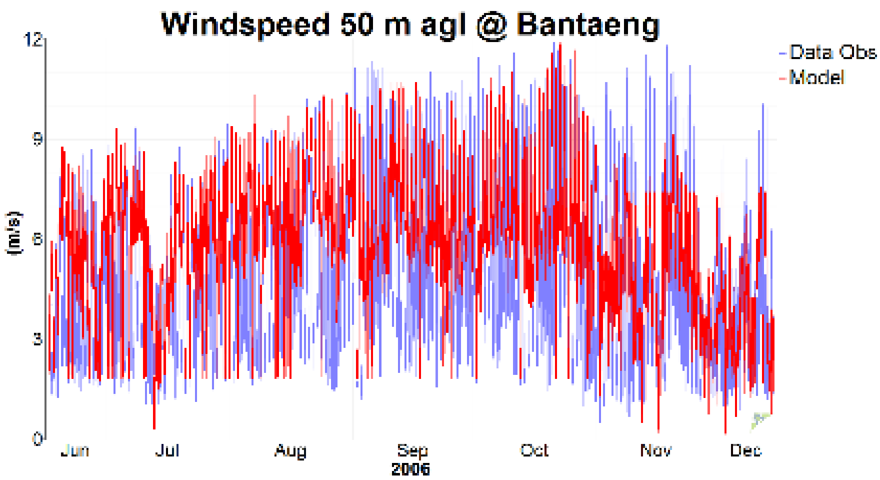
Site	Coordinate		Measuring periods
Jayapura	-2.58249	140.6575	October 2005 to December 2006
Sukabumi	-7.2688	106.5288	January 2008 to December 2008
Bantaeng,	-5.5825	120.0475	June to December 2006



(a) Jayapura site



(b) Sukabumi site



(c) Bantaeng site

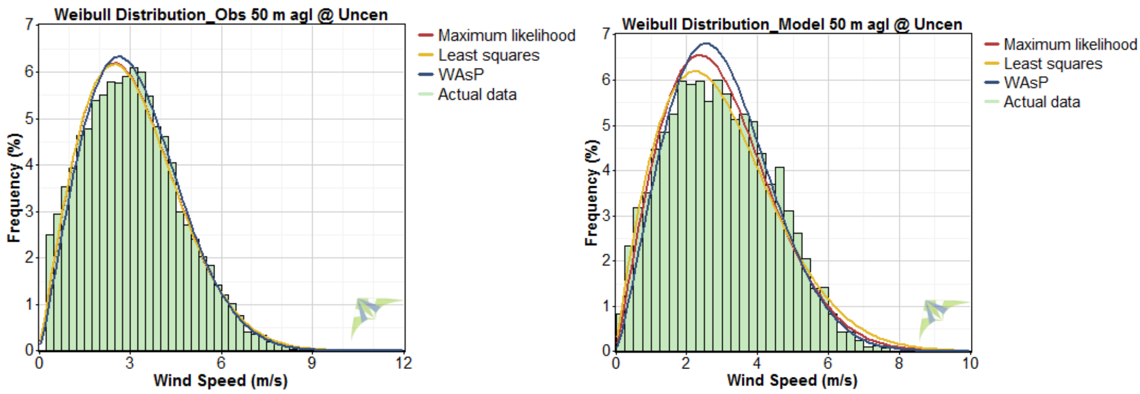
Figure 3. Wind speed data at 50 m agl from met masts in three sites

Table 3 summarizes statistical parameters of bias, root mean square error (RMSE), and correlations between model and observed wind data. The RMSE for the Bantaeng is the highest among the other sites; however, the bias is below 0.5 m/s for all sites or lower than the maximum bias (i.e., ± 0,5) proposed by Emery et al. (2001). The correlations for all sites are between 0.6 and 0.7. The WRF model produces overestimated results at low wind speeds and underestimated results at wind speed above 9 m/s at all sites.

Table 3. Bias, RMSE and correlation of model results and actual data

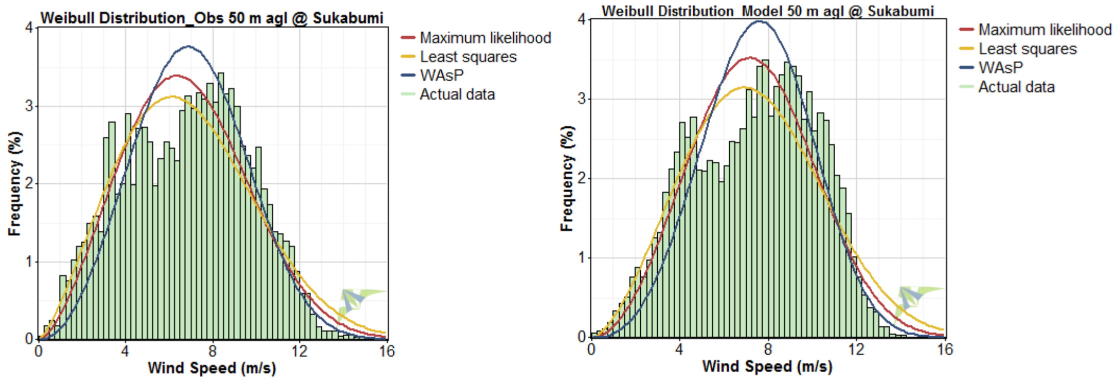
	Bias	RMSE	Correlation
Jayapura	0.324	2.300	0.734
Sukabumi	0.368	2.373	0.736
Bantaeng	0.324	2.870	0.667

