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Short-Term Wind Energy Resource Prediction Using Weather Research Forecasting Model for a Location in Indonesia

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Abstract. This study presents the performance of the Weather Research and Forecasting (WRF) with the 5-km horizontal grid as a tool for wind energy forecasting within and along the Indonesian coast for the next 72 hours. The modeled data is then validated using wind measurements from the meteorological mast in East Sumba at several heights. Global Forecast System (GFS) operational forecasting data with a resolution of 0.25 degrees are used as the initial and boundary conditions (IC/BC) model. The findings demonstrate that wind speed and wind power density are much higher above ground level (50 m) than at ground level (10 m) and are significantly higher towards the shore than inland. The model slightly overpredicts low-level wind speeds. The results suggest that the WRF model is feasible for forecasting Indonesia's wind flow and wind energy.

Keywords: Renewable energy; Wind forecasting; Wind power density; Windrose model

1. Introduction

Indonesia has a 23% renewable energy target in its total energy mix by 2025 (as stated in the National Electricity General Plan or RUKN), reducing greenhouse gas emissions by 29-41% by 2030 and achieving Net-Zero emissions by 2060. In line with those, several studies on renewable energy development in reducing the greenhouse gas effect have been conducted, especially from the potential view. They are estimating not only national coverage, such as hydro (Pranoto *et al.,* 2021), wind (Hesty *et al.,* 2021), and solar (Wahyuono and Julian, 2018) but also provincial level and specific sites (Syahputra and Soesanti, 2021). Moreover, a web-based application has been developed to calculate the energy potential of a rooftop solar PV system installed in a home (Nurliyanti *et al.,* 2021).

Wind power is a promising renewable energy to achieve the target because of its high

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efficiency and low pollution. The Ministry of Mineral and Energy Resources (MMER) of Indonesia states that Indonesia has a wind energy potential of 154.88 GW, consisting of an onshore potential of 60.65 GW and an offshore potential of 94.2 GW. According to Indonesia's wind resource assessment by Hesty *et al.* (2022), onshore locations on the south coasts of Java, South Sulawesi, Maluku, and NTT have high wind energy potential wind speeds of 6 to 8 m/s, power densities of 400 to 500 watt/m^2, and Annual Energy Production (AEP) of 4-5 GWh/year. In addition, wind energy has a large potential to be explored in the urban area, whether using Horizontal and Vertical Axis wind turbines (Krasniqi, Dimitrieska, and Lajqi 2022), and improves performance and efficiency, simplicity, and reliability of construction of wind turbines using a permanent magnet (PMGs) (Nur and Siregar, 2020).

However, the high reliance on seasonal variations, which causes a huge primary power generation fluctuation on a daily and annual timescale, is a significant obstacle for a 100% renewable energy source (Guenther, 2018). Atmospheric conditions and wind speed strongly influence the power generated by wind energy conversion systems (Chang, 2013a, Chang, 2013b). So unexpected fluctuations can increase system operating costs for primary backup requirements and pose a potential risk to the reliability of the power supply (Sideratos and Hatziargyriou, 2007). Network operators must overcome the challenges of intermittent wind conditions to schedule spare capacity, stability, planning, and the power system's reliability (Soman *et al.,* 2010). Precise short-term wind speed forecasts are essential to reduce the risk of intermittent wind and allow for more penetration (Peng *et al.,* 2016).

Some wind power forecasting methods for approaching wind energy forecasting include statistical models, Artificial Intelligence (AI) models, and physical models. The autoregressive (AR), autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), Bayesian approach, and gray forecasts are all statistical methods. Lopez et al. (2019) show that the seasonal ARIMA model is a fast, precise, straightforward, and adaptable load forecasting method. Artificial neural networks (ANN), fuzzy logic approaches, adaptive neuro-fuzzy inference systems (ANFIS), neuro-fuzzy networks, support vector machines (SVM), and evolutionary optimization algorithms are some of the AI methods for wind forecasting. Temperature, pressure, solar radiation, and altitude were used as inputs to the ANN by Ramasamy, Chandel, and Yadav (2015) to estimate wind speed in 11 sites in India's mountainous region. Neuro-fuzzy network method for short-term wind power forecasting was applied to the wind power forecasting of a real wind farm located in China by Xia, Zhao, and Dai (2010). The physical method is based on numerical weather prediction (NWP) using weather forecast data for large-scale area weather prediction. Tan *et al.* (2021) evaluated the efficacy of the weather research forecasting (WRF) model in predicting wind speed and direction up to 72 hours in advance in the western portion of Turkey. Except for low wind speeds, the model can accurately reproduce wind directions.

