



# FORECASTING SOLAR RADIATION FROM OTHER METEOROLOGICAL FACTORS FOR RENEWABLE ENERGY SUSTAINABILITY IN OGUN STATE: A PANEL DIHYBRID RECURRENT NEURAL NETWORK APPROACH

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ISSN: 3121-9837

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## History:

Volume 1, Number 1  
Published: 20/04/2026

## Keywords:

Covariate shift analysis, Deep learning, Gated Recurrent Unit (GRU), Time-series modeling, Solar radiation forecasting, Renewable energy prediction

## ABSTRACT

Proper forecasting of solar radiation is crucial in the optimization of photovoltaic systems, integration into the grid and planning renewable energy systems in tropical areas that have high climatic variability. This paper compares the predictive efficacy and construction strength of three dihybrid deep learning models, namely, CNN/LSTM, CNN/GRU, and CNN/LSTM/GRU, in the daily prediction of solar radiation in Ogun State, Nigeria. Model assessment was conducted using long-term meteorological data and goes beyond traditional measures of accuracy to include blocked cross-validation, Monte Carlo perturbation testing, seed sensitivity analysis, and Population Stability Index (PSI) evaluation to identify covariate drift between the training and validation timeframes. The three architectures had high performance in terms of their explanatory ability ( $R^2 \approx 0.99$ ), but there were significant differences under robustness and stability diagnostics. The CNN/GRU model had the lowest Root Mean Square Error (RMSE) as well as Mean Absolute Error (MAE), a better temporal generalization as indicated by rolling validation, and low sensitivity to random initialization. Despite slightly elevated stochastic perturbation resistance in the deeper CNN/LSTM/GRU configuration, it failed to transfer into a better baseline predictive accuracy and had a higher optimization variability. The PSI outcomes indicated that there was a significant distributional change that was mainly in long-term trend, evaporation, and relative humidity variables, which were indicative of moderate climatic non-stationarity. In spite of this drift, CNN/GRU architecture shows more predictive stability. Parsimonious dihybrid models are optimally accurate, stable and efficient in forecasting tropical solar radiation time series.

## 1. INTRODUCTION

The world energy structure is experiencing a major change that is informed by the rising energy needs, the increasing effects of climate change and the necessity to diminish overreliance on fossil fuels. This has led renewable energy to take center stage in the strategies of sustainable energy production in the world. The solar power is considered one of the cleanest and the most numerous sources of energy among renewable ones (Kalogirou, 2014; International Energy Agency, 2022). Nonetheless, successful integration of solar energy with

the existing electricity systems entails proper estimation and prediction of the solar radiance. Accurate predictions of solar radiation are necessary to optimise the design of photovoltaic systems, enhance integration of systems into the grid and aid in long-term energy planning. The effects of cloud formation, concentration of aerosols, humidity, fluctuation of temperatures, and precipitation, are complex atmospheric processes that affect the solar radiation. This nonlinearity, stochasticity, and time-



dependency of solar radiation time series render them extremely difficult to forecast (Voyant *et al.*, 2017). This variability is further exaggerated in the tropical areas like sub-Saharan Africa; strong seasonal variability, convective atmospheric cycles, and wet-dry climatic patterns of alternating climate contribute greatly to the variability of solar radiation distribution. Historical methods of estimating solar radiation were the Angstrom-Prescott equations and sunshine-based regression models which utilised traditional empirical methods. These models are helpful but as is common, they rely on linear associations and thus do not capture the nonlinear atmospheric processes that are characteristic of tropical climates (Ahmed *et al.*, 2020).

Nigeria has a high potential on solar energy yet it still experiences lasting electricity deficiency. Nigeria is the most populated nation in Africa and this factor presents chronic power supply because of insufficient capacity of the grid and high dependency on generators that use fossil fuel. There are significant economic, environmental, and health impacts of this dependence. Solar energy has now made it into the major part of renewable energy transition strategy in Nigeria. Ogun State is a region in southwestern Nigeria and a neighbour to Lagos State whose industrial and residential development has evolved at a high growth rate over the past years. The area has a wet- dry tropical climate and a high potential of solar energy. Nevertheless, the ground-based measurements of the amount of solar radiation are sparse, intermittent, and spatially non-congruent (Ohunakin *et al.*, 2014) and new measurements have

to be made over years, which makes the design of photovoltaic systems and energy planning prone to uncertainty.

Where the direct solar radiation is not available, radiations can be predicted based on variables that are normally recorded by the meteorologist including temperature, relative humidity, rain, wind speed, sunshine duration and evapotranspiration. This is an indirect method that is cheaper to use compared to radiometric measurements, however, the nonlinear relationships between these variables make proper modeling difficult. Classical statistical methods have served the climate research well in determining patterns, trends, and the variability of the atmospheric data. Time series analysis, spectral analysis, empirical orthogonal functions (EOFs), and singular spectrum analysis (SSA) are some of the commonly used techniques in the study of climatic variability and atmospheric dynamics (Storch and Navarra, 1995; Wilks, 2006; Wilks, 2011; Storch and Zwiers, 2001). These techniques can still be used in the pre-processing and interpretation of data.

Nevertheless, regression-based and empirical models tend to assume that there are linear relationships between meteorology factors and solar radiation, which restrict them to nonlinear climatic interactions. Empirical models, such as sunshine duration and temperature have been found to give viable estimates in Nigeria, but their efficiency heavily relies on model specification and the specifics of the local climatic conditions (Akpootu, Tijjani, and Gana, 2019). The use of machine learning techniques in the



prediction of solar radiation thus has been on the rise. Artificial Neural Networks (ANNs) have shown high predictive efficiency in comparison to most of the conventional statistical models but the predictive performance relies on the selection of input variables, training algorithms and network structure (Yadav and Chandel, 2014).