Comparing geographical characteristics on different sites is useful to identify the effects of terrain on wind distribution data. Figures 4, 5, and 6 show wind speed distributions and their Weibull-fits for both the observed and modelled wind speed at 50 m agl for each mast. The figures show that the distribution shapes are different for each location. Sukabumi data in Figure 5 shows the widest range of wind speeds while the lowest range of wind speed is in Jayapura site as in Figure 4. In Bantaeng, most observed data is low wind speed while the modelled data is mostly high wind speed as in Figure 6. The deviation is due to the inaccurate representations of surface roughness elements like forests and buildings. Therefore, the representation in numerical weather models should be improved for this specific site. The application of a roughness length alone is not enough to characterize the interaction of atmospheric flows with the surface.



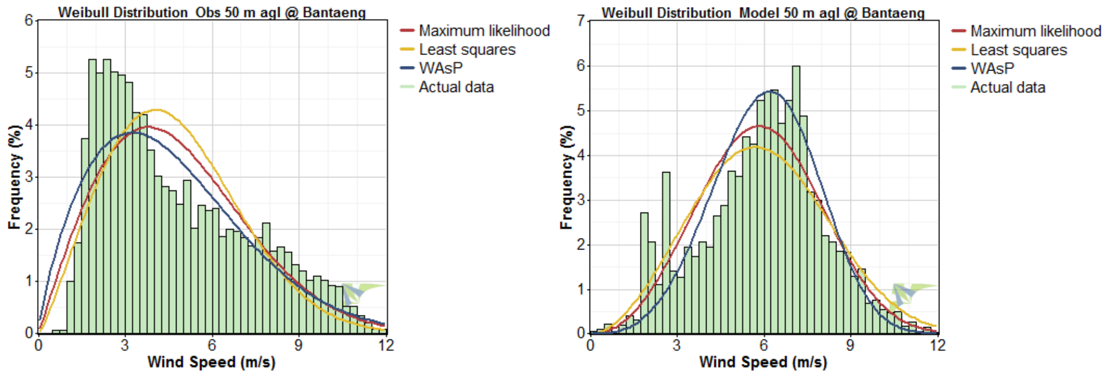
(a) Observation (b) Modelled

Figure 4. Histograms for wind speeds at Jayapura at 50 m agl



(a) Observation (b) Modelled

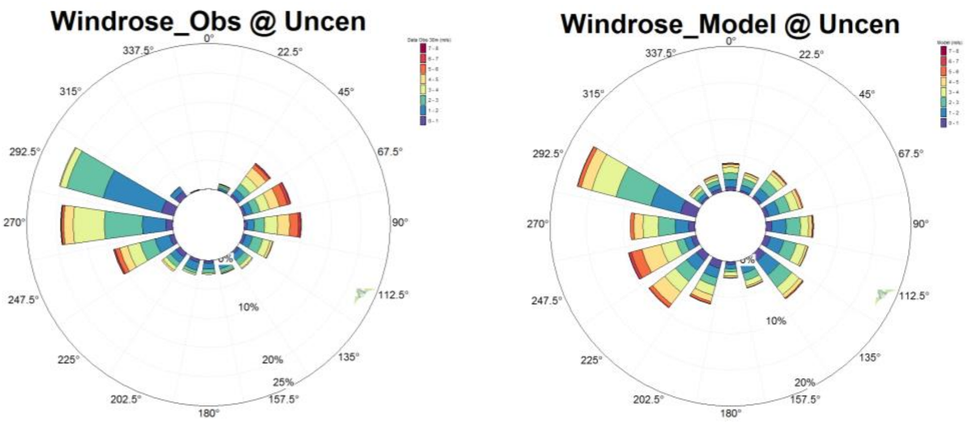
Figure 5. Histograms for wind speeds at Sukabumi at 50 m agl



(a) Observation (b) Modelled

Figure 6. Histograms for wind speeds at Bantaeng at 50 m agl

Figures 7, 8, and 9 show the related wind roses that display wind speed, frequency, and direction. The modelled data appears to capture the directional wind distribution of observation data quite well. Figure 7 shows that the modelled wind speed in Jayapura is stronger than the observed data, but the wind direction in both modelled and observed data is similar. The channeling in Sukabumi (Figure 8) is clearly visible; however, the modelled wind speeds are lower than in the observations. One of the possible causes is that terrain model is too smooth. Moreover, Figure 9 shows that the WRF model cannot precisely replicate wind directions in Bantaeng even though the terrain is flat. The observation data has higher wind speeds and more northerly component than the modelled data.