Several institutions in Indonesia have issued a weather prediction system for an early warning system and education. The Meteorology, Climatology and Geophysics Agency (BMKG), the agency appointed by the Government of Indonesia to provide information and forecasts related to weather, climate, and natural disasters, that the public can access to find out about weather predictions for the next seven days. The Center for Atmospheric Science and Technology (PSTA) developed a weather prediction system for the next three days with a resolution of 5 km (Suaydhi, 2016). Meteorological Analysis Laboratory, Bandung Institute of Technology (ITB), developed a weather prediction for the next three days with a resolution of 27 km (Junnaedhi, 2017). However, there is no weather prediction system for energy purposes, especially wind energy. Therefore, the proposed short-term wind energy forecasting represents a significant scientific contribution to Indonesia's reliable large-scale wind power integration.

The purpose of the study presented here is to develop a short-term wind forecasting model for Indonesia's energy management needs and investigate the accuracy and performance of the model. Answering this question, we will conduct the WRF regional mesoscale model for short-term (up to 72 h) prediction of wind at hub level height. WRF simulation results were then compared to in-situ wind observations retrieved from weather stations in terms of root mean squared error (RMSE) and correlation. The performance of the WRF model's ability to forecast wind speed and direction will be analyzed. This work contributes to a better understanding of the wind conditions and the predictability of the hub-height winds.

The rest of this paper is organized as follows. Section 2 describes the data and methodology used, including the WRF Model setup and brief descriptions of the model configuration and parameterization schemes. Section 3 provides results followed by a discussion about model performance. Section 4 concludes with a summary of the findings and suggestions for future work.

2. Data and Methods

2.1. Data

The model relies on data from the Global Forecast System (GFS). The Global Forecast System (GFS) provides data for NOAA's (National Oceanic and Atmospheric Administration) prediction models. Global GFS data is often used as a reference for regional models or even used directly for regional predictions because of its accuracy. This input data has a resolution of 0.25 ° for the world region and has four cycles: 00, 06, 12, and 18. In this study, cycle 00 is used.

2.2. Model Setup

The NWP model used in this study is the WRF model, a fully compressible, non-hydrostatic algorithm. To more accurately replicate airflow across difficult terrain, it uses sigma pressure in the vertical direction. The model solves the governing equations in flux-form, which enables the conservation of mass and scalar quantities.

The model has a single primary domain that spans the entire Indonesian territory between latitudes 7° N and 11° S and longitudes 94° E and 144° E. Using initial data from GFS, the model simulation was run for 72 hours forecast lead time, increasing its input model resolution to 5 km spatial resolution over 35 vertical pressure levels with a temporal resolution of 1 hour. The spatial resolution of 5 km is expected to be good enough for reviewing detailed weather patterns according to local conditions such as topography and coastline.

The parameterization method configuration significantly impacts the near-surface wind field in the WRF model, particularly for complex terrain. Consideration should be given to parameterization schemes like the Surface, Land Surface (LS), and Planetary Boundary Layer (PBL) schemes that can capture the interaction between the land surface and the wind field. We used the Noah land surface model in WRF because it integrates prescribed data and dynamic modeling to simulate the surface. It also provides the user with multiple options to simulate land surface interactions (Niu *et al.,* 2011). Land surface models and initialization datasets impacted the WRF's ability to predict accurately. The surface layer approach used in this study to compute turbulent surface fluxes is based on the Monin Obukhov similarity theory (Van *et al*., 2017). More details regarding the configuration of the WRF parameter scheme are shown in Table 1.

Table 1 WRF Model Configuration and Parameterization

Parameter	Configuration	Parameter	Configuration
Spatial resolution	5 km	Schematic of microphysics	WRF Single Moment 3 class (WSM3)
Temporal resolution	Hourly	Cumulus scheme	Kain-Fritsch
Spatial size (west-east x north-south)	1046 x 441	Schematic of shortwave radiation	Dudhia
Spatial size (top-bottom)	35	Schematic of longwave radiation	Rapid Radiative Transfer Model (RRTM)
Prediction	Three days forward	Surface scheme	MM5 Medium-Range Forecast (MRF) Monin-Obukhov Similarity Theory
		Land cover scheme	NCEP, OSU, Air Force and Office of Hydrology (NOAH) Land Surface Model
		Planetary Boundary Layer (PBL) scheme	Yonsei University (YSU) PBL Scheme

2.3. Model Verification

The quantitative analysis of wind data was carried out by finding the correlation coefficient (r) and Mean Square Error (RMSE) using Equation 1 and Equation 2.