Recent developments of artificial intelligence and deep learning have contributed even more complexity and temporal nonlinear relationships modeling in the meteorological data. Time-series prediction Time-series prediction has been demonstrated to be particularly effective based on Recurrent Neural Networks (RNNs), specifically the Long Short-Term Memory (LSTM) and the Gated Recurrent Unit (GRU) architectures, as they are able to capture the long-term dependencies and address the issue of the vanishing gradient problem (Hochreiter and Schmidhuber, 1997; Cho et al., 2014; Goodfellow et al., 2016). It has been empirically proven that models which are based on LSTM can effectively predict solar radiation. Indicatively, Abayomi et al. (2019) have reported good predictive capability of LSTM models in Nigeria. Recent research has also investigated standalone and hybrid recurrent neural network designs, with hybrid models showing a higher level of accuracy and fewer forecasting errors (Alabi and Ojo, 2024; Alabi and Ojenike, 2024).

There are also dihybrid deep learning models that combine Convolutional Neural Networks (CNNs) and recurrent networks which are applied in the field

of solar radiation forecasting. In such architectures, CNN layers learn feature patterns of meteorological inputs and recurrent layers learn time-based dependencies (Ladjal *et al.*, 2025). Outside the predictive effectiveness, other implications of artificial intelligence in climate science have been mentioned. Cows *et al.* (2023) also emphasize the two-fold nature of AI in climate mitigation and adaptation due to its positive analytical capabilities as well as its negative impact on computational energy usage and the environment. With increasing research, there is still a scarcity of explicit comparative studies on hybrid deep learning systems assessed using long-term meteorological in tropical African context (Yadav and Chandel, 2014). To fill this gap, the current paper formulates and critically tests dihybrid deep learning models to predict the amount of daily solar radiations in Ogun State, Nigeria. Modern meteorological data is used in 1994-2024 and model performance is evaluated through the evaluation of Root Mean square error (RMSE), mean absolute error (MAE) and coefficient of determination ( $R^2$ ). The results are likely to provide more effective photovoltaic system design, grid integration planning, and renewable energy policy development in accordance with the Sustainable Development Goals (United Nations, 2015).

## 2.0 MATERIALS AND METHODS

### 2.1 Materials

The meteorological variables used in this study include solar radiation (sr), temperature (temp), relative humidity (rh), sunshine hours (sh), evaporation (ep), wind speed (ws), and rainfall (rf).



These variables represent key atmospheric processes influencing solar radiation dynamics. The dataset contains approximately 8,066 daily observations. In order to maintain the temporal causality, the dataset was divided in chronological order. Eighty percent of observations were trained on the model and the remaining twenty percent comprised of the hold-out validation set. In this way, there will be no information leakage and the future observations will never be used to explain past values. In order to further evaluate robustness, blocked cross-validation was used. The variability and predictability of solar radiation is one key concept to the development of reliable solar energy systems. Solar radiation time series are generally non-stationary, seasonal, and are affected by a variety of interacting climatic factors including temperature, humidity, cloud cover, wind speed, and precipitation. The conventional forecasting techniques have proven to be insufficient to capture these complicated relations, which has led to studies on data-driven models, especially deep learning models that have the ability to learn nonlinear relationships and long-term trends. The section is a review of theoretical and application literature in the area of solar radiation prediction, with a focus on the modern machine and deep learning techniques such as CNNs, RNNs, and their variants. This paper has a dihybrid recurrent neural network structure that incorporates pure RNN structure (LSTM, GRU) variants, and CNN-aided recurrent dihybrid, multi-stage dihybrid variants. The CNN elements are considered as feature extractors into the recursive forecasting framework. The dihybrid used in this work is a combination of two complementary deep learning

models convolutional and recurrent networks into a single forecasting model. To guarantee the methodological rigor and eliminate the model-selection bias, several recurrent architectures and hybrid recurrent architectures were tested in the same preprocessing and validation conditions.

## 2.2 Methods

### 2.2.1 Machine Learning Methods for Solar Forecasting

The initial models used to approximate solar radiations were mainly based on the physical features of the solar geometry and some proxies in meteorology like sunshine time. Angstrom Prescott formulation of one of the classical models correlates measured global solar radiation  $G$  with sunshine duration  $S$  and extraterrestrial radiation. Even though they are simple and common, these empirical models are not always flexible to measurably nonlinear atmospheric processes, particularly in changing cloud conditions, and in tropical climates where seasonal precipitation and convection affect solar irradiance (Yorukoglu & Celik, 2006). The statistical time series models (AutoRegressive Integrated Moving Average ARIMA models) explicitly represent autocorrelation structures but are based on linear relationships and stationarity, which is not applicable with a complex meteorological data (Box et al., 2015). Such constraints have prompted scholars to research data-driven and machine learning solution.

Support Vector Regression (SVR), Random Forest (RF), and Artificial Neural Networks (ANNs) are machine learning (ML) modeling approaches that have been implemented in solar forecasting with



varying levels of success because they can model the nonlinear relationships.

As an example, random forest and SVR models have been demonstrated to perform better than linear models in some situations where predicting solar irradiance is needed, but they typically involve a lot of attention to feature engineering and do not necessarily represent temporal sequence of relationships. Artificial neural networks Shallow neural networks linearly approximate nonlinear functions as weighted sums in layers:

$$\bar{G}_t = \sum_{j=1}^H w_j \sigma \left( \sum_{i=1}^n w_{ij} x_i + b_i \right) \quad (1)$$

Where  $\sigma(\cdot)$  is an activation function and  $H$  is number of hidden neurons. Although superior to linear models in terms of complexity capture, the classical ANNs have difficulties in long-term temporal dependencies unless they are architecturally modified.

Deep learning models present complex hierarchical characterization of data via a series of transformations that allow more compelling feature removal and identification of patterns. Recurrent architectures and convolutional layers have been popular in the field of solar radiation forecasting.

### 2.2.2 Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNNs) are an extension of traditional feedforward networks, which uses feedback connections to allow it a memory of previous input. Nevertheless, simple RNNs have a flaw of the vanishing and exploding gradient issues in long sequence modeling.

