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Research Article

Machine learning-driven wind energy mapping enhanced by natural neighbor interpolation

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Abstract: In the present work, a prediction on the wind energy potential in Semarang City (Central Java Province, Indonesia) has been performed by leveraging a novel combination of machine learning and natural neighbor interpolation (NNI) methodology. This integrated approach uniquely combines the predictive power of machine learning to estimate wind speeds based on historical and spatial data, with the spatial mapping capabilities of NNI, which provides a more accurate and seamless visualization of wind speed distribution. This combination addresses challenges of data sparsity and variability, offering a more reliable and localized mapping approach than traditional methods. Additionally, air density is considered to calculate energy density, enabling a comprehensive evaluation of wind energy potential. The results show an average monthly wind speed of 5.23 m/s, ranging from 3.38 m/s to 7.39 m/s. Wind speeds between 7 m/s and 10 m/s are predicted to occur for up to 10 months annually, with an estimated energy density of 102.7 W/m². These findings underscore the feasibility of small-scale wind power generation in the study area and provide actionable insights for advancing renewable energy policies and implementations at the local level.

Keywords: *Wind energy, Machine learning, Natural neighbor interpolation*

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Nomenclature:

ANN	Artificial Neural Networks	NSF	Number Sequence Feature
GIS	Geographic Information Systems	PWh	Petawatt Hours
GW	Gigawatt	R^2	Coefficient of Determination
kW	Kilowatt	RNN	Recurrent Neural Networks
LSTM	Long Short-Term Memory	RMSE	Root Mean Squared Error
MAE	Mean Absolute Error	SFSPSO	Stochastic Fractal Search and Particle Swarm Optimization
MW	Megawatt	TWh	Terawatt Hours
MSE	Mean Squared Error	W	Watt
NN	Natural Neighbor Interpolation	WPD	Wind Power Density
NSE	Nash-Sutcliffe Efficiency	XAI	Explainable Artificial Intelligence

1. INTRODUCTION

The use of wind energy is rapidly increasing and gaining global attention. Its consumption is observed to be the highest compared to other renewable energy sources throughout the world [1]. At a certain level, it can fulfill significant energy needs and minimize pollution caused by fossil fuels [2,3]. This is necessary because energy generated by power plants reduces fossil fuel consumption and has a significant influence on the layout of the electricity market. Moreover, wind power stands out as a prominent technology in the context of the renewable energy transition as evidenced by the increasing number of wind turbines and industry workers each year [4]. Throughout the last decade, global installed wind energy capacity has tripled by hitting 837 GW in 2021 up from 283 GW in 2012 [5]. Some major challenges such as the intermittent fluctuations caused by weather conditions are usually linked to the use of wind energy [6]. Therefore, there is a need for careful analysis of locations with the potential to plan for wind turbine and power generation output. Wind energy can generate power continuously throughout the day, demonstrating its suitability for systems that need sustainable energy. It is also possible to predict seasonal fluctuations and install turbines in different locations without losing coverage. Moreover, wind energy forecasting contributes to system stability and has the potential to save significant costs in the whole system [7]. Accurate forecasts can also maximize wind farm operation and energy system management. Extensive studies are currently being conducted on wind energy forecasting using several analytical methods at different time horizons. Certain methods rely on the statistical characteristics of wind time series data while new ones have also been designed using machine learning methods [8,9]. This shows that machine learning is now playing a crucial role in the energy sector as indicated by the application of its methods in interpreting historical data and predicting the future to improve the performance of wind power generation forecasts [10,11]. Machine learning algorithms are mainly being used due to their ability to adapt to changing trends in the dataset and generate models based on input data. They have been successfully applied to describe the behavior of datasets, input features into models, and generate output based on historical records. These algorithms provide an alternative for forecasting using wind speed data [12]. Wind characteristics of a region are a key factor in the process of generating energy. Therefore, this study evaluates wind resources of Semarang City which is geographically located on the northern coast of Central Java of Indonesia. The area has been identified to be naturally windy and has relatively constant speeds throughout the year [13]. The main aim was to obtain information about wind speed potential, speed distribution maps, and energy density. This was achieved through the adoption of a machine learning method to predict wind speeds using daily data and the distribution was subsequently mapped through the application of natural neighbor interpolation (NNI) methods. The density per unit area, a measure of wind energy intensity, was also determined through the air mass flow parameters in the study area.

The major insight from this study was to provide information on the process of planning local-scale wind power production systems. This was mainly due to the variations in wind energy potential based on the different areas in Indonesia. It was previously reported that the use of this source remains relatively low as indicated by the installed capacity of 157.41 MW out of the possible 154.9 GW [14]. This prompted the government to establish national energy policies aiming to raise the use of renewable energy to 23% by 2025 and 31% by 2050.

