

Article

Simulation and Correction Study of Solar Irradiance in Guangdong Based on WRF-Solar and Random Forest

Yuanhong He, Zheng Li, Fang Zhou and Zhiqiu Gao * 

School of Atmospheric Physics, Nanjing University of Information Science and Technology, Nanjing 210044, China; heyuanhong0917@nuist.edu.cn (Y.H.); lizheng@nuist.edu.cn (Z.L.); zhoulfang2001@nuist.edu.cn (F.Z.)

* Correspondence: zgao@nuist.edu.cn

Abstract

To improve solar irradiance simulation accuracy for precise photovoltaic power forecasting, we developed a hybrid framework combining WRF-Solar numerical simulation and random forest (RF) machine learning for a PV plant in Guangdong, China. Weather conditions were objectively classified into clear, intermittent cloudy, and overcast using the Daily Variability Index (DVI) and Daily Clear-sky Index (DCI). We calibrated the WRF-Solar model's microphysics and radiative transfer schemes via sensitivity tests to optimize overcast-sky performance, then applied RF correction to the simulated irradiance. Results show that RF correction significantly reduces simulation errors for intermittent and overcast conditions, while the original WRF-Solar outperforms the corrected results under clear skies due to RF overfitting.

Keywords: WRF-Solar; random forest (RF); solar irradiance; Guangdong Province

1. Introduction

Against the backdrop of global warming, tightening fossil fuel supplies, and environmental degradation, the efficient utilization of solar energy has garnered widespread international attention. Given China's relative scarcity of petroleum and natural gas resources, coupled with the inability of domestic production to meet its rapidly growing energy demand, the long-standing reliance on a coal-dominated energy structure has become increasingly misaligned with the needs of a modern economy. The disproportionately high share of coal in the energy mix has led to severe issues such as air pollution and greenhouse gas emissions, thereby generating significantly negative impacts on public health and climate change [1–5].

As a plentiful and renewable energy source, solar energy boasts the advantages of being clean and non-polluting, making it the most ideal new energy source in the world today. Governments across the globe regard it as a crucial component of their national sustainable development strategies [6]. Solar power generation is highly dependent on solar irradiance [7]. However, solar radiation is influenced not only by stable factors such as climate zone, season, and geographical location but also exhibits seasonal oscillations and diurnal variations. Variable weather conditions can exert immediate impacts on radiation intensity [8].

The numerical weather prediction (NWP) model describes weather processes across different scales through the parameterization of physical processes [9], and it can also be utilized to predict solar radiation via complex physical models [10–12]. NWP models can be categorized as follows: Global NWP models, which depict atmospheric processes



Academic Editors: Mohammadreza Aghaei and Aref Eskandari

Received: 8 March 2026

Revised: 7 April 2026

Accepted: 17 April 2026

Published: 24 April 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

on a global scale, such as General Circulation Models (GCM) and the European Centre for Medium-Range Weather Forecasts (ECMWF) model; and Mesoscale NWP models (or regional models), which are applied to specific regions with relatively high resolution. Examples like the fifth-generation Mesoscale Model (MM5) and the Weather Research and Forecasting (WRF) model have been widely used in solar radiation forecasting. However, the accuracy of these forecasts remains a major challenge, as comprehensively reviewed by Blaga et al. [13], who highlighted the persistent errors in incoming solar energy prediction. To address such limitations, region-specific verification and correction of solar radiation products—such as the FY-4A surface solar radiation data over Anhui Province—are essential for improving forecast reliability [14].

As demonstrated by Jia, D. et al. [15], output data from multiple global climate models within CMIP5 were utilized, along with a median ensemble approach, to project global surface solar radiation under both RCP4.5 and RCP8.5 scenarios. Results under cloud-free conditions indicated an increasing trend in solar radiation over southeastern China. Regional climate models employ low-resolution global climate models as boundary conditions to conduct dynamic downscaling experiments, thereby obtaining high-resolution projection data for regional climates. Numerous scholars have adopted regional climate models such as WRF and PRECIS for solar irradiance forecasting research. For instance, Dasari, H.P. [12] employed the WRF-Solar model to simulate solar energy potential in the Arabian Peninsula, establishing a regional solar radiation parameter dataset for the period 1980–2017. Liu, B. et al. [16] utilized the T255 global high-resolution climate system model to evaluate projections of surface shortwave radiation over China and three typical sub-regions. Kwon, Y. et al. [17] conducted irradiance prediction studies using publicly available weather forecast data as model input. Vateanui, S. et al. [18] performed irradiance forecasting research using output data (with a spatial resolution from the numerical weather prediction model AROME). Bin, L. et al. [19] developed a short-term photovoltaic forecasting model that couples WRF-Solar with irradiance correction, achieving accurate solar radiation predictions. Numerous researchers worldwide have also conducted in-depth studies on irradiance forecasting using artificial intelligence methods. For instance, Yang, C. et al. [20] developed a short-term irradiance prediction model based on a Gated Recurrent Unit (GRU) neural network. They applied Principal Component Analysis (PCA) to reduce the dimensionality of historical meteorological data and satellite data, which were then used as model inputs to accomplish short-term solar irradiance forecasting. Jikai, D. [21] trained five fully convolutional networks using solar radiation simulation data from the WRF-Solar model and historical satellite observation data, and obtained the final solar radiation predictions through the Chaotic Aquila Optimization (CAO) algorithm. Âzeddine, F. et al. [22] proposed a short-term probabilistic forecasting model for solar irradiance based on a non-homogeneous Markov model, which automatically adapts the correct model complexity and scale to achieve autonomous adaptation to various weather conditions and geographical locations. The model can be directly applied globally by simply inputting historical time-series data of the clear-sky index. Alfadda, A. et al. [23] introduced an hourly solar irradiance forecasting model based on a novel feature scheme. This model uses aerosol optical depth data, Ångström exponent data, and other meteorological elements from ground observation stations from the previous hour as inputs, and was tested on various data-driven models, including Multilayer Perceptron (MLP), Support Vector Regression (SVR), k-Nearest Neighbors, and Decision Tree Regression. The results indicate that MLP is particularly suitable for clear-sky conditions in desert regions under different feature selection schemes. However, many forecasting models do not account for the influence of meteorological and geographical factors on irradiance prediction. Research has identified cloud cover, aerosols, and water vapor as the predominant meteorological