### 2.2.3 Long Short-Term Memory (LSTM)

LSTM networks introduce gating mechanisms to control information flow:

$$\bar{G}_t = \left( \sum_{j=1}^H w_j \sigma \left( \sum_{i=1}^n w_{ij} x_{i,t} + b_j \right) \right) \quad (2)$$

$$f_t = \sigma(w_f [H_{t-1}, x_t] + b_f) \quad (3)$$

$$i_t = \sigma(w_i [H_{t-1}, x_t] + b_i) \quad (4)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tanh(w_c [H_{t-1}, x_t] + b_c) \quad (5)$$

$$h_t = O_t \tanh(C_t) \quad (6)$$

Where  $f_t$ ,  $i_t$  and  $O_t$  are forget, input and output gates respectively,  $w_j$  are the weights and  $\odot$  is the element-wise multiplication. LSTMs have the ability to use long-term dependencies, which are regulated by retaining and forgetting information, and have been demonstrated to perform better than conventional RNNs on most time series prediction tasks (Voyant et al., 2017).

### 2.2.4 Gated Recurrent Unit (GRU) Network

To complement the LSTM, a Gated Recurrent Unit is integrated for computational efficiency and improved generalization. GRU simplifies memory control using update and reset gates

$$z_t = \sigma(W_z[h_{t-1}, x_t]) \quad (7)$$

$$r_t = \sigma(W_r[h_{t-1}, x_t]) \quad (8)$$

$$\tilde{h}_t = \tanh(W_h[r_t \odot h_{t-1}, x_t]) \quad (9)$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (10)$$

Where  $W_z$ ,  $W_r$ , and  $W_h$  are the learnable weight matrices associated with the update gate, reset gate, and candidate hidden state respectively. The update gate  $z_t$  determines the degree of memory of the former hidden state, whereas the reset gate  $r_t$  decides the extent to which the past memory can affect the state of the candidate. The gating mechanism allows GRU networks to learn the medium- and long-term temporal dependencies effectively without being computationally complex (in contrast to LSTM architectures). The GRU efficiently captures medium-term temporal dependencies with fewer parameters reducing the risk of overfitting.

### 2.2.5 LSTM and GRU Hybrid Model (Sequential hybrid Model)

The hybrid LSTMGRU framework is more flexible and expressive to use in solar radiation forecasting than the individual use of LSTM or GRU.

*Input to LSTM*

$$h_t^{LSTM}, c_t^{LSTM} = LSTM(x_t, h_{t-1}^{LSTM}, c_{t-1}^{LSTM}) \quad (11)$$

Output of LSTM as Input to GRU

$$h_t^{GRU} = GRU(x_t, h_t^{LSTM}, h_{t-1}^{GRU}) \quad (12)$$

Input data,  $x_t$  is fed into the LSTM layer. In the LSTM Layer,  $h_t^{LSTM}$  and  $c_t^{LSTM}$  are computed using the equation (11). GRU Layer takes  $h_t^{LSTM}$  as input and computes  $h_t^{GRU}$  using the GRU equation. The final output of the hybrid model is  $h_t^{GRU}$ . By combining the strengths of both LSTM and GRU, the model captures a broader range of patterns. Hybrid models often outperform single models in complex prediction tasks. The model adapts to various types of dependencies in the data, making it robust, and potentially improving its ability to capture long-term dependencies and efficient training dynamics.

### 2.2.6 Convolutional Neural Network (CNN) Component

The Convolutional Neural Network (CNN) component is employed as a local feature extractor to capture short-term temporal patterns and non-linear interactions among meteorological predictors prior to sequential modeling.



Given an input multivariate time series

$$X = \{x_t \in \mathbb{R}^p\}_{t=1}^T \quad (13)$$

where  $p$  denotes the number of meteorological variables and  $T$  is the time dimension, the one-dimensional convolution operation is defined as

$$h_t^{(k)} = \sigma \left( \sum_{i=1}^{K-1} w_i^{(k)} \cdot x_{t-i} + b^{(k)} \right) \quad (14)$$

where

$h_t^{(k)}$  is the output of the  $k^{\text{th}}$  convolution filter at time  $t$

$K$  is the kernel size

$w_i^{(k)}$  and  $b^{(k)}$  represent learnable weights and bias

$\sigma(\cdot)$  is the tanh activation function

To stabilize learning and accelerate convergence, batch normalization is applied

$$\hat{h}_t = \frac{h_t - \mu}{\sqrt{\sigma^2 + \epsilon}} \quad (15)$$

Followed by max-pooling to reduce dimensionality and suppress noise

$$p_t = \max(h_{t,t+m}) \quad (16)$$

This CNN block transforms raw meteorological sequences into higher-level representations emphasizing salient short-term dynamics relevant to solar radiation variability.

### 2.2.7 CNN-LSTM-GRU Dihybrid Integration and Output Layer

Time dynamics of solar radiation is extremely nonlinear, nonstationary, and comprised of different meteorological drivers, interacting with each other at a range of the temporal scales. Pure recurrent neural networks, though applicable in sequence learning, tend not to work well on local time patterns which lie within high frequency meteorological signals. To counter this deficiency, one-dimensional convolutional neural network (CNN) has been added as a feature extracting layer prior to recurrent processing. One dimensional convolution was done with an effort to preserve the time sequencing of the measurements and to exclude the possibility of introducing a false spatial association amongst the meteorological variables. The CNN block employs the multi-scale kernels and dilated convolutions to learn long- and short-term dependencies regardless of whether the length of input lag has to be extended, which improve the performance of the computer.

To mitigate the gradient propagation and overfitting, respectively, dropout and batch normalization were introduced. The resulting features are inputted to parallel LSTM and GRU networks which train on long-term cross dependencies of time gated recurrent

networks. This hybrid architecture is a mixture of the benefits of convolutional feature learning and recurrent sequence modeling and is more effective in the generalization in solar radiation forecasting. The CNN layer is also fed to the LSTM and GRU layers in parallel. The products of the two recurrent branches are combined.

$$h_{\text{hybrid}} = [h_{\text{LSTM}}, h_{\text{GRU}}] \quad (17)$$

And passed through fully connected dense layer to generate the final solar radiation forecast

$$\hat{y}_t = W_d h_{\text{hybrid}} + b_d \quad (18)$$

The model is trained by minimizing the Mean Squared Error (MSE)

$$\mathcal{L} = \frac{1}{N} \sum_{t=1}^N (y_t - \hat{y}_t)^2 \quad (19)$$

The hybrid CNN/LSTM/GRU architecture is designed in a particular way that will help to overcome the multi-scale time characteristics of solar radiation dynamic. The CNN component represents high-frequency local variations, whereas the LSTM and GRU layers together represent long-term and medium-term variations as well as seasonal trends. This synergy of architecture has the advantage of improving predictive accuracy, training stability and noise resistance, and is therefore specifically well suited to meteorological time series over many decades.