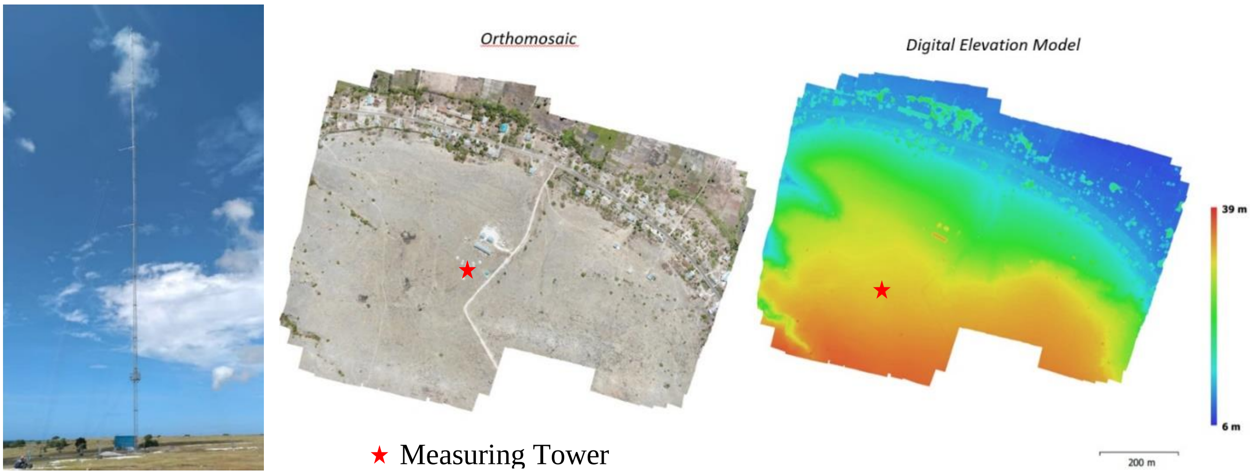
$$\boldsymbol{r} = \frac{\sum_{i=1}^{N}(x_{model,i}-x_{model,bar})(x_{obs}-x_{obs,bar})}{\sqrt{\sum_{i=1}^{N}(x_{model,i}-x_{model,bar})^2 \sum_{i=1}^{N}(x_{obs,i}-x_{obs,bar})^2}} \quad (1)$$

$$\boldsymbol{RMSE} = \left[\frac{1}{N}\sum_{i=1}^{N}(x_{obs,i} - x_{model,i})^2\right]^{1/2} \quad (2)$$

The RMSE value measures the error generated between the model data and the observations. Therefore, this RMSE value can describe accuracy; the smaller the RMSE, the better the level of accuracy. The observation data used to verify the WRF model comes from a wind measuring tower owned by Pondera/PT Hywind Energy Solution in Kadumbul Village, Pandawai District, East Sumba, with latitude coordinates 09°41'42.7" South Latitude and Longitude 120°31'55.5" East Longitude. The measuring tower is equipped with two arrangements of anemometers at various heights. Two A-B anemometers are placed at 40 and 80 m in height. At the same time, a single anemometer is placed at 60, 97, and 102 m of height. In addition, there is a wind vane installed at an altitude of 60 m and 97 m.

Figure 1(a) shows the wind measurement tower and (b) the orthomosaic map location. Pandawai District is a hilly area with the highest altitude of 255 m above sea level. In the southern part of the district is a coastal area directly adjacent to the sea. For the slope class, the Pandawai District area is dominated by the 0–8% (flat) slope class. The location where observation tower is located in a natural grassland, which is included in the less productive dry land with an elevation of 30 – 39 m above sea level.