factors influencing solar radiation. Specifically, Yuzhu [24] proposed an irradiance-based interval prediction method for solar resources, while Yu [25] investigated the variation and influencing factors of clear-sky surface solar radiation over China. Under intermittent cloudy conditions, the accuracy of solar irradiance simulation deteriorates, leading to higher absolute errors than those under overcast or clear skies. Specifically, Prasad and Kay [26] assessed simulated solar irradiance on days of high intermittency using WRF-Solar, while Chen et al. [27] developed a correction technique for ERA5 surface downward total solar irradiance based on routine surface meteorological observation data. Furthermore, the long-range transport of dust aerosols has been identified as a significant factor contributing to larger errors in solar radiation estimation. For instance, Dhar et al. [28] quantified atmospheric aerosol radiative forcing over a semi-continental site in Northeast India; Zhang et al. [29] and Cao et al. [30] examined the impact of dust weather on surface solar radiation and forecast correction in northern China; Jin et al. [31] focused on dust effects in the desert hinterland of southern Xinjiang; and Zeng et al. [32] assessed dust impacts on both air quality and solar radiation in Beijing. Cheng, K. et al. [33] applied LASSO regression to select characteristic variables, established training and test sets, and employed RF (random forest), XGBoost, and LightGBM algorithms to train models for correcting the total irradiance forecasts from the CMA-WSP2.0 model in Henan Province. Shang, Y. et al. [34] proposed a correction model based on Multilayer Perceptron (MLP) and Stepwise Cluster Analysis (SCA) neural network algorithms under different weather conditions. Their results indicated that both neural network algorithms significantly reduce irradiance forecast errors, although SCA performed relatively poorly during rainy conditions. Dong, X. et al. [35] analyzed the diurnal distribution characteristics of errors and implemented corrections for both forecast phase bias and forecast values. Verbois, H. et al. [10] introduced a novel multivariate Model Output Statistics (MOS) correction method that combines stepwise variable selection with dimensionality reduction techniques. Results demonstrated that this approach effectively enhances prediction accuracy and outperforms simple univariate linear regression methods. Hu et al. [36] proposed a probability density matching-based correction method for FY-4A surface incident solar radiation. Compared to direct model outputs, this method significantly reduced the bias and improved the overall accuracy of solar radiation estimation.

2. Materials and Methods

2.1. Ground Observation Data

This study utilizes ground-measured solar irradiance and meteorological data collected from a photovoltaic farm in Guangdong Province, China, during the period from June to September 2023. The farm is located in the southwestern region of Guangdong (latitude 22.245° N, longitude 112.523° E, and elevation 6.64 m). Solar irradiance parameters, including global horizontal irradiance, direct normal irradiance, and diffuse horizontal irradiance, are measured using a Kipp & Zonen RT1 radiometer, manufactured by Kipp & Zonen B.V., Delft, The Netherlands. In addition to solar irradiance data, the station's Davis Instruments Vantage Pro2 automatic weather station records surface meteorological variables such as relative humidity, air temperature, wind speed, and wind direction. All data are logged at a temporal resolution of 15 min, with specific parameters detailed in Table 1.

Table 1. Parameters of the observation instruments at the photovoltaic farm.

