Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control
Journal homepage: http://kinetik.umm.ac.id
ISSN: 2503-2267
Vol. 9, No. 3, August, Pp. 231-238

Spatial interpolation long-term patterns capacity of solar energy in Sumatera

Arie Vatresia*[1,2], Ferzha Putra Utama[3], Novalio Daratha[4], Etika Dwi Lestari[5]
Informatics Department, Universitas Bengkulu, Bengkulu, Indonesia[1]
Research Center for Computing, The National Research and Innovation Agency, Bogor, Indonesia[2]
Information System Department, Universitas Bengkulu, Bengkulu, Indonesia[3]
Electrical Engineering Department, Universitas Bengkulu, Bengkulu, Indonesia[4]
Forest Department, Wildlife Conservation Society, Bogor, Indonesia[5]

Article Info
Keywords:
Renewable Energy, IDW, Arima, Sumatera, Indonesia

Article history:
Received: December 12, 2023
Accepted: March 05, 2024
Published: August 31, 2024

Cite:
A. Vatresia, F. P. Utama, N. Daratha, and E. D. Lestari, "Spatial Interpolation Long-Term Patterns Capacity of Solar Energy in Sumatera", KINETIK, vol. 9, no. 3, Aug. 2024.
https://doi.org/10.22219/kinetik.v9i3.1929

*Corresponding author.
Arie Vatresia
E-mail address:
arie.vatresia@unib.ac.id

Abstract
Indonesia possesses considerable capacity for renewable energy as a result of its plentiful natural resources, including geothermal, solar, wind, hydro, and biomass. However, the nation's existing energy composition is predominantly dependent on non-renewable resources, with fossil fuels constituting approximately 95% of its overall energy consumption. Recently, Indonesia has made notable advancements in augmenting its renewable energy output in years. Nevertheless, there is still obscurity about the identification of suitable regions for the installation of solar power plants in order to facilitate the development of solar energy. This study employed a methodology to investigate and forecast the solar energy potential in Sumatra, Indonesia. The data utilized consists of MERRA-2 reanalyzing information spanning from 1980 to 2019, collected on a daily basis. The data is analyzed and shown using Inverse Distance Weighting and ARIMA techniques to visualize the spatial variation of solar energy potential in Sumatra. ARIMA is employed as a supplementary method to the interpolation technique in order to get long-term projections of solar energy potential for the period spanning from 2020 to 2029. The analysis of the best interpolation method for estimating solar energy potential reveals that the IDW approach with a power of 5 yields the most accurate findings, with an RMSE value of 28.33. For long-term prediction of solar potential in Aceh province, the ARIMA (1,0,0) method is recommended, which has a MAPE value of 0.0219. The findings indicated that Lampung and Bengkulu frequently experience the distribution of solar energy with an intensity ranging from 1400 to 1450 kWh. In addition, the forecast of the potential over Sumatera Island yielded encouraging results using the GAM model, with a root mean square error rate of 0.05103.

1. Introduction
Indonesia has abundant potential for clean and environmentally-benign renewable energy sources, such as wind, sun, biomass, geothermal, and hydro (including small hydro) [1], [2], [3]. Solar power plants (PLTS) might be viewed as a feasible alternative solution given the underutilization of various renewable energy sources and the absence of affordable electricity access in some parts of Indonesia due to the unavailability of PLN power grid [1]. Energy is in greater demand, especially in the area of electrical power. The three main energy sources used by Indonesia are coal, natural gas, and petroleum. Indonesia's energy grid would be greatly impacted by the long-term use of fossil fuels for conventional electricity generation [4]. Under this scenario, Indonesia will become a net importer of fossil fuels and have easier access to fossil energy [5]. Due to this circumstance, fossil fuel availability will rise and Indonesia will become a net importer of fossil fuels. The development and application of renewable energy sources are potential steps to reduce imports [2], [6], [7].

Indonesia, as a tropical country, has a significant quantity of solar energy potential, thanks to its average daily solar irradiation of 12 hours. According to data from the Institute for Essential Services Reform (IESR), Indonesia has an estimated solar energy capacity of 207,898 MW, which is comparable to generating 4.8 kWh per day [8], [9]. The IESR study conducted in Sumatra found that the solar energy capacity in Sumatra is 68,576 MW. The maximum capacity of South Sumatra is 17,233 MW. The electricity capacity of several regions in Indonesia are as follows: North Sumatra has a capacity of 11,851 MW, Jambi has a capacity of 8,674 MW, Aceh has a capacity of 7,881 MW, Riau Islands has a capacity of 7,763 MW, Riau has a capacity of 7,753 MW, West Sumatra has a capacity of 5,898 MW, Bengkulu has a capacity of 3,475 MW, Bangka Belitung Islands has a capacity of 2,810 MW, and Lampung has a capacity of 2,238 MW. Prior to assessing the energy output of a solar power plant in Sumatra, it is imperative to get this data in advance through either direct measurement or use of satellite data, taking into account the acknowledged solar energy potential in the area. Regrettably, there is often a lack of direct observational data for long-term data sets. Afterwards, satellite data is used to estimate solar energy output data, although there are limitations regarding the time period provided by satellite data. Another alternative that could be utilized is to once again make use of reanalysis data.

