ISSN 2797-7889

A Hybrid GRU-BiLSTM Deep Learning Framework for Solar Radiation Forecasting and Photovoltaic Energy Yield Assessment in Timor Island, Indonesia

Yobel Eliezer Mahardika[1*], Agustina Rachmawardani[2], Marzuki Sinambela[3]
[1,2] Undergraduate Program in Applied Instrumentation Meteorology Climatology Geophysics, STMKG, Tangerang, Indonesia
Email: yobel.em69@gmail.com, agustina.rahmawardani@stmkg.ac.id, sinambela.m@gmail.com

Timor Island in East Nusa Tenggara possesses abundant solar energy resources, yet the technical feasibility of solar power plant (PLTS) development in the region has rarely been assessed using data-driven quantitative methods. This study aims to develop and validate a hybrid GRU-BiLSTM deep learning model for short-term solar radiation forecasting, to assess whether this model can be reliably extended into long-horizon autoregressive projection, to estimate the solar radiation potential and photovoltaic energy production across five locations in Timor Island, and to characterize the radiation variability relevant to PLTS design. A hybrid GRU-BiLSTM deep learning model was developed and evaluated for short-term hourly solar radiation forecasting using ERA5 reanalysis data (2015-2025), achieving R^2 of 0.9507-0.9584 across five locations. Because chained autoregressive projection using this model was found to be unreliable for annual-horizon estimation (R^2 = -0.53, +46% overestimation), a climatological approach based on 2015-2025 historical averages was applied instead for potential assessment. The results show that the five locations possess high and relatively uniform solar potential, with annual totals ranging from 2,023 to 2,109 kWh/m² (5.54-5.78 kWh/m²/day), corresponding to estimated photovoltaic energy production of 273.1-284.8 kWh/m² per year. Coefficient of variation values (69.6-71.0%) indicate substantial short-term fluctuation despite the locations' consistent seasonal pattern, with the lowest production occurring in June and the highest in October. These findings provide a quantitative basis for PLTS capacity planning and energy storage design in Timor Island, demonstrating that a validated short-term forecasting model can be meaningfully extended into practical renewable energy resource assessment.
Keywords: solar radiation forecasting, GRU-BiLSTM, photovoltaic potential assessment, climatological approach, Timor Island.

Corresponding Author:
Yobel Eliezer Mahardika
STMKG
Tangerang, Indonesia
Yobel.em69@gmail.com

1. Introduction

Indonesia's eastern regions, particularly East Nusa Tenggara (NTT) including Timor Island, face persistent electricity supply limitations despite being situated in an area with high year-round solar irradiance due to its position south of the equator and its pronounced dry season. The regional electricity grid in NTT relies heavily on diesel-based generation in several districts, and the contribution of renewable energy, including solar photovoltaic (PV), remains limited relative to the region's natural potential [1].

Expanding solar power plant (Pembangkit Listrik Tenaga Surya, PLTS) capacity in NTT is increasingly urgent given the province's dependence on costly fuel-based generation and its vulnerability to supply disruption in remote and border areas such as Kupang, Soe, Kefamenanu, Atambua, and Betun. However, PLTS planning decisions require more than qualitative statements about high solar potential; they require quantitative, location-specific estimates of radiation resources and expected energy yield to support capacity and storage design decisions.

This study focuses specifically on four aspects: (1) developing and validating a hybrid GRU-BiLSTM model for short-term solar radiation forecasting, (2) evaluating whether this short-term model can be reliably extended into long-horizon autoregressive projection, (3) estimating solar radiation potential and photovoltaic energy production at five locations across Timor Island using a climatological approach, and (4) characterizing radiation variability as a consideration for PLTS storage design. A broader comparative evaluation against alternative forecasting architectures (e.g., gradient boosting or single-branch recurrent models) falls outside the scope of this study and is addressed elsewhere.

The objectives of this study are to: (1) develop and validate a hybrid GRU-BiLSTM model for short-term solar radiation forecasting at five locations in Timor Island; (2) evaluate the reliability of autoregressive projection for annual-horizon radiation estimation; (3) estimate the solar radiation potential and photovoltaic energy production of five locations using a climatological approach; and (4) characterize the radiation variability of each location and discuss its implications for PLTS system design.