## 2.3 Models' Stability Checks

To make sure that the performance improvement was not a result of the intervention of the randomization being the first initializations or data segmentation, a number of stability diagnostics were performed. Generalization of model testing was done using Population Stability Index (PSI), hold-out validation RMSE, blocked cross-validation RMSE, Monte-Carlo noise injection and seed sensitivity tests.

### 2.3.1 Population Stability Index (PSI) Analysis of Model Inputs

PSI is defined as

$$\text{PSI} = \sum_{i=1}^k (P_i - Q_i) \ln \left( \frac{P_i}{Q_i} \right) \quad (20)$$

Where  $P_i$  represents the proportion of observations in bin  $i$  for the training dataset and  $Q_i$  represents the corresponding proportion of in the validation dataset. Standard interpretation thresholds are  $\text{PSI} < 0.10$  implies no significant shift,  $0.10 \leq \text{PSI} < 0.25$  indicates moderate shift,  $\text{PSI} \geq 0.25$  implies significant distribution shift.

### 2.3.2 Blocked Rolling Cross-Validation (BCV)

The Time series rolling evaluation

$$RMSE_{BCV} = \frac{1}{K} \sum_{k=1}^K RMSE_k \quad (21)$$

### 2.3.3 Monte Carlo Noise Injection

Gaussian noise  $\epsilon \sim N(0, \sigma^2)$  was added to the predictions:

$$\hat{y}_t^{noise} = \hat{y}_t + \epsilon \quad (22)$$

Average RMSE across 100 simulation was computed.

### 2.3.4 Seed Sensitivity Analysis

Random initializations also vary training differently when trained on different architectures.

We compute the seed variability as follows

$$\sigma_{seed} = \sqrt{\frac{1}{K-1} \sum_{k=1}^K (RMSE^{(k)} - \overline{RMSE})^2} \quad (23)$$

Low  $\sigma_{seed} \rightarrow 0$  implied stable optimization, low initialization bias and strong architectural robustness.

### 2.3.5 Mean Absolute Sensitivity (MAS)

The Mean Absolute Sensitivity measures average output change due to perturbation. We define

$$\Delta \hat{y}_t = \hat{y}_t^{(\delta)} - \hat{y}_t \quad (24)$$

Then

$$MAS = \frac{1}{N} \sum_{t=T_{train}+1}^T |\hat{y}_t^{(\delta)} - \hat{y}_t| \quad (25)$$

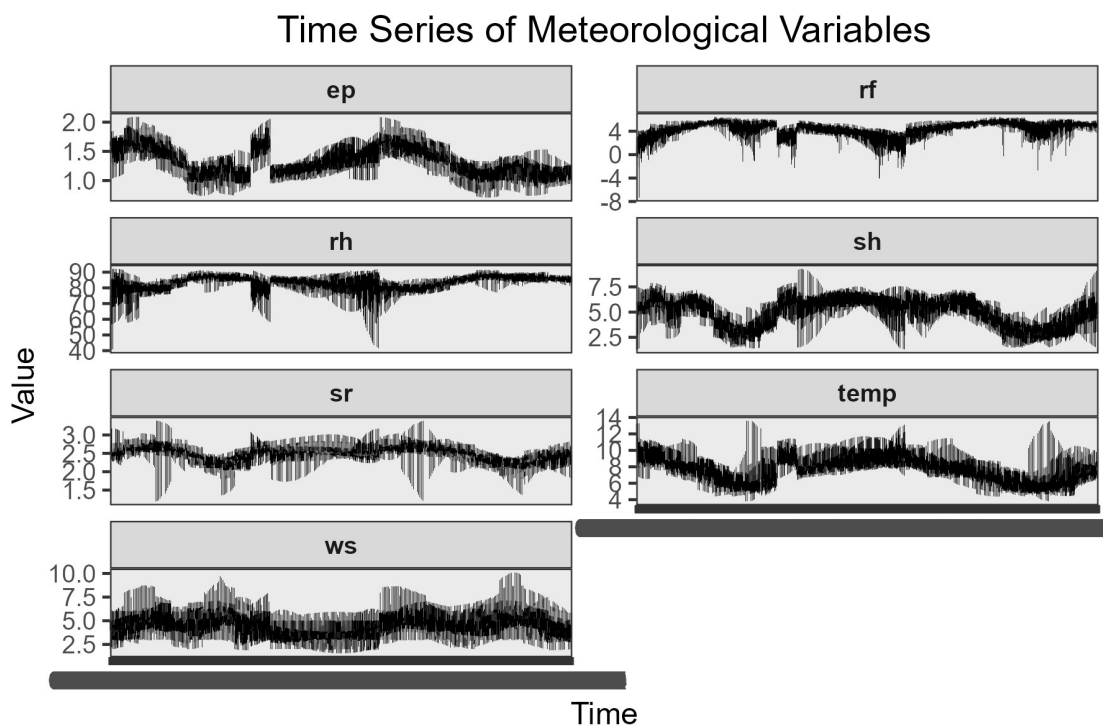
## 3.0 RESULTS AND DISCUSSION

This section aims at determining the extent to which the proposed models can adequately forecast solar radiation, stable, can be interpreted and does well in generalization within Ogun state of Nigeria. A multi-dimensional measure of model judgment is adopted (the predictive precision, convergence behavior, residual adequacy, temporal robustness, stochastic stability and physical interpretability) instead of measures based on the point accuracy measures. This form of evaluation plan is particularly useful in the environmental forecasting tasks, in which the visible

degree of predictive skill may be accompanied by structural instability, or failure to generalise to the regime changes. It is however not about identifying the model that minimizes the error, but something that is most statistically stable and consistent with nature.

