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Prediction of Global Horizontal Irradiance for Composite Climatic Zone in India

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Abstract. Prediction of Global Horizontal Irradiance (GHI) is integral for solar energy applications. The current study focused on the prediction of GHI for 14 days ahead in New Delhi, India, by Weather Research Forecasting Solar (WRF-Solar). The forecasting of solar radiation is performed for various seasons in a year. A two-way nesting domain with a grid spacing of 9 km for the outer domain and 3 km for the inner domain has been used. The Rapid Radiative Transfer model has been used for shortwave radiation scheme. The outputs were fetched directly from the model and validated against the values provided by Solcast®. The evaluation was performed individually for all days, and results were shown from Day 5 to Day 14, since the first four days were considered spin-off time. Root Mean Square Error (RMSE) for the summer season ranges from 3% - 29%, monsoon season ranges from 10% - 112%, winter season ranges from 12% - 364%, and post-monsoon season ranges from 30% - 115%. WRF-Solar predicts the GHI with low uncertainty for the summer season and possesses high error during the monsoon season. Even though the statement is made against the average values over the time horizon. There are instances in winter and post-monsoon which possess high error for certain times and not for most of the time. It indicates that the WRF-Solar model performs well for clear days and average for over cloudy and overcast sky conditions.

Keywords: Global Horizontal Irradiance, WRF-Solar, Cloud Opacity, Day-Ahead Forecasting

1. Introduction

The promotion of renewable energy resources around the world has been increasing exponentially to reduce global warming. From the early 2000's, the growth of solar PV has been increased persistently and is expected to be 30% by 2040 of total power generation in India [1]. India has been blessed with a vast solar energy potential of 4-7 kWh/m^2/day for most parts of the country [2]. As a consequence of increasing solar power generation, solar radiation forecasting has been integral in effectively managing the demand and supply, scheduling the maintenance, energy trading and real-time dispatch [3]. Numerical Weather Prediction (NWP) model has been a workhorse for many years for predicting atmospheric variables. Among many NWP models, Weather Research Forecasting (WRF) models are computationally efficient and provide accurate forecasts up to 14 days ahead using advanced physics, numerics and data assimilation [4]. It is currently used by many meteorological centres to predict weather conditions. There are many extensions in WRF such as WRF-Hydro, WRF-Chem, WRF-Fire, WRF-LES, WRF-Solar, and WRF-Urban. Among these models, WRF-Solar is specially designed to meet the operational requirements of solar energy applications [5]. The reason for opting WRF-Solar model is to predict the GHI for 14 days ahead instead of going with machine learning models. Satellite imaging, sky imagers and machine learning models are apt for short-term forecasting. Since those models provide reliable accuracy for short-term horizons such as within a day [6]. Several research works have been performed for various locations across the world with different time horizons [7], [8]. The WRF-Solar model has not been explored extensively for the 14 days ahead to predict Global Horizontal Irradiance (GHI).

In this study, an attempt has been made to predict the GHI for 14 days ahead. It covers different seasons for a composite climatic zone. The purpose of predicting the GHI for a time horizon is to serve for effective management of demand and supply, scheduling the maintenance and grid integration.

2. Site selection and model setup

The location considered for the analysis is New Delhi, India. New Delhi has a composite climate that consists of hot and dry, humid and warm, along with a cold climate. The coordinates of the location are 28.54°N latitude and 77.19°E longitude. The simulations have been performed for the first 14 days of selected months that represent different seasons in a year. January month represents the winter season, April represents the summer season, August represents the rainy season and October represents the post-monsoon season. The data used for the validation of the model has been provided by Solcast® [9]. The data provided by the Solcast® are retrieved by analyzing the satellite images.