2. Literature Review And Problem Statement

Deep learning architectures combining Gated Recurrent Unit (GRU) and Bidirectional Long Short-Term Memory (BiLSTM) have been widely applied to solar irradiance forecasting due to their ability to capture nonlinear temporal dependencies [2], [3]. Techniques such as attention mechanisms have further improved photovoltaic-related prediction performance [4], while hyperparameter optimization strategies, including topology-search and tuning-impact studies, have been shown to meaningfully affect deep learning forecasting accuracy [5], [6]. Beyond forecasting accuracy, translating radiation predictions into usable energy estimates requires established photovoltaic yield formulas relating radiation intensity, module efficiency, and system performance ratio [7], [8]. Provincial-level assessments have reported average solar irradiation of approximately 5.1 kWh/m²/day for Indonesia's eastern regions [9], providing a broad empirical benchmark against which location-specific estimates such as those derived in this study can be evaluated. The tropical, markedly seasonal climate of the region [10], combined with cloud and aerosol effects on surface radiation [11], further shapes the variability that any resource assessment must account for.

However, most prior deep learning solar forecasting studies, including comparative evaluations of multiple architectures based on anomaly-based accuracy metrics, focus exclusively on identifying the best-performing model for short-term prediction [12], [13]. Critically, prior work rarely addresses whether models validated for one-step-ahead forecasting can be reliably extended, through chained autoregressive projection, to estimate annual-scale radiation potential, which is a question directly relevant to PLTS planning that requires long-horizon resource assessment rather than short-term operational forecasts. This concern is consistent with broader findings on the limited validity of autoregressive time-series projection as the prediction horizon grows [14], a concern also echoed in comparative studies of statistical and deep learning forecasting approaches across different horizons [15]. Furthermore, few studies translate validated forecasting outputs into concrete photovoltaic energy yield estimates and variability characterizations suitable for system design decisions.

Based on this gap, the present study formulates the following problem statements: (1) can a hybrid GRU-BiLSTM model developed for short-term forecasting be reliably extended, through autoregressive projection, to estimate annual-scale solar radiation potential; (2) what is the quantitative solar radiation potential and corresponding photovoltaic energy production at five locations across Timor Island; and (3) how does radiation variability differ across these locations, and what are its implications for PLTS energy storage design.

3. Method

This study developed a hybrid GRU-BiLSTM deep learning model for short-term (hourly) solar radiation forecasting at five locations in Timor Island: Kupang, Soe, Kefamenanu, Atambua, and Betun. Input data were obtained from ERA5 reanalysis (Copernicus Climate Data Store) [16], covering hourly atmospheric and radiation variables from January 2015 to December 2025, comprising 11 years of continuous data for each location.

Multivariate atmospheric input variables were first preprocessed and transformed into fixed-length input sequences using a sliding-window scheme, in which each input sample is represented as a sequence of lagged multivariate features (e.g., x1(t-7), x2(t-7), x3(t-7), ..., x1(t), x2(t), x3(t)) rather than a single time step, allowing the model to learn temporal dependencies across a fixed historical window. The resulting sequences were then passed through the architecture illustrated in Fig. 1: (1) a GRU network, consisting of stacked Gated Recurrent Unit layers with dropout regularization, which processes the input sequence and extracts short-term temporal features into a GRU output representation; (2) a multi-head self-attention layer, which re-weights the GRU output across time steps to emphasize the most informative segments of the input sequence; and (3) a Bidirectional Long Short-Term Memory network, consisting of stacked bidirectional LSTM layers followed by dense and dropout layers, which processes the attention-weighted sequence in both forward and backward directions before producing the final radiation forecast output. This GRU-then-BiLSTM configuration allows the model to first compress short-term sequential patterns through GRU before capturing longer-range bidirectional context through BiLSTM.