2. RELATED WORKS

Machine learning techniques have been extensively utilized to analyze historical data and forecast future trends, thereby enhancing the accuracy of wind power generation predictions. A previous study identified four broad wind speed modeling methods including [15],

1. Physical models,

2. Statistical models,
3. Spatial algorithms,
4. Artificial intelligence (metaheuristic algorithms).

Several wind speed prediction methods have also been proposed but some studies neglected the importance of parameter optimization and data preprocessing. For example, Shao et al. (2021) proposed advanced optimization algorithms as superior to other well-known metaheuristic algorithms [16]. Wang et al. (2021) also applied a combined method for wind farm management and decision-making in China based on sub-model selection and optimization algorithms to improve forecasting performance [17]. In another study conducted by Tarek et al. (2023), a novel optimization approach employing stochastic fractal search and particle swarm optimization (SFSPSO) was introduced to optimize the parameters of the long short-term memory (LSTM) network [18]. The method involved assessing the efficacy of the regression model based on five evaluation criteria: mean absolute error (MAE), Nash Sutcliffe Efficiency (NSE), mean square error (MSE), coefficient of determination (R2), and root mean squared error (RMSE). The analysis revealed that the proposed LSTM optimization using the SFS-PSO model yielded superior results in wind energy prediction, achieving an R2 value of 99.99% [18]. Moreover, Cheng and Wang (2020) combined four artificial neural networks to estimate wind speed through optimal weighting coefficients and data preprocessing, including decomposition and denoising. The results showed that multi-objective optimization algorithms could enhance accuracy and stability, achieve excellent precision and stability, and outperform other combined models [19]. Krechowicz et al. (2022) also reviewed 262 relevant study articles from the Scopus database and showed that extreme learning machine and ensemble methods were the most popular applied to forecast the generation of power from renewable energy sources in the last three years (2020–2022), particularly for wind energy systems and short-term models [20].

Yürek et al. (2021) applied various machine learning algorithms to forecast wind energy production in Turkey using historical wind power generation data and weather forecasts. The results showed that more accurate energy production was predicted for each hour [21]. Buturache et al. (2021) also proposed a prediction model using several machine learning algorithms, including artificial neural networks, support vector regression, random trees, and random forest, and achieved very good accuracy [22]. Furthermore, Alkesaiberi et al. (2022) suggested a machine learning model to efficiently predict univariate wind time series using wind speed and direction input variables. The validation of the actual measurement of three turbines in France, Turkey, and Kaggle was observed to have improved the model efficiency [23]. Tarek et al. (2023) also proposed the application of several machine learning models to predict wind power generation using a dataset with 4 features and 50,530 samples, and the results showed good accuracy [18].

GIS is a technology with unique capabilities to organize, analyze, and edit geographical reference data and spatial maps. B. Kilic (2019) applied GIS to map land wind dissipation and its potential in Turkey [24] using data obtained from artificial neural networks. The outcome revealed regions with promising potential for future wind energy integration, hinting at the feasibility of employing Artificial Neural Networks (ANN) and Geographic Information Systems (GIS) as convenient alternatives to conventional prediction approaches. Zahedi et al. (2022) also applied a practical method to measure wind resource potential for electricity generation using a GIS as part of the criteria for wind power plant selection [25]. Moreover, Noorollahi et al. (2016) used GIS to assess wind resources in the western region of Iran and also applied a decision-making method with different location selection criteria. The findings indicated that 28% of the surveyed area could accommodate large-scale wind power installations capable of generating electricity meeting international standards [26]. Feng et al. (2020) combined GIS modeling, turbine performance, and daily speed distribution to estimate wind and clean energy potential on Chinese land with due consideration for the impact of local topographic conditions such as changes in air density, surface roughness, air density, and placement efficiency. The technical potential for the onshore wind was estimated to be 2,560 TWh/year and 3,501 TWh/year respectively while clean energy had 2,335 TWh/year and 3,194 TWh/year based on agricultural land scenarios [27].

Assouline et al. (2019) proposed a methodology that combined Machine Learning, GIS, and parametric wind models to estimate speed potential in Switzerland. The monthly speeds were approximated based on measurements and several meteorological, topographical, and specific wind features available nationwide, and the installed capacity of wind turbines was found to average between 80 kW and 1,600 kW in the most suitable regions [28]. Moreover, Sachit et al. (2022) presented a method for global wind and solar mapping based on eXplainable Artificial Intelligence (XAI), made the first attempt to create a global map to determine the locations of land-based wind and solar energy systems, and formulated new criteria for decision-making. A total of thirteen conditioning factors or independent variables were determined through a comprehensive literature review and multicollinearity analysis, thereby providing support to decision-makers on sustainable energy planning worldwide [29]. Grassi et al. (2015) suggested an evaluation of the worldwide wind energy capacity on a national level employing Geographic Information Systems (GIS). This was accomplished by integrating GIS-formatted global data on land usage, topography, administrative borders, and wind speed recordings from around 12,000 surface stations worldwide. Wind speed measured at 10 m height from surface stations was used to generate worldwide wind maps at 50 m, 80 m, and 130 m through the application of co-Kriging. The validation results showed an average uncertainty of 1.1 m/s and this was used to map the spatial uncertainty distribution. Theoretical, geographical, and technical potentials for each country were assessed. Moreover, the global technical potential at a height of 130 meters was projected to be 400 PWh/year, assuming a power density of 5 MW/km^2. This figure was approximately 20 times the global electricity consumption of 19.3 PWh in 2011 [30].