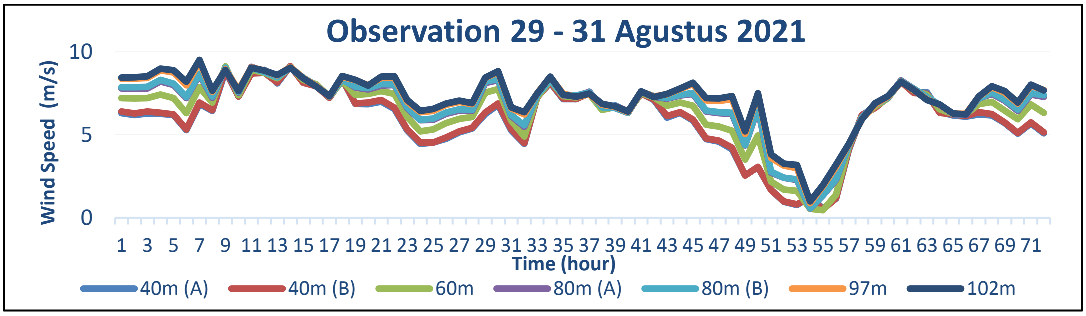
The observation data used to verify the prediction model is 29-31 August 2021 for 10 minutes. Verification using data from August is necessary since the monsoonal type over Indonesia was identified by the flow of wind circulation that blows continuously for one particular period and in the other direction with transitional intervals in between.



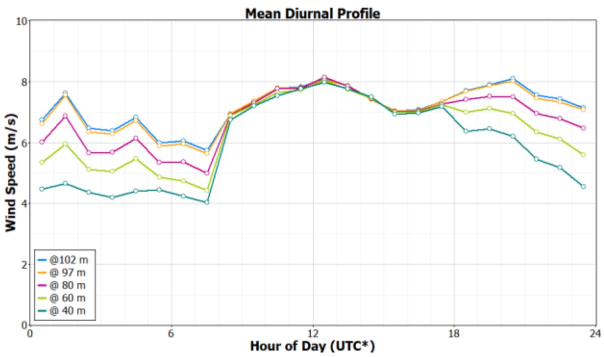
(a) (b) (c)

Figure 1 (a) Wind measurement tower; (b) orthomosaic map; and (c) Topography of the measurement tower location

The dry season, which reaches its maximum in August, is caused by the south-easterly wind that blows from the Australian Continent to the equator from around June to August. Indonesia often has higher wind speeds during this June-July-August (JJA) month (Abdillah *et al.*, 2022).



(a)



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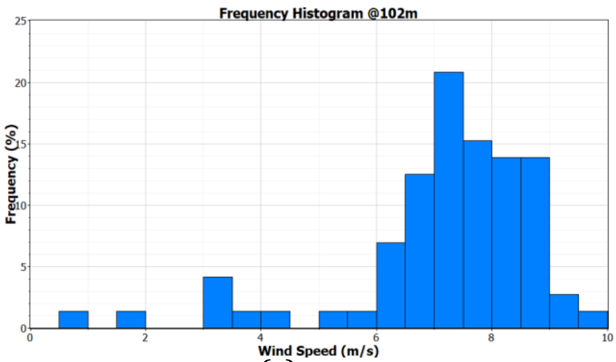


(c)

Figure 2 Wind measurement tower observation data on 29–31 August 2021; (a) time series; (b) mean diurnal profile; and (c) Frequency histogram

Figure 2a shows the observation data of the wind gauge tower on 29 – 31 August 2021. The average wind speed at an altitude of 40 m, 60 m, 80 m, and 97 m - 102 m are 5.9 m/s, 6.4 m/s, 6.8 m/s, and 7.1 m/s, respectively. Figure 2 b shows a diurnal profile showing the daily variation of wind speed at five altitudes; 40 m, 60 m, 80 m, 97 m, and 102 m. At an altitude of 102 m, the daily wind speed is evenly distributed throughout the day, with wind speeds between 6.29 - 8.08 m/s. Meanwhile, at an altitude of 40 m, the daily wind speed is between 4.20 - 7.98 m/s. Maximum wind speed occurs during the day at 11 AM – 2 PM. The frequency histogram of wind speed at the height of 102 m can be seen in Figure 2 c. Wind speed distribution is concentrated at low speeds, and the duration of days with high wind speeds is 7 m/s, as much as 21%.

3. Results and Discussion

Figures 3 - 4 show the output of the WRF model in the form of predictions of Indonesia's wind speed and direction on 29 - 31 August 2021 at 08 and 09 UTC at four altitude levels. Very few locations on land experience wind speed above 6.0 m/s.