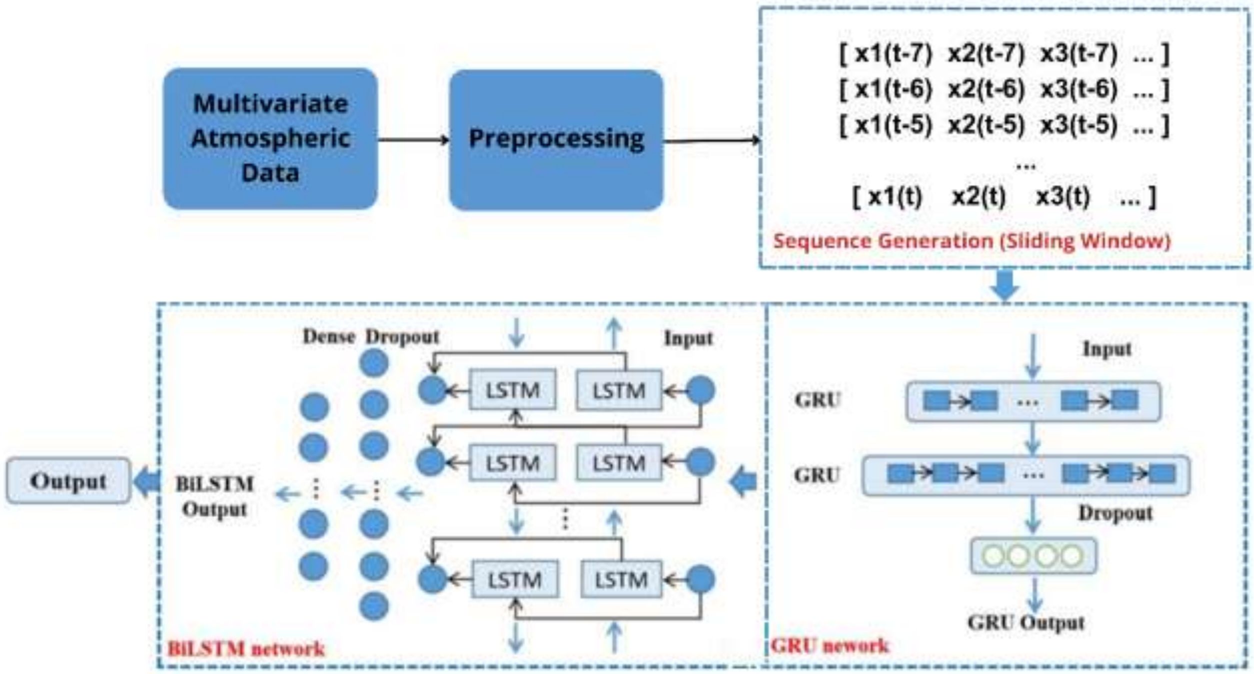

Fig. 1. GRU-BiLSTM model architecture: sequence generation via sliding window, GRU network, and BiLSTM network with dense and dropout layers [17].

The model was trained using data from 2015 to 2024 and tested on 2025, with hyperparameter tuning performed via random search [18]. Table 1 presents the model's performance on the 2025 test set.

ISSN 2797-7889

Table 1. Model performance on hourly solar radiation forecasting (2025 test data)

Location	R^2	RMSE (kWh/m²)	MAE (kWh/m²)	SMAPE (%)
Kupang	0.9553	0.0630	0.0402	21.99
Soe	0.9584	0.0606	0.0391	21.99
Kefamenanu	0.9507	0.0659	0.0428	22.11
Atambua	0.9526	0.0659	0.0408	20.38
Betun	0.9554	0.0634	0.0407	20.31

The model demonstrated strong and consistent performance across all five locations, with R^2 ranging from 0.9507 to 0.9584. These results are confirming that the model developed in this study achieved reliable short-term forecasting accuracy sufficient to serve as the basis for the subsequent long-horizon reliability assessment and photovoltaic resource assessment presented below.

Autoregressive projection validation

To determine whether the validated hourly forecasting model could be used for long-horizon estimation, a chained autoregressive projection was performed for the year 2025 (the period with available ground truth for comparison), where each predicted output was fed back into the model as the lagged input for the subsequent time step. The resulting year-long projection was compared against actual 2025 values using the coefficient of determination (R^2) and the total annual bias.