(a) Observation (b) Modelled

Figure 7. Windrose for wind speeds in Jayapura

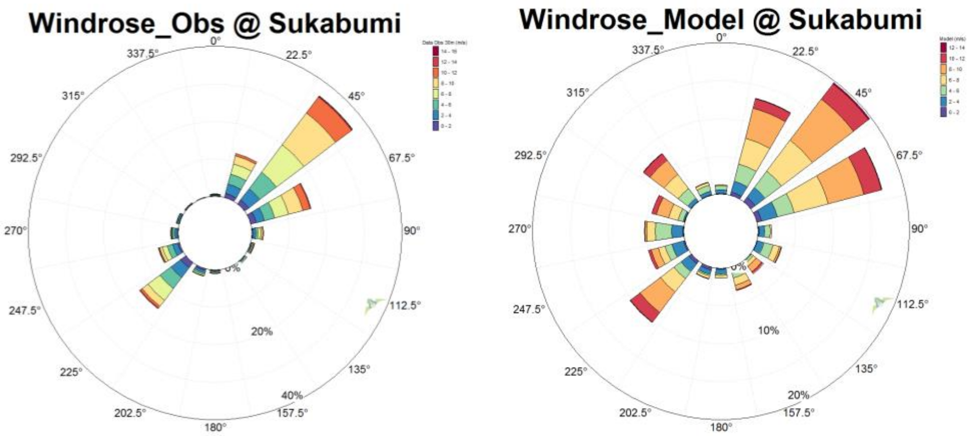
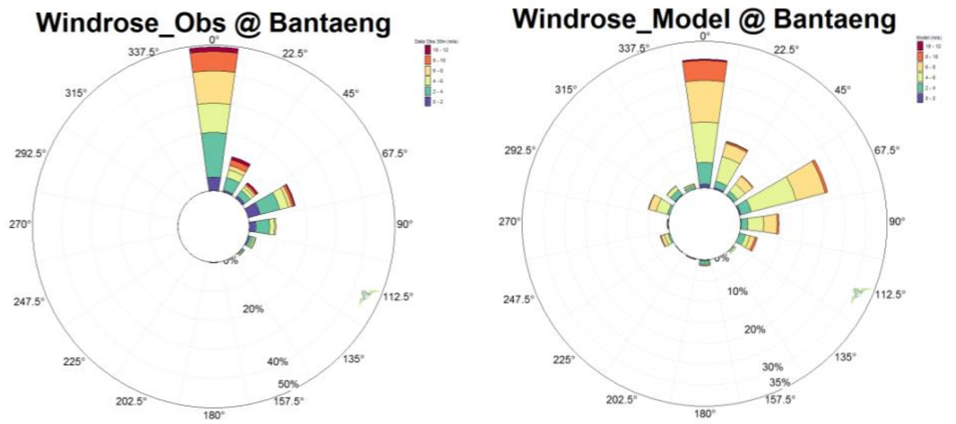


Figure 8. Windrose for wind speeds in Sukabumi



(a) Observation (b) Modelled

Figure 9. Windrose for wind speeds in Bantaeng

5. Investment Opportunities

We convert the average wind speed data in Figure 2 into wind energy potentials. The potential data is then used by RUEN (GOI, 2017) as seen in Table 4 and Figure 10. The largest potentials are on systems of Java, Madura, and Bali (JAMALI) (24,011 MW) and East Nusa Tenggara (10,188 MW). RUEN has expected to build wind farms with total capacity for 716 MW and 266 MW in those regions respectively (GOI, 2017). Yet, the feasibility of wind farm should consider at least two other factors that are grid flexibility and electricity tariffs.

The JAMALI system is the largest electricity grid system with total electricity supply 149,9 TWh in 2019. Currently, the main electricity supply in the JAMALI system is mainly coal-fired power plants and combined cycle gas turbine (CCGT) for 70.3% and 22.6% of respectively (DGE, 2020b). The JAMALI system does not have neither solar farms nor wind farm yet; however, PV rooftop in the system is growing with installed capacity 4,849 kWp in December 2019 (DGE, 2020a). Moreover, RUEN (GOI, 2017) also expects that the JAMALI system will have wind farms with total capacity 716 MW by 2025. However, wind farm investment in JAMALI system is less interesting since the average PLN generation cost in the JAMALI system is only 6.91 ¢US$/ kWh (please see Table 4), which is the ceiling price for PLN to buy renewable-based electricity from independent power producers (IPP). The regulation of Minister of Energy and Mineral Resources (MEMR) No. 53 /2018 (MEMR, 2018) and No. 50 /2017 (MEMR, 2017) sets PLN regional generation cost in previous year as the ceiling price for regions with generation costs lower than the PLN's average national generation cost, i.e., 7.86 ¢US$/ kWh in 2019.