Instrument	Measured Parameters	Key Specifications
Kipp & Zonen RT1y	Global Horizontal Irradiance (GHI)	Range: 0–2000 W/m ² ; Resolution: 1 W/m ²
	Direct Normal Irradiance (DNI)	Range: 0–2000 W/m ² ; Resolution: 1 W/m ²
	Diffuse Horizontal Irradiance (DHI)	Range: 0–2000 W/m ² ; Resolution: 1 W/m ²
	PV Module Backsheet Temperature	Range: −20 °C to 100 °C; Resolution: 0.1 °C
Davis Instruments Vantage Pro2	Air Temperature	Range: −40 °C to 65 °C; Resolution: 0.1 °C
	Relative Humidity (RH)	Range: 0–100% RH; Resolution: 0.1% RH
	Wind Speed	Range: 0–60 m/s; Resolution: 0.1 m/s
	Wind Direction	Range: 0–360°; Resolution: 1°
	Atmospheric Pressure	Range: 600–1100 hPa; Resolution: 0.1 hPa
	Rainfall	Resolution: 0.2 mm; Measurement accuracy: ±4%

2.2. Model Configuration

The Weather Research and Forecasting (WRF) Model is a next-generation mesoscale numerical weather prediction system jointly developed by four institutions: the Mesoscale and Microscale Meteorology Laboratory of the National Center for Atmospheric Research (NCAR), the Environmental Modeling Center of the National Centers for Environmental Prediction (NCEP), the Forecast Systems Laboratory (FSL), and the Center for Analysis and Prediction of Storms (CAPS) at the University of Oklahoma [37,38]. Its physical processes encompass horizontal and vertical atmospheric turbulence diffusion, cumulus convection parameterization schemes, a range of cloud microphysics schemes from simple to complex, shortwave solar radiation and longwave atmospheric radiation schemes, planetary boundary layer parameterizations, and subgrid-scale turbulent diffusion processes. The WRF modeling system offers high portability, maintainability, extensibility, and computational efficiency, along with user-friendly features, making it one of the most advanced mesoscale numerical weather prediction systems currently available. It has been widely adopted for operational forecasting and research by meteorological services and scientific institutions in most countries worldwide.

Studies indicate that indirect effects of clouds and aerosols are among the primary factors influencing solar radiation. However, the standard WRF model does not fully account for aerosol chemical processes, leading to considerable uncertainties in solar radiation forecasts. To address this limitation, the National Center for Atmospheric Research (NCAR) coupled the WRF V3.6 model with a solar extension to develop the WRF-Solar model [12,21,39], which is specifically designed for solar energy resource assessment and irradiance forecasting.

In contrast to the conventional WRF model, WRF-Solar incorporates indirect aerosol radiative effects and radiative feedback from shallow cumulus clouds. It calculates total, direct, and diffuse radiation at each model time step [40,41], significantly improving the accuracy of solar radiation predictions. Moreover, by enabling the auxinput15 option, users can introduce external aerosol optical depth (AOD) data as initial conditions into the model.

In this study, WRF-ARW version 4.2 was employed for numerical simulation. The simulation domain is centered at the photovoltaic plant in the study area (22.245° N, 112.523° E, the position marked by the five-pointed star in Figure 1.), with a three-domain two-way nested grid configuration where the outer domain provides dynamic boundary conditions for the inner domains. The key parameters of each domain are as follows: the outermost domain D01 has a horizontal resolution of 9 km with 150 × 150 grid points in the zonal and meridional directions; the middle domain D02 has a horizontal resolution of 3 km with 136 × 136 grid points; the innermost domain D03 has a horizontal resolution of 1 km with 124 × 124 grid points, and the configuration of the simulation domain is shown

in Figure 1. The model integration period spans from 1 June to 1 September 2023, with an integration time step of 30 s, and the simulation results are output at 15 min intervals to match the temporal resolution of the ground observation data. The initial conditions and 6-hourly updated lateral boundary conditions are derived from the $0.25^\circ \times 0.25^\circ$ resolution NCEP Global Forecast System (GFS) Final Analysis (FNL) data.

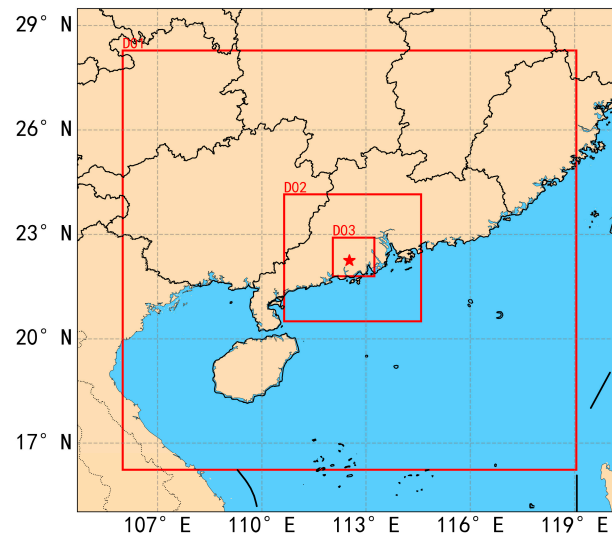


Figure 1. Configuration of the simulation domain.