Climatological approach

Because reliable long-horizon projection could not be assumed a priori, this study additionally applied a climatological approach for potential estimation, based on historical averages of solar radiation intensity for each month-hour combination over the 2015-2025 period at each location. This method does not depend on the model's projection but reflects the long-term, stable radiation characteristics of each site, which is appropriate for potential assessment rather than year-specific forecasting.

Photovoltaic energy yield estimation

Radiation potential was converted into estimated photovoltaic energy production per unit panel area using Eq. (1):

$$E = H \times \eta \times PR \tag{1}$$

where E is the electrical energy produced per unit panel area (kWh/m²), H is the solar radiation intensity (kWh/m²), η is the photovoltaic module efficiency, and PR is the system performance ratio. A module efficiency of 18%, representative of commercial silicon modules [7], and a performance ratio of 0.75, a conservative value accounting for thermal, inverter conversion, and other environmental losses under tropical conditions [8], were applied. Estimates were computed at daily, monthly, and annual scales for each location.

Variability characterization

To characterize radiation variability relevant to PLTS design, the coefficient of variation (CV), defined as the ratio of the standard deviation to the mean radiation intensity, and the standard deviation of the anomaly component (residual radiation after removing the mean diurnal pattern) were computed for each location

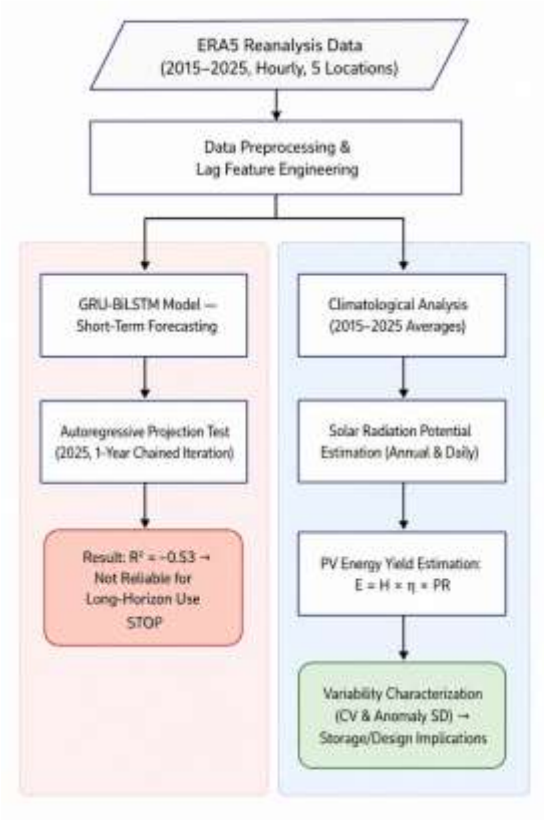

Fig. 2. Research methodology and energy potential assessment workflow.

4. Results And Discussion

Reliability of Autoregressive Projection

The chained autoregressive projection for 2025 showed poor agreement with actual observations (R^2 = -0.53), with the model overestimating the total annual radiation by approximately 46% (2,915 kWh/m² projected vs. 1,993 kWh/m² actual, Kupang station). As shown in Fig. 3, the projection systematically overestimated both the monthly averages and the diurnal midday peak (projected approximately 1.2 kWh/m² vs. actual approximately 0.78 kWh/m² around solar noon), indicating that prediction errors compounded across the recursive feedback loop rather than remaining stable.