In contrast, East Nusa Tenggara systems have average regional generations costs (i.e., 17.58 ¢US$/ kWh) higher than the PLN's average national generation cost. East Nusa Tenggara actually has several separated grid systems with different generation costs. The largest system (and the generation cost in 2019) are Sumba system (20.81 ¢US$/ kWh), Timor system (18.17 ¢US$/ kWh), West Flores (17.58 ¢US$/ kWh), and East Flores (21.28 ¢US$/ kWh). The generation costs for smaller systems in Nusa Tenggara reached 21.34 ¢US$/ kWh in 2019. For such regions, MEMR (2018) and MEMR (2017) allows PLN to buy renewables-based electricity at maximum 85% of regional electricity production costs. It means that the ceiling tariff will be between 14.94 and 18.14 ¢US$/ kWh, which are higher than average levelized cost of energy (LCOE) of wind power plants around the world, i.e., 4.6 to 9.9 ¢US$/ kWh in 2019 (IRENA, 2020). However, by assuming VRE only can supply 20% of total electricity productions, East Nusa Tenggara only can take 200 GWh electricity generated from wind turbine. If the capacity factor is 35% (IRENA, 2020), total capacity of wind farms that could be installed in East Nusa Tenggara is around 65 MW. Beyond the attractive ceiling tariff, the Indonesia government offers three incentives that are:

a. Import duty exemptions for two years that can be extended for one year (MoF, 2015);

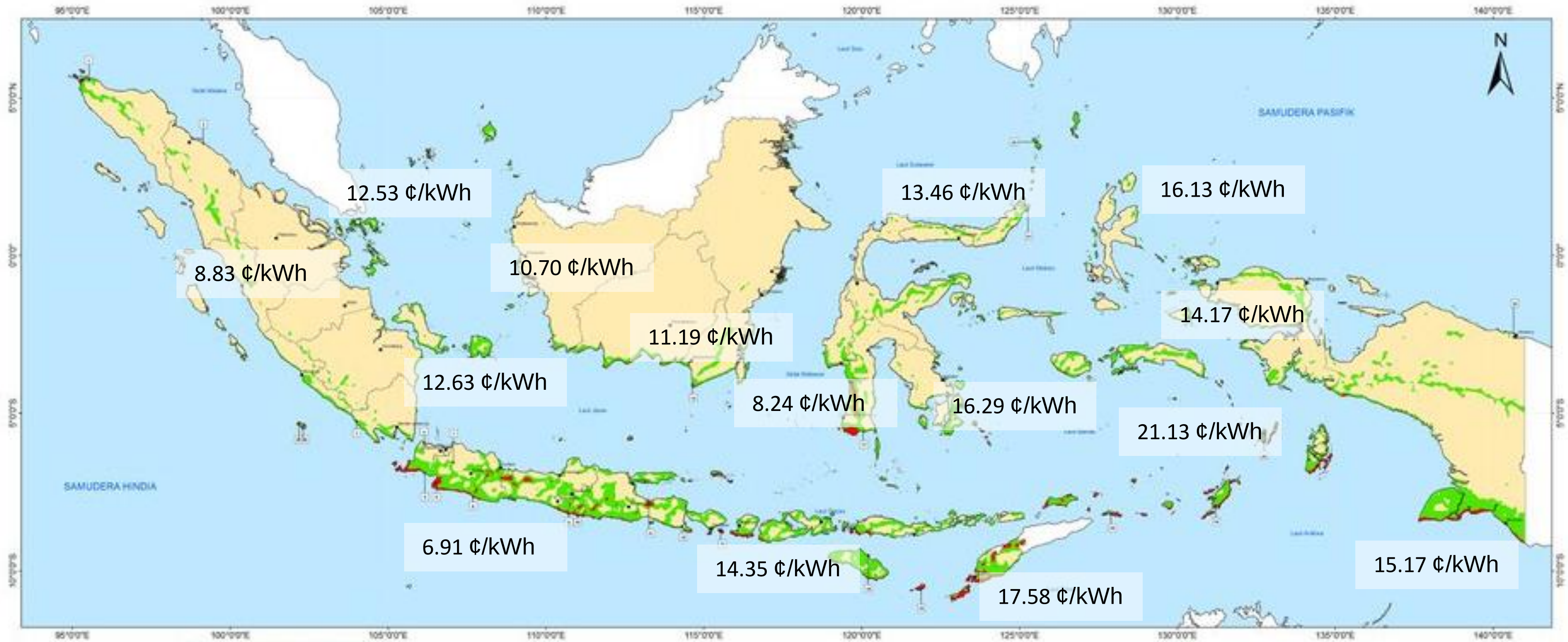
b. Tax holiday up to 20 years (MoF, 2020b);

c. Tax allowance (MoF, 2020a).