Reanalysis data is often used to simulate energy output, especially in the context of solar power plants. The Modern-Era Retrospective Analysis for Research and Applications Version 2 (MERRA-2) dataset, provided by NASA, is widely used for reanalysis purposes. The MERRA-2 dataset, extensively utilized in previous studies, has been documented by [10] and [11]. The BMKG dataset has benefited from the utilization of this data, as it closely resembles observed data and has an R2 value ranging from 0.59 to 0.78. The estimation strategy employed in this study involves the utilization of spatial interpolation techniques [12], [13], [14]. Spatial interpolation can be employed to obtain meteorological estimation data at randomly dispersed location points. The Inverse Distance Weighting (IDW) method has been widely utilized [15], [16], [17], [18], [19]. Studies conducted by [17], [20] and [17] have showed that the IDW interpolation method produces more precise outcomes when compared to other methodologies. The purpose of utilizing the Inverse Distance Weighting (IDW) technique is to visually depict the spatial distribution of potential solar energy generation across the Sumatra region. The MERRA-2 reanalysis data is included in the time series data because of its temporal characteristics. Time series data can be employed to predict an event at a particular point in time. ARIMA, which stands for Auto Regressive Integrated Moving Average, is a widely used technique for modeling time series data [8], [21], [22], [23]. The ARIMA model will be employed to predict future solar energy production using existing data [21], [24]. This projection can be used as a reference point for comprehending the solar energy capacity in Sumatra.

2. Research Method

The research areas in this study are 10 provinces in Sumatra, Indonesia. The electrification data used is data in the period 1980-2019 collected from the https://www.renewables.ninja/ platform, the coordinate points used according to the points of climatology observation stations in each province. The raw data obtained is 350641 data per province from the period 01-01-1980 00:00 to 31 December 2019 23:00. The electrification data obtained in the proprietary format data .csv, which is a raw record. The data contains time, electricity, irradiance direct, diffuse irradiance and temperature. Data is collected based on province, time, and electricity. Furthermore, to produce a map of annual distribution of solar energy, the electrification data was collected and accumulated for a year. Then, the solar energy electrification data is spatially analyzed using R software, in this case Inverse Distance Weighting (IDW) interpolation method was used to produce the annual distribution. IDW is a method used to analyze geo-statistics and interpolate the variable values used based on the sample data, taken at random locations or points. This study also used ARIMA method to predict future energy capacity and Generalized Additive Model (GAM) [25], [26], [27], [28] to determine the distribution of solar energy capacity forecasts [26], [27], [29], [30]. This study will utilize the entire data collected from Sumatera Island. Sumatra Island is situated at coordinates 6°N-6°S and 95°E-105°E, in terms of its geographical location. Sumatra spans an area of 473,481 square kilometers and is divided into 10 provinces: Aceh, North Sumatra, West Sumatra, Riau, Jambi, South Sumatra, Bengkulu, Lampung, Bangka Belitung Islands, and Riau Islands. The mainland of Sumatra Island exhibits a diverse geography, with mountains, hills, and lowlands. Sumatra Island is situated in a region characterized by a tropical climate. For data collection, this research used documentation, which involved retrieving information pertaining to the data by reviewing written reports containing numerical or informational content. Data collection is conducted indirectly through the retrieval of metadata from the Renewable Ninja platform. To receive the data, you need to input the coordinates of climatological stations for each province and specify the desired data year for download. The dataset used in this study consists of data acquired by the NASA MERRA-2 satellite between the years 1980 and 2020.

2.1 Spatial Interpolation (Inverse Distance Weighting)

Interpolation is the method of estimating a value at a non-sample point by using the values of neighboring sample points. IDW interpolation is a method used to calculate the cell values by assigning the linear weights based on a set of sample points. The Equation 1 presents the general formula for IDW interpolation.

$$u(x) = \sum_{i=0}^{N} \frac{w_i(x)u_i}{\sum_{j=0}^{N} w_j(x)} \tag{1}$$

Where u_i = u(xi) and I = 0.1, ... N, N = number of dots, p = power, when real, positive. Then, the weight is the reverse distance function. The closer the distance between the sample point and the block to be estimated, the greater the weight, generally calculated by the general Equation 2.

$$w_i(x) = \frac{1}{d(x, x_i)^p} \tag{2}$$

Where X = the point you want to interpolate; X_i = known point; d = distance point x to x_i.

Figure 1 illustrates the processing flow of time series in this investigation. Spatial interpolation is utilized to estimate the spatial variability of the continents based on data acquired from specific sample points. Interpolation is the method used to estimate the value at a non-sample location by considering the values of the neighboring sampled points [20], [31], [32]. Accurate spatial analysis cannot be performed without including this interpolation step. In the field of cartography, interpolation refers to the method of approximating values in regions with lack of sampling or measurement data, aiming to create a map or spreading values across the entire mapped region. There are two assumptions associated with spatial interpolation: first, the data attributes are continuous in space, and second, these attributes have a spatial relationship [33], [34]. The three methods that often employed interpolation techniques for representing the spatial distribution of point data are Inverse Distance Weighting (IDW), Spline, and Kriging. Various techniques will yield distinct results. The IDW interpolation method will be employed in this study. The spatial interpolation technique in this study is conducted using the R Studio software.