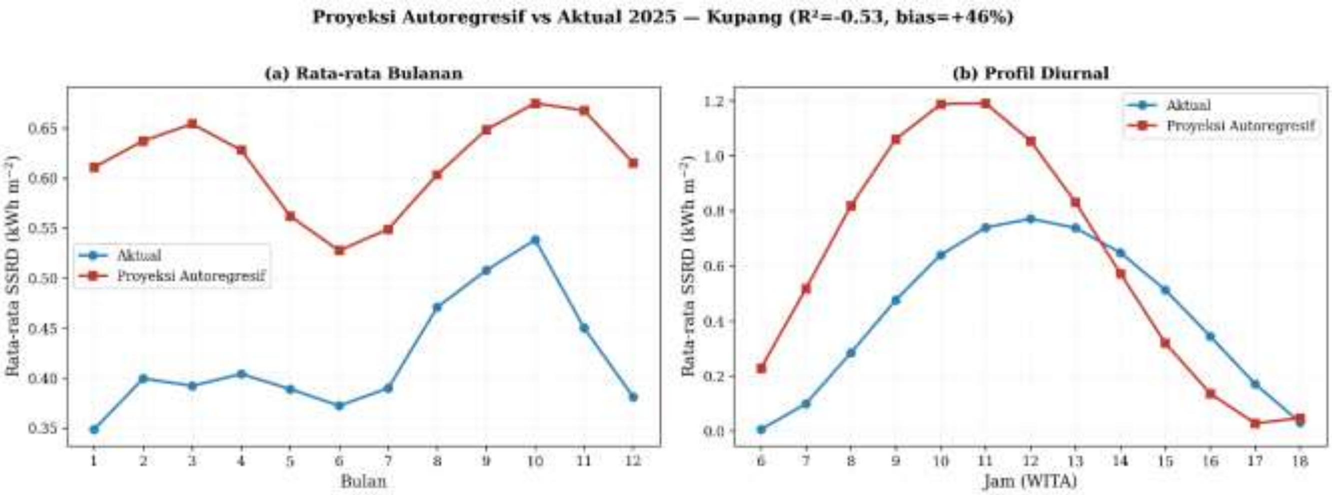

Fig. 3. Autoregressive Projection vs. Actual 2025, Kupang

This result is consistent with established concerns regarding the limited validity of autoregressive time-series projection as prediction horizon increases [14], and reinforces that short-term forecasting accuracy does not guarantee reliability for long-horizon extrapolation [15]. Based on this finding, annual-scale potential estimation in this study was conducted using the climatological approach rather than model-based projection, while the GRU-BiLSTM model developed in this study is retained strictly as a short-term operational forecasting tool.

Solar Radiation Potential

The climatological estimation of solar radiation potential across the five locations is presented in Table 2.

Table 2. Estimated solar radiation potential per location

Location	Annual Total (kWh/m²)	Daily Average (kWh/m²/day)
Kupang	2,106	5.77
Soe	2,106	5.77
Kefamenanu	2,106	5.77
Atambua	2,106	5.77
Betun	2,106	5.77

All five locations show high and relatively uniform annual potential (2,023-2,109 kWh/m²), somewhat higher than, but broadly consistent with, the 5.1 kWh/m²/day average reported at the provincial level for Indonesia's eastern regions [9], reflecting Timor Island's favorable local climate within that broader region. As shown in Fig. 4, radiation follows a clear seasonal pattern across all locations, peaking in October (approximately 200-221 kWh/m²/month) and reaching a minimum in June (approximately 136-151 kWh/m²/month), consistent with the region's monsoon-influenced dry-wet seasonal cycle [10].

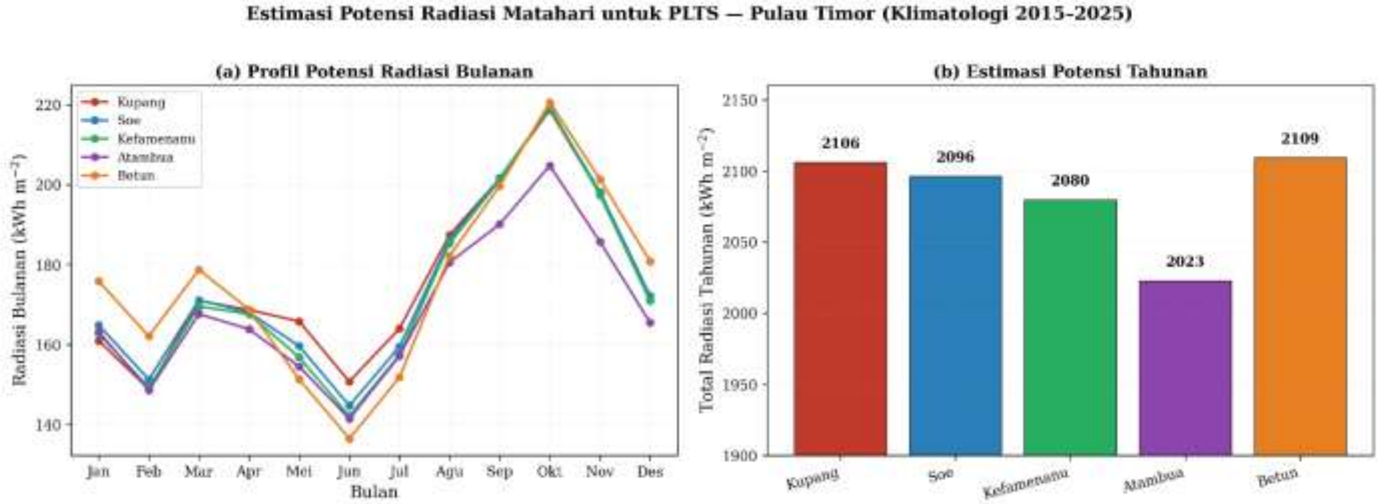

Fig. 4. Estimated Solar Radiation Potential for PLTS, Timor Island (Climatology 2015–2025)

Photovoltaic Energy Production Estimation

Applying Eq. (1) to the climatological radiation potential yields the estimated photovoltaic energy production shown in Table 3.

Table 3. Estimated photovoltaic energy production per location (η = 18%, PR = 0.75)

Location	Annual Production (kWh/m²/year)
Kupang	284.3
Soe	283.0
Kefamenanu	280.8
Atambua	273.1
Betun	284.8

Estimated production follows the same seasonal pattern as radiation potential, with monthly production ranging from approximately 18.5-20.5 kWh/m² in June to 27.5-29.6 kWh/m² in October (Fig. 5), representing a seasonal difference of roughly 35% between the lowest- and highest-producing months.

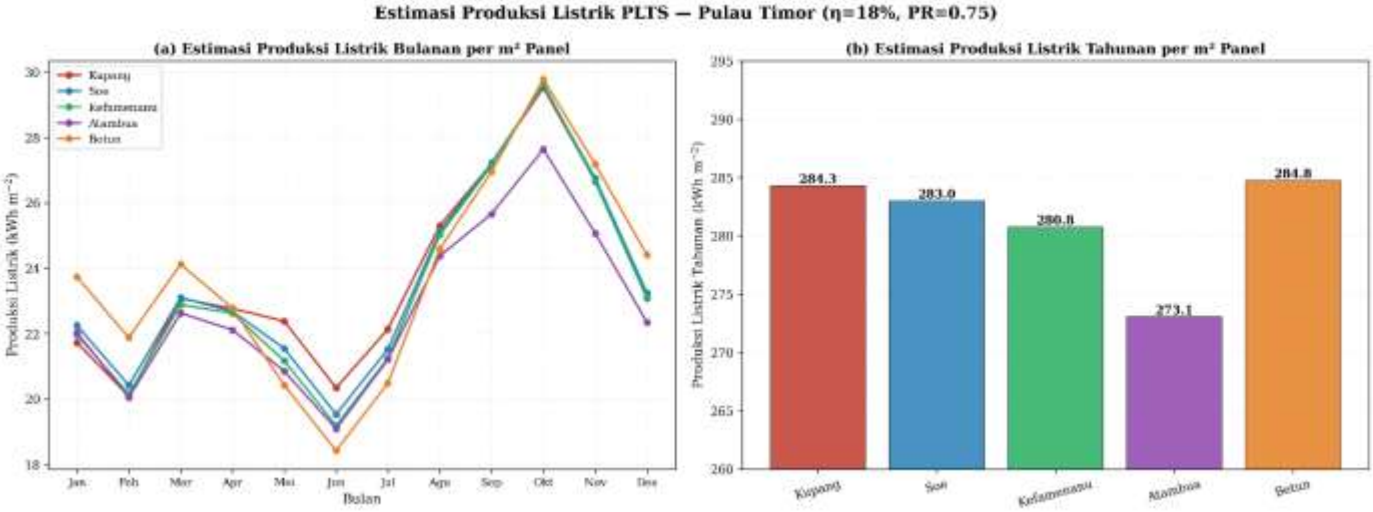

Fig. 5. Estimated PLTS Electricity Production, Timor Island (η=18%, PR=0.75)