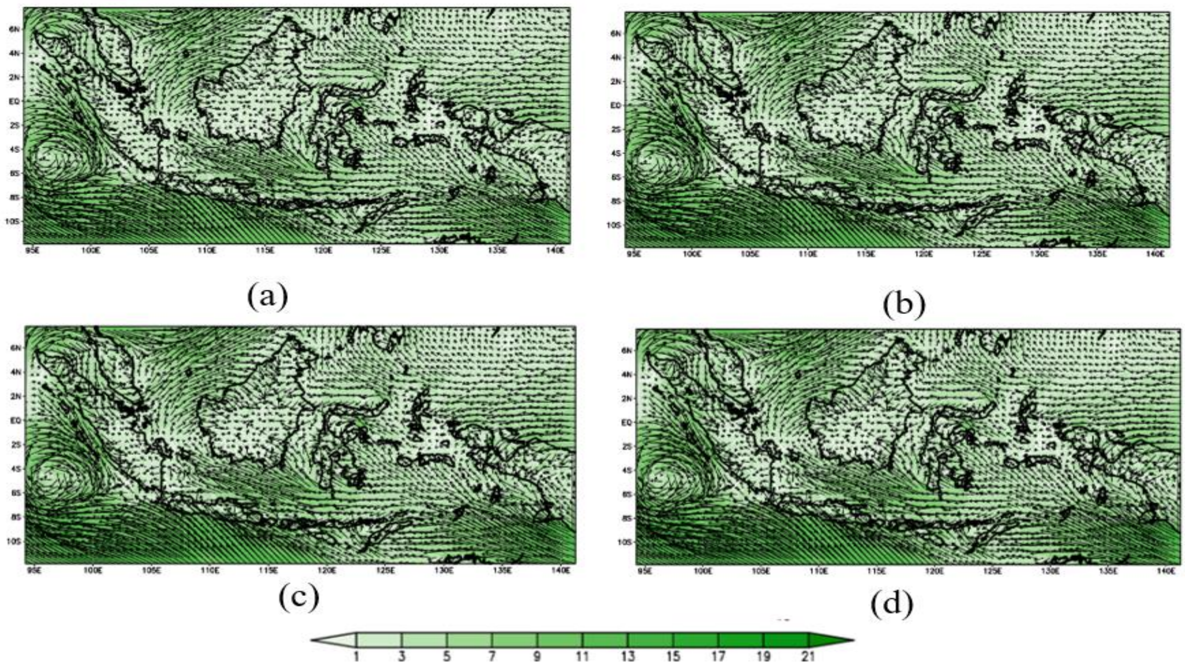


Figure 3 Model Result of Predicted Wind Direction and Speed (m/s) on 29-31 August 2021 @08 UTC at altitude (a) 10 m (b) 30 m (c) 50 m (d) 100 m