2.3. Aerosol Optical Depth (AOD) Data

The aerosol optical depth at 550 nm (AOD550 nm) data used in this study are obtained from the MOD08_M3 version 6.1 monthly gridded product of the Moderate-resolution Imaging Spectroradiometer (MODIS) onboard the TERRA satellite, with a spatial resolution of $1^\circ \times 1^\circ$. The MODIS sensor can provide continuous global aerosol observations, and its data quality and reliability have been widely verified by relevant studies worldwide, making it one of the most widely used aerosol data sources in atmospheric radiation simulation research. In this study, quality control is first performed on the MOD08_M3 product, where pixels marked as invalid by the quality flag are removed, and a small number of missing values are filled with the mean value of adjacent grid points, to obtain the monthly global $1^\circ \times 1^\circ$ AOD550 nm gridded data from June to August 2023. To achieve spatial matching between the coarse-resolution AOD data and the 1 km model grid, the bilinear spatial interpolation method is adopted to downscale the preprocessed monthly AOD data to the 9 km grid of the outermost model domain D01. Then, through the two-way feedback mechanism of the three-domain nested WRF model, the AOD data are automatically transferred to the 3 km grid of the inner domain D02 and the 1 km grid of D03, ensuring the spatial consistency between the aerosol field and the model dynamic framework. In the temporal dimension, the monthly average AOD data of the corresponding month are used as the aerosol background field for the entire model integration process of that month, to provide stable physical constraints for radiative transfer calculation. Although there is a scale difference between the $1^\circ \times 1^\circ$ resolution of the original AOD data and the 1 km grid of the innermost model domain, this study focuses on the monthly-to-seasonal scale characteristics of solar irradiance simulation, rather than local instantaneous aerosol fluctuations. The MOD08_M3 monthly average product can stably characterize the large-scale climatological background features of aerosols in the coastal area of South China, and can provide reasonable physical constraints for the radiative transfer calculation in WRF-Solar, effectively reducing the systematic simulation deviation caused by the neglect of aerosol effects in the conventional WRF model.

2.4. Random Forest Algorithm

Random forest is a tree-based ensemble approach. Since decision tree models typically exhibit high variance, predictions from a single tree often perform poorly. The random forest method employs an ensemble strategy, sacrificing a certain degree of bias to achieve a substantial reduction in variance, thereby minimizing overall error and enhancing prediction accuracy.

A decision tree consists of a recursive partitioning algorithm that uses a greedy approach to divide training samples from the top down into distinct units, corresponding to the nodes of the tree. After the splitting process is completed, each terminal node corresponds to a constant output. The regression tree model can be summarized as follows:

$$f(x) = \sum_{j=1}^J C_j \cdot I_{(x \in R_j)} \quad (1)$$

$$C_j = \text{ave}(y_i | x_i \in R_j) \quad (2)$$

where J is the number of units, C_j is the average response value of the samples within each unit, $R_j (j = 1, 2, \dots, J)$ represents the non-overlapping sample regions, and I denotes the indicator function.

For each split, the regression tree aims to minimize the residual sum of squares. Given a candidate split variable j and a split point s , two child nodes are defined as follows:

$$R_1(j, s) = \{X | X_j \leq s\} \text{ and } R_2(j, s) = \{X | X_j > s\} \quad (3)$$

Then, seek the split variable j and split point s that minimize:

$$\min_{j,s} \left[\min_{c_1} \sum_{x_i \in R_1(j,s)} (y_i - c_1)^2 + \min_{c_2} \sum_{x_i \in R_2(j,s)} (y_i - c_2)^2 \right] \quad (4)$$

For each pair of j and s obtained from the optimization, we have:

$$c_1 = \text{ave}(y_i | x_i \in R_1(j, s)) \text{ and } c_2 = \text{ave}(y_i | x_i \in R_2(j, s)) \quad (5)$$

After identifying the optimal split, the data is partitioned into two regions, and the splitting process is recursively repeated on each resulting subregion to progressively build the complete regression tree.

A key limitation of a single decision tree is its high variance, as minor perturbations in the training data can lead to significant structural changes in the tree. This instability can be mitigated by combining multiple trees into a single ensemble model, thereby reducing variance and improving predictive accuracy. This approach gives rise to the Bagging (Bootstrap Aggregating) method.

In Bagging, B subsets are generated by repeatedly sampling from the original training set with replacement. A model is then fitted on each of the b -th subsets to obtain predictions denoted as $f^{*b}(x)$. Once all models are trained, their predictions are aggregated by averaging:

$$\hat{f}_{\text{bog}} = \frac{1}{B} \sum_{b=1}^B f^{*b}(x) \quad (6)$$

The random forest algorithm extends this concept by introducing an additional layer of randomization. During each split, rather than evaluating all p potential variables ($m \leq p$), it

considers only a randomly selected subset of m candidate splitting variables. This constraint serves to decorrelate the individual trees within the ensemble.

By averaging the predictions of these decorrelated trees, the variance of the final model is further reduced. Formally, random forest can be viewed as a specialized case of Bagging. The two methods become equivalent when the subset size $m = p$ is chosen to be equal to the total number of features:

$$\hat{f}_{rf} = \frac{1}{B} \sum_{b=1}^B \hat{f}^{*b}(X; m) \quad (7)$$

2.5. Daily Variability Index (DVI) and Daily Clear-Sky Index (DCI)

To evaluate the accuracy of simulated irradiance under cloudy and clear conditions, this study introduces the Daily Variability Index (DVI) and Daily Clear-sky Index (DCI) to distinguish different weather types for subsequent categorical analysis [26,27]. The formulas for calculating DVI and DCI are as follows:

$$DVI = \frac{\sum_{i=2}^n |GHI_i - GHI_{i-1}|}{\sum_{i=2}^n |CSI_i - CSI_{i-1}|} \quad (8)$$

$$DCI = \frac{\sum_{i=1}^n GHI_i}{\sum_{i=1}^n CSI_i} \quad (9)$$

where GHI_i is the measured Global Horizontal Irradiance (GHI) for the i -th time interval, with units typically W/m^2 . CSI_i is the Global Horizontal Irradiance (GHI) calculated by a clear-sky model for the i -th time interval, with units typically W/m^2 . n is the total number of samples taken in a day, and it is dimensionless.