Numerical Weather Prediction (NWP) Models are known for medium-term forecasting. Among many NWP models, WRF-Solar is the model developed specifically tailoring for solar energy needs. WRF-Solar is a mesoscale NWP model developed for the operational forecasting and research needs. The dynamical core used in the model is the non-hydrostatic mesoscale model. The model has a vertical resolution of 30 sigma levels and 4 soil types. In this study, the WRF-Solar model is used for predicting Global Horizontal Irradiance (GHI) for a time horizon of 14 days ahead. The first four days results were discarded since it was a spin-up time for the model. The initial and boundary conditions were accessed from the National Centre for Environmental Protection – Global Forecast System (NCEP GFS) 0.25 Degree Global Forecast Grids Historical Archive [10]. Two-way nesting with one input file is used for two domains with a horizontal grid spacing of 9 km for the outer domain (D01) and 3 km for the inner domain (D02). Figure. 1 (a) and (b) represent the study area, and a point location is considered for the analysis. The parameterization schemes used in the model are listed out in Table 1.

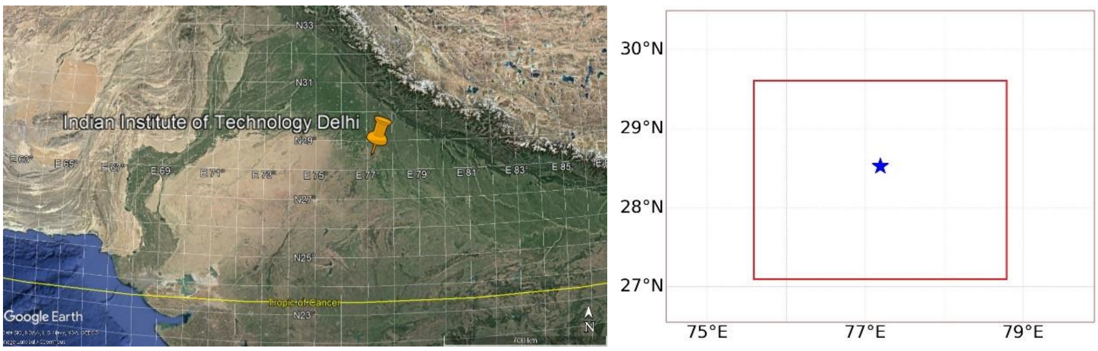

Figure 1. *a) Location of Site (left) b) Modelling domain (right)*

Table 1. *List of parameterization schemes [5]*

Parameterization	Name of the scheme
Longwave radiation	Rapid Radiative Transfer Model
Shortwave radiation	Rapid Radiative Transfer Model
Surface layer	Mesoscale Model 5
Planetary boundary layer	Mellor-Yamada Nakanishi and Niino Level
Microphysics	Thompson
Land surface model	Noah land surface model

3. Evaluation procedure

The hourly outputs are derived from the model for the selected location. In the model, the reference latitude and longitude are the same as the coordinates mentioned as mentioned above. The outputs for the point location are fetched and validated with the Solcast® data.

The metrics used for the evaluation of the model are root mean square error (RMSE), mean absolute error (MAE), mean bias error (MBE) and anomaly correlation coefficient (ACC). The values of RMSE, MAE and MBE are shown in terms of percentage. The equation for all four evaluation metrics is given below: [11][12].

$$rRMSE = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{n}\left(I_{forecast} - I_{measured}\right)^2}}{I_{measured_{(\max)}} - I_{measured_{(\min)}}} \times 100 \tag{1}$$

$$MAPE = \frac{\frac{1}{N}\sum_{i=1}^{N}\left|I_{forecast} - I_{measured}\right|}{I_{measured_{(\max)}} - I_{measured_{(\min)}}} \times 100 \tag{2}$$

$$rMBE = \frac{\frac{1}{N}\sum_{i=1}^{n}\left(I_{forecast} - I_{measured}\right)}{I_{measured_{(\max)}} - I_{measured_{(\min)}}} \times 100 \tag{3}$$

$$ACC = \frac{\sum_{i=1}^{n}\left(I_{measured} - \bar{I}_{measured}\right) \times \left(I_{forecast} - \bar{I}_{forecast}\right)}{\sqrt{\sum\left(I_{measured} - \bar{I}_{measured}\right)^2} \times \sqrt{\sum\left(I_{forecast} - \bar{I}_{forecast}\right)^2}} \tag{4}$$

4. Results and discussion

The predicted values for different seasons are compared with the observed values that are depicted in Figure. 2. It is vivid that the predicted values coincide well with the observed values