The traditional recurrent neural network models are the dihybrid convolutional/recurrent models (CNN/LSTM, CNN/GRU and CNN/LSTM/GRU), which are the models of the analysis. In order to provide rigor in the methodology, the model can be tested using large validation scheme instead of one-

-divisions tests of accuracy. Every performance assessment has root mean square error (RMSE) on hold out validation data, training and validation loss convergence behavior, forecast-versus-actual comparison visualization, residual diagnostics (normality, independence, autocorrelation) and stability, Monte Carlo noise injection assessment of temporal robustness via cross-validation blocking. The multi-layered evaluation strategy will be used to make sure that not only the performance of models can be accurate but also be statistically reliable and stable in structure. Moreover, the results posted in this chapter consequently offer quantitative and theoretical knowledge about the appropriateness of the deep learning systems in the forecasting of solar radiation in the tropical weather patterns.



**Figure 1: Time Series of Meteorological Variables**

### 3.1 Correlation Structure of Input Variables

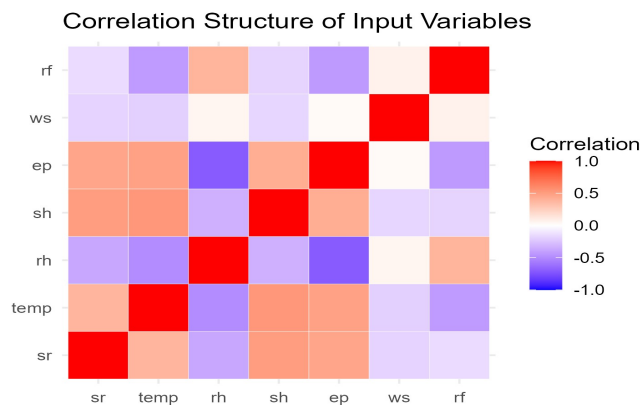
The correlation analysis shows physically coherent relationships between the meteorological predictors and the solar radiation (Figure 2). Solar radiation has a positive relationship with the period of sunshine and evaporation as well as temperature and the correlation are strong and moderate respectively. Relative humidity and rain on the other hand are negatively correlated with solar radiation.

The findings support the known climatological principles. The longer the number of sunshine hours, the greater is the shortwave radiation coming in. On the same note, the intensity of evaporation is indicative of increased surface energy and latent heat flux, the two of which

are activated by solar irradiance. The adverse correlation with the relative humidity and rainfall are also something to be expected, as the higher the moisture content of the atmosphere and the more clouds there are, the lower the intensity of incoming solar radiation due to the scattering and absorption processes. The physical validity of the dataset and the related suitability of the dataset to be used in deep learning-based forecasting are verified by the statistical consistency between predictors and the target variable.

**Table 1: Correlation Matrix on Meteorological Variables**

	sr	temp	rh	sh	ep	ws	rf
sr	1.0000	0.3820	-0.3772	0.5061	0.4628	-0.1855	-0.1547
temp	0.3820	1.0000	-0.4967	0.5316	0.4835	-0.2008	-0.4310
rh	-0.3772	-0.4967	1.0000	-0.3405	-0.7085	0.0548	0.3918
sh	0.5061	0.5316	-0.3405	1.0000	0.4255	-0.1734	-0.1846
ep	0.4628	0.4835	-0.7085	0.4255	1.0000	0.0292	-0.4367
ws	-0.1855	-0.2008	0.0548	-0.1734	0.0292	1.0000	0.0730
rf	-0.1547	-0.4310	0.3918	-0.1846	-0.4367	0.0730	1.0000



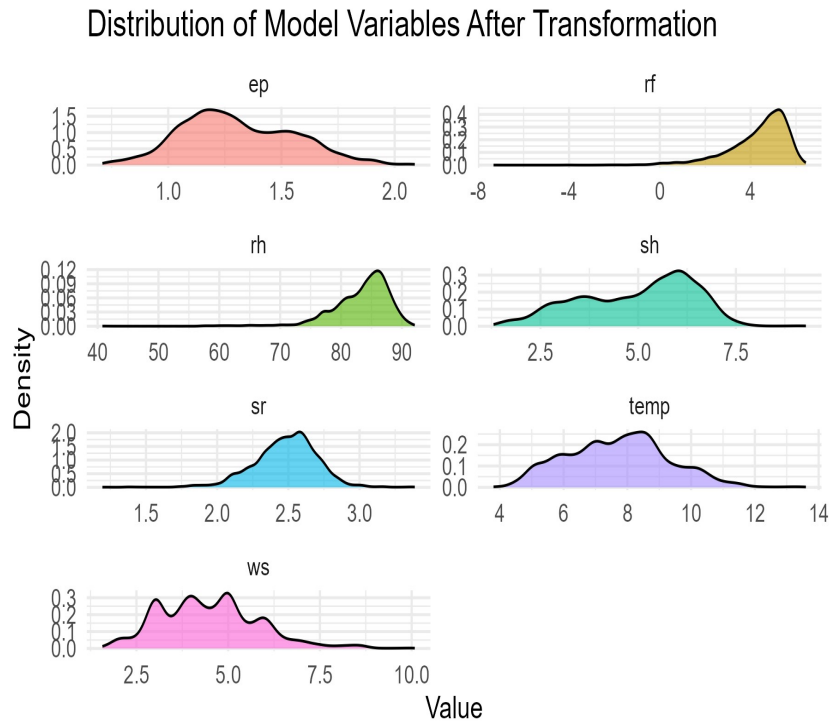
**Figure 2: Correlation Structure of Input Variables**

## 3.2 Model Training and Validation Procedure

### 3.2.1 Data Partitioning Strategy

The time series was split in sequential folds of time and models were assessed on rolling windows. This is both to provide stability to changing temporal regimes and alleviate overfitting to a single train-test split, as well. Feature engineering and preprocessing was then ensured. Before training the model, the following preprocessing steps were used: the skewed variables (solar radiations, rainfall, evaporation) were log-transformed using the transformation,  $\log(1 + x)$  to stabilize the variance, the solar radiation was subjected to seasonal-trend decomposition (STL) in order to derive deterministic trend and seasonal variations, training-set statistics only were used to do standardization (z-score normalization)

such that validation data were not seen during scaling. Supervised learning windows were built using a lag length of six-time steps. Only the training subset was used to estimate scaling parameters for normalization