The calculation formula for CSI_i is:

$$CSI = c_1 \cdot I_0 \cdot \cos(\theta_z) \cdot \exp[-c_2 \cdot AM \cdot (f_1 + f_2 \cdot (T_{L2} - 1))] \cdot \exp[0.01 \cdot AM^{1.8}] \quad (10)$$

where

I_0 : The solar irradiance received at the top of the Earth's atmosphere. The calculation formula is:

$$I_0 = I_{sc} \cdot \left[1 + 0.033419 \cdot \cos\left(\frac{2\pi J}{365.25}\right) \right] \quad (11)$$

where I_{sc} is the solar constant (approximately $1361 W/m^2$), and J is the day of the year (January 1st is 1).

θ_z : Solar zenith angle, the angle between the sun's rays and the local zenith direction. The calculation formula is:

$$\theta_z = \arccos(\sin \phi \cdot \sin \delta + \cos \phi \cdot \cos \delta \cdot \cos \omega) \quad (12)$$

where ϕ is the local geographical latitude, δ is the solar declination angle, and ω is the solar hour angle.

AM : Air mass, the relative path length of solar radiation through the atmosphere. The calculation formula is:

$$AM = \frac{1}{\cos \theta_z + 0.50572(96.07995 - \theta_z)^{-1.6364}} \quad (13)$$

T_{L2} : The 2nd order Linke turbidity factor is a dimensionless parameter characterizing the overall atmospheric turbidity. It integrates the scattering and absorption of radiation by dry air molecules, water vapor, aerosols, etc. This value typically comes from climatological datasets or field measurements.

c_1, c_2, f_1, f_2 : Empirical coefficients of the model, with values $c_1 = 0.0387$, $c_2 = 0.046$, $f_1 = 1.5$, and $f_2 = 0.84$.

The DVI reflects the degree of daily solar radiation variation, indicating radiation instability caused by factors such as cloud movement, and is used to determine whether cloud conditions are stable or exhibit intermittent changes. In contrast, the DCI reflects the ratio of the total solar radiation reaching the ground relative to the total under ideal clear-sky conditions, directly indicating the weather's cloudiness or clarity.

2.6. Error Evaluation Metrics

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (I_i^m - I_i^o)^2} \quad (14)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |I_i^m - I_i^o| \quad (15)$$

The evaluation metrics employed in this study include root mean square error:

$$Bias = \frac{1}{n} \sum_{i=1}^n (I_i^m - I_i^o) \quad (16)$$

(RMSE), Mean Absolute Error (MAE), and Bias (*Bias*):

where I_i^m is defined as the simulated value of the i^* -th sample, I_i^o as its observed value, and n as the total sample size.

3. Results

3.1. Classification of Weather Conditions

Based on the measured irradiance data from the photovoltaic plant and the calculation results of daily theoretical clear-sky irradiance, a scatter-box plot of DVI and DCI was drawn (Figure 2). Figure 2 presents the scatter-box distribution of daily DVI and DCI during the simulation period, where each scatter point represents one simulation day. The upper and lower edges of the light blue-filled box correspond to the 75th and 25th percentiles of DVI in the corresponding DCI bin, respectively, reflecting the concentration range of DVI values. The thick red line inside the box is the median (50th percentile) of DVI, representing the central tendency of DVI within the DCI bin. The thick gray whiskers extending from the top and bottom of the box mark the 10th and 90th percentiles of DVI, indicating the dispersion range of DVI values. The red dot inside the box denotes the mean DVI value in each DCI bin, reflecting the overall trend of mean DVI with varying DCI. The distribution characteristics of DVI under different weather types can be clearly compared via this plot.

It can be seen from the Figure that DVI shows a unimodal distribution with DCI. Combined with the research results of Prasad and Huang [26,27], the weather conditions during the simulation period are classified into three categories according to DCI values: overcast conditions, intermittent conditions, and clear conditions, corresponding to DCI intervals of (0, 0.50), (0.50, 0.90), and [0.90, 1.1], respectively. DVI values are generally low under overcast and clear conditions, while the fluctuation amplitude of DVI increases significantly under intermittent conditions.