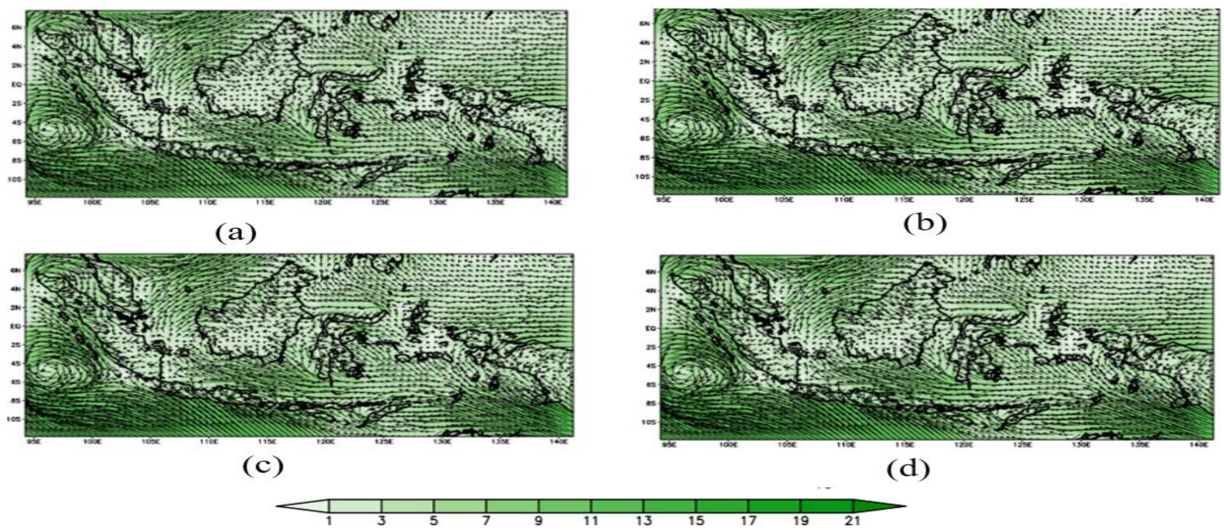
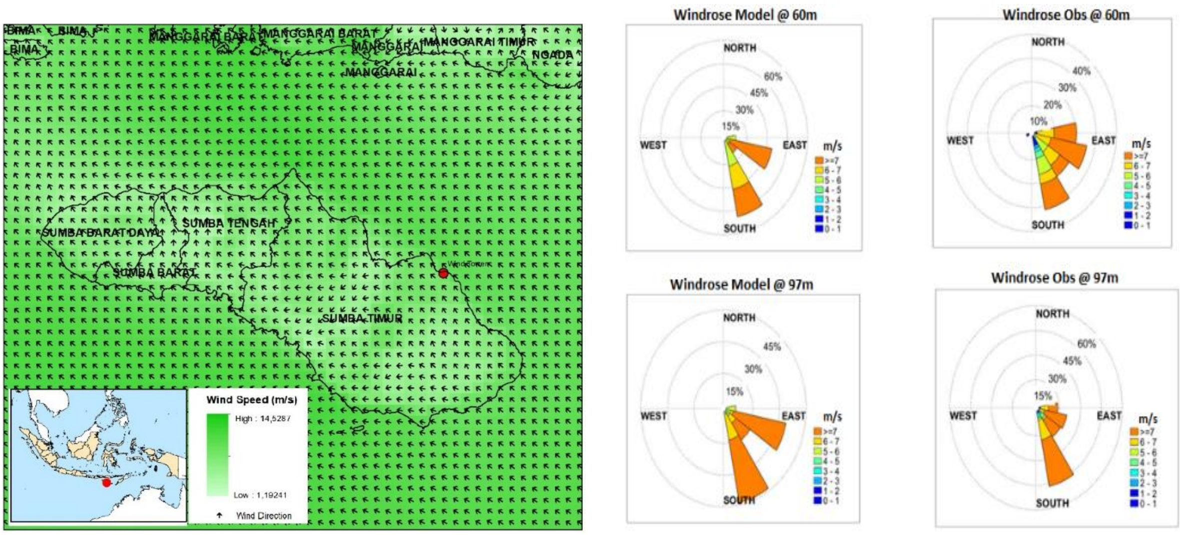


Figure 4 Model Result of Wind Direction and Speed (m/s) on 29-31 August 2021 @09 UTC at altitude (a) 10 m (b) 30 m (c) 50 m (d) 100 m

The model predicts high wind speeds (6 - 8 m/s) onshore only occur in coastal areas (southern Java, South Sulawesi, Maluku, and NTT). This wind speed can generate electricity using small-scale wind turbines because the cut-in wind requirements of commercial wind turbines are generally 5 m/s (Akour *et al.,* 2018; Li and Chen, 2008). Wind speeds in offshore areas of more than 8 m/s occur in southern Indonesia, i.e., Banten, Sukabumi, Kupang, Wetar Island, Jeneponto Regency, and Tanimbar Islands. Therefore, the potential for electrical power output will be much more significant.

The dominant wind direction comes from the southeast due to the different seasons. In Asia, the summer months fall in June, July, and August, so the Australian monsoon is getting stronger. In almost all parts of Indonesia, the easterly wind blows, except in Sumatra, starting from West Sumatra to the northern end of the island of Sumatra. The easterly wind from Australia blows across Nusa Tenggara, Bali, Java, to the southern tip of Sumatra. Others turn north after passing the equator in Kalimantan. The easterly wind that blows over Papua and northern Sulawesi is dominant from the Pacific Ocean east of Papua New Guinea. This wind direction is influenced by the east monsoon wind phenomenon, active in JJA (June-July-August). Monsoon winds are wind circulations that reverse direction seasonally caused by differences in heating between the northern and southern hemispheres. Indonesia has two monsoon winds: the west monsoon and the east monsoon. The west monsoon winds occur in the month of DJF (December-January-February). The dominant wind direction comes from the Asian Continent, which carries a lot of water vapor, while the east monsoon winds carry little water vapor because it comes from the dry mainland of Australia. The model predicts that offshore and onshore wind speed fluctuations in Indonesia are small; there is no significant change between wind speed at 08 UTC and 09 UTC.