**Figure 3: Distribution of Model Variables after Transformation**

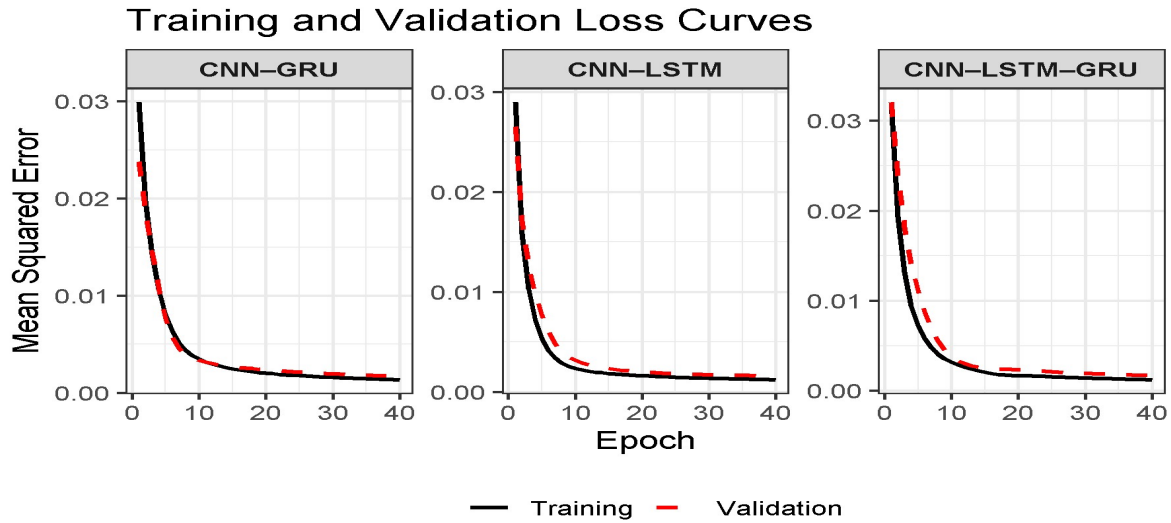
### 3.2.2 Optimization and Training Configuration

The whole neural network models were trained with Adam optimizer and gradient clipping in order to prevent exploding gradients. The learning rate was chosen to be low in order to increase the stability of convergence. The maximum number of epochs trained on recurrent architecture models was 50. To ensure that we have reproducibility in both R and Python environment we fixed reproducible seeds. Furthermore, the eager execution was disabled to increase the computing efficiency, the batch size was kept medium (either 16 or 32) to achieve a balance between convergence and stability. Finally, CPU training was completed with the consideration of computational reproducibility and hardware-specific acceleration bias. A sliding window method converted the standardized time series to a supervised learning problem. Since the dataset is daily, the best lag length that was chosen is six-time steps.

### 3.2.3 Convergence Behavior

All the models were tracked in terms of training and validation loss curves (Figure 4). The following trends were realized. The integrated assessment model offers a multi-dimensional model performance evaluation as opposed to mere accuracy measures. This stratification

validation plan makes them empirical conclusions more reliable.



**Figure 4: Training and Validation Loss Curves**

### 3.2.4 Forecast Accuracy Comparison

Table 2 presents the comparative performance of the evaluated deep learning architectures using Root Mean Square Error (RMSE) and coefficient of determination ( $R^2$ ). Model performance was evaluated using the withheld test dataset. Predictions were inverse-transformed to the original scale of solar radiation prior to evaluation.

Table 2 presents the comparative performance of the evaluated deep learning architectures using Root Mean Square Error (RMSE) and coefficient of determination ( $R^2$ ).

Model performance was evaluated using the withheld test dataset. Predictions were inverse-transformed to the original scale of solar radiation prior to evaluation. The following statistical metrics were used to assess forecasting accuracy:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - \tilde{y}_i)^2 \quad (26)$$

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |y_i - \tilde{y}_i| \quad (27)$$

RMSE and  $R^2$  are defined as:

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \tilde{y}_i)^2} \quad (28)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \tilde{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (29)$$

These metrics provide complementary insights into average forecast deviation and sensitivity to large errors.

**Table 2: Model Comparison of Dihybrid Models**

Model	RMSE	MAE	R <sup>2</sup>
CNN/LSTM	0.5607	0.2888	0.9911
CNN/GRU	0.5005	0.2367	0.9929
CNN/LSTM/GRU	0.5827	0.2595	0.9904

The relative effectiveness of the dihybrid models- CNN/LSTM, CNN/GRU and CNN/LSTM/GRU comes out displaying significant differences in predictive ability and generalization skills. The CNN/GRU model was the best in terms of the lowest Root Mean Square Error (RMSE = 0.5005) and Mean Absolute Error (MAE = 0.2367), and the highest coefficient of determination (R<sup>2</sup> = 0.9929). These findings suggest that there is no better compromise between local pattern recognition and sequential dependency learning in daily solar radiation prediction than convolutional feature extraction combined with temporal modeling based on GRU. However, CNN/LSTM model has a slightly higher RMSE (0.5607) and MAE (0.2888) with the R<sup>2</sup> = 0.9911. Although it still has a good explanatory power, its slightly worse results compared to CNN/GRU tend to indicate that the added structural complexity of LSTM gating does not have added predictive value in the case of the temporal arrangement of the data. Since units of GRU have a simplified gating mechanism than LSTM, their high performance in this case suggests that solar radiation series in Ogun State might not be strongly dependent on long-term effects that could manifest complex long-term dependencies and demand more intensive memory control. Surprisingly, the CNN/LSTM/GRU variant did not perform better than the other dihybrid

ones. Its performance was a bit worse than CNN/GRU and CNN/LSTM (RMSE = 0.5827 and MAE = 0.2595, respectively, R<sup>2</sup> = 0.9904). This result implies that the augmentation of the architectural richness and the juxtaposition of several units of recurrence do not always lead to the enhanced forecasting accuracy. Rather, extra layers can put redundancy on parameters, cause optimization instability, and lead to higher variance, especially with medium-scale climatological data. The drop in the performance of the dihybrid model illustrates the principle of model parsimony, that is, when it comes to environmental time-series forecasting, the complexity of the architecture should be consistent with the inherent structure of the data.