Table 4. Wind energy potentials and other feasibility parameters of wind farm investments

Regions	Potentials (MW)	Wind turbine plan by 2025* (MW)	Average PLN's generation cost+ (¢ US$/kWh)	Electricity demand+ (GWh)	Peak loads+ (MW)	Available capacity of power plant+ (MW)
Sumatera	4,688	82	8.83	34,645	7,866	22,493
Riau Archipelago	922	-	12.53	3,346	647	723
Bangka Belitung	1,787	-	12.63	1,167	254	287
Java, Madura, & Bali (JAMALI)	24,011	716	6.91	179,299	26,608	27,745
West Kalimantan	554	28	10.70	2,573	122	336
South Kalimantan, East Kalimantan, North Kalimantan & Central Kalimantan	2,109	255	11.19	8,131	2,107	2,440
North Sulawesi & Gorontalo	1,351	21	13.46	2,325	81	95
South Sulawesi, Central Sulawesi & West Sulawesi	5,615	313	8.24	7,472	2,627	2,798
Southeast Sulawesi	1,414	57	16.29	987	39	45
West Nusa Tenggara	2,605	72	14.35	1,950	497	609
East Nusa Tenggara	10,188	266	17.58	1,000	227	304
Maluku	3,188	114	21.13	519	159	278
North Maluku	504	-	16.13	538	52	58
Papua	1,411	69	15.17	1,058	92	122
Papua Barat	437	11	14.17	510	294	336

Note: * is derived from RUEN (GOI, 2017) and + is 2019 data and derived from PLN (2020).

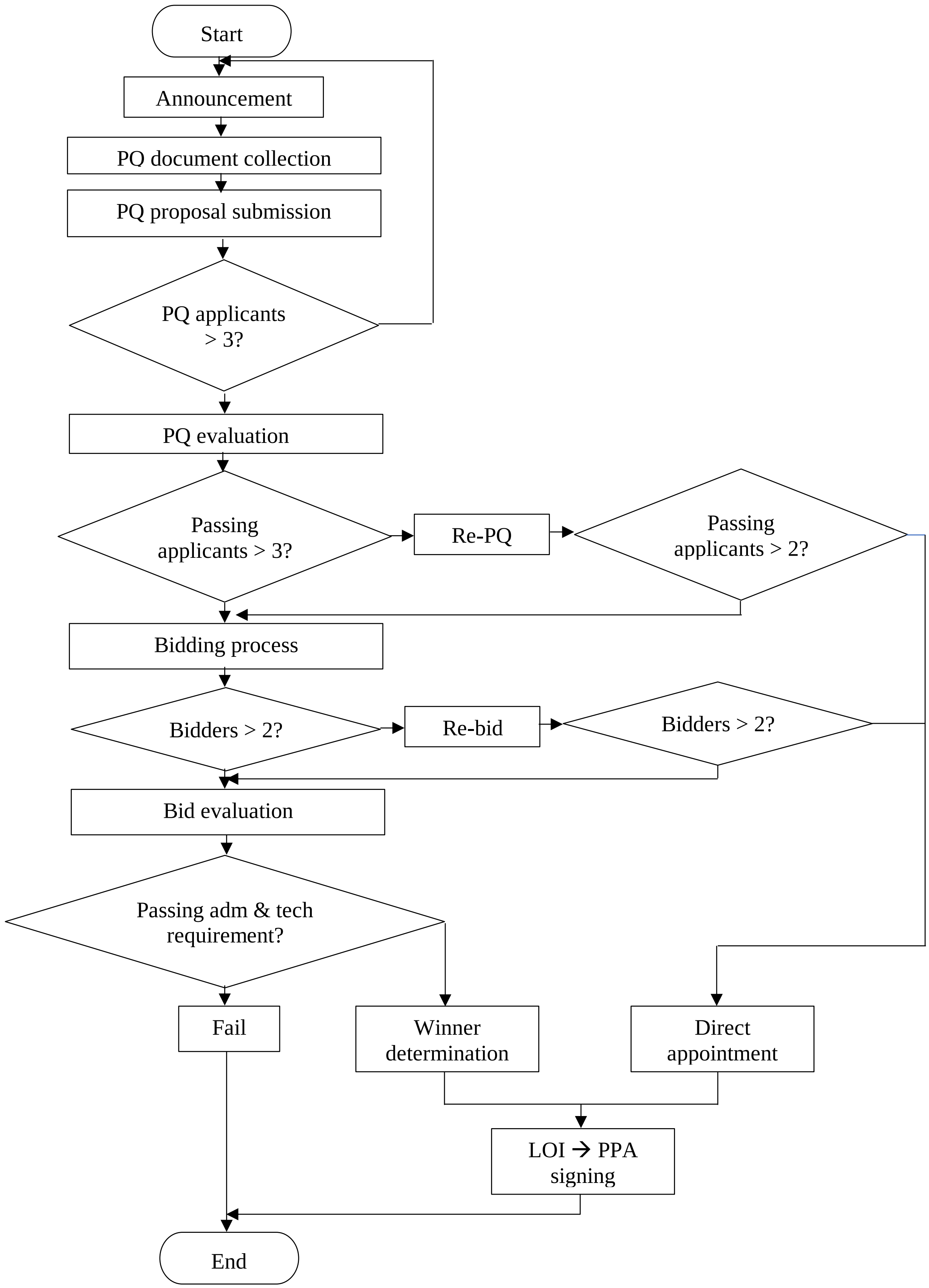


The red coloured areas have average wind energy speed larger than 6 m/s while the green coloured area have average wind energy speed between 4 to 6 m/s.