(a) (b)

Figure 5 **(a)** Wind direction and wind speed from WRF model at measurement tower location, and (b) Comparison of wind rose between model result and observation

Figure 5 (a) shows Sumba Island's wind map at hub height (80 magl) as stimulated through WRF. The measurement tower is represented by a red dot image. The topography of Sumba Island is an area of steep hills, especially in the southern area, where the hillsides are a quite fertile land, while the northern area is a rocky plain and less fertile. The measurement tower is located on a flat, sloping area, location on the coast. These maps show that the wind speed at the island's center was quite low (less than 3 m/s). In contrast to the center, the coastal region experienced much stronger wind. The existence of the Savu Sea in the east and the Indian Ocean to the south and west of the island may have contributed to the variance by demonstrating disparities in temperature and pressure between land and seas, resulting in powerful winds. It is discovered that the island's predominant wind direction is from the southeast because of the east monsoon.

The observation and model wind roses at altitudes 60 m and 97 m are compared in Figure 5 (b). The circles show, in percentage, how frequently the wind blows in various directions. The wind speed is indicated by the color bar, with blue representing the lowest wind speed and orange representing the highest wind speed. The model can accurately represent the distribution of wind directions when comparing the wind roses for the observed data with the model findings. The model is able to capture the distribution but has some higher wind speeds than the observations. The observational data demonstrate a distinct southeast main wind direction.

Table 2 shows the correlation and RMSE values between the WRF model and observation data. Based on these data, the lowest correlation value is at an altitude of 40 m (A), with a correlation value of 0.26, while the highest is at an altitude of 80 meters. Meanwhile, the highest RMSE value is 2.07 m/s at an altitude of 40 m (A), and the lowest is 1.44 m/s at 102 meters. Like the correlation value, the WRF model is quite good at modeling the upper-level wind compared to the lower-level wind. Furthermore, it shows that the WRF model is quite good at estimating the wind at the top level, especially at an altitude of 80 meters. In comparison, the lower-level wind (height of 40 meters) tends to be less good, owing to the strong influence of various factors such as turbulence, surface roughness, and atmospheric stability.

Table 2 Correlation and RMSE value of WRF model with observation data

CORRELATION						
40m (A)	40m (B)	60m	80m (A)	80m (B)	97m	102m
0.26128	0.265574	0.469246	0.637211	0.637238	0.60667	0.601631
RMSE (m/s)						
40m (A)	40m (B)	60m	80m (A)	80m (B)	97m	102m
2.076566	2.059937	1.829749	1.529857	1.513156	1.461564	1.44696

Figure 6 shows that the wind at the lower level of the WRF model tends to overestimate the observed value. The WRF model tends to overestimate lower wind speeds and underestimate higher wind speeds (Al-Yahyai, Charabi, and Gastli, 2010). The overestimated wind speed prediction can be observed in the wind measured at 40 meters, where the wind speed is low. Predictions that underestimate are in the wind measured at 102 meters, where the wind speed is moderate to high. Similar model results were also reported in studies conducted in Greece (Giannaros, Melas, and Ziomas, 2017) and Hawaii (Argüeso and Businger, 2018).

Local topographical features can also induce RMSE. Numerical weather prediction models simplify the topography and physical processes to approximate the problem result (Carvalho *et al.*, 2013). The wind speed from Automatic Weather Station (AWS) single-point measurements at 10-meter elevation differ significantly from the model, whereas the wind speeds derived using the model are the grid cell average, which equates to a 5 km × 5 km area. The assumed topography and roughness of the grid cells model can differ significantly from the actual conditions (Larsén *et al.*, 2013).