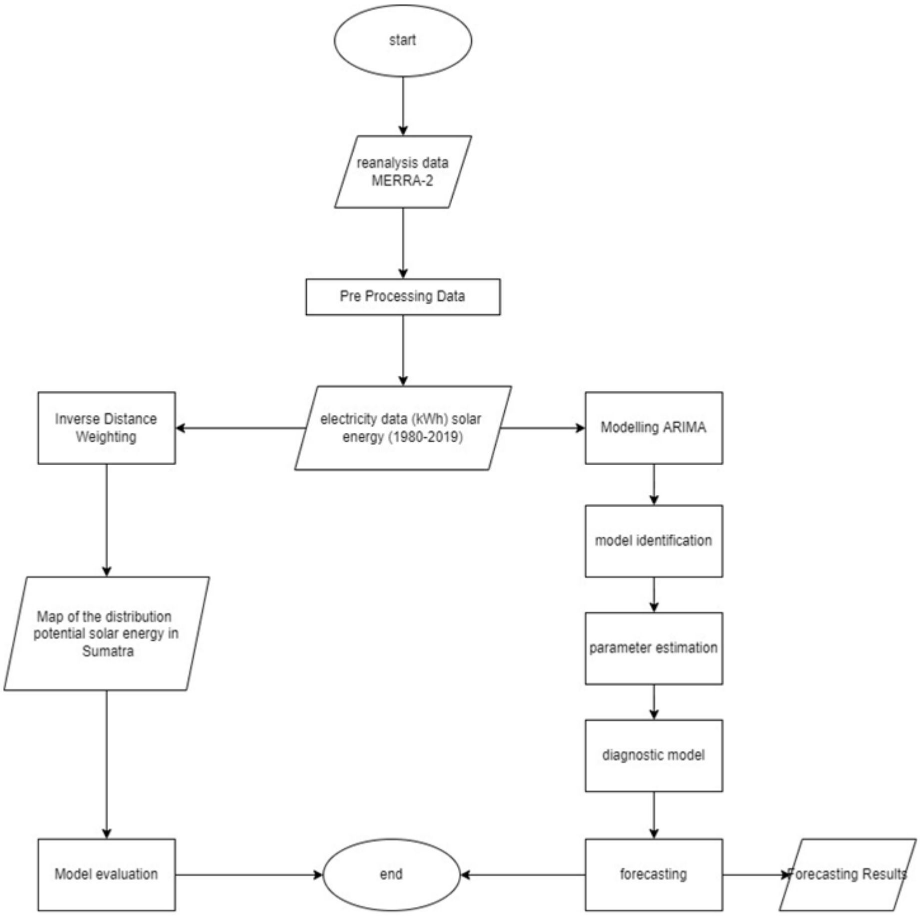

Figure 1. Research Flow Diagram: Describing the Process of How the Forecasting can be Produced Properly

2.2 ARIMA

The raw data obtained is 350,641 data per province from the period 01-01-1980 00:00 to December 31 2019 23:00. Data is obtained in data format with extension .csv, which is a raw record. The identification for each column of the table were as follows: column 1 is time (time of year, month, date and time according to UTC time); column 2 (time of year, month, date and time according to Asian/Jakarta time); column 3 (potential data (electricity) in kW units); column 4= irradiance direct (solar radiation in units of (kW/h/m2)); column 5 = irradiance diffuse (unit of solar radiation (kW/h/m2)) and column 6 = temperature (unit of ^oC). Time series data analysis is used to perform forecasting using the ARIMA method. The steps in this forecasting are:

1. Model identification is done to see the significance of autocorrelation and data stationarity, whether the process of transformation or differencing occurs. The ACF and PACF plots are used to determine the p and q order of the ARIMA model (p, d, q).
2. Parameter Estimation is carried out against the model with the value of the alleged parameter that is significant.

3. The formation of a time series model is an iterative procedure preceded by the identification of the model and the estimating of parameters. Furthermore, it is necessary to check the adequacy of the model by checking whether the model assumptions have been met.
4. Forecasting: After going through the three stages above, the last stage of the time series analysis is forecasting. Forecasting is carried out for each province as well as evaluating the models with RMSE and MAPE, and followed by conducting an annual forecast of solar energy capacity for the period 2020 - 2029 using the best model.

Prior to applying the IDW approach to solar energy data interpolation based on the measurements made at the Sumatran climatological observation station. The data set used in this study contains annual averages for the period 1980-2019. Data is stored as Spatial Points Data Frame and modelled using Generalized Additive Model (GAM). It is an extension of the Generalized Linear Model (GLM) to replace the linear function jp=1jXj with the additional function of $\sum_{j}^{p} = \beta_j K_j$. GAM generalizes $\sum_{j}^{p} = f_j(X_j)$ the additive model into an exponential distribution. In general, GAM uses a smoothing curve to model the relationship between solar energy potential (response variable) and the year variable which in this case is called prediction variable. Broadly speaking, it can be said that GAM is used to see forecasts of solar energy potential in each province in Sumatra.

3. Results and Discussion

3.1 Potential Distribution

The results obtained from the IDW spatial interpolation method provide a thorough depiction of the data related to the distribution map. The values of the mapping distribution on Sumatra's annual energy power production vary. The range of values at each location is shown by a color gradient that goes from light to dark. Strong potential is shown by regions with brilliant colors, whereas weak potential is indicated by parts with faded hues. The study evaluated the interpolation results using power parameters with integer values 1, 2, 3, 4, and 5 [32], [35]. Finding the lowest RMSE value computed for each power level will help define the best IDW model, according to this evaluation. With a rating of 996.85, the Riau Islands Province demonstrated the lowest potential for renewable energy in Sumatra during the course of the observation period. On the other hand, the Lampung Province, with a rating of 1468, shown the most potential. Over 39 years, Sumatra's potential for renewable energy has increased by 2.46%. The 39-year observation period's descriptive data are shown in Table 1. Over a 39-year period, Lampung Province showed the highest middle and average values.