Figure 10. Map of on-shore wind energy potentials and PLN's average generation costs in 2018

An IPP establishing a wind farm project in Indonesia should obtain various permits and documents from Ministry of Energy and Mineral Resources (MEMR), Investment Coordinating Board (BKPM), other ministries, Bank of Indonesia, PLN, and local governments as in Table A.1 in the Appendix. The IPP should also follow IPP procurement procedures in MEMR (2007). PLN could select IPP through three procedures that are direct appointment, direct selection, and open tender. The direct appointment is only for emergency or crisis of electricity power supply and expansion project in the same location of the same system. The direct selection procedure is for energy diversification and expansion project in the different location of the same system. The eligible power plant under these two procedures are coal-fired power plant, gas-fired power plant, and hydroelectric power plant. An IPP project that is not eligible for direct appointment or direct selection should follow open tender procedure to seek the lowest price proposal submitted by the bidders. The open tender procedure can be used for all types of power plant (MEMR, 2007).

Figure 11 shows the process of open tender procedure. First of all, the wind farm project should be listed in PLN's Electricity Supply Business Plan (RUPTL) published annually. PLN announces its plan to build wind energy power plants and invites IPP to submit pre-qualification proposal. If applicants passing requirements are higher than one then PLN uses tender scheme; otherwise, PLN uses direct appointment. PLN and the selected IPP then sign the power purchase agreement (PPA).



Note: PQ = Pre-qualification; adm = administration; and tech = technical

Figure 11. The process for power purchase agreement for wind energy power plants

6. Conclusions and Recommendations

This study uses WRF and GIS models to estimate theoretical wind energy resources in Indonesia. The modelled data is then validated by using empirical data measured by three met masts in Jayapura, Bantaeng and Sukabumi. As results, the WRF model is reliable to estimate mean wind speeds in all Indonesia provinces. The wind speeds, presented in a GIS map, are useful information for wind energy planning in national and regional levels. It is the first map for Indonesia context and it also has been used officially by the General National Energy Plan (PRI, 2017). Thereafter, we discuss the implications of our analysis results into wind farm investment opportunity in Indonesia. We review other influencing factors especially data for assessing regional power system flexibility and ceiling prices of renewable energy in Indonesia. Specifically, investment feasibilities in JAMALI and East Nusa Tenggara systems are briefly discussed as examples.

Our WRF model validated by three measurement data is the initial stage to provide more robust wind maps for the entire of Indonesia. Once more data is available, future studies should conduct spatial analysis by points by using other prominent methods such as Inverse Distant Weight and Kriging in GIS environment. Moreover, wind energy potential data should be extended to offshore wind energy potentials. Compared to the on-shore wind farm, the off-shore wind farm can produce higher and more stable electricity (Bilgili et al., 2011; Perveen et al., 2014). Therefore, this advantage should be further evaluated to examine its technical feasibility especially its impacts on grid stability in other regions.

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References

Akour, S.N., Al-Heymari, M., Ahmed, T., Khalil, K.A., 2018. Experimental and theoretical investigation of micro wind turbine for low wind speed regions. Renewable Energy 116, 215-223.

Al-Yahyai, S., Charabi, Y., Al-Badi, A., Gastli, A., 2012. Nested ensemble NWP approach for wind energy assessment. Renewable energy 37, 150-160.

Al-Yahyai, S., Charabi, Y., Gastli, A., 2010. Review of the use of numerical weather prediction (NWP) models for wind energy assessment. Renewable and Sustainable Energy Reviews 14, 3192-3198.