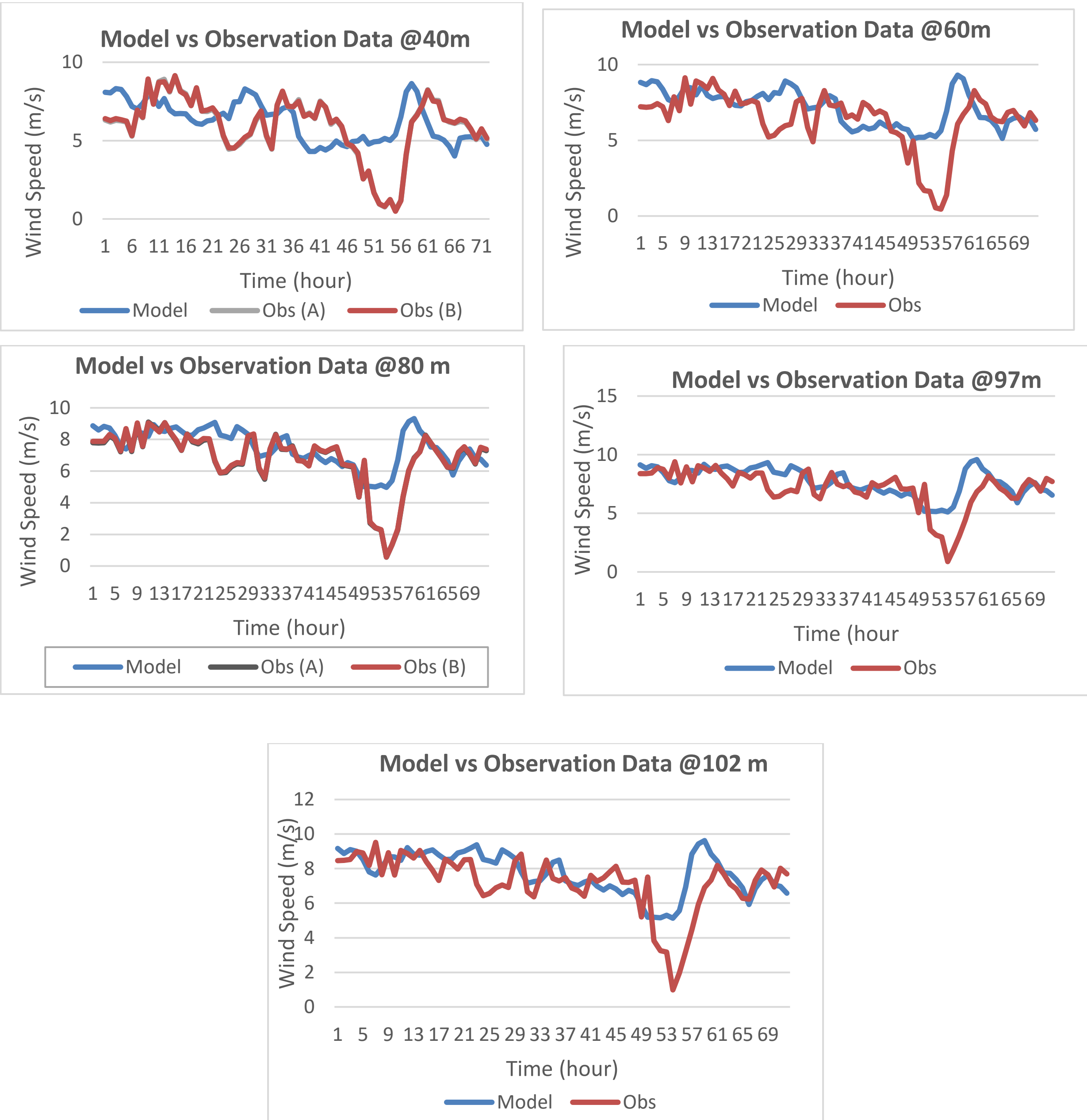


Figure 6 Comparison of wind speed time series between model result and observation

The WRF model could not accurately simulate the wind speed at low-level wind speed. The error can be caused by the initial and boundary conditions dataset; the selection of physical parameterization techniques, which relies on the study area and time period; and the model's capacity to replicate topographical features realistically. Because of the sub-grid scale processes, the model tends to smooth the actual topography; as a result, when flat terrain is present, the friction between the surface and the atmosphere is minimized, causing the model to overestimate wind speed.

4. Conclusions

This study uses WRF to forecast 72 h wind energy prediction in Indonesia. The modeled data is then validated using wind measurements from a meteorological mast in East Sumba Timur at several heights. As a result, the WRF model predicted wind-resource parameters show a good agreement with the observations. The WRF model is quite good at modeling the upper-level wind (> 50 m) compared to the lower-level wind (< 50 m). Furthermore, it shows that the WRF model is quite good at estimating the wind at the top level, especially at an altitude of 80 meters. In general, the model slightly overestimates the wind speed, and the deviations are related to local topographical features and low wind speed. Therefore, the model can be a valuable tool for forecasting the wind flow around Indonesia to get reliable information on wind resources. Further research should evaluate the WRF model in couple with a microscale model such as the computational fluid dynamics (CFD) model. By considering high-resolution micro-scale topography and vegetation characteristics, such a method could improve the accuracy of wind speed forecasts.

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