Despite advances in wind energy research, many studies still rely on traditional spatial interpolation methods which can be limited by data sparsity and variability, particularly in under-researched regions. This study addresses this gap by combining machine learning for wind speed predictions with the Natural Neighbor Interpolation (NNI) method to generate more accurate, localized wind energy maps. The motivation behind this approach is to provide a more reliable tool for energy planners, particularly in areas with insufficient wind data, to enhance the feasibility of wind energy development.

3. MATERIALS

3.1. Study Case Area

Semarang is the capital of Central Java Province, Indonesia, and serves as the administrative and economic center of the province. It is the country's sixth-largest metropolitan city, covering approximately 373.7 square kilometers and comprising 16 Subdistricts. The location ranges in elevation from 0 to 348 meters above sea level and topographically comprises coastal areas, lowlands, and hills, leading to its designation as the lower and upper city. Semarang is geographically situated between 109°35'-110°50' East Longitude and 6°50'-7°10' South Latitude as shown in Fig. 1 and this means it is influenced by a tropical climate with both rainy and dry seasons. From November to May, wind blows from the north to the northwest, creating the rainy season with moisture and rainfall. Meanwhile, from June to October, wind blows from the Southeast, creating a dry season with less moisture. The average hourly wind speed in Semarang experiences significant seasonal variations throughout the year. Moreover, the kinetic energy of wind is highly attractive to drive turbines and generate clean electricity without emissions, and the potential energy resources of this local area are expected to contribute to the future energy transition plan.

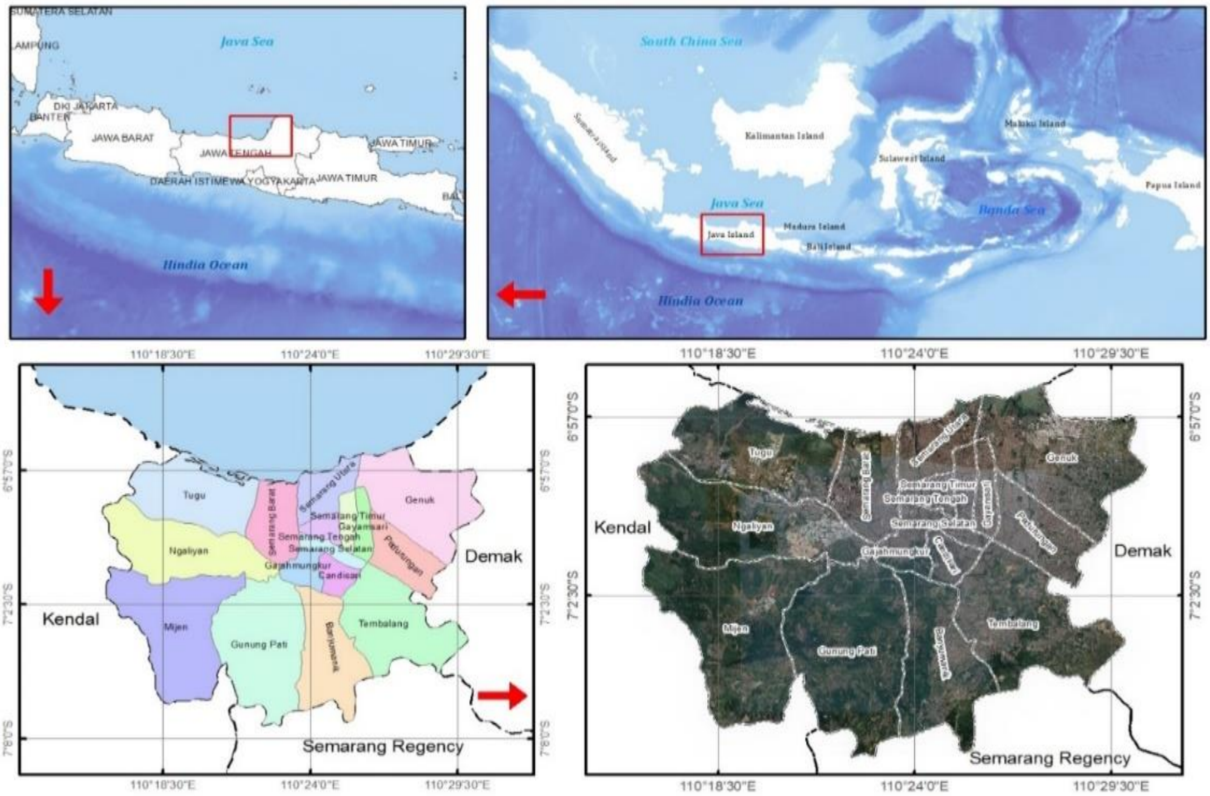
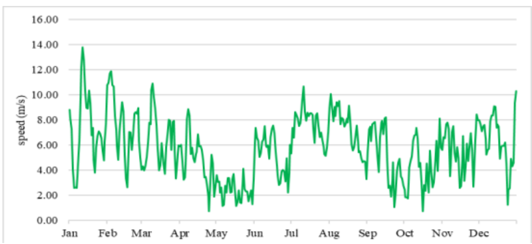