Radiation Variability and Design Implications

follows a pronounced and predictable seasonal cycle, considerable day-to-day fluctuations remain at every site. Interestingly, Atambua showed the lowest anomaly standard deviation among the five locations while simultaneously recording the lowest anomaly-based forecasting R^2 during model validation. This pattern may be explained by Atambua's relatively higher humidity and less consistent cloud formation, in agreement with previous studies identifying atmospheric moisture and stability as major determinants of solar radiation predictability in tropical island environments [19], These conditions tend to reduce not only the magnitude of radiation anomalies but also their short-term predictability. Consequently, Atambua's solar radiation regime appears to be less variable in terms of anomaly magnitude, yet more challenging to forecast over short time horizons. This distinction is particularly important when differentiating between forecasting-assisted operational control strategies and static energy storage sizing.

Practical Implications

Taken together, these results indicate that Timor Island possesses substantial and geographically consistent PLTS potential, allowing capacity planning approaches developed for one location to be reasonably transferable to the other four. However, the marked seasonal difference between June (lowest) and October (highest) implies that storage or backup capacity should be specifically sized to accommodate the June trough rather than the annual average, particularly for standalone or micro-grid PLTS installations in border areas without strong grid backup.

5. Conclusion

This study developed a short-term hybrid GRU-BiLSTM solar radiation forecasting model for five locations in Timor Island and evaluated the reliability of extending it into long-horizon estimation for photovoltaic resource assessment. The model achieved strong and consistent short-term forecasting performance (R^2 = 0.9507-0.9584), but chained autoregressive projection was found unreliable for annual-scale estimation (R^2 = -0.53, +46% bias), confirming that short-term forecasting accuracy does not extend automatically to long-horizon projection. Using a climatological approach instead, the five locations were found to possess high and relatively uniform solar radiation potential (2,023-2,109 kWh/m²/year) and corresponding

ISSN 2797-7889

photovoltaic energy production (273.1-284.8 kWh/m²/year), consistent with provincial-level estimates for Indonesia's eastern regions. Radiation variability (CV approximately 70%) was consistently high across locations despite their predictable seasonal pattern, with Atambua showing a distinct combination of lower anomaly variability but lower short-term predictability. These findings provide a quantitative, location-specific basis for PLTS capacity and storage design in Timor Island. A key limitation of this study is that the climatological approach assumes historical radiation patterns remain representative of future conditions; future work may examine hybrid approaches that combine short-term model-based forecasting for operational control with climatological estimation for long-term capacity planning.

6. References

[1] J. Giwangkara and B. van Campen, "Planning the Electrification of Rural Villages in East Nusa Tenggara Using Renewable Energy Generation," Indones. J. Energy, vol. 1, no. 1, pp. 5-21, 2018, doi: 10.33116/ije.v1i1.10.

[2] M. A. Bou-Rabee, M. Y. Naz, I. E. D. Albalaa, and S. A. Sulaiman, "BiLSTM Network-Based Approach for Solar Irradiance Forecasting in Continental Climate Zones," Energies, vol. 15, no. 6, 2022, doi: 10.3390/en15062226.

[3] J. B. Fernandes and K. Mannepalli, "Enhanced Deep Hierarchal GRU & BiLSTM Using Data Augmentation and Spatial Features for Tamil Emotional Speech Recognition," Int. J. Mod. Educ. Comput. Sci., 2022, doi: 10.5815/ijmecs.2022.03.03.

[4] X. Lei, "A Photovoltaic Prediction Model With Integrated Attention Mechanism," Mathematics, vol. 12, no. 13, 2024, doi: 10.3390/math12132103.

[5] A. Al Bataineh and D. Kaur, "Immunocomputing-Based Approach for Optimizing the Topologies of LSTM Networks," IEEE Access, vol. 9, pp. 78993-79004, 2021, doi: 10.1109/ACCESS.2021.3084131.