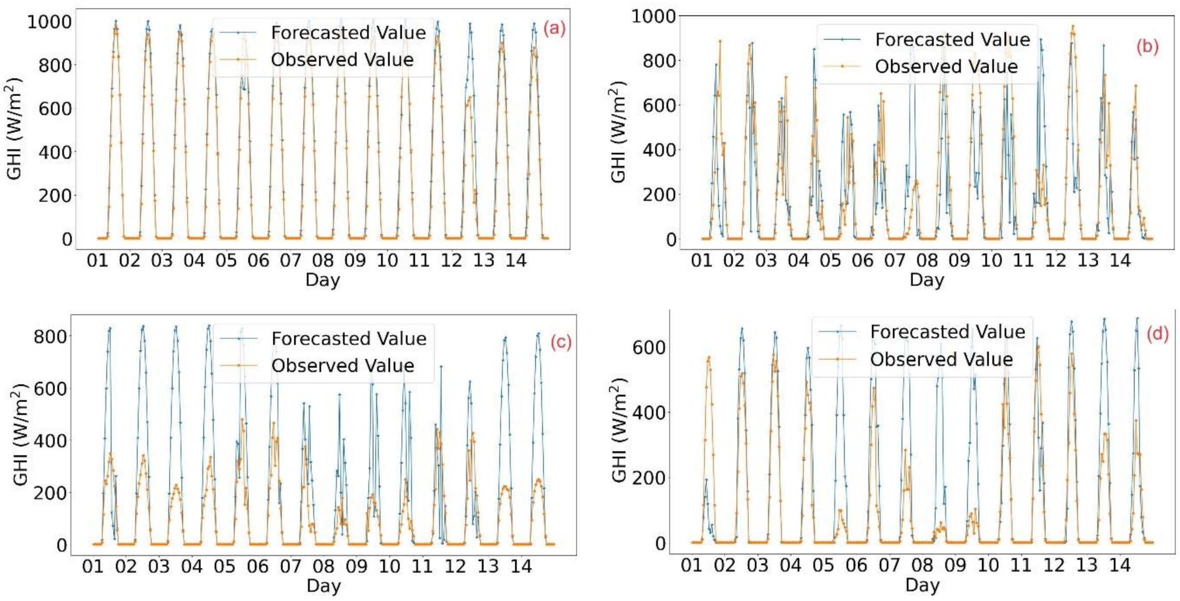

Figure 2. *Comparison of predicted values with observed values a) Summer (Top left) b) Monsoon (Top right) c) Post-monsoon (Bottom left) d) Winter (Bottom right)*

during the summer season. It is due to the most number of days being clear i.e. cloud-free days. In the winter season, especially for days 8 and 9, the predictability is poor due to high cloud opacity. During monsoon season also, days 7 and 11 had poor agreement with the observed values. It is happening due to the frequent formation and dissipation of clouds resulting in precipitation. Among the four seasons, the model prediction is poor for the post-monsoon season. The model consistently overpredicted for all days. Due to the hourly fluctuations of cloud opacity values among all the days in the post-monsoon season resulted in poor disagreement for time series comparison between the predicted and observed values.