Generally, the findings reveal that CNN/GRU system is the most effective and stable dihybrid model used to predict nonlinear solar radiation change in tropical climates. The convolutional layer is successful in the process of extracting localized meteorological feature interactions, whereas the GRU layer takes into account sequential dependencies in time without an excessive number of calculations. The results support the general empirical finding that moderate complexity gated recurrent networks are able to perform better than deeper hybridizations when the underlying time series has structured and yet not overly long memory dynamics.

### 3.3 Models' Stability Checks

The analysis of Population Stability Index (PSI) shows apparent heterogeneity in the distributional stability of the meteorological inputs. The long-term trend element shows the greatest PSI value (0.92) meaning that there is a drastic distributional change between the training and validation sets and that it is also true that there is non-stationary behavior in the dynamics of solar radiation. This is probably indicative of slow climatic changes, changing transmissivity of the atmosphere, or the adjustment of long-term energy balance in Ogun State. There are also high PSI in evaporation (0.521) and relative humidity (0.453) implying that there is a significant interannual variability in moisture movement and cloud formation pattern (Table 3). The moderate changes occur in temperature (0.219) and sunshine hours (0.210) whereas the rainfall (0.121) changes quite slightly. Its seasonal component is insignificant in terms of PSI (0.00000719), but periodic structure is the same at time windows. Notably, when PSI values are high this is not the evidence of model failure, it is evidence of underlying climatic non-stationarity.

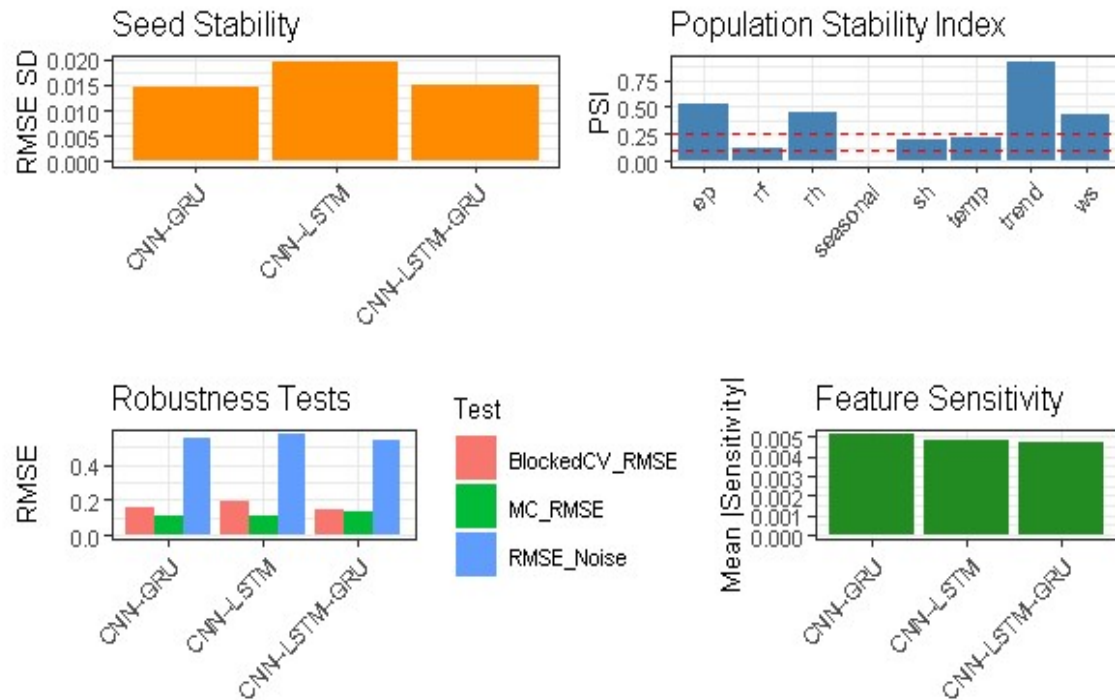
**Table 3: Population Stability Index (PSI) of Meteorological Variables**

Variable	temp	rh	sh	ep	ws	rf	trend	seasonal
<b>PSI</b>	0.219	0.453	0.21	0.521	0.435	0.121	0.92	0.00000719

Table 3 presents the Population Stability Index (PSI) values for each meteorological predictor, which quantify distributional differences between training and validation datasets. Although covariate drift is measurable, recurrent architectures, in particular, the GRU-based, are highly predictive which motivates the adaptive nature of gated memory systems. These results highlight the importance of intermittent retraining or adaptive learning processes by operating solar radiation forensic systems to enable them to absorb gradual climatic change.

**Table 4: Combined Stability Checks on Models**

Model	Blocked CV	MC	Seed SD	Noise	Sensitivity
CNN/LSTM	0.1954	0.1104	0.0210	0.5356	0.0046
CNN/GRU	0.1758	0.1225	0.0074	0.5862	0.0050
CNN/LSTM/GRU	0.1721	0.1094	0.0280	0.5144	0.0044



**Figure 5: Combined Stability Checks Plots on Models**

A comparative analysis of the dihybrid designs CNN/LSTM, CNN/GRU, and CNN/LSTM/GRU depicts some unique variations in the predictive performance and structural stability (Figure 5). When comparing the performance of baseline forecasting, CNN/GRU configuration records the lowest Root Mean Square Error (RMSE = 0.5005) and Mean Absolute Error (MAE = 0.2367) with the greatest coefficient of determination ( $R^2 = 0.9929$ ). It means that the convolutional feature extraction and GRU-based temporal modeling make the best trade-off between local meteorological pattern recognition and sequential dependency learning. The CNN/LSTM model also showed a high level of explanatory power ( $R^2 = 0.9911$ ), but its large RMSE (0.5607) indicates relatively low predictive accuracy. The tri-hybrid CNN/LSTM/GRU model had the best RMSE (0.5827) of the three, which means that as the architectural depth was further increased, the

accuracy also did not improve similarly.