[6] N. Sutarna, C. Tjahyadi, P. Oktivasari, M. Dwiyaniti, and Tohazen, "Hyperparameter Tuning Impact on Deep Learning Bi-LSTM for Photovoltaic Power Forecasting," J. Robot. Control, vol. 5, no. 3, pp. 677-693, 2024, doi: 10.18196/jrc.v5i3.21120.

[7] A. Barnett and X. Wang, "The Evolving Value of Photovoltaic Module Efficiency," Appl. Sci., vol. 9, no. 6, 2019, doi: 10.3390/app9061227..

[8] N. Sugiartha, "Energy Yield of a 1.3 kWp Grid-Connected Photovoltaic System Design: Case for a Small House in Bali," Matrix J. Manaj. Teknol. Inform., vol. 10, no. 1, pp. 19-25, 2020, doi: 10.31940/matrix.v10i1.1838.

[9] A. J. Veldhuis and A. H. M. E. Reinders, "Reviewing the Potential and Cost-Effectiveness of Grid-Connected Solar PV in Indonesia on a Provincial Level," Renew. Sustain. Energy Rev., vol. 27, pp. 315-324, 2013, doi: 10.1016/j.rser.2013.06.010.

[10] C. A. Alvares, P. C. Sentelhas, and H. B. Dias, "Southeastern Brazil Inland Tropicalization: Köppen System Applied for Detecting Climate Change Throughout 100 Years of Meteorological Observed Data," Theor. Appl. Climatol., vol. 149, no. 3-4, pp. 1431-1450, 2022, doi: 10.1007/s00704-022-04122-4.

[11] Z. M. Abbood and O. T. Al-Taai, "Study of Absorbance and Emissivity Solar Radiation by Clouds, Aerosols and Some Atmospheric Gases," J. Appl. Adv. Res., vol. 3, no. 5, pp. 128-134, 2018, doi: 10.21839/jaar.2018.v3i5.222.

[12] D. I. Prasetyo, A. Rachmawardani, B. Satrio, and D. B. Adinara, "Comparative Analysis of Machine Learning and Deep Learning Models for PM2 . 5 and PM10 Time Series Forecasting Using the SISANAPAS Web Platform," vol. 14, no. November, pp. 377–386, 2025.

[13] L. Benali, G. Notton, A. Fouilloy, C. Voyant, and R. Dizene, "Solar Radiation Forecasting Using

Artificial Neural Network and Random Forest Methods: Application to Normal Beam, Horizontal Diffuse and Global Components," Renew. Energy, vol. 132, pp. 871-884, 2019, doi: 10.1016/j.renene.2018.08.044.
[14] C. Bergmeir, R. J. Hyndman, and B. Koo, "A Note on the Validity of Cross-Validation for Evaluating Autoregressive Time Series Prediction," Comput. Stat. Data Anal., vol. 120, pp. 70-83, 2018, doi: 10.1016/j.csda.2017.11.003.
[15] K. Bhatt and M. Kambli, "Comparative Analysis of Ocean Color Forecasting Models: A Case Study on Indian Southern Peninsula Using SARIMA and Deep Learning Approaches," Int. Res. J. Modernization Eng. Technol. Sci., no. 11, 2023, doi: 10.56726/irjmets46878.
[16] H. Hersbach et al., "The ERA5 Global Reanalysis," Q. J. R. Meteorol. Soc., vol. 146, no. 730, pp. 1999-2049, 2020, doi: 10.1002/qj.3803.
[17] Y. Li, L. Guo, J. Wang, Y. Wang, D. Xu, and J. Wen, "An Improved Sap Flow Prediction Model Based on CNN-GRU-BiLSTM and Factor Analysis of Historical Environmental Variables," *Forests*, vol. 14, no. 7, pp. 1–21, 2023.
[18] O. J. Ilemobayo *et al.*, "Hyperparameter Tuning in Machine Learning: A Comprehensive Review," J. Eng. Res. Rep., vol. 26, no. 6, pp. 388-395, 2024, doi: 10.9734/jerr/2024/v26i61188.
[19] M. Bessafi et al., "Spatial and Temporal Non-Linear Dynamics Analysis and Predictability of Solar Radiation Time Series for La Reunion Island (France)," Entropy, vol. 20, no. 12, 2018, doi: 10.3390/e20120946.