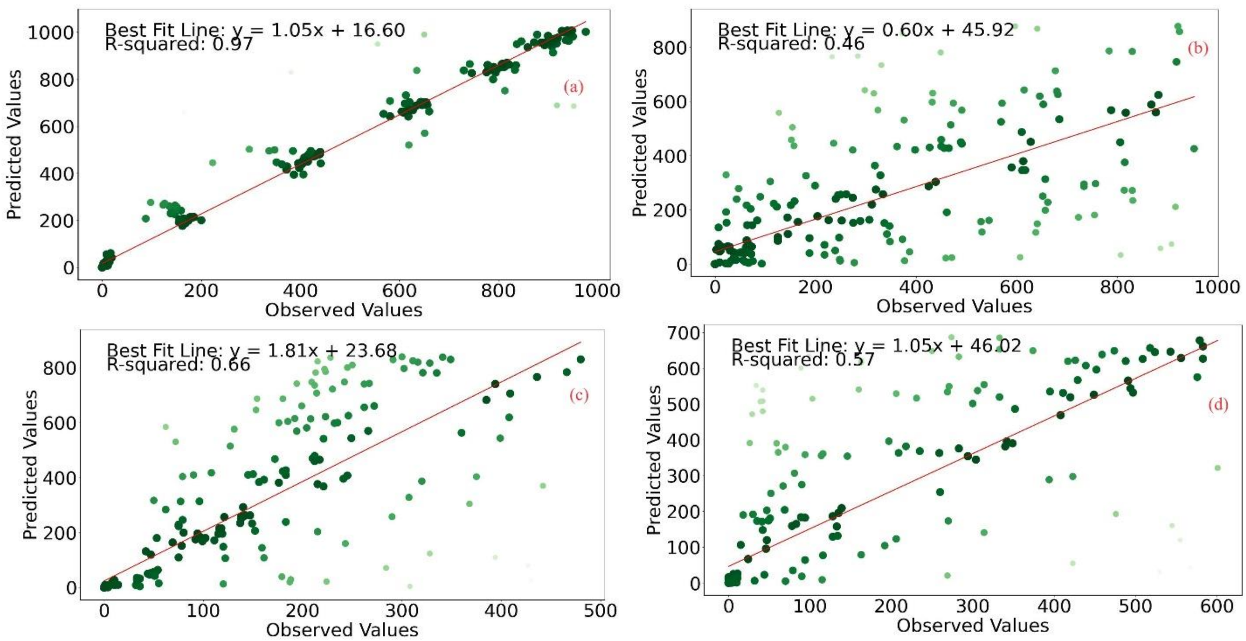

Figure 3. *R^2 values for different seasons a) Summer (Top left) b) Monsoon (Top right) c) Post-monsoon (Bottom left) d) Winter (Bottom right)*

The dispersion of observed values and predicted values are shown in Figure 3, along with the coefficient of determination (R^2) values. R^2 values evaluate the dependent variable variance attributed to the independent variable. In the scatter plots, the dispersion of observed values and predicted values is more in the monsoon season and less in the summer season. R^2 values also depict the same; after the summer season and the post-monsoon season performs better than the other two seasons.