Al Irsyad, M.I., Halog, A., Nepal, R., 2019. Renewable energy projections for climate change mitigation: An analysis of uncertainty and errors. Renewable Energy 130, 536-546.
Al Irsyad, M.I., Halog, A., Nepal, R., Koesrindartoto, D.P., 2020. Economical and environmental impacts of decarbonisation of Indonesian power sector. Journal of Environmental Management 259, 109669.
Al Irsyad, M.I., Halog, A.B., Nepal, R., Koesrindartoto, D.P., 2017. Selecting Tools for Renewable Energy Analysis in Developing Countries: An Expanded Review. Frontiers in Energy Research 5.
Archer, C.L., Jacobson, M.Z., 2005. Evaluation of global wind power. Journal of Geophysical Research: Atmospheres 110.
Babatunde, O., Munda, J., Hamam, Y., 2020. Power system flexibility: A review. Energy Reports 6, 101-106.
Beaucage, P., Brower, M.C., Tensen, J., 2014. Evaluation of four numerical wind flow models for wind resource mapping. Wind Energy 17, 197-208.
Bilgili, M., Yasar, A., Simsek, E., 2011. Offshore wind power development in Europe and its comparison with onshore counterpart. Renewable and Sustainable Energy Reviews 15, 905-915.
BPPT, 2018. Outlook Energi Indonesia 2018: Energi Berkelanjutan untuk Transportasi Darat. Badan Pengkajian dan Penerapan Teknologi (BPPT), Tangerang Selatan.
Brower, M.C., 2006. The use of NCEP/NCAR reanalysis data in MCP, EWEC 2006 conference proceedings.
Carta, J.A., Velázquez, S., Cabrera, P., 2013. A review of measure-correlate-predict (MCP) methods used to estimate long-term wind characteristics at a target site. Renewable Sustainable Energy Reviews 27, 362-400.
Carvalho, D., Rocha, A., Gómez-Gesteira, M., Santos, C., 2012. A sensitivity study of the WRF model in wind simulation for an area of high wind energy. Environmental Modelling Software 33, 23-34.
Carvalho, D., Rocha, A., Gómez-Gesteira, M., Santos, C.S., 2014a. Offshore wind energy resource simulation forced by different reanalyses: comparison with observed data in the Iberian Peninsula. Applied energy 134, 57-64.
Carvalho, D., Rocha, A., Gómez-Gesteira, M., Santos, C.S., 2014b. WRF wind simulation and wind energy production estimates forced by different reanalyses: Comparison with observed data for Portugal. Applied Energy 117, 116-126.
DGE, 2020a. Kebijakan Pemanfaatan Pembangkit Listrik Tenaga Surya (PLTS) Atap. Directorate General of Electricity (DGE) - Ministry of Energy and Mineral Resources (MEMR), Jakarta, Indonesia, p. 19.
DGE, 2020b. Statistik Ketenagalistrikan Tahun 2019, 33 ed. Directorate General of Electricity (DGE) - Ministry of Energy and Mineral Resources (MEMR), Jakarta, Indonesia, p. 122.
Emery, C., Tai, E., Yarwood, G., 2001. Enhanced meteorological modeling and performance evaluation for two Texas ozone episodes. ENVIRON International Corporation, California, US, p. 235.
GOI, 2017. Presidential Decree No. 22/ 2017 on General National Energy Plan. Government of Indonesia (GOI), Jakarta.
He, G., Kammen, D.M., 2014. Where, when and how much wind is available? A provincial-scale wind resource assessment for China. Energy Policy 74, 116-122.
Heggarty, T., Bourmaud, J.-Y., Girard, R., Kariniotakis, G., 2020. Quantifying power system flexibility provision. Applied Energy 279, 115852.
Hesty, N.W., Hadi, T.W., 2015. Reanalisis weather research and forecast-four dimension data assimiliation (WRF-FDDA) untuk meningkatkan akurasi estimasi potensi energi angin

di daerah lepas pantai (studi kasus: pantai selatan Jawa Barat). Jurnal Sains Dirgantara 13.

Hossain, J., Sinha, V., Kishore, V., 2011. A GIS based assessment of potential for windfarms in India. Renewable energy 36, 3257-3267.

Hwang, Y., Paek, I., Yoon, K., Lee, W., Yoo, N., Nam, Y., 2010. Application of wind data from automated weather stations to wind resources estimation in Korea. Journal of mechanical science technology 24, 2017-2023.

IRENA, 2018. Power system flexibility for the energy transition: Part 1, Overview for policy makers. International Renewable Energy Agency (IRENA), Abu Dhabi, UAE, p. 49.

IRENA, 2020. Renewable Power Generation Costs in 2019. International Renewable Energy Agency (IRENA), Abu Dhabi, UAE, p. 160.

Jimenez, B., Durante, F., Lange, B., Kreutzer, T., Tambke, J., 2007. Offshore wind resource assessment with WAsP and MM5: comparative study for the German Bight. Wind Energy 10, 121-134.

Jung, S., Arda Vanli, O., Kwon, S.-D., 2013. Wind energy potential assessment considering the uncertainties due to limited data. Applied Energy 102, 1492-1503.

Jung, S., Kwon, S.-D., 2013. Weighted error functions in artificial neural networks for improved wind energy potential estimation. Applied Energy 111, 778-790.

Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., Iredell, M., Saha, S., White, G., Woollen, J.J.B.o.t.A.m.S., 1996. The NCEP/NCAR 40-year reanalysis project. 77, 437-472.

Kwon, S.-D., 2010. Uncertainty analysis of wind energy potential assessment. Applied Energy 87, 856-865.

Latinopoulos, D., Kechagia, K., 2015. A GIS-based multi-criteria evaluation for wind farm site selection. A regional scale application in Greece. Renewable Energy 78, 550-560.

Lazić, L., Pejanović, G., Živković, M., 2010. Wind forecasts for wind power generation using the Eta model. Renewable Energy 35, 1236-1243.

Li, H., Chen, Z., 2008. Overview of different wind generator systems and their comparisons. IET Renewable Power Generation 2, 123-138.