Table 1 . RMSE Value Result from IDW Interpolation

Power	RMSE
1	32.57968
2	31.40251
3	30.25209
4	29.24624
5	28.33074

The IDW model with 5 power parameters has the lowest RMSE, measuring 28.33074, based on the RMSE value shown in Table 1. A model that generates more exact and accurate results has a lower root mean square error (RMSE) score. The results of the IDW power 5 interpolation method are shown in Figure 2. Black indicates that the lowest amount of solar energy that can be produced is between 1000 and 1050 kilowatt-hours. The color yellow indicates the maximum energy units for renewable energy, which are 1400–1450 kilowatt-hours (KWh). The distribution map produced by applying the IDW spatial interpolation approach is shown in Figure 2, demonstrating the non-uniform distribution of solar energy availability across the provinces of Sumatra Island.

The provinces of Lampung and Bengkulu have the most significant potential for renewable energy, whereas the province of North Sumatra displays the least potential for renewable energy. The combined energy output from these provinces exceeds 1350-1400 kWh (specifically 1416.676 kWh), with North Sumatra having the lowest average power output of 1210.029 kWh. The renewable energy production in Sumatra peaked at around 1.250 kWh in the early 1980s, but then experienced a significant decrease until it reached a level just above 1000 kWh between 1995 and 2003. However, only the provinces of Lampung and Bengkulu were able to achieve a recovery to the level of 1400 kWh in 2019.

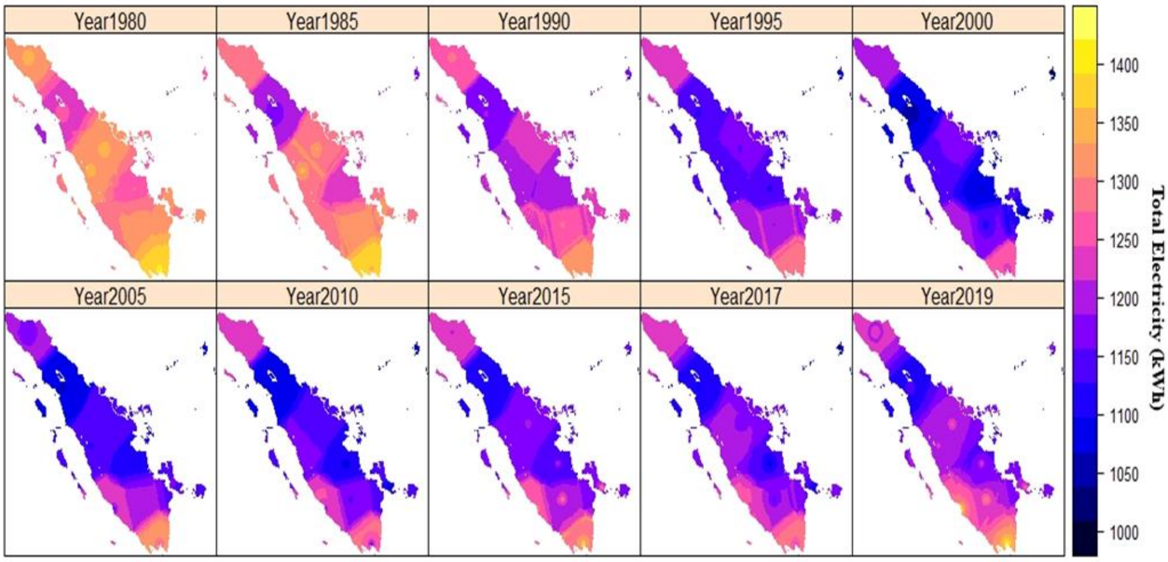

Figure 2. Total Energy (KWh) for 1980-2020 for 1 KW Power Plants

3.2 Forecasting

Renewable energy potential data is a collection of time series data that relies on both present and future observations. The renewable energy potential data in Sumatra is characterized by a consistent time interval of 1 hour between each data point. Time series models can be used to represent data that exhibit correlation and share the same time interval. The selected modeling approach for this analysis is a stationary time series model. Therefore, it is imperative to assess the stationarity of the renewable energy potential data.

The selection of forecasting techniques for annual solar energy power output data using ARIMA relies on the examination of ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots. The modeling of the annual data from 1980 to 2019 was performed after verifying that the data displayed stationary behavior and negligible volatility, obtained from the estimated value (λ) and the value of one on the Box-Cox curve. Furthermore, the data was subjected to alignment testing utilizing the mean to examine the ACF and PACF plots, along with the Dickey Fuller Augmented test (ADF). If the p-value obtained from doing the Augmented Dickey-Fuller (ADF) test in each province of Sumatra exceeds the threshold of 0.05, it signifies that, on average, the data is non-stationary. To evaluate the efficacy of differencing and testing, one can analyze the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, together with the outcomes of the augmented Dickey-Fuller (ADF) test. The data, which exhibited an initially consistent range and subsequently attained greater stability, was subjected to analysis utilizing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) to detect patterns need differencing. The study employed an assumption on the parameters of the model obtained from the automobile. The Arima approach, as described by [24], [36]. The model was subjected to model diagnostics using the Ljung-Box test. The results imply that the residual model of the solar energy power distribution data follows a random distribution, indicating its excellent effectiveness for forecasting purposes.