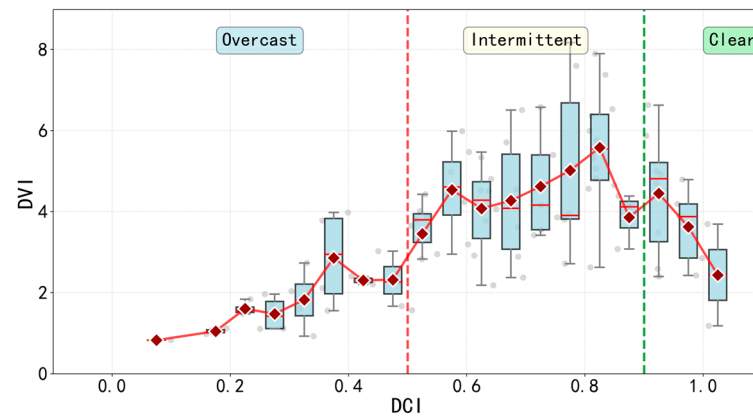


Figure 2. DVI-DCI scatter-box plot (Each scatter point represents one simulation day. The upper and lower edges of the light blue-filled box correspond to the 75th and 25th percentiles of DVI in the corresponding DCI bin, respectively, reflecting the concentration range of DVI values. The thick red line inside the box is the median (50th percentile) of DVI, representing the central tendency of DVI within the DCI bin. The thick gray whiskers extending from the top and bottom of the box mark the 10th and 90th percentiles of DVI, indicating the dispersion range of DVI values. The red dot inside the box denotes the mean DVI value in each DCI bin, reflecting the overall trend of mean DVI with varying DCI).

3.2. Irradiance Analysis for Clear Conditions, Intermittent Conditions, and Overcast Conditions

Based on a review and comparison of the literature related to radiation simulation in the Guangdong region, and considering the specific simulation area of this study, cloud and aerosol are identified as the core parameters influencing solar radiation. Therefore, in configuring the WRF-Solar model, this study focuses on conducting combinatorial experiments with parameterization schemes for microphysics and radiative transfer.

The simulation period is set from 1 June to 1 September 2023. Corresponding AOD data for this period are incorporated into the initial conditions to perform the WRF-Solar simulation. Due to the specific characteristics of radiation variables, only data from 08:00 to 18:00 Beijing Time each day are extracted from the wrfout files. A direct-diffuse separation output method is adopted, outputting simulated values for global horizontal irradiance, direct normal irradiance, diffuse horizontal irradiance, and various meteorological elements.

Due to the fact that only two radiation parameterization schemes in the WRF-Solar model—the RRTMG scheme and the Goddard scheme—allow for external aerosol file input, the RRTMG scheme was ultimately selected as the radiation scheme for this study based on preliminary tests and comparisons. However, in terms of microphysics scheme selection, as shown in Figure 3 and Table 2, it can be observed that the model generally overestimates irradiance under overcast conditions. This is likely because the selected microphysics scheme inaccurately simulates clouds, resulting in a significant underestimation of cloud cover, which in turn leads to an overestimation of irradiance.

Based on this hypothesis, this study conducted a separate investigation into cloudy days, performing sensitivity experiments on microphysics schemes. A consecutive period of cloudy days from 14 June to 18 June 2023 was selected for analysis. The microphysics parameterization schemes considered for comparison included: the Goddard Scheme, Kessler Scheme, Purdue–Lin Scheme, Thompson Scheme, WRF Single-Moment 3-class Scheme, WRF Single-Moment 5-class Scheme, and WRF Single-Moment 6-class Scheme.

The simulation results, compared as shown in Figure 4, reveal that most microphysics parameterization schemes overestimated irradiance. Among them, the WRF Single-Moment 3-class, 5-class, and 6-class schemes performed the worst, producing smooth curves that closely resembled the theoretical clear-sky radiation profile. These schemes

failed to capture the irradiance fluctuations and the characteristically low irradiance levels typical of overcast conditions.

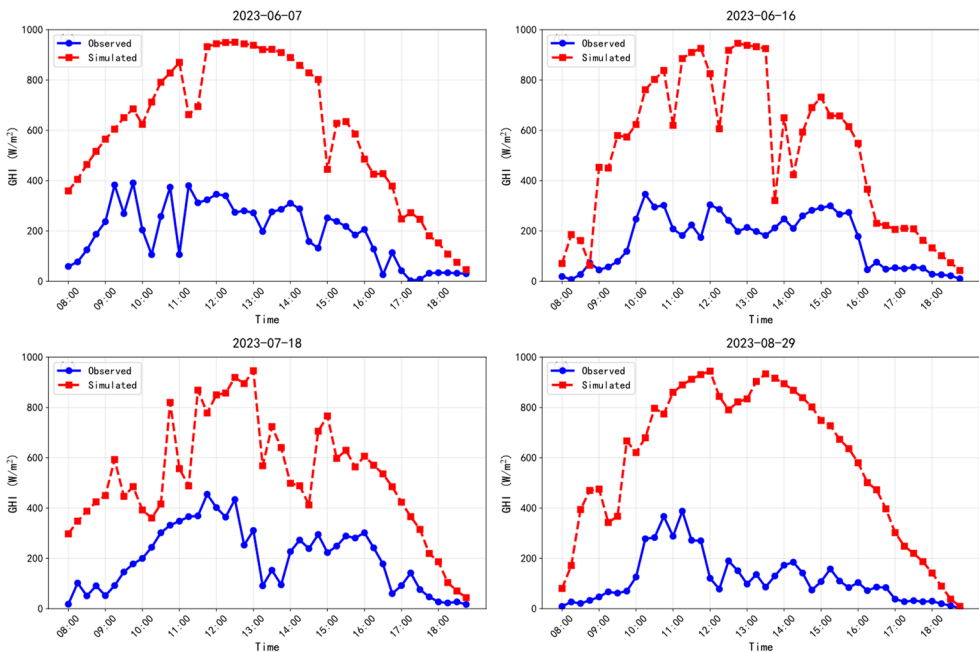


Figure 3. Comparison of WRF simulated and measured values under overcast conditions.