Lorenc, A.C., 1986. Analysis methods for numerical weather prediction. Quarterly Journal of the Royal Meteorological Society 112, 1177-1194.

Martosaputro, S., Murti, N., 2014. Blowing the wind energy in Indonesia. Energy Procedia 47, 273-282.

MEMR, 2007. Peraturan Menteri ESDM No. 04 Tahun 2007 tentang Perubahaan Atas Peraturan Menteri Energi Dan Sumber Daya Mineral Nomor 01 Tahun 2006 Tentang Prosedur Pembelian Tenaga Listrik Dan Atau Sewa Menyewa Jaringan Dalam Usaha Penyediaan Tenaga Listrik Untuk Kepentingan Umum. Ministry of Energy and Mineral Resources (MEMR), Jakarta, Indonesia.

MEMR, 2017. Peraturan Menteri Energi dan Sumber Daya Mineral Nomor 50 Tahun 2017 tentang Pemanfaatan Sumber Energi Terbarukan untuk Penyediaan Tenaga Listrik. Ministry of Energy and Mineral Resources (MEMR), Jakarta.

MEMR, 2018. Peraturan Menteri Energi dan Sumber Daya Mineral Nomor 53 Tahun 2018 tentang Perubahan atas Peraturan Menteri Energi dan Sumber Daya Mineral Nomor 50 Tahun 2017 tentang Pemanfaatan Sumber Energi Terbarukan untuk Penyediaan Tenaga Listrik. Ministry of Energy and Mineral Resources (MEMR), Jakarta.

Mentis, D., Siyal, S.H., Korkovelos, A., Howells, M., 2016. A geospatial assessment of the techno-economic wind power potential in India using geographical restrictions. Renewable energy 97, 77-88.

MoF, 2015. Peraturan Menteri Keuangan Nomor 66/PMK.010/2015 tentang Pembebasan Bea Masuk atas Impor Barang Modal dalam Rangka Pembangunan atau Pengembangan

Industri Pembangkit Tenaga Listrik untuk Kepentingan Umum. Ministry of Finance (MOF), Jakarta, Indonesia.

MoF, 2020a. Peraturan Menteri Keuangan Nomor 11/PMK.010/2020 tentang Pelaksanaan Peraturan Pemerintah Nomor 78 Tahun 2019 tentang Fasilitas Pajak Penghasilan untuk Penanaman Modal di Bidang-bidang Usaha Tertentu dan/ atau di Daerah-Daerah Tertentu. Ministry of Finance (MOF), Jakarta, Indonesia.

MoF, 2020b. Peraturan Menteri Keuangan Nomor 130/PMK.010/2020 tentang Pemberian Fasilitas Pengurangan Pajak Penghasilan Badan. Ministry of Finance (MOF), Jakarta, Indonesia.

Nepal, R., Sharma, B., al Irsyad, M.I., 2020. Scarce data and energy research: Estimating regional energy consumption in complex economies. Econ. Anal. Pol. 65, 139-152.

Papaefthymiou, G., Haesen, E., Sach, T., 2018. Power System Flexibility Tracker: Indicators to track flexibility progress towards high-RES systems. Renewable energy 127, 1026-1035.

Perveen, R., Kishor, N., Mohanty, S.R., 2014. Off-shore wind farm development: Present status and challenges. Renewable and Sustainable Energy Reviews 29, 780-792.

PLN, 2020. Statistik PLN 2019. PT Perusahaan Listrik Negara (PLN), Jakarta.

PRI, 2017. Presidential Decree No. 22/ 2017 on General National Energy Plan. Pemerintah Republik Indonesia (PRI), Jakarta.

REN21, 2019. Renewables 2019 Global Status Report. Renewable Energy Policy Network for the 21 Century (REN21) Secretariat, Paris.

Santos-Alamillos, F., Pozo-Vázquez, D., Ruiz-Arias, J., Lara-Fanego, V., Tovar-Pescador, J., 2013. Analysis of WRF model wind estimate sensitivity to physics parameterization choice and terrain representation in Andalusia (Southern Spain). Journal of Applied Meteorology Climatology 52, 1592-1609.

Weekes, S., Tomlin, A., 2014a. Comparison between the bivariate Weibull probability approach and linear regression for assessment of the long-term wind energy resource using MCP. Renewable energy 68, 529-539.

Weekes, S., Tomlin, A., 2014b. Data efficient measure-correlate-predict approaches to wind resource assessment for small-scale wind energy. Renewable energy 63, 162-171.

Weekes, S., Tomlin, A., Vosper, S., Skea, A., Gallani, M., Standen, J., 2015. Long-term wind resource assessment for small and medium-scale turbines using operational forecast data and measure–correlate–predict. Renewable energy 81, 760-769.

Zakeri, B., Syri, S., Rinne, S., 2015. Higher renewable energy integration into the existing energy system of Finland–Is there any maximum limit? Energy 92, 244-259.