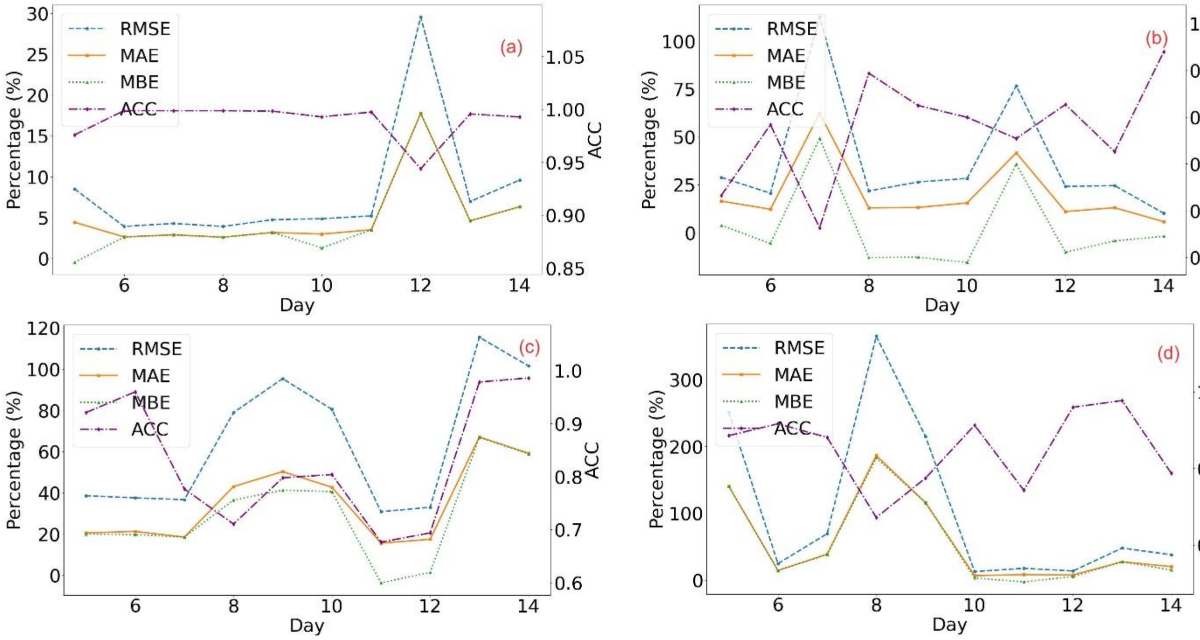

Figure 4. *Forecasting skill of WRF-Solar model for different seasons a) Summer (Top left) b) Monsoon (Top right) c) Post-monsoon (Bottom left) d) Winter (Bottom right)*

Since the initial four days were considered a spin-off time period for the stabilization of the model, the results were presented for the next ten days. In the winter season, the percentage of RMSE starts with a high error value such as 250% keeps on showing a fluctuating trend. The maximum value of RMSE was recorded on day 8 with 364%. Apart from days 5, 8, and 9, the other days showed the value of RMSE less than 25%. It is happening due to high cloud opacity values recorded for days 5, 8 and 9. The mean and median values of cloud opacity ranges from 65 to 72 and 68 to 78. On day 11, the model underestimates slightly with an MBE of -2.5%. The model provided satisfactory results over the summer region. The average RSME value is 8% over the 10 days. The values of ACC is also consistent with a value of 0.99. In the monsoon region, the model consistently underpredicts except day 7 and day 11. This is due to the accurate prediction of cloud formation and dissipation during this period. RMSE value for those two days also resulted in larger values of 112% and 76%. ACC ranges from 0.56 to 0.93 and varies continuously within the range. This is due to the high opacity value of 96 recorded on both days. In post-monsoon season, the high RMSE values recorded for days 8, 9, 10, 13 and 14 were 78%, 95%, 80%, 115% and 110%, respectively. The cloud opacity value was recorded more than 90 for those days. In this season, the model slightly underpredicts for day 11 with MBE of -3.66%. Among the four seasons, the WRF-Solar model performs better in the summer season.

5. Conclusions

For solar photovoltaic power production, demand & supply management, and maintenance scheduling, the model-derived GHI was conducted successfully for the national capital in India. The selected region falls under the composite climatic zone, and evaluation of WRF-Solar has been performed. It has been noted that, among all four seasons, the model-derived results are in good agreement with the observed values for the summer season. It depicts that most days or seasons fall undercloud-free days. The error metrics such as RMSE ranges from 3% - 29%, MAE ranges from 2% - 17%, MBE ranges from -0.46% - 17.76% and ACC ranges from 0.94-0.99 are computed for the summer season. R^2 score concludes the WRF-Solar model derived the worst results for the monsoon season among the other three seasons. This is due to high cloud opacity values, which are recorded for most of the days. The high cloud opacity values are changing spontaneously with time in those durations. The error metrics such as RMSE ranges from 10% - 112%, MAE ranges from 5% - 62%, MBE ranges from -15% - 49% and ACC ranges from 0.56 - 0.93 are computed for the monsoon season. The model performed average over the winter and post-monsoon season. It is happening due to cloud opacity and high aerosols during the seasons. The error metrics such as RMSE range from 12% - 364% & 30% - 115%, MAE ranges from 6% - 186% & 15% - 67%, MBE ranges from -2% - 182% & -3% - 66% and ACC ranges from 0.83 - 0.98 & 0.67 – 0.98 are computed for the winter and post-monsoon season respectively. The model performance could be further improved by enhancing the cloud and aerosol parametrization schemes. Another possible way to enhance the performance is to improve the initial and boundary conditions through the data assimilation process.

Data availability statement

Data will be made available on request.

Author contributions

Naveen Krishnan: Conceptualization, Methodology, Investigation Validation, Formal Analysis, Resources, Writing - Original draft, Writing – Review and Editing, Visualization. K. Ravi Kumar: Conceptualization, Methodology, Investigation, Visualization, Supervision, Writing – Review and Editing.

Competing interests

The authors declare that they have no competing interests.

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