Table 2. Parameterization scheme configuration table.

Observed Cloud Fraction		Simulated Cloud Fraction
2023-04-22	0.419	0.137
2023-06-05	0.552	0.152
2023-09-17	0.432	0.203
2023-12-02	0.513	0.109

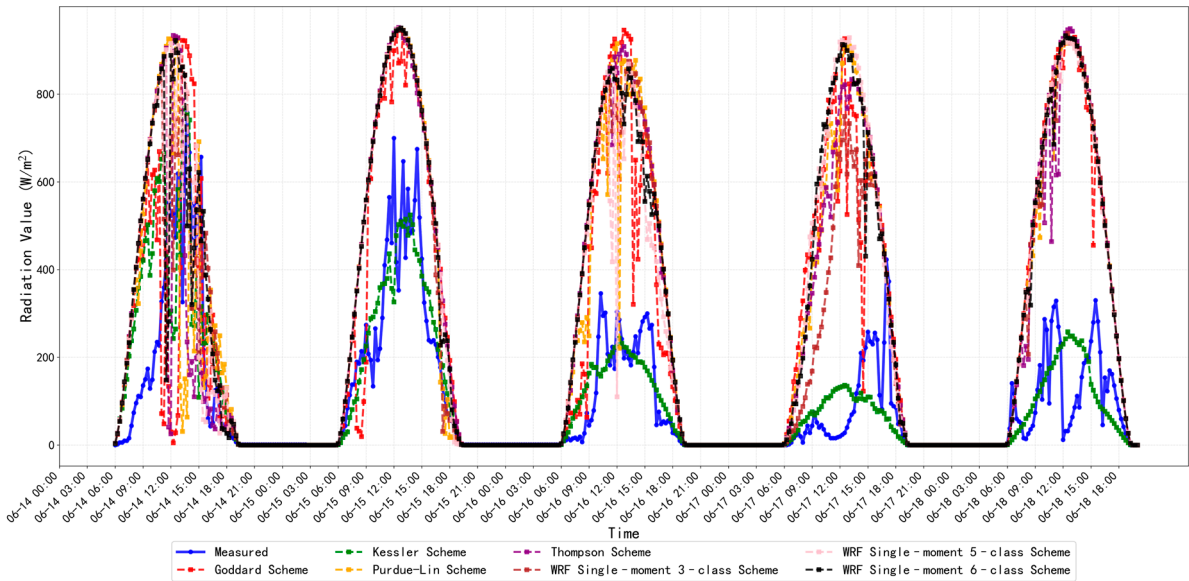


Figure 4. Results of microphysics scheme sensitivity experiments.

In contrast, the Kessler scheme demonstrated the best performance, effectively simulating both the overall trend and the fluctuating characteristics of irradiance. Consequently, the Kessler scheme was selected as the microphysics scheme for this study.

Based on the above experimental results, the optimal configuration of parameterization schemes for the WRF-Solar model in the numerical simulation phase of this study was finally determined, as shown in Table 2. Using the optimized model configuration, we conducted WRF-Solar simulation experiments from 17 June 2022 to 31 December 2023. The simulation was divided into 116 consecutive runs, with each run covering a 5-day target period and a total integration length of 132 h, including a 12 h spin-up period to eliminate the influence of initial field disturbances. The simulation results were output at a 15 min temporal resolution, yielding a total of 54,050 time steps of valid simulation data.

To comprehensively evaluate the irradiance simulation performance of the WRF-Solar model under different weather conditions, two continuous periods covering clear conditions, high-intermittent cloudy conditions, and overcast conditions were selected for comparative analysis: 6–14 July 2022 and 29 January–5 February 2023 (Figures 5 and 6). Meanwhile, the overall error metrics were calculated based on the simulation and observation data from 17 June 2022 to 1 January 2024 (Table 3).