The ten-year forecasting procedure includes 2020–2029 in its scope. The projected outcomes for the island of Sumatra during the next ten years are shown in Figure 3. It is possible to conduct ARIMA analysis in each province to evaluate whether the ARIMA approach is suitable for building solar energy output forecasting models in Sumatra. Ten Sumatra provinces provided the solar energy data, which was collected using the most accurate ARIMA model. The greatest predicted values differ significantly amongst the provinces. In 2020, the provinces of South Sumatra and the Riau Islands are expected to have the highest values, 1283.762 and 1175.751, respectively. The Bangka Belitung archipelago is predicted to have the highest value in 2021 (1239.979), followed by Jambi (12202.019) and West Sumatra Province (1223.051). At 1333.924, the projection for Bengkulu Province in 2022 is the highest of all the provinces. The province of Lampung is predicted to have the highest predicted value in 2025, with 1336.556. With a predicted value of 1297.580 in 2026, the province of Riau is expected to have the highest predicted value. North Sumatra Province is expected to have the highest projection in 2029, with a value of 1165.816; Province Aceh is forecasted to achieve the highest predicted value by 2028, at 1261.562. The uniformity of solar energy capacity in Bengkulu and Lampung Provinces is evidenced by the spatial distribution of solar energy capacity in Sumatra. The majority of solar energy observational activities are focused on areas with significant solar energy potential. This location can be utilized for the construction of solar-powered plants in order to provide future energy needs. The ten provinces—Aceh, North Sumatra, Riau, Bengkulu, and Lampung—saw a generally positive trend, with annual projected results steadily rising. For the provinces of Aceh and North Sumatra, the rise is noteworthy. In the meantime, South Sumatra, Bangka Belitung Islands, and Riau Archipelago appear to be declining steadily annually, according to the forecast statistics.

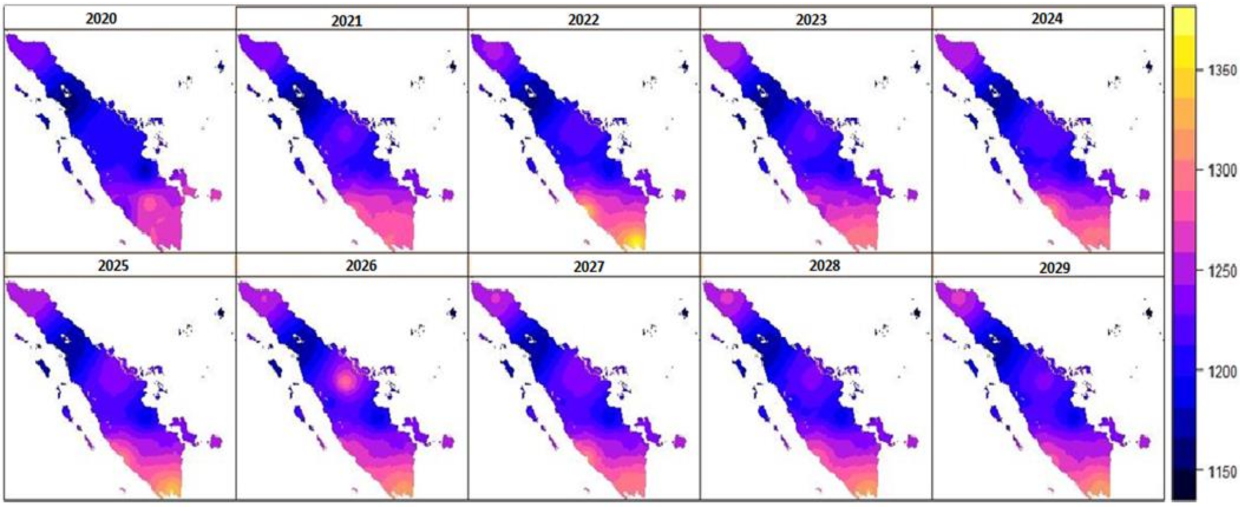

Figure 3. Forecasting for potential Energy over Sumatera Island 2020-2029

3.3 GAM Model

Generalized Additive Modeling (GAM) is utilized to analyze temporal data and investigate patterns within the data. GAM provides a versatile method for determining patterns. The R library MGCV offers a plethora of valuable functions for modeling. Generalized Additive Models (GAM) are a nonparametric regression method that is employed to incorporate nonlinear effects. Nonparametric regression modeling offers considerable flexibility in choosing the shape of the curve, as it does not require a priori determination. Instead, the curve is constructed based on the available data. The analysis of GAM is conducted by calculating the potential of renewable energy based on the annual functional connection. Figure 4 illustrates the spatial allocation of potential energy across Sumatera Island during a span of 40 years. It is evident that the trend is resuming an upward trajectory after 2005.

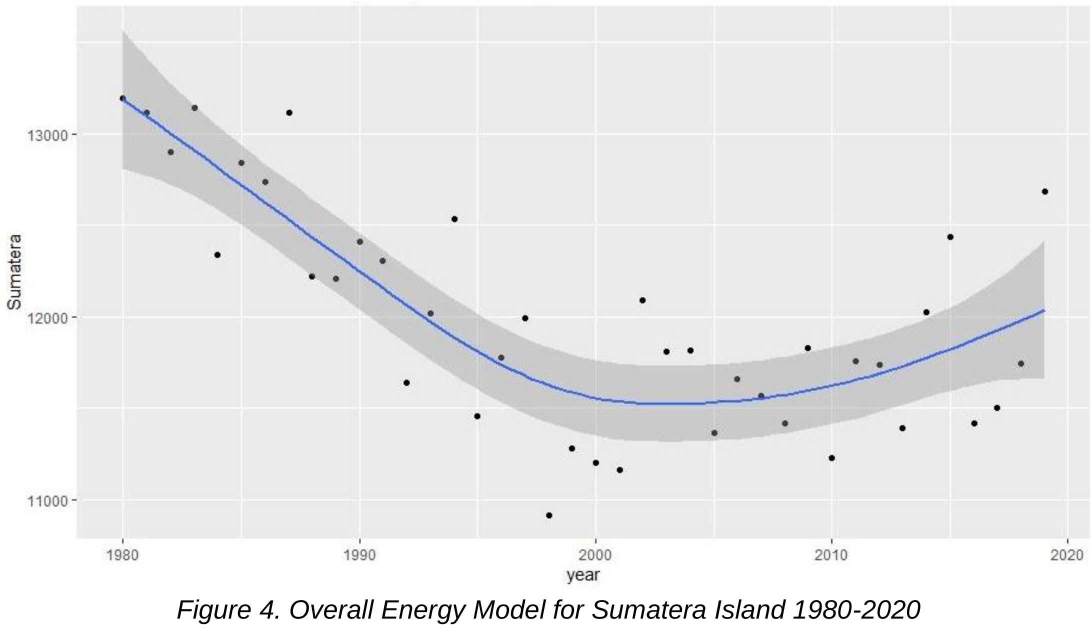

Figure 4. Overall Energy Model for Sumatera Island 1980-2020

3.4 Validation

Figure 5 presents a comparison between the ARIMA forecasted data and the MERRA-2 data for the provinces of South Sumatra and the Bangka Belitung Islands in 2020. The MERRA-2 data exhibits a larger disparity compared to the projected data, with an average difference value of 133.533. In the provinces of Lampung, Jambi, and Riau Islands, the comparison of ARIMA and MERRA-2 forecasting data shows a relatively low correlation. The average discrepancy between the two datasets is 31.640. Moreover, in the provinces of Aceh, Bengkulu, West Sumatra, and Riau, the ARIMA forecasting data exhibits a reduced magnitude compared to the data from MERRA-2, with an average discrepancy of 34.971. Only the data for North Sumatra Province in 2020 shows agreement between the ARIMA predicting results and MERRA-2 data, according to the comparison graphic. Based on Figure 5, the data obtained from ARIMA modeling exhibits a distribution that is nearly identical to the MERRA-2 data. The graph illustrates that the ARIMA model's solar energy capacity projections generally increase and eventually intersect with the actual data. The ARIMA method's modeling has a Mean Absolute Percentage Error (MAPE) of 0.05103.

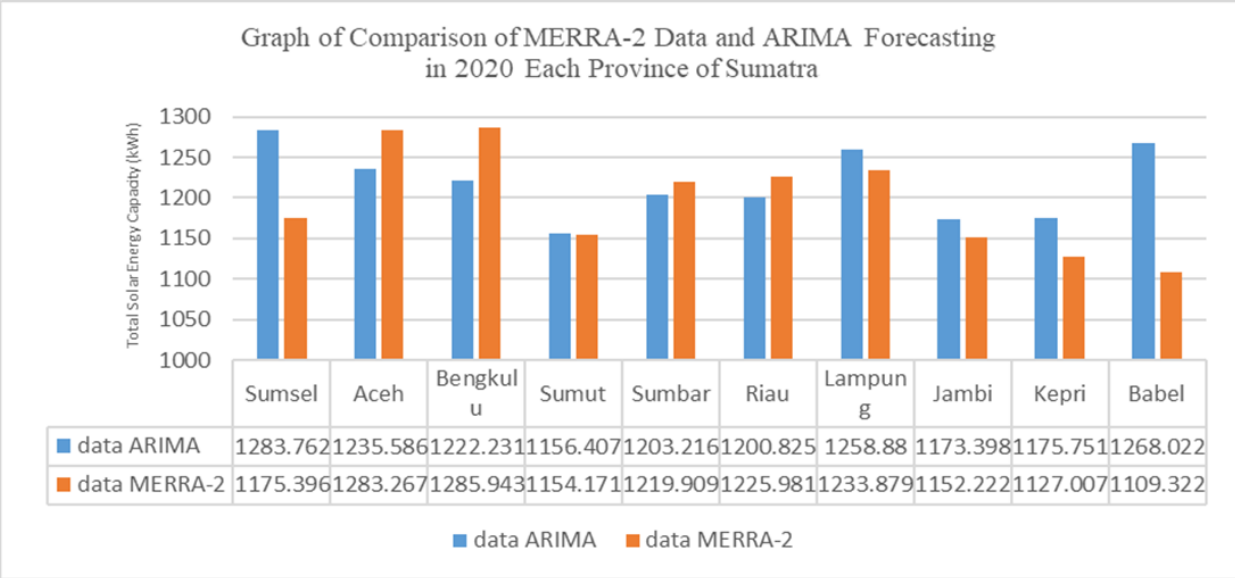

Figure 5. Validation and Comparison

4. Conclusion

In an effort to encourage the use of renewable energy sources, this study presented a methodical technique for locating areas with a sizable potential for producing renewable energy. With a score of 996.85, the study indicated that the Province of the Riau Islands had the least potential for renewable energy in Sumatera Island. On the other hand, Lampung Province, with a rating of 1468, had the highest potential. Over 39 years, Sumatra's capacity for renewable energy has increased by 2.46%. With an average of 1416.676 kWh, Lampung Province has the highest solar energy capacity, according to research using the Inverse Distance Weighting (IDW) Interpolation technique, while North Sumatra Province has the lowest, with an average of 1210.029 kWh, for a power plant with a 1 kW capacity. The IDW interpolation method, with a power value of 5, yields the lowest RMSE value or the maximum level of accuracy, which is evaluated at 28.33, according to the results of this experiment. The analysis conducted with the ARIMA technique indicates that there is non-stationarity in the variance of the collected time series data. Considering that it has the lowest Mean Absolute Percentage Error (MAPE) value when compared to other arima models in other provinces, the ARIMA(1,0,0) model in Aceh Province is the most suitable for prediction. The Mean Absolute Percentage Error (MAPE) for the Aceh Province ARIMA (1,0,0) model is 0.0219.

References

[1] D. F. Silalahi, A. Blakers, M. Stocks, B. Lu, C. Cheng, and L. Hayes, “Indonesia’s vast solar energy potential,” *Energies (Basel)*, vol. 14, no. 17, 2021. https://doi.org/10.3390/en14175424

[2] D. Hartono, S. H. Hastuti, A. Halimatussadiah, A. Saraswati, A. F. Mita, and V. Indriani, “Comparing the impacts of fossil and renewable energy investments in Indonesia: A simple general equilibrium analysis,” *Heliyon*, vol. 6, no. 6, 2020. https://doi.org/10.1016/j.heliyon.2020.e04120

[3] J. Langer, J. Quist, and K. Blok, “Review of renewable energy potentials in indonesia and their contribution to a 100% renewable electricity system,” *Energies*, vol. 14, no. 21. 2021. https://doi.org/10.3390/en14217033

[4] M. I. al Irsyad, A. Halog, R. Nepal, and D. P. Koesrindartoto, “The Impacts of Emission Reduction Targets in Indonesia Electricity Systems,” *Indonesian Journal of Energy*, vol. 2, no. 2, 2019. https://doi.org/10.33116/ije.v2i2.42

[5] S. Suhono, S. Sarjiya, and S. P. Hadi, “Electricity Demand and Supply Planning Analysis for Sumatera Interconnection System using Integrated Resources Planning Approach,” *Jurnal Ilmiah Teknik Elektro Komputer dan Informatika*, vol. 5, no. 1, 2019. http://dx.doi.org/10.26555/jiteki.v5i1.13178

[6] Y. Sugiawan and S. Managi, “The environmental Kuznets curve in Indonesia: Exploring the potential of renewable energy,” *Energy Policy*, vol. 98, 2016. https://doi.org/10.1016/j.enpol.2016.08.029

[7] A. Hidayatno, R. Dhamayanti, and A. R. Destyanto, “Model conceptualization for policy analysis in renewable energy development in Indonesia by using system dynamics,” *International Journal of Smart Grid and Clean Energy*, vol. 8, no. 1, 2019. https://doi.org/10.12720/sgce.8.1.54-58

[8] A. S. Ahmar, “A comparison of α-Sutte Indicator and ARIMA methods in renewable energy forecasting in Indonesia,” *International Journal of Engineering and Technology(UAE)*, vol. 7, 2018. https://doi.org/10.14419/ijet.v7i1.6.12319
[9] M. Anggraini and S. N. Indah, “IESR Efforts to Accelerate Indonesia Renewable Energy Transition Through Media Relations,” *RSF Conference Series: Business, Management and Social Sciences*, vol. 1, no. 4, 2021. https://doi.org/10.31098/bmss.v1i4.314
[10] D. Akritidis, A. Pozzer, J. Flemming, A. Inness, and P. Zanis, “A Global Climatology of Tropopause Folds in CAMS and MERRA-2 Reanalyses,” *Journal of Geophysical Research: Atmospheres*, vol. 126, no. 8, 2021. https://doi.org/10.1029/2020JD034115
[11] H. Kuswanto and A. Naufal, “Evaluation of performance of drought prediction in Indonesia based on TRMM and MERRA-2 using machine learning methods,” *MethodsX*, vol. 6, 2019. https://doi.org/10.1016/j.mex.2019.05.029
[12] G. Y. Lu and D. W. Wong, “An adaptive inverse-distance weighting spatial interpolation technique,” *Comput Geosci*, vol. 34, no. 9, 2008. https://doi.org/10.1016/j.cageo.2007.07.010
[13] Z. K. Barsi, I. L�szl�, G. Szab�, and H. M. Abdulmutalib, “Accuracy dimensions in remote sensing, International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives,” vol. 42, no. 3, pp. 61–67, 2018. https://doi.org/10.5194/isprs-archives-XLII-3-61-2018
[14] S. Shekhar, M. R. Evans, J. M. Kang, and P. Mohan, “Identifying patterns in spatial information: A survey of methods,” *Wiley Interdiscip Rev Data Min Knowl Discov*, vol. 1, no. 3, pp. 193–214, 2011. https://doi.org/10.1002/widm.25
[15] A. Bemporad, “Global optimization via inverse distance weighting and radial basis functions,” *Comput Optim Appl*, vol. 77, no. 2, 2020. https://doi.org/10.1007/s10589-020-00215-w
[16] Z. Li, X. Zhang, R. Zhu, Z. Zhang, and Z. Weng, “Integrating data-to-data correlation into inverse distance weighting,” *Comput Geosci*, vol. 24, no. 1, 2020. https://doi.org/10.1007/s10596-019-09913-9
[17] J. Tan *et al.*, “Coupling random forest and inverse distance weighting to generate climate surfaces of precipitation and temperature with Multiple-Covariates,” *J Hydrol (Amst)*, vol. 598, 2021. https://doi.org/10.1016/j.jhydrol.2021.126270
[18] R. Varatharajan, G. Manogaran, M. K. Priyan, V. E. Balaş, and C. Barna, “Visual analysis of geospatial habitat suitability model based on inverse distance weighting with paired comparison analysis,” *Multimed Tools Appl*, vol. 77, no. 14, 2018. https://doi.org/10.1007/s11042-017-4768-9
[19] D. F. Watson and G. M. Philip, “A Refinement of Inverse Distance Weighted Interpolation,” *Geoprocessing*, vol. 2, no. 4, pp. 315–327, 1985.
[20] J. P. Musashi, H. Pramoedyo, and R. Fitriani, “Comparison of Inverse Distance Weighted and Natural Neighbor Interpolation Method at Air Temperature Data in Malang Region,” *CAUCHY – JURNAL MATEMATIKA MURNI DAN APLIKASI*, vol. 5, no. 2, pp. 48–54, 2018.
[21] J. Fattah, L. Ezzine, Z. Aman, H. El Moussami, and A. Lachhab, “Forecasting of demand using ARIMA model,” *International Journal of Engineering Business Management*, vol. 10, 2018. https://doi.org/10.1177/1847979018808673
[22] G. C. Tiao, “Time Series: ARIMA Methods,” in *International Encyclopedia of the Social & Behavioral Sciences: Second Edition*, 2015. https://doi.org/10.1016/B978-0-08-097086-8.42182-3
[23] P. G. Zhang, “Time series forecasting using a hybrid ARIMA and neural network model,” *Neurocomputing*, vol. 50, 2003. https://doi.org/10.1016/S0925-2312(01)00702-0
[24] E. Chodakowska, J. Nazarko, and Ł. Nazarko, “Arima models in electrical load forecasting and their robustness to noise,” *Energies (Basel)*, vol. 14, no. 23, 2021. https://doi.org/10.3390/en14237952
[25] C. H. Chang, S. Tan, B. Lengerich, A. Goldenberg, and R. Caruana, “How Interpretable and Trustworthy are GAMs?,” in *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2021. https://doi.org/10.1145/3447548.3467453
[26] S. N. Wood, “Mixed GAM Computation Vehicle with Automatic Smoothness Estimation,” *Generalized Additive Models: An Introduction with R, Second Edition*, vol. 1.8-33, 2020.
[27] S. N. Wood, “mgcv: GAMs and generalized ridge regression for R,” *R News*, vol. 1, 2001.
[28] P. J. Mavares Ferrer, “Visualization of the Chaos Game for non-hyperbolic iterated function system,” *REVISTA ODIGOS*, vol. 1, no. 2, pp. 9–20, 2020. https://doi.org/10.35290/ro.v1n2.2020.302
[29] D. Bera, N. Das Chatterjee, and S. Bera, “Comparative performance of linear regression, polynomial regression and generalized additive model for canopy cover estimation in the dry deciduous forest of West Bengal, Remote Sensing Applications: Society and Environment,” vol. 22, p. 100502, Dec. 2021. https://doi.org/10.1016/j.rsase.2021.100502
[30] E. J. Pedersen, D. L. Miller, G. L. Simpson, and N. Ross, “Hierarchical generalized additive models in ecology: An introduction with mgcv, PeerJ,” vol. 2019, no. 5, pp. 1–42, 2019. https://doi.org/10.7717/peerj.6876
[31] A. Deniz and Y. Özdemir, “Graph-directed fractal interpolation functions,” *Turkish Journal of Mathematics*, vol. 41, no. 4, 2017. https://doi.org/10.3906/mat-1604-39
[32] V. Chaplot, F. Darboux, H. Bourennane, S. Leguédois, N. Silvera, and K. Phachomphon, “Accuracy of interpolation techniques for the derivation of digital elevation models in relation to landform types and data density,” *Geomorphology*, vol. 77, pp. 126–141, 2006. https://doi.org/10.1016/j.geomorph.2005.12.010
[33] G. Gertner, G. Wang, S. Fang, and A. B. Anderson, “Mapping and uncertainty of predictions based on multiple primary variables from joint co-simulation with Landsat TM image and polynomial regression,” *Remote Sens Environ*, vol. 83, no. 3, pp. 498–510, 2002. https://doi.org/10.1016/S0034-4257(02)00066-4
[34] A. Terlizzi, D. Scuderi, S. Fraschetti, and M. J. Anderson, “Quantifying effects of pollution on biodiversity: A case study of highly diverse molluscan assemblages in the Mediterranean,” *Mar Biol*, vol. 148, no. 2, pp. 293–305, 2005. https://doi.org/10.1007/s00227-005-0080-8
[35] H. Y. Wang, S. Z. Yang, and X. J. Li, “Error analysis for bivariate fractal interpolation functions generated by 3-D perturbed iterated function systems,” *Computers and Mathematics with Applications*, vol. 56, no. 7, 2008. https://doi.org/10.1016/j.camwa.2008.03.026
[36] C. C. Nwokike and E. W. Okereke, “Comparison of the Performance of the SANN, SARIMA and ARIMA Models for Forecasting Quarterly GDP of Nigeria,” *Asian Research Journal of Mathematics*, 2021. https://doi.org/10.9734/arjom/2021/v17i330280