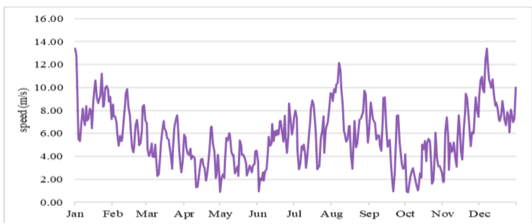
Figure 1. Semarang City Area, Central Java

3.2. Data Description

Wind patterns and speeds are observed to vary significantly across the entire Indonesian region and are influenced by bodies of water, vegetation, and terrain differences. These characteristics are presented in the form of time series data consisting of observations of wind speed, temperature, humidity, pressure, wind direction, density, and others for several years. The spatial data in Fig. 2 show the daily speeds at a height of 10 meters above the ground at an original resolution of 0.5° latitude x 0.625° longitude with coordinates at Latitude 7.0 and Longitude 110.0. Successive Figs. 2(a-e) show daily wind speed variations for the successive years 2018, 2019, 2020, 2021, and 2022. This historical data of daily wind speeds was studied and analyzed. In another section, Fig. 2f presents daily wind speeds over 5 years. These characteristics are crucial in assessing energy resources as indicated by the importance of surface wind flow or kinetic energy for several purposes, including energy generation.



(a)



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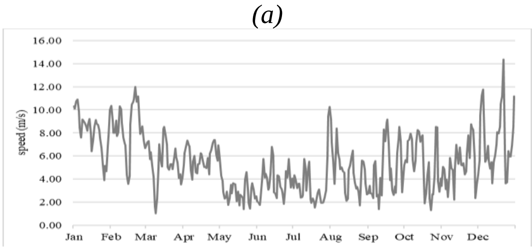

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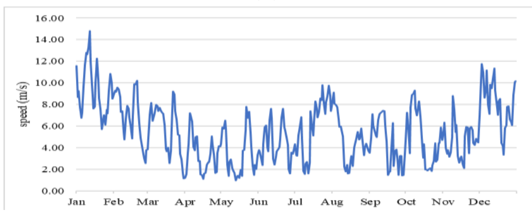

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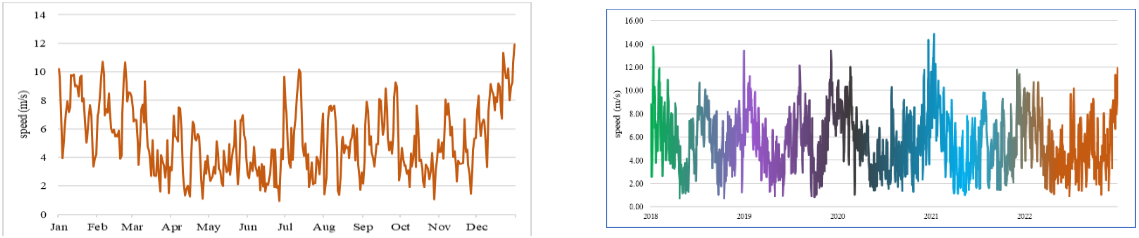


(e) *(f)*

Figure 2. Wind speed at a height of 10 meters in Semarang City.

4. METHODS

This study aims to gather information on wind energy potential using the framework presented in the flowchart shown in Fig. 3. The daily wind speed data served as the starting point for the estimation of this resource potential. Moreover, the machine learning method was adopted to obtain estimated wind speed values while the information regarding the distribution was presented in the form of a digital map using NNI methods. Wind energy density was also determined by considering the air mass within the study area. This was necessary because these characteristics were considered highly significant in assessing wind resources but often not adequately addressed.