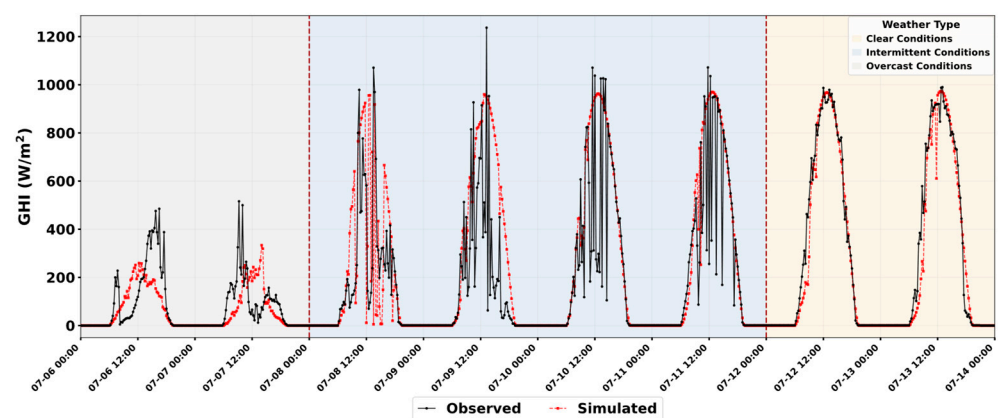


Figure 5. Comparison of observed and simulated global horizontal irradiance (GHI) from 6 to 14 July 2022 (The black curve denotes in situ observed GHI, and the red curve denotes GHI simulated by the WRF-Solar model. Background colors mark weather types from left to right: overcast conditions, high-intermittent cloudy conditions, and clear conditions).

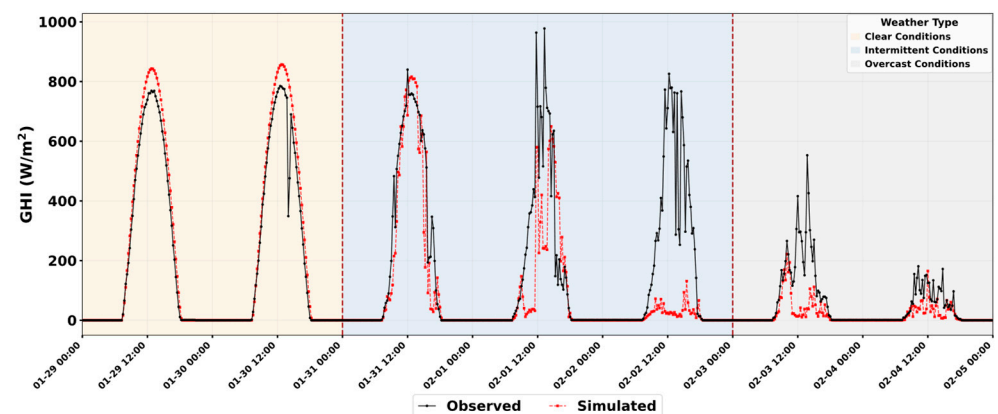


Figure 6. Comparison of observed and simulated global horizontal irradiance (GHI) from 29 January to 5 February 2023. The black curve denotes in situ observed GHI, and the red curve denotes GHI simulated by the WRF-Solar model. Background colors mark weather types from left to right: clear conditions, high-intermittent cloudy conditions, and overcast conditions.

Table 3. Parameterization scheme configuration table.

Physics Options	Scheme Selection
Micro Physics Options	Kessler Scheme
Cumulus Parameterization Options	Kain–Fritsch Scheme
Shortwave and Longwave Options	RRTMG Shortwave and Longwave Schemes
Planetary Boundary Layer Physics Options	Yonsei University Scheme (YSU)
Land Surface Options	Noah–MP Land Surface Model

Based on the comprehensive analysis of the time-series variation and error metrics, the following conclusions can be drawn.

Under clear conditions, the simulated irradiance from the model is highly consistent with the diurnal variation trend of the in situ observations. Both show the typical radiation profile characteristics of clear-sky conditions: rising rapidly after sunrise, peaking at noon, and decreasing slowly in the afternoon. The magnitude and occurrence time of the peak are in good agreement, with no significant systematic bias. From the perspective of error metrics, the RMSE (176.26 W/m^2) and MAE (103.94 W/m^2) under clear conditions are the lowest among the three weather types, with a bias of 21.23 W/m^2 , indicating that the model can accurately capture the transmission law of solar radiation, with stable simulation accuracy and the best overall performance.

Under high-intermittent cloudy conditions, although the model can effectively capture the sharp fluctuations in irradiance caused by the formation, dissipation, and movement of cloud systems, and reproduce the dynamic variation characteristics of abrupt rise and fall of radiation, there are certain deviations between the simulated curve and the observed values in terms of fluctuation amplitude and peak magnitude. In addition, there is still a temporal lag issue, and underestimation of irradiance occurs in individual periods (e.g., 2 February 2023). The error metrics are significantly higher than those under clear conditions, with an RMSE of 246.53 W/m^2 , MAE of 166.63 W/m^2 , and bias of 98.04 W/m^2 . This reflects that the model still has deficiencies in the simulation of intermittent cloud systems, and cannot fully match the instantaneous characteristics of radiation under the rapid change in cloud systems, resulting in a moderate simulation effect.

Under overcast conditions, after optimization through the targeted sensitivity experiment of the microphysical parameterization scheme, the simulated irradiance from the model has no obvious systematic overestimation, and the simulation effect is effectively improved. However, from the perspective of error levels, the RMSE (280.59 W/m^2), MAE (189.77 W/m^2), and bias (126.17 W/m^2) under overcast conditions are still the highest among the three weather types. Meanwhile, there are still large deviations between the simulated curve and the observed values in terms of fluctuation amplitude and instantaneous peak value, which fail to fully reproduce the low-level characteristics and actual fluctuation law of irradiance under overcast conditions. This indicates that although the optimized microphysical scheme can well capture the overall attenuation effect of overcast cloud systems on solar radiