

Comparison of Global Horizontal Irradiance Prediction Using LSTM and M-LSTM Across Seasonal Conditions

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Abstract—Short-term prediction of Global Horizontal Irradiance (GHI) is challenging because solar radiation exhibits dynamic temporal patterns and rapidly responds to changing atmospheric conditions. This study compares univariate Long Short-Term Memory (LSTM) and multivariate LSTM models using four and six predictor variables (M-LSTM-4 and M-LSTM-6) for 30-minute-ahead GHI forecasting using Automatic Solar Radiation Station data from Malang, East Java. One-minute observations were aggregated into 30-minute intervals and evaluated using sliding windows of 12, 24, and 36 timesteps. Model performance was assessed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2) for full-year, wet-season, and dry-season datasets. For the full-year dataset, M-LSTM-6 with a 12-timestep window achieved the best performance, with an MAE of 37.700 W/m², an RMSE of 79.340 W/m², and an R^2 of 0.9283. In contrast, M-LSTM-4 provided the best performance for both seasonal datasets using a 36-timestep window, achieving an MAE of 36.551 W/m² and an R^2 of 0.9378 during the wet season, and an MAE of 39.181 W/m² and an R^2 of 0.9454 during the dry season. M-LSTM-6 showed substantial performance degradation with longer historical windows, particularly during the dry season. This result suggests that combining a larger number of predictors with longer historical sequences increases the amount of input information processed by the model, which may be less effective when the additional historical information does not provide proportional predictive benefit under rapidly varying irradiance conditions. The results demonstrate that the effectiveness of multivariate information depends on predictor relevance, historical window length, and seasonal conditions. The main contribution of this study is the identification of different optimal combinations of predictor complexity and historical window length between full-year and seasonal GHI forecasting. Overall, the findings indicate that input-variable complexity and window length should be jointly optimized for local short-term GHI forecasting.

Keywords: Global Horizontal Irradiance; LSTM; Multivariate LSTM; Solar Irradiance Forecasting; Sliding Window

1. INTRODUCTION

The increasing demand for energy and the need to reduce greenhouse gas emissions have accelerated the development of renewable energy sources, including solar energy. Solar energy has substantial potential for electricity generation through photovoltaic (PV) technology, creating a growing need for accurate solar radiation information to support energy planning and operational management [1], [2]. Global Horizontal Irradiance (GHI) is a key parameter in solar resource assessment because it represents the total solar radiation received by a horizontal surface. GHI is influenced by solar geometry and atmospheric conditions, including cloud cover, aerosols, and water vapor [3], [4]. These factors produce dynamic, nonlinear, and temporally dependent GHI behavior, making short-term forecasting challenging [5], [6].

Various approaches have been developed for solar irradiance forecasting, ranging from physical and statistical methods to machine learning and deep learning models. Recent reviews indicate that deep learning has become increasingly important because of its ability to learn complex nonlinear relationships and temporal patterns directly from time-series data [7], [8], [9]. Among deep learning approaches, Long Short-Term Memory (LSTM) networks are particularly suitable for sequential forecasting because their memory cells and gate mechanisms enable the learning of both short- and long-term dependencies [10]. LSTM-based models have consequently been applied to solar irradiance forecasting at different temporal resolutions and prediction horizons [11], [12].

Multivariate LSTM models can further incorporate variables related to solar radiation and solar geometry. Net Radiation and Reflective Radiation describe components of the radiation balance, while Direct Normal Irradiance (DNI) and Diffuse Radiation represent direct and scattered components of solar radiation, respectively. Solar Altitude and Azimuth describe the geometric position and apparent movement of the sun. These variables are physically related to the radiation received at the surface and may provide complementary information for GHI forecasting. This relationship is particularly relevant in tropical environments, where rapid changes in cloud and atmospheric conditions can modify the balance between direct and diffuse radiation. However, physical relevance alone does not indicate that all variables provide independent predictive information. Therefore, this study examines the empirical relationships between candidate predictors and GHI using Pearson correlation before defining the multivariate input configurations [13], [14].

Another important factor is the amount of historical information provided to the forecasting model. In LSTM-based forecasting, this information is commonly represented through a sliding window that determines the number of previous observations used as input. Previous studies have demonstrated that model performance can be sensitive to window length and data characteristics, and a longer historical sequence does not necessarily result in better

forecasting accuracy [15], [16], [17]. This issue may become more important in tropical environments, where rapid atmospheric changes and seasonal variability can influence GHI dynamics. Previous research has demonstrated differences in solar irradiance forecasting performance across climatic conditions and tropical environments [18], [19], [20].

These characteristics indicate that GHI forecasting performance may depend jointly on the selected predictors, the amount of historical information, and the evaluation period. Consequently, assessing a model only using an annual dataset may not reveal whether a particular input configuration remains effective under different seasonal conditions. A systematic evaluation combining predictor complexity, sliding-window length, and seasonal characteristics is therefore needed for short-term GHI forecasting in tropical environments.

Previous research has demonstrated the applicability of deep learning and LSTM-based models to solar irradiance forecasting under different temporal and geographic conditions. Alkhatib et al. [13] investigated deep learning techniques for GHI forecasting across US cities, while Bektas and Altas [15] developed DWT-BiLSTM models for day-ahead hourly GHI forecasting. Zuo et al. [20] investigated ten-minute solar irradiance prediction using cloud detection and LSTM, and Bounoua and Mechaqrane [21] examined hourly and sub-hourly GHI forecasting using deep learning. These studies demonstrate the suitability of recurrent and deep learning models but differ substantially in forecasting horizon, temporal resolution, location, and input configuration.

Other studies have focused on input information and model configuration. Kaysal et al. [14] investigated a hybrid M/LSTM-GRU approach for solar radiation estimation, while Nourani et al. [16] examined multi-step-ahead solar irradiance modeling using multi-frequency deep learning and climatic data. Jeon and Kim [17] investigated solar irradiance prediction using reinforcement learning with limited historical data, while Tsai and Lo [22] applied LSTM with SHAP-based evaluation for solar radiation forecasting. These studies highlight the relevance of input information and historical observations, while differences in their experimental settings limit direct assessment of the joint effect of predictor complexity and historical window length.

Seasonal and climatic conditions also require consideration. Chaaban and Alfadl [18] compared machine-learning approaches for solar energy generation, while Otuka et al. [19] reviewed deep learning techniques for solar irradiance forecasting. Hoyos-Gómez et al. [23] specifically examined short-term global solar irradiance forecasting in a tropical environment. Together, these studies indicate that local climatic characteristics and forecasting conditions can influence model performance [18], [19], [23].

Previous studies have therefore established the effectiveness of LSTM and other deep learning approaches for solar irradiance forecasting [12], [15], [20], [22], as well as the potential relevance of multiple input variables [13], [14], [16]. However, these factors have generally been investigated using different datasets, locations, temporal resolutions, forecasting horizons, and model configurations. As a result, it remains difficult to determine whether differences in forecasting performance are associated with predictor-variable complexity, historical window length, seasonal characteristics, or their interaction.

In particular, limited research has systematically evaluated input-variable complexity and sliding-window length simultaneously across full-year, wet-season, and dry-season conditions for 30-minute-ahead GHI forecasting in a tropical environment. It therefore remains unclear whether additional radiation and solar-geometry variables consistently improve forecasting performance when different amounts of historical information are used. This study addresses this gap by applying a consistent experimental framework to ASRS observations from Malang, East Java, comparing univariate LSTM with four- and six-variable M-LSTM configurations using 12-, 24-, and 36-timestep windows across full-year, wet-season, and dry-season datasets.

2. RESEARCH METHODOLOGY

The research methodology was designed to evaluate the effects of input-variable complexity, sliding-window length, and seasonal conditions on short-term GHI forecasting. The experiments compared a univariate LSTM with M-LSTM models using four and six predictor variables. Pearson correlation analysis was conducted to examine the relationships between candidate predictors and GHI before defining the multivariate configurations.

2.1 Research Stages

The research stages consisted of data acquisition, preprocessing, correlation analysis, input-variable selection, sliding-window construction, model development, training, and performance evaluation. Figure 1 illustrates the overall workflow of the research, from raw ASRS data preparation to the evaluation of LSTM and M-LSTM forecasting performance.

The dataset was obtained from an Automatic Solar Radiation Station (ASRS) located in Malang, East Java, Indonesia, which records solar radiation and related variables at one-minute temporal resolution. Global Horizontal Irradiance (GHI) was used as the forecasting target. The observations were cleaned and aggregated into 30-minute intervals before model development. The dataset was evaluated for the full-year period and divided into wet-season and dry-season subsets to examine differences in forecasting performance under different seasonal conditions.

The prediction results were transformed back to the original scale and evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). The evaluation was conducted

separately for the full-year, wet-season, and dry-season datasets. The study focused on short-term forecasting performance within the available observation period and did not aim to establish long-term climatic-scale model validity. The research flow is presented in Figure 1.

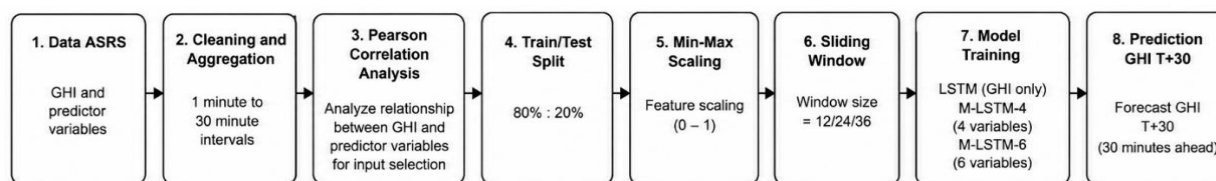


Figure 1. Research flow for evaluating LSTM and M-LSTM configurations with different input complexities and sliding-window lengths.

2.2 Dataset and Preprocessing

The dataset used in this study was obtained from observations recorded by the Automatic Solar Radiation Station (ASRS) at the East Java Climatology Station, Malang Regency, Indonesia. The dataset covered the period from May 1, 2025, to April 30, 2026. The original observations had a temporal resolution of one minute and were cleaned and aggregated into 30-minute intervals using the mean value. After preprocessing and aggregation, a total of 17,520 observations were obtained and used as the final dataset for the forecasting experiments.

To investigate the influence of seasonal conditions on forecasting performance, the dataset was divided into dry-season and wet-season periods. The dry-season dataset covered May 1 to September 30, 2025, comprising 7,344 observations, whereas the wet-season dataset covered October 1, 2025, to April 30, 2026, comprising 10,176 observations. Each dataset was divided sequentially according to time, with 80% of the observations used for training and the remaining 20% used for testing [23].

Table 1. Characteristics of the research dataset

Characteristics	Value
Period	May 1, 2025–April 30, 2026
Initial resolution	1 minute
Research resolution	30 minutes
Observations after aggregation	17,520
Training/testing	80% / 20%
Target	GHI T+30
Season	Dry and wet seasons

Table 1 shows the characteristics of the dataset used in this study. The observations covered a one-year period from May 1, 2025, to April 30, 2026, with an original temporal resolution of one minute. The data were aggregated into 30-minute intervals, resulting in 17,520 observations for the forecasting experiments. The dataset was divided chronologically into 80% training data and 20% testing data. The forecasting target was defined as GHI 30 minutes ahead (GHI T+30), and the analysis was conducted for the full-year dataset as well as the dry- and wet-season datasets.

Before aggregation and model development, the data were examined for timestamp consistency, chronological order, duplicate records, and missing values. Based on the latest dataset revision, no missing values were identified; therefore, no imputation procedure was required. The aggregation process was performed by calculating the mean value of numerical observations within each 30-minute interval. Consequently, 30 one-minute observations were represented by one observation in the final research dataset.

The processed 30-minute dataset was subsequently transformed into sequential samples for GHI forecasting. The same preprocessed dataset was used to evaluate the LSTM baseline and M-LSTM models under different input-variable configurations, sliding-window lengths, and seasonal periods.

2.3 Normalization and Sliding-Window Construction

After aggregation and sequential data splitting, all variables used in each experimental configuration were normalized using Min-Max scaling. The minimum and maximum values were calculated exclusively from the training data, and the resulting scaling parameters were subsequently applied to the testing data. This procedure prevented information leakage from the testing data into the training process. The Min-Max normalization transformation is expressed as:

$$x' = (x - x_{\min}) / (x_{\max} - x_{\min}) \quad (1)$$

where x represents the original value, x' is the normalized value, and $x_{\min}$ and $x_{\max}$ are the minimum and maximum values calculated from the training dataset.

To investigate the effect of input-variable complexity on forecasting performance, Pearson correlation analysis was conducted between GHI and the six candidate predictor variables. The six-variable configuration included all available predictor variables, whereas the four-variable configuration used the four variables with the strongest Pearson correlations with GHI. The selected variables for M-LSTM-4 were Net Radiation, Reflective Radiation, Solar

Altitude, and DNI. The M-LSTM-6 configuration included all six candidate variables, including Diffuse Radiation and Azimuth, to evaluate whether increasing input complexity improved forecasting performance. GHI was defined as the forecasting target for all multivariate experiments.

Table 2. Variables used in the forecasting experiments

Variable	Role
GHI	Forecasting target
DNI	Input variable
Diffuse Radiation	Input variable
Reflective Radiation	Input variable
Net Radiation	Input variable
Azimuth	Input variable
Solar Altitude	Input variable

Table 2 presents the variables used in the forecasting experiments, consisting of GHI as the target and six candidate input variables. M-LSTM-4 used the four highest-correlated predictors, while M-LSTM-6 used all six candidate predictors.

2.3.1 Sliding-Window Construction

A sliding window is a data transformation technique used to convert sequential time-series observations into supervised learning samples. In this approach, a fixed number of consecutive past observations is grouped as one input sequence, while an observation at a specified future time is defined as the prediction target. The term *sliding* refers to the process in which the input window moves forward sequentially through the time-series data, typically one timestep at a time, generating multiple overlapping input-target pairs. This approach enables the LSTM model to learn temporal patterns and dependencies from historical observations for future forecasting.

After normalization, the time-series data were transformed into input-target pairs using a sliding-window approach. For a window size w , the input sequence consisted of observations from the previous w timesteps, while the forecasting target was defined as the GHI value at the subsequent timestep.

$$X_t = [x_{t-w+1}, x_{t-w+2}, \dots, x_t] \quad (2)$$

where X_t represents the input sequence, x represents the observation vector at each timestep, and w represents the number of consecutive historical timesteps included in the window. The forecasting target was defined as:

$$y_t = GHI_{t+1} \quad (3)$$

where X_t represents the input sequence, w represents the number of historical timesteps, and y_t represents the forecasting target. Because the research dataset had a temporal resolution of 30 minutes, the subsequent timestep corresponds to the T+30 forecasting horizon.

Three sliding-window lengths were evaluated to investigate the effect of historical information on forecasting performance. Because each timestep represents 30 minutes, the window lengths correspond to different historical periods, as summarized in Table 3.

Table 3. Sliding-window configurations used in the experiments

Window	Resolution	History
12 timesteps	30 minutes	6 hours
24 timesteps	30 minutes	12 hours
36 timesteps	30 minutes	18 hours

Table 3 summarizes the sliding-window configurations evaluated in the experiments. The three window lengths were applied consistently to the LSTM, M-LSTM-4, and M-LSTM-6 models under the full-year, wet-season, and dry-season datasets. The resulting sequential input data were structured as three-dimensional tensors in the format:

$$(samples, timesteps, features) \quad (4)$$

where *samples* represents the number of generated input-target pairs, *timesteps* represents the number of observations contained in each sliding window, and *features* represents the number of input variables. For example, the six-variable configuration with a 12-timestep window produced an input structure of $(samples, 12, 6)$, where 12 represents the historical timesteps and 6 represents the predictor variables. The corresponding target for each sample was the GHI value at the subsequent timestep, representing the 30-minute-ahead forecasting target.

2.4 Pearson Correlation Analysis

Pearson correlation analysis was conducted to examine the relationships among the variables used in the forecasting experiments. The Pearson correlation coefficient measures the strength and direction of the linear relationship between two variables and is expressed as:

$$r_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (5)$$

where r_{xy} represents the Pearson correlation coefficient between variables x and y .

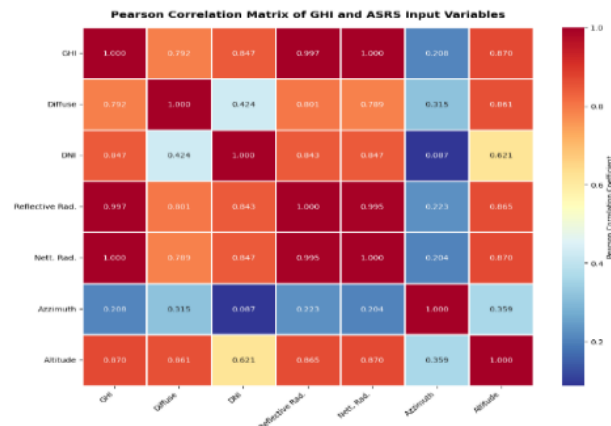


Figure 2. Pearson correlation heatmap of GHI and the ASRS input variables.

Figure 2 presents the Pearson correlation heatmap between GHI and the ASRS variables used in the forecasting experiments. The heatmap provides a visual representation of the strength and direction of the linear relationships among the variables. The correlation values between the individual predictor variables and GHI were subsequently examined to rank the candidate input variables according to their relationship with the forecasting target. The Pearson correlation values between each input variable and GHI are presented in Table 4.

Table 4. Pearson correlation between input variables and GHI

No.	Input Variable	Pearson Correlation
1	Net Radiation	0.999769
2	Reflective Radiation	0.997265
3	Solar Altitude	0.869527
4	DNI	0.846573
5	Diffuse Radiation	0.792484
6	Azimuth	0.208308

Table 4 presents the Pearson correlation coefficients between the six candidate input variables and GHI. Net Radiation had the strongest correlation with GHI, followed by Reflective Radiation, Solar Altitude, DNI, Diffuse Radiation, and Azimuth. Based on this ranking, Net Radiation, Reflective Radiation, Solar Altitude, and DNI were used in M-LSTM-4, while M-LSTM-6 retained all six candidate predictors.

2.5 LSTM and M-LSTM Architecture

LSTM was used as the baseline model with one input feature, namely historical GHI observations. The M-LSTM models used either four or six ASRS predictor variables as input features, with GHI as the prediction target. Both models employed the same stacked LSTM architecture consisting of two LSTM layers with 64 units each. The first LSTM layer used `return_sequences=True` to pass the output sequence to the subsequent LSTM layer. A dropout layer with a rate of 0.2 was applied after each LSTM layer to reduce overfitting. The final output was generated using a dense layer with one neuron and linear activation. The model configuration was adopted from the stacked LSTM approach reported by Tsai and Lo [22], with adaptations to the present GHI forecasting task.

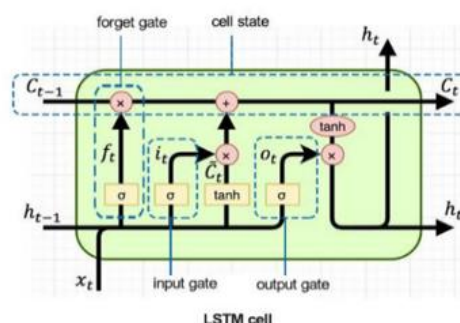


Figure 3. Basic LSTM mechanism

Figure 3 illustrates the basic LSTM mechanism used to process sequential information. The LSTM unit consists of a cell state and three gates: forget, input, and output gates. These components regulate the information retained, updated, and passed to the next timestep, enabling the model to learn temporal dependencies in sequential GHI data.

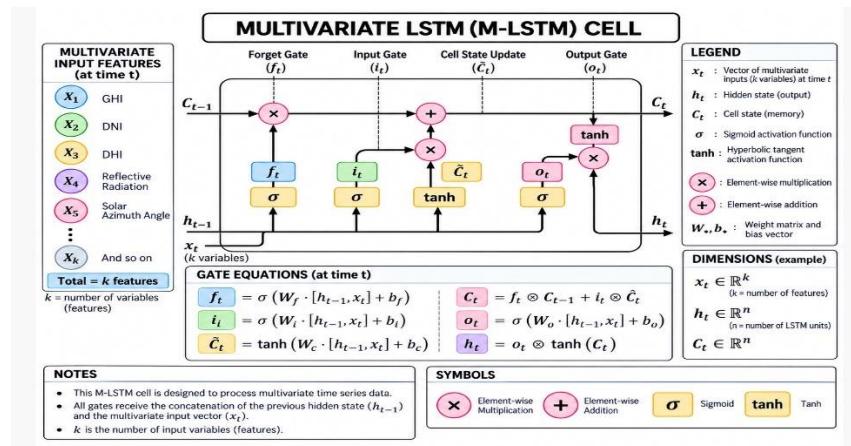


Figure 4. M-LSTM architecture

Figure 4 illustrates the M-LSTM architecture used in this study. The model consists of two stacked LSTM layers with 64 units in each layer, followed by dropout layers with a rate of 0.2 and a final dense layer with one neuron. For M-LSTM-4, four predictor variables were provided at each timestep, whereas M-LSTM-6 used six predictor variables. The model generated a single output representing the predicted GHI value for the subsequent timestep, corresponding to the 30-minute-ahead forecasting horizon (T+30).

The LSTM mechanism uses a *forget gate*, *input gate*, *cell state*, and *output gate*. The main equations used to describe these mechanisms are as follows:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (6)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (7)$$

$$C_t = \tanh(W_C[h_{t-1}, x_t] + b_C) \quad (8)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot C_t \quad (9)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (10)$$

$$h_t = o_t \odot \tanh(C_t) \quad (11)$$

In the M-LSTM models, x_t represents a vector containing either four or six predictor variables at each timestep, whereas in the LSTM model, x_t contains only historical GHI observations. This difference in input configuration allows the evaluation of multivariate information while maintaining the same network capacity.

2.6 Training Configuration and Evaluation

Table 5. LSTM and M-LSTM model configuration

Parameter	Value
Architecture	Stacked LSTM
LSTM layers	64 + 64 units
Dropout	0.2 after each LSTM layer
Dense	1 neuron, linear
Optimizer	Adam
Learning rate	0.001
Loss	MSE
Epoch	100
Batch size	128
Window	12, 24, 36
Horizon	T+30

Table 5 presents the training configuration and forecasting settings used for both the LSTM and M-LSTM models. The models used the same architecture and training parameters to ensure a consistent comparison. Three sliding-window lengths were evaluated, namely 12, 24, and 36 timesteps, corresponding to 6, 12, and 18 hours of historical observations, respectively. The forecasting horizon was fixed at T+30, representing GHI prediction 30 minutes after the end of the input sequence. The *training loss function* uses Mean Squared Error (MSE).

$$MSE = (1/n)\sum(y_i - \hat{y}_i)^2 \quad (12)$$

After predictions were returned to their original units through inverse scaling, model performance was evaluated using MAE, RMSE, and R^2 . MAE measures the mean absolute error, RMSE assigns greater penalties to large errors, and R^2 measures the proportion of target variation explained by the model.

$$MAE = (1/n)\sum|y_i - \hat{y}_i| \quad (13)$$

$$RMSE = \sqrt{(1/n)\sum(y_i - \hat{y}_i)^2} \quad (14)$$

$$R^2 = 1 - [\sum(y_i - \hat{y}_i)^2 / \sum(y_i - \bar{y})^2] \quad (15)$$

MAE measures the average absolute difference between observed and predicted GHI values, while RMSE gives greater weight to larger prediction errors. R^2 measures the proportion of variation in GHI explained by the model. Lower MAE and RMSE values indicate smaller prediction errors, whereas a higher R^2 indicates better explanatory performance. Evaluation was performed for three evaluation periods: the full-year dataset, the dry season, and the wet season. The same model configurations and evaluation metrics were applied to each period to enable comparison of forecasting performance under different seasonal conditions.

3. RESULTS AND DISCUSSION

The test results of the LSTM, M-LSTM-4, and M-LSTM-6 models were analyzed using three sliding-window sizes, namely 12, 24, and 36 timesteps, for the full-year, dry-season, and wet-season periods. Model performance was evaluated using MAE, RMSE, and R^2 based on 30-minute-ahead GHI (GHI T+30) forecasts.

3.1 Overall Forecasting Performance

The forecasting performance of the univariate LSTM and multivariate LSTM (M-LSTM) models was evaluated across the full-year, wet-season, and dry-season datasets. The M-LSTM model was examined using two input configurations consisting of four and six predictor variables. All configurations were evaluated using sliding-window lengths of 12, 24, and 36 timesteps for the 30-minute-ahead forecasting horizon. Model performance was assessed using MAE, RMSE, and R^2 .

Table 6. Overall forecasting performance of LSTM and M-LSTM models

Period	Window	Model	MAE (W/m ²)	RMSE (W/m ²)	R^2
Full Year	12	LSTM	41.42	83.35	0.92
Full Year	12	M-LSTM-4	43.173	81.598	0.9231
Full Year	12	M-LSTM-6	37.7	79.34	0.9283
Full Year	24	LSTM	41.25	82.4	0.9216
Full Year	24	M-LSTM-4	45.178	82.618	0.9212
Full Year	24	M-LSTM-6	65.83	101.74	0.8823
Full Year	36	LSTM	39.77	82.19	0.9222
Full Year	36	M-LSTM-4	43.969	81.764	0.9228
Full Year	36	M-LSTM-6	63.44	101.69	0.8827
Wet Season	12	LSTM	65.31	107.56	0.8801
Wet Season	12	M-LSTM-4	43.012	81.129	0.9313
Wet Season	12	M-LSTM-6	58.16	102.72	0.891
Wet Season	24	LSTM	63.61	106.15	0.8833
Wet Season	24	M-LSTM-4	42.859	80.16	0.933
Wet Season	24	M-LSTM-6	77.08	102.3	0.8911
Wet Season	36	LSTM	61.85	107.71	0.8799
Wet Season	36	M-LSTM-4	36.551	77.228	0.9378
Wet Season	36	M-LSTM-6	68.25	94.34	0.9078
Dry Season	12	LSTM	52.16	97.45	0.915
Dry Season	12	M-LSTM-4	51.94	85.786	0.9339
Dry Season	12	M-LSTM-6	72.09	139.96	0.8244
Dry Season	24	LSTM	49.69	98.06	0.9143
Dry Season	24	M-LSTM-4	40.485	79.173	0.9437
Dry Season	24	M-LSTM-6	137.05	223.67	0.553
Dry Season	36	LSTM	51.18	98.94	0.9112
Dry Season	36	M-LSTM-4	39.181	78.059	0.9454
Dry Season	36	M-LSTM-6	164.03	272	0.3416

Table 6 presents the complete forecasting performance of the LSTM, M-LSTM-4, and M-LSTM-6 models across the full-year, wet-season, and dry-season datasets. The results show that model performance varied according

to the seasonal period, sliding-window length, and number of input variables. The lowest MAE and RMSE values and the highest R^2 values within each experimental setting indicate better forecasting performance.

For the full-year dataset, the best overall result was obtained by M-LSTM-6 using a 12-timestep window, with an MAE of 37.700 W/m², an RMSE of 79.340 W/m², and an R^2 of 0.9283. However, this advantage was not maintained when the historical window was extended. At the 24-timestep window, the MAE and RMSE increased to 65.830 W/m² and 101.740 W/m², respectively, while R^2 decreased to 0.8823. A similar pattern was observed at the 36-timestep window, with an MAE of 63.440 W/m², RMSE of 101.690 W/m², and R^2 of 0.8827. This indicates that increasing the amount of historical information did not provide additional predictive benefit for the six-variable configuration. For the wet-season dataset, M-LSTM-4 consistently achieved the best performance across all evaluated window lengths. The best wet-season result was obtained using a 36-timestep window, with an MAE of 36.551 W/m², an RMSE of 77.228 W/m², and an R^2 of 0.9378. These results indicate that the reduced multivariate configuration was more effective than both the univariate LSTM and the six-variable M-LSTM under wet-season conditions. A similar pattern was observed for the dry-season dataset. M-LSTM-4 achieved the strongest performance, particularly at the 36-timestep window, with an MAE of 39.181 W/m², an RMSE of 78.059 W/m², and an R^2 of 0.9454. In contrast, M-LSTM-6 showed considerable performance degradation as the window length increased. The poorest result was observed for M-LSTM-6 with a 36-timestep window, which produced an MAE of 164.030 W/m², an RMSE of 272.000 W/m², and an R^2 of 0.3416.

Overall, the results demonstrate that the effectiveness of multivariate input information depended on the combination of predictor variables, historical window length, and evaluation period. The univariate LSTM also achieved competitive performance, particularly for the full-year dataset, indicating that historical GHI observations contain substantial temporal information for 30-minute-ahead forecasting. This finding is consistent with previous studies reporting the effectiveness of LSTM-based approaches for short-term solar irradiance forecasting [11], [22]

Overall, Table 6 demonstrates that increasing the number of predictor variables or extending the historical window did not automatically improve GHI forecasting performance. The contrasting responses of M-LSTM-4 and M-LSTM-6 indicate that the usefulness of historical information depended on the input configuration. M-LSTM-4 benefited from the 36-timestep window during both seasonal periods, whereas M-LSTM-6 achieved its best full-year performance using the shorter 12-timestep window and deteriorated at longer windows. This result indicates that a larger input configuration is not necessarily advantageous when combined with a longer historical sequence. However, the observed degradation should not be attributed conclusively to overfitting or curse of dimensionality based solely on test-set metrics. The results instead provide empirical evidence that predictor complexity and historical window length should be optimized jointly for short-term GHI forecasting.

3.2 Effect of Input Variable Complexity

The comparison between LSTM, M-LSTM-4, and M-LSTM-6 was conducted to evaluate whether increasing input-variable complexity improved GHI forecasting performance. The univariate LSTM used historical GHI as the input, whereas M-LSTM-4 and M-LSTM-6 used four and six predictor variables, respectively. Figure 5 presents the MAE, RMSE, and R^2 values for the three model configurations across different window lengths under full-year, wet-season, and dry-season conditions. Overall, the results indicate that increasing the number of input variables did not consistently lead to improved forecasting performance.

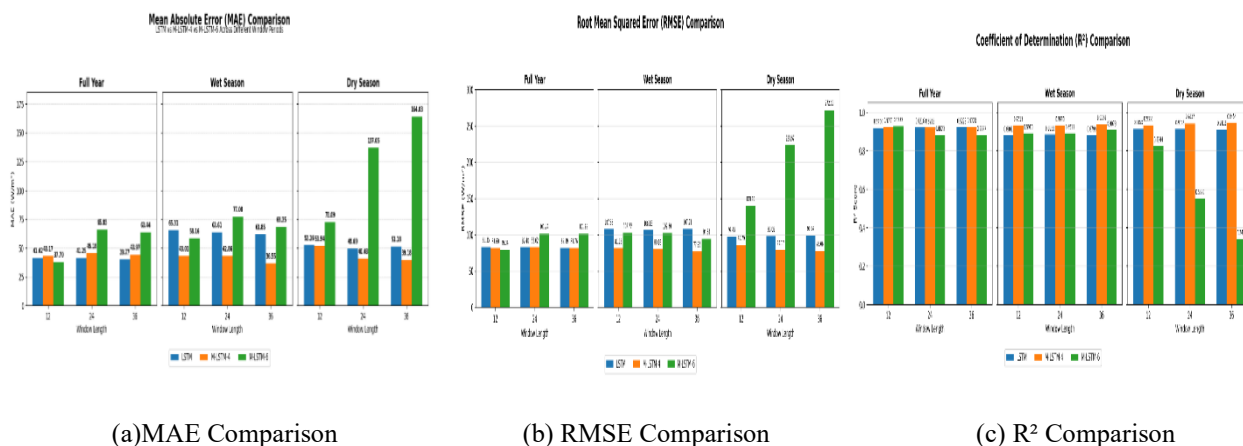


Figure 5. Performance comparison of LSTM, M-LSTM-4, and M-LSTM-6 across different input configurations, window lengths, and seasonal periods based on (a) MAE, (b) RMSE, and (c) R^2 .

Figure 5 illustrates the effect of input-variable complexity on forecasting performance. The three panels compare the models based on MAE, RMSE, and R^2 , where lower MAE and RMSE and higher R^2 indicate better performance. The figure shows that the relationship between the number of input variables and forecasting accuracy was not consistent across window lengths and seasonal periods.

For the full-year dataset, M-LSTM-6 achieved the best individual result at the 12-timestep window, with an MAE of 37.700 W/m², RMSE of 79.340 W/m², and R² of 0.9283. This configuration outperformed both LSTM and M-LSTM-4 at the same window length. However, its performance was not maintained at longer windows. At the 24- and 36-timestep windows, the LSTM baseline achieved the lowest MAE values of 41.250 W/m² and 39.770 W/m², respectively, while M-LSTM-6 showed substantial increases in prediction errors. M-LSTM-4 provided relatively stable performance across the three window lengths.

The benefit of the four-variable configuration was more evident in the seasonal datasets. During the wet season, M-LSTM-4 consistently outperformed both LSTM and M-LSTM-6 and achieved its best performance at the 36-timestep window, with an MAE of 36.551 W/m², RMSE of 77.228 W/m², and R² of 0.9378. A similar pattern was observed during the dry season, where M-LSTM-4 achieved the best overall performance at the 36-timestep window, with an MAE of 39.181 W/m², RMSE of 78.059 W/m², and R² of 0.9454. In contrast, M-LSTM-6 exhibited substantial performance degradation during the dry season as the window length increased.

The differences in performance indicate that the effect of input-variable complexity was dependent on the historical sequence length and evaluation period. The Pearson correlation analysis in Table 4 showed that several radiation-related predictors had strong relationships with GHI. Therefore, including additional predictors does not necessarily provide proportional predictive benefit. The combination of six predictor variables with longer historical sequences also resulted in a larger input representation. For example, at the 36-timestep window, each sequence contained 36 input values for the univariate LSTM, 144 input values for M-LSTM-4, and 216 input values for M-LSTM-6. This indicates that increasing both the number of predictors and the historical window substantially increased the amount of information processed by the model.

The results therefore suggest that the four-variable configuration provided a more favorable balance between predictor information and input complexity for the seasonal datasets. However, the poorer performance of M-LSTM-6 at longer windows should not be interpreted conclusively as overfitting based solely on the prediction metrics. Additional evidence from training and validation loss behavior is required to assess model convergence and training stability.

To further examine the learning behavior of the best-performing configurations, Figure 6 presents the training and validation loss curves for M-LSTM-6 with Window 12 for the full-year dataset and M-LSTM-4 with Window 36 for both the wet- and dry-season datasets. The loss curves show convergence during training, with training and validation losses decreasing during the initial epochs and subsequently becoming relatively stable. Overall, M-LSTM-6 achieved the best individual full-year result under the shortestest window, whereas M-LSTM-4 provided the best and most consistent performance across the seasonal datasets. These findings indicate that input-variable complexity and window length should be optimized jointly rather than assuming that additional variables will automatically improve forecasting accuracy.

Training and Validation Loss of M-LSTM Models Across Different Data Periods

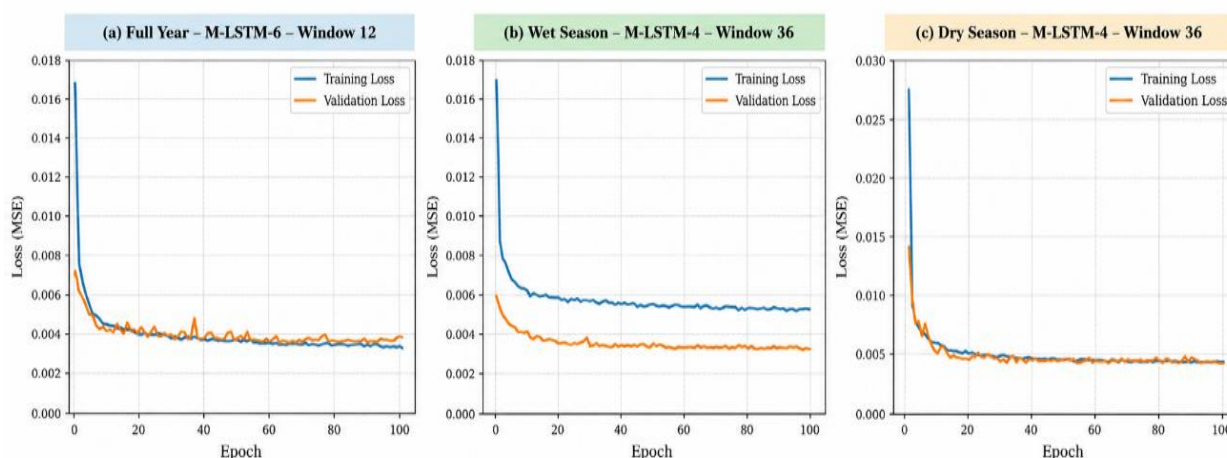


Figure 6. Training and validation loss curves of the best-performing models for (a) Full Year M-LSTM-6 with Window 12, (b) Wet Season M-LSTM-4 with Window 36, and (c) Dry Season M-LSTM-4 with Window 36.

Figure 6 illustrates the training and validation behavior of the best-performing configurations identified in Table 6. The results show that M-LSTM-6 performed best with the shortestest window for the full-year dataset, while M-LSTM-4 performed best with the 36-timestep window for both seasonal datasets.

3.3 Effect of Sliding-Window Length

The effect of sliding-window length varied across the model configurations and seasonal periods. For the LSTM model, longer windows generally provided comparable or slightly improved performance, particularly for the full-year dataset, where the lowest MAE of 39.770 W/m² was obtained using the 36-timestep window.

Effect of Sliding-Window Length on MAE Performance

Across Different Model Configurations and Evaluation Periods

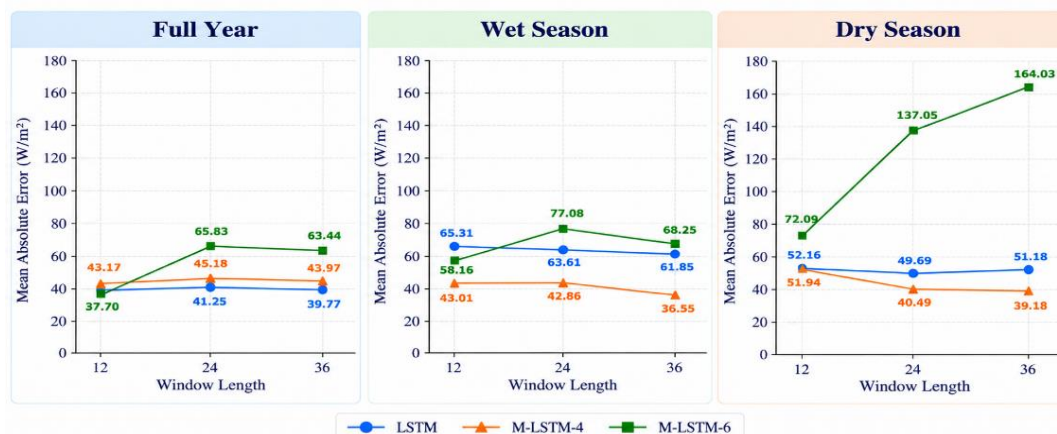


Figure 7. Effect of sliding-window length on MAE performance across different model configurations and evaluation periods.

Figure 7 illustrates the effect of increasing the amount of historical information on forecasting error. Lower MAE values indicate better forecasting performance. The results show that the effect of window length was not uniform across the three model configurations or evaluation periods.

For M-LSTM-4, longer windows were particularly beneficial during the wet and dry seasons. The best performance was obtained at the 36-timestep window, with MAE values of 36.551 W/m² and 39.181 W/m² for the wet and dry seasons, respectively. In contrast, M-LSTM-6 did not benefit consistently from longer windows and showed substantial performance degradation, particularly during the dry season.

Overall, Figure 7 shows that increasing the amount of historical information did not automatically improve GHI forecasting performance. Longer windows were beneficial for M-LSTM-4 during seasonal forecasting but were less effective for M-LSTM-6, which used a larger number of input variables. This finding is consistent with previous studies indicating that the optimal historical window depends on the characteristics of the data and model configuration [13]. Therefore, the window length and number of input variables should be optimized jointly.

3.4 Seasonal Performance Analysis

The forecasting results showed differences between the full-year, wet-season, and dry-season datasets. Figure 8 presents the seasonal performance comparison of LSTM, M-LSTM-4, and M-LSTM-6 based on the best MAE obtained for each model.



Figure 8. Seasonal performance comparison of LSTM, M-LSTM-4, and M-LSTM-6 based on the best MAE obtained for each model.

Figure 8 illustrates the differences in the best forecasting performance across the evaluation periods. M-LSTM-4 provided the most consistent performance across the seasonal datasets. During the wet season, its best performance was obtained using the 36-timestep window, with an MAE of 36.551 W/m² and an R² of 0.9378. Similarly, during the dry season, M-LSTM-4 achieved its best result using the 36-timestep window, with an MAE of 39.181 W/m² and an R² of 0.9454.

In contrast, M-LSTM-6 showed greater sensitivity to seasonal conditions and window length. Its performance decreased substantially during the dry season as the window length increased, whereas the LSTM model remained relatively stable across the three window configurations. Seasonal atmospheric characteristics can influence solar irradiance variability and consequently affect the usefulness of additional input information in forecasting models [16], [23].

Overall, the seasonal experiments demonstrate that separating the data by season can result in different optimal forecasting configurations. M-LSTM-4 showed the most consistent performance across the wet and dry seasons, whereas M-LSTM-6 achieved the best full-year MAE but showed greater sensitivity to seasonal conditions.

3.5 Best Model Configurations

The overall experimental results showed that the optimal forecasting configuration varied across the full-year, wet-season, and dry-season datasets. All evaluated LSTM and M-LSTM configurations were compared using MAE, RMSE, and R^2 . The final configurations were selected based on the combined performance ranking across these three evaluation metrics. Table 7 summarizes the best overall forecasting configuration for each evaluation period.

Table 7. Best forecasting configuration for each evaluation period

Period	Best Model	Best Window	Input Variables	MAE (W/m ²)	RMSE (W/m ²)	R^2	Total Rank Score
Full Year	M-LSTM-6	12	6	37.7	79.34	0.9283	3
Wet Season	M-LSTM-4	36	4	36.551	77.228	0.9378	3
Dry Season	M-LSTM-4	36	4	39.181	78.059	0.9454	3

Table 7 presents the best forecasting configuration for each evaluation period. The full-year dataset achieved its best performance using M-LSTM-6 with a 12-timestep window, whereas both seasonal datasets achieved their best performance using M-LSTM-4 with a 36-timestep window. The wet-season configuration produced the lowest MAE and RMSE, while the dry-season configuration achieved the highest R^2 . These results indicate that the optimal combination of input variables and historical information depended on the evaluation period.

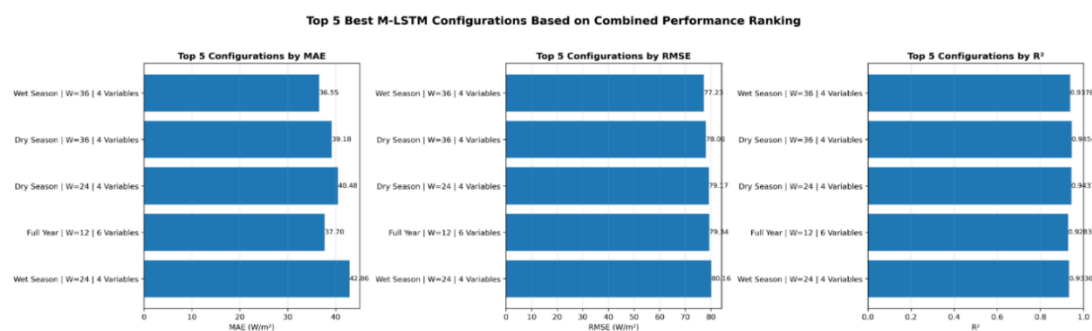


Figure 9. Top five M-LSTM configurations based on combined performance ranking across the full-year, wet-season, and dry-season datasets according to (a) MAE, (b) RMSE, and (c) R^2 .

Figure 9 summarizes the five best M-LSTM configurations based on the combined performance ranking. The results show that the optimal configuration differed across the three evaluation periods. The full-year dataset achieved its best performance using six input variables and a 12-timestep window, whereas the wet- and dry-season datasets achieved better results using four input variables and longer historical windows. This finding further confirms that the optimal combination of input complexity and window length depends on seasonal characteristics and should therefore be evaluated jointly.

The prediction performance was further examined using representative one-week periods. Figure 10 compares the actual and predicted GHI values for the best configuration of each dataset. Overall, the predicted values followed the main temporal patterns of the observed GHI, although differences were still visible during rapid fluctuations and peak irradiance periods. These results further demonstrate that the optimal forecasting configuration varied according to the characteristics of each evaluation period.

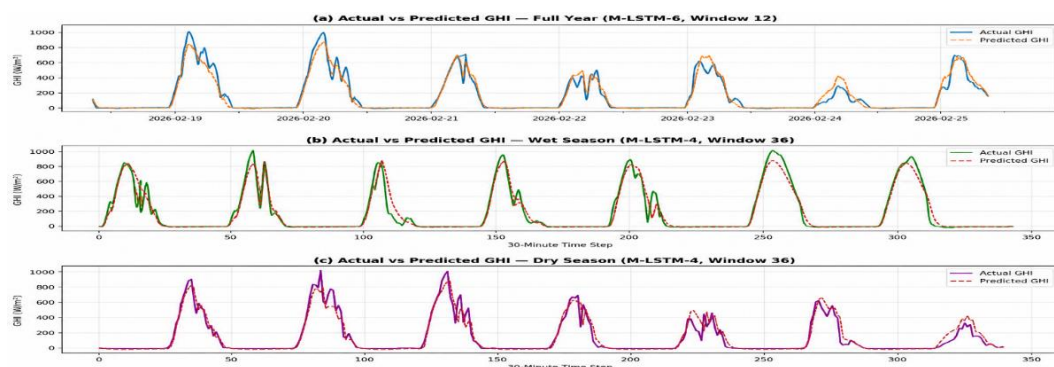


Figure 10. Comparison between actual and predicted GHI values for representative one-week periods using the best forecasting configuration for (a) the full-year dataset, (b) the wet season, and (c) the dry season.

Figure 10 illustrates the agreement between the observed and predicted GHI patterns for the selected representative periods. The models were generally able to capture the temporal variation of GHI, while larger deviations occurred during rapid changes and high-irradiance periods. These visual comparisons complement the quantitative evaluation presented in Table 7 by showing how the selected models reproduced the temporal dynamics of GHI.

3.6 Discussion

The experimental results reveal that the effect of multivariate information on GHI forecasting was conditional on the interaction between input-variable complexity, sliding-window length, and evaluation period. Rather than showing a consistent advantage from using more predictors, the results indicate that different combinations of input variables and historical information were optimal for different datasets. The full-year dataset achieved its best performance using M-LSTM-6 with a 12-timestep window, whereas both wet- and dry-season datasets achieved their best performance using M-LSTM-4 with a 36-timestep window. This pattern suggests that predictor complexity and historical sequence length should be considered jointly when developing short-term GHI forecasting models [11], [21].

The seasonal results provide further insight into the role of predictor selection. M-LSTM-4, which consisted of Net Radiation, Reflective Radiation, Solar Altitude, and DNI, consistently achieved the best performance in both seasonal datasets. Its best configuration used the 36-timestep window, achieving an MAE of 36.551 W/m² in the wet season and 39.181 W/m² in the dry season. These variables were also the four predictors with the strongest Pearson correlations with GHI. The consistency of this configuration across both seasons indicates that the selected high-correlation predictors were effective for seasonal GHI forecasting under the evaluated conditions. This finding is consistent with previous studies emphasizing the importance of appropriate feature selection and input configuration in solar irradiance forecasting [13], [22], [23].

A notable finding was the contrasting response of M-LSTM-6 to increasing window length. Although M-LSTM-6 produced the best full-year result at the 12-timestep window, its performance deteriorated substantially when longer historical sequences were used. The degradation was particularly pronounced during the dry season, where its MAE increased from 72.090 W/m² at window 12 to 137.050 W/m² and 164.030 W/m² at windows 24 and 36, respectively. In contrast, M-LSTM-4 showed the opposite tendency during the dry season, with MAE decreasing from 51.940 W/m² at window 12 to 40.485 W/m² and 39.181 W/m² at windows 24 and 36. This contrasting response indicates that the usefulness of additional historical information depended on the input-variable configuration rather than on window length alone [15], [16].

The observed pattern can be interpreted in relation to input dimensionality. At each timestep, M-LSTM-6 processes six predictor variables, so extending the window increases the sequence representation from 72 input values at window 12 to 144 and 216 input values at windows 24 and 36. In comparison, M-LSTM-4 processes 48, 96, and 144 input values for the same windows. The results suggest that adding predictors together with a longer historical sequence may not necessarily provide additional independent predictive information. However, the present results do not allow the degradation of M-LSTM-6 to be attributed conclusively to overfitting or redundancy, because such conclusions would require additional evidence from training-validation behavior. Instead, the findings demonstrate empirically that higher input dimensionality was not consistently advantageous under the evaluated seasonal conditions.

Overall, the main contribution of this study is the identification of a condition-dependent relationship between predictor complexity and historical window length in 30-minute-ahead GHI forecasting. The full-year dataset benefited from a higher-dimensional input configuration combined with a short historical window, while both seasonal datasets favored a smaller, highly correlated predictor set combined with a longer historical window. This result indicates that the optimal forecasting configuration is not universal and should be determined according to the temporal and seasonal characteristics of the dataset. Such configuration-specific evaluation provides a more informative basis for GHI forecasting than assuming that either additional predictors or longer historical windows will inherently improve model performance.

4. CONCLUSION

This study compared univariate LSTM and multivariate LSTM models for 30-minute-ahead GHI forecasting using different input configurations and sliding-window lengths across full-year, wet-season, and dry-season datasets. The results demonstrate that the optimal forecasting configuration varied according to the evaluation period and the interaction between input-variable complexity and historical window length. For the full-year dataset, the best performance was achieved by M-LSTM-6 using a 12-timestep window, with an MAE of 37.700 W/m², an RMSE of 79.340 W/m², and an R² of 0.9283. In contrast, both seasonal datasets achieved their best performance using M-LSTM-4 with a 36-timestep window. The wet-season model achieved an MAE of 36.551 W/m², an RMSE of 77.228 W/m², and an R² of 0.9378, while the dry-season model achieved an MAE of 39.181 W/m², an RMSE of 78.059 W/m², and an R² of 0.9454. A key finding of this study is the contrasting response of the four- and six-variable configurations to historical window length. M-LSTM-6 achieved the best full-year performance with the shortest 12-timestep window,

but its performance deteriorated substantially with longer windows, particularly during the dry season. In contrast, M-LSTM-4 consistently benefited from the longer 36-timestep window in both wet- and dry-season forecasting. The four predictors in M-LSTM-4 Net Radiation, Reflective Radiation, Solar Altitude, and DNI were also the predictors with the strongest Pearson correlations with GHI. This consistent seasonal performance suggests that the effectiveness of predictor information depended not only on the number of variables but also on how much historical information was provided to the model. These results provide a more specific insight than simply showing that additional variables do not always improve accuracy: predictor complexity and historical window length exhibited different optimal combinations under full-year and seasonal conditions. The full-year dataset favored a higher-dimensional input with a shorter historical window, whereas both seasonal datasets favored a smaller set of strongly correlated predictors with a longer historical window. Therefore, for short-term GHI forecasting in the evaluated tropical setting, model configuration should be determined jointly based on predictor composition, historical window length, and seasonal characteristics rather than by increasing input variables alone.

5. DECLARATIONS

5.1 Author Contributions

Conceptualization: R.K., and T. C.;

Methodology: R. K., and M. F.;

Software: R. K., and T. C.;

Validation: R.K., and M. A. Y.;

Formal Analysis: R. K., and M. I.;

Investigation: R.K., and T. C.;

Resources: R. K., and M. F.;

Data Curation: R.K.;

Writing Original Draft Preparation: R.K., and M. I.;

Writing Review and Editing: R. K., and M. A. Y.;

Visualization: R. K., M. F., and T. C.;

5.2 Data Availability

The data used in this study were obtained from the East Java Climatology Station (Stasiun Klimatologi Jawa Timur) and are available upon request, subject to the data access policy of the institution.

5.3 Funding

This research received no external funding and was fully funded by the authors' personal funds.

5.4 Institutional Review Board Statement

Not applicable.

5.5 Informed Consent Statement

Not applicable.

5.6 Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

5.7 Generative AI and AI-assisted Technologies in The Writing Process

The authors used Generative AI to improve the writing clarity of this paper. They reviewed and edited the AI-assisted content and took full responsibility for the final publication.

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