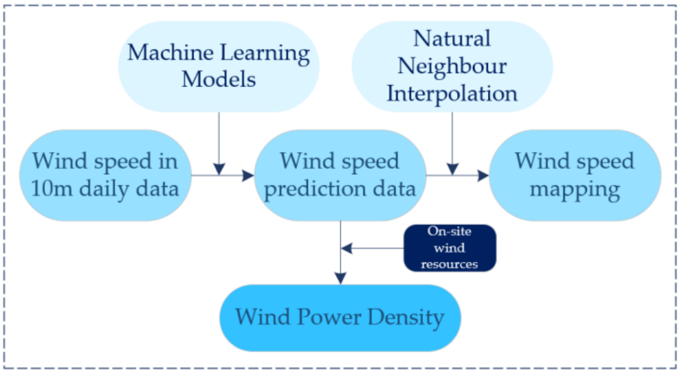


Figure 3. Framework for investigating wind energy potential

Recurrent Neural Networks (RNN) were selected for time-series prediction in this study due to their capability to model temporal dependencies in sequential data, which is essential for wind speed prediction. Unlike traditional feed-forward neural networks, RNNs are specifically designed to handle sequences by maintaining a memory of previous inputs, making them effective for modeling time-series data where the current wind speed depends on previous values. Although Long Short-Term Memory (LSTM) networks, a specialized form of RNN, are known for their ability to capture long-term dependencies, they are more computationally expensive due to their complex architecture, which includes gates to control the flow of information over time. While LSTM networks excel in datasets with long sequences where long-term dependencies are critical, they tend to require more training data and computational resources. In contrast, the wind speed data in this study is relatively short-term and exhibits periodicity, where dependencies are typically limited to a few previous time steps rather than long sequences. Therefore, RNNs, with their simpler structure and faster training times, were sufficient for capturing the short-term dependencies inherent in the wind speed data without overfitting or excessive computational costs. Moreover, RNNs were able to provide robust performance in accurately forecasting wind speeds, which meets the requirements of the study while offering a more efficient solution compared to LSTM. This choice of RNN was validated through preliminary testing, where the model demonstrated satisfactory accuracy in predicting wind speeds while maintaining lower computational overhead, making it well-suited for real-time or large-scale applications in wind energy forecasting.

4.1. Wind Speed Forecasting

Knowledge of wind speed is observed to have a crucial role in estimating energy potential at each location. This is because accurate speed forecasting is a key factor in wind farm planning and economic potential calculations. Moreover, wind parameters are essential for regulating energy systems and aiding wind farm maintenance. The wind speed forecasting strategy followed in the study is presented in the following in Fig. 4. It is important to state that most of the existing models usually use all historical data for prediction and this can be influenced by the variations in seasons. Therefore, daily historical wind data was used as the input in the machine learning method in the form of a recurrent neural network (RNN) model applied to forecast the speed. This RNN is currently highly suitable for time series prediction due to its unique structure [31,32].

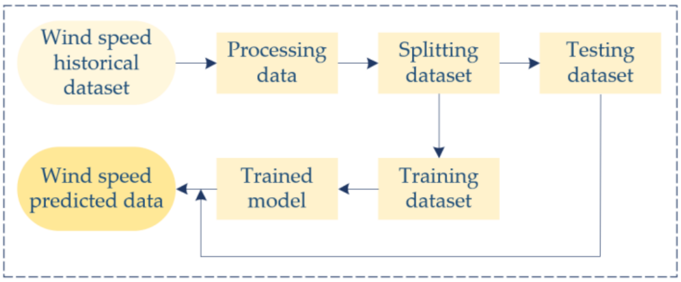


Figure 4. Wind speed forecasting strategy.

A standard RNN consists of input, hidden, and output layers [33]. For example, the input layer is provided with a time series $x = (x_1\, x_2 \ldots x_t)$. At time t, the outputs in the hidden layer h_t and the output layer y_t can be calculated using the following equation [33]:

$$h_t = F\,(W_{hh}\, h_{t-1} + W_{xh}\, X_t + b_h\ ) \qquad (1)$$

$$y_t = \sigma\,(W_{hy}\, h_t + b_y\,) \qquad (2)$$

In this context, h_t represents the output of the hidden layer of a neural network at a specific time instance t, y_t denotes the output of the output layer of a neural network at a specific time instance t, F is the activation function for the hidden layer, σ is the activation function for the output layer, x_t is the input at time t, h_{t-1} is the output of the previously hidden layer, while W_{hh} and W_{xh} are the weight matrix corresponding to the output of the previously hidden layer and the weight matrix corresponding to the input at time t. Moreover, W_{hy} is the weight matrix corresponding to the output layer while b_h and b_y are deviations associated with the hidden and output layers, respectively.

An appropriate neural network architecture can be trained to predict future values of the dependent variable [34]. This was achieved in this study using the architecture and configuration of the RNN model in Fig. 5 where the input size = 5, Optimizer = Adam W, Output size = 1, Learning rate = 0.001, Hidden size = 32, Criterion = MSE, Hidden layer = 2, Sequence length = 21, and Batch Size = 16. In this context, the shape of wind speed data was expressed in the NSF format. Here, N represented the amount of data, S was the number of data sequence groups, and F indicated the features or variables used. Moreover, interpolation was conducted to rectify the issues of missing or unrecorded data. Time series data, specifically those related to daily wind speed, were used in another part of the study. Furthermore, some features were added by dividing the time data into four quarters within a year to optimize the RNN model and this led to the application of five features for data arrangement. The amount of data used led to the designation of N as 366 to maintain a balanced data shape, S was determined to be 21, and F was 5, representing Wind Speed, Quarter 1, Quarter 2, Quarter 3, and Quarter 4. Therefore, the NSF arrangement became Data Training (N, S, F) = (69, 21, 5) and Data Test (N, S, F) = (17, 21, 5).

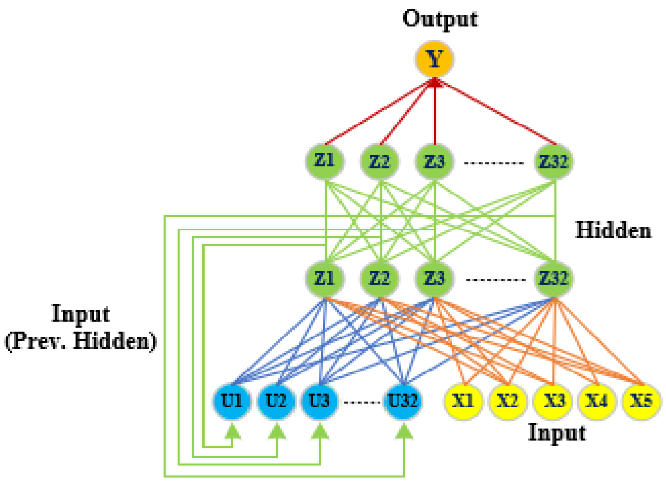


Figure 5. Architectural model for wind speed forecasting.