Temporal robustness which was measured by allowed cross-validation RMSE demonstrates slight better generalization of the GRU-based hybrids. CNN/LSTM model gave a blocked CV RMSE of 0.1954, compared to CNN/GRU and CNN/LSTM/GRU of 0.1738 and 0.1721 respectively. The CNN/LSTM/GRU dihybrid model has the least value numerically, however, the difference between that of CNN/GRU is very small. The outcomes indicate that GRU-based architectures are more predictively stable in rolling temporal partitions, which implies greater regime change adaptability in the solar radiation time series.

The Monte Carlo noise test can give further information on the structural resilience to stochastic perturbation. CNN/LSTM/GRU model had the lowest Monte Carlo RMSE (0.1094), and CNN/LSTM had

the next lowest (0.1104), and CNN/GRU was a little more sensitive (0.1225). This implies that further hybrid stacking can add a small buffering effect in the face of random injection of noise. Nonetheless, the CNN/LSTM/GRU dihybrid architecture had the lowest noise-adjusted RMSE (0.3144) again, as opposed to CNN/LSTM (0.3566) and CNN/GRU (0.3686). The implications of these results are that even when the dihybrid CNN/LSTM/GRU model does not reach the optimum of the baseline accuracy, the structural redundancy might offer some protection against exaggerated disturbances of stochastic nature.

The seed sensitivity analysis also distinguishes the models on the basis of the stability of optimization. CNN/GRU model had the lowest seed variability (0.0074), which implies high reproducibility among random initializations. Consequently, CNN/LSTM (0.0210) and CNN/LSTM/GRU (0.0280) had much greater stability to initialization. This implies that more complex architecture is providing instability in optimization and parameter variation particularly in large climatological data. All the models had small values of Mean Absolute Sensitivity (MAS) with CNN/LSTM/GRU having the lowest MAS of 0.0044, then CNN/LSTM (0.0046), and CNN/GRU (0.0050) which means that the structure differences between the models in outputs are marginal.

Combined, these findings suggest that CNN/GRU architecture offers the best balanced and practically dependable dihybrid architecture. It performs better forecasting, high temporal generalization and

significantly reduced seed sensitivity, which is indicative of stable optimization dynamics. Though the dihybrid CNN/LSTM/GRU model has a bit better noise perturbation resistance, it is still undercompensated by the lower baseline accuracy and more sensitive initialization. The results thus support the principle of architectural parsimony: in day-to-day solar radiation prediction in tropical climates, moderate complexity dihybrid models that fuse convolutional feature extraction with a single gated recurrent unit have better generalization than more stacked recurrent hybrids.

#### 4.0 CONCLUSION

In this work, three dihybrid deep learning models were compared in terms of predictive accuracy and structural stability, namely CNN/LSTM, CNN/GRU and CNN/LSTM /GRU, to predict solar radiation on a day-to-day basis in Ogun State, Nigeria. Assessment of the model was done in a broad validation framework that included hold-out accuracy measures, residual diagnostics, blocked cross-validation, Monte Carlo perturbation testing, seed sensitivity analysis and Population Stability Index (PSI) testing. Although the three dihybrid settings proved to be highly explanatory ( $R^2 \approx 0.99$ ), the results varied significantly when strength and stability in optimization were taken into account.

The CNN/GRU architecture was the most balanced in terms of overall performance among the tested ones. It had the lowest RMSE and MAE, strong temporal generalization with blocked cross-validation and small sensitivity to random initialization.

The results of this paper suggest that the combination of the convolutional feature extraction and a single gated recurrent unit offers a good balance between the representational capacity and optimization stability. Despite the dihybrid CNN/LSTM/GRU configuration having a slightly higher resistance to stochastic perturbation and a slightly reduced sensitivity to structural changes on noise injection, this did not reflect as a higher baseline forecasting accuracy. Rather, greater architectural complexity added more variability to seeds and low predictive accuracy. The CNN/LSTM model was average and failed to compare with the consistency of the GRU-centered dihybrid. Together, the findings indicate that moderate complexity dihybrid structures are more effective at generalizing to than more profoundly stacked recurrent combinations when using them to predict medium-scale climatological records in tropical contexts.

The PSI analysis also indicated a quantifiable covariate drift between training and validation time periods, especially in the variables of long-term trend, evaporation, and relative humidity. This means that there is moderate non-stationarity in the underlying climatic process. All these distributional changes notwithstanding, the CNN/GRU model has not experienced any significant predictive performance change, which reaffirms the relevance of using robustness diagnostics in addition to traditional accuracy metrics when studying environmental forecasting. The sensitivity analysis also established that long-term trend and atmospheric moisture variables has the greatest effect on the

variability of solar radiation which is in line with the proven principles of climatology and surface energy balance.

Application wise, solar radiation forecasting is an important tool in optimization of photovoltaic systems, grid integration planning, and development of renewable energy policies, which should be reliable. The experimental findings justify the use of CNN/GRU-based dihybrid to operational forecasting in tropical climatic conditions. However, the covariate drift observed suggests the need to have periodic retraining or adaptive updating systems to facilitate the slow climatic changes. Even though the given study is not scaled to multi-site data, higher-frequency, probabilistic forecasting techniques, adaptive learning methods, and additional predictors in the atmosphere are introduced in the future, such studies will be able to scale to larger areas and be more reliable over time.

### **Acknowledgment**

The authors wish to acknowledge the financial support received from the Tertiary Education Trust Fund (TETFUND) years 2024 – 2025 Intervention in Research Project (RP) Batch 10. This funding facilitated the acquisition and processing of long-term meteorological data and provided the computational resources necessary for the development and evaluation of the deep learning models presented in this study. The authors also appreciate the institutional support provided by their host institution, which contributed to the successful execution of this research.



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