4.2. Wind Speed Mapping

GIS is a comprehensive system designed to generate, organize, evaluate, and visualize diverse datasets. It connects data to maps, merging geographical data with various descriptive details about existing entities. Additionally, it aids users in comprehending geographical trends, correlations, and backgrounds. This system enhances communication and productivity, facilitating more effective management and decision-making processes.

In mapping, interpolation refers to the technique of predicting values in areas or points that lack direct measurement or sampling, thereby enabling the creation of maps or distributions representing values across the entire area. It is a method normally used to predict grid values that are not represented by sample points [35]. Some of the methods include Inverse Distance Weighting, Kriging, Natural Neighbor, Spline, and Triangulated Irregular Network.

NNI was used in this study for wind speed mapping. NNI method, also known as Sibson interpolation, is local and focuses on using only the samples around the point to be interpolated. Typically, interpolation involves identifying the nearest subset of input samples to the query point and assigning weights based on the proportional areas to interpolate a value [36]. The basic equation for NNI method is provided in the following Eq. 3 [36]:

$$G(x, y) = \sum_{i=1}^{N} w_i \ f(x_i, y_i) \tag{3}$$

where, $G(x, y)$ presents the estimated value at (x, y), w_i is the weight, $f(x_i, y_i)$ is the known data at (x_i, y_i), and N is the total number of sample points. The weight w_i was calculated based on the area around the points to be interpolated as follows [36]:

$$w_i(x, y) = \frac{A(x_i, y_i)}{A(x, y)} \tag{4}$$

where, $A(x, y)$ is the area of the new cell centered at (x, y) while $A(x_i, y_i)$ it represents the area of intersection between the new cell centered at coordinates (x, y) nd the old cell centered at coordinates (x_i, y_i).

The predicted wind speed data were interpolated to determine the values forecasted for the target locations. The flowchart of wind data processing transformed into GIS-based data is presented in Fig.

6. The predicted speed data were transformed into wind location points to create interpolation of this energy distribution followed by a process to produce the mean wind speed raster data.

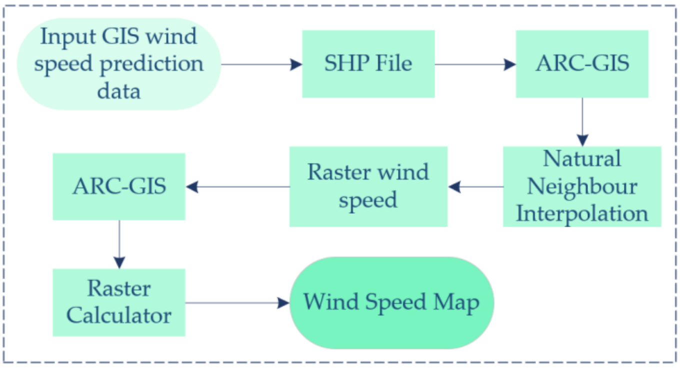


Figure 6. Wind speed mapping flowchart.

4.3. Estimation of Wind Power Density (WPD) Potential

Calculating energy density is crucial for assessing the wind resources available at a specific location. The emphasis lies on the kinetic energy resulting from the mass of air and its velocity. This implies that the kinetic energy potential, also referred to as Wind Power Density (WPD), serves as a valuable method to evaluate the available resources at a potential location, and it is expressed as follows [37]:

$$WPD_t = \frac{1}{2}\,\rho\,U_t^3 \tag{5}$$

where, WPD_t is wind power per swept area in [W/m^2] at time *t*, ρ is the air density in [kg/m^3], and U is the speed in [m/s] at each grid point [37].

The amount of known speed data was observed to be limited and this led to the formulation of the equation related to the time interval as follows [37]:

$$WPD = \frac{1}{2}\frac{1}{n}\sum_{j=1}^{n}\rho_j\,U_j^3 \tag{6}$$

where n is the number of wind speed readings, ρ_j and U_j are the readings of the j-th air density and wind speed at a specific location. Meanwhile, the air density was determined by considering the altitude h of the location in meters as follows [38]:

$$\rho\ = 1.225 - (1.194\ x\ 10^{-4})\,h \tag{7}$$

The estimation of the air density was more accurate because altitude played a crucial role in its variance. Moreover, Eq. 7 provided a more precise estimate of air and WPD.

5. RESULTS AND DISCUSSION

5.1. Wind Speed Data

This study was conducted using the database containing the daily wind speed values measured in Semarang City by The National Aeronautics and Space Administration (NASA). The data collected were daily speed readings for 5 years from 2018 to 2022 at a height of 10 meters. Time series analysis was performed by examining and grouping the daily data by each month and this was used to predict the speed potential as shown in Fig. 7. Monthly average speeds were also predicted as presented in Fig. 8. It was discovered that wind exhibited relatively homogeneous behavior over a month, making it essential to conduct monthly calculations. Furthermore, most wind system design calculations were performed monthly.

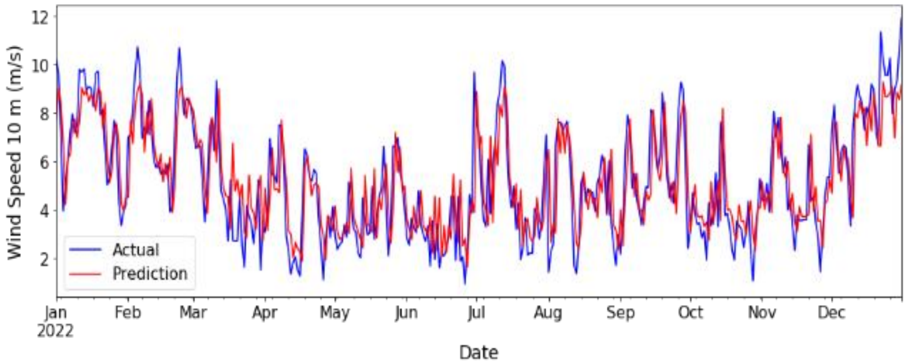


Figure 7. Wind Speed Forecasting of Semarang City.

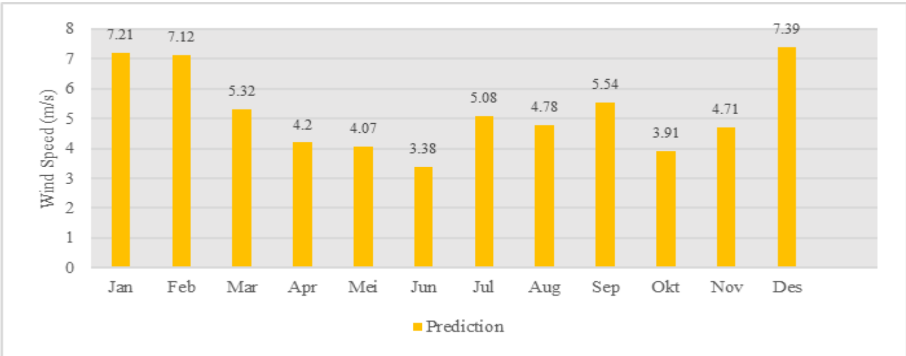
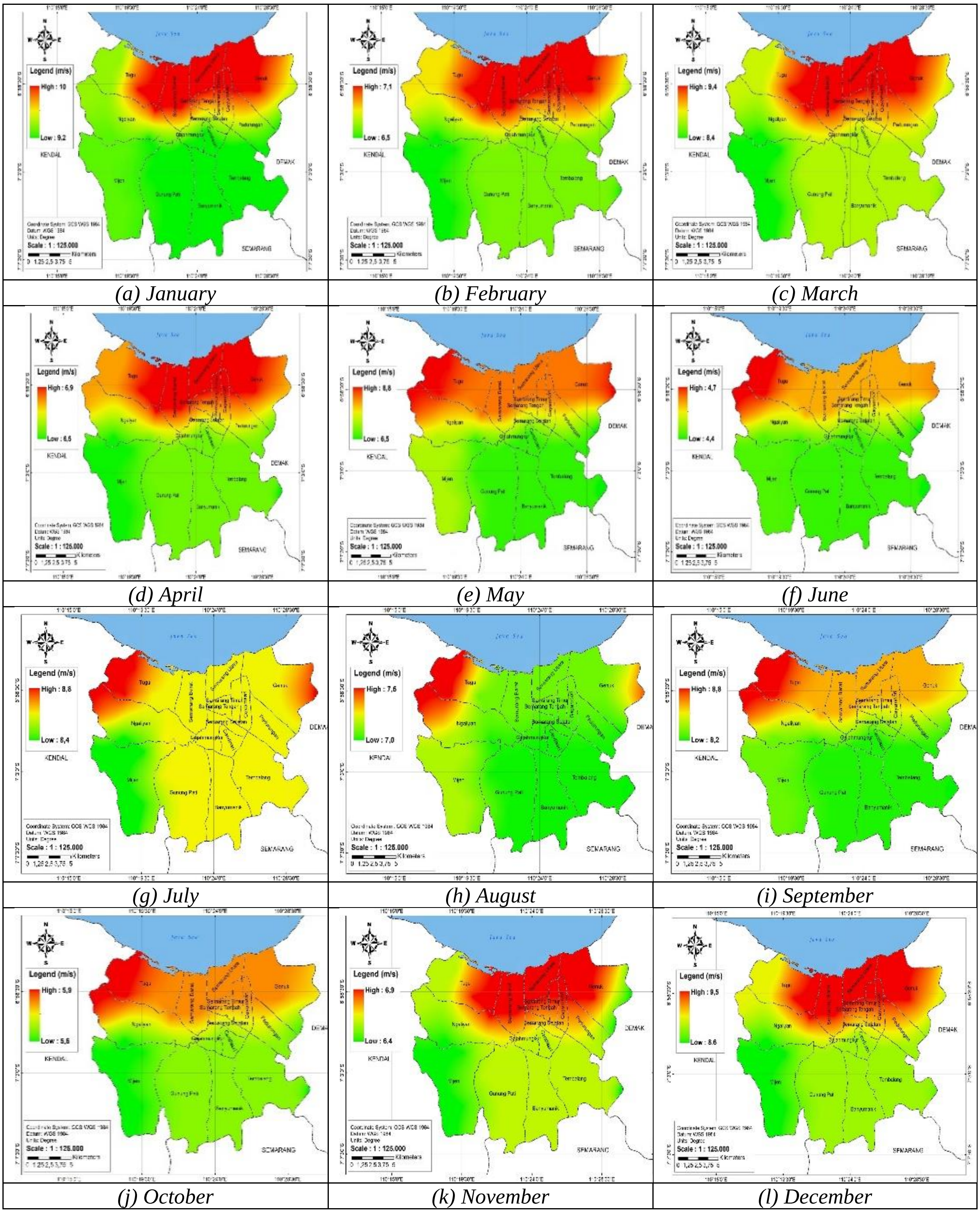


Figure 8. The monthly average wind speed of Semarang City.

Wind speed variations were predicted to generally range from 3.38 to 7.39 m/s with the maximum exceeding 7 m/s in December, January, and February while the minimum was estimated at 3.38 m/s and recorded in June. The prediction for an entire year suggested that the monthly average speed of 5.23 m/s remained highly suitable to be harnessed. These results showed the availability of potential energy to be harvested, thereby leading to the consideration of the area as a possible location for wind farms to use renewable energy.

5.2. Wind Speed Mapping

Using the ArcGIS version 10.8, wind energy maps were created by integrating spatial data and wind speed predictions derived from machine learning models. The process involved interpolating wind speed values using the Natural Neighbor Interpolation (NNI) method, a tool within the Spatial Analyst extension, to visualize distribution patterns across the study area and the Raster Calculator was used to calculate wind power density (WPD) by incorporating air density. The characteristics of monthly wind potential were identified to be essential and valuable, leading to the combination of the results from the deep learning model predictions with the NNI method to generate distribution maps (Figs. 9(a-l)). Geographically, Semarang City covers 16 sub-districts, with 4 bordering the coastline, 3 adjacent to the coast, and 9 located further inland or in the upper city areas (Figs. 9(a-l)). The predicted wind speed potential distribution map for each month from January to December is visualized in Fig. 8. Based on the wind speed distribution map legend, it was predicted that the maximum speed ranged from 7 to 10 m/s for 10 months of the year, while the minimum was between 4 and 6 m/s for 2 months. Moreover, the maximum speed distribution was concentrated in the 7 sub-districts near the coastline (lower areas), while the minimum was observed in the 9 sub-districts farther from the coast (upper areas). This map highlights the identified areas with potential for wind energy systems.



(a) January; (b) February; (c) March; (d) April; (e) May; (f) June; (g) July; (h) August; (i) September; (j) October; (k) November; (l) December

Figure 9. Monthly Wind Speed Estimate Mapping.

5.3. Wind Power Density (WPD) Potential

The magnitude of WPD is crucial to identify potential locations for energy deployment. Generally, there are suitable sites or locations for wind energy to be connected to a grid or isolated to serve only local needs. The monthly WPD estimations presented in Table 1, showed that the average over a year was 102.7 W/m² but the value fluctuated between 36.0 W/m² and 243.3 W/m². The maximum was recorded in December, January, and February at an average of 228.9 W/m² and this showed the high potential of the location to harness wind energy to generate electricity. The WPD was estimated with due consideration for the air density at a height of 10 meters.

Table 1. Wind Power Density

Monthly	**WPD**,Watt/m^2 (20 ^{O}C)
January	226.1
February	217.3
March	90.5
April	44.5
May	40.6
Jun	23.3
July	79.1
August	65.7
September	102.4
October	36.0
November	63.1
December	243.3
Total	1231,9

6. CONCLUSIONS

In conclusion, the availability of wind resource potential data is crucial for the planning and development of renewable energy systems. This study introduced a novel approach by combining machine learning for wind speed predictions with the Natural Neighbor Interpolation (NNI) method to create detailed wind energy maps. By estimating the monthly average wind speeds (as shown in Fig. 8) and visualizing the distribution in Figs. 9(a-l), we analyzed the energy potential of Semarang City, located in Central Java Province, at a height of 10 meters. The results revealed that the wind speeds ranged from 3.38 m/s to 7.39 m/s each month, with an average of 5.23 m/s. Maximum wind speeds between 7 m/s and 10 m/s were observed in 7 sub-districts near the coastline, while the monthly average wind power density (WPD) was recorded at 102.7 W/m². These findings provide valuable insights into harnessing wind energy for local-scale clean electricity generation, with implications for future energy policy and regional development. Further research could explore integrating solar energy forecasts with wind data to enhance the sustainability of renewable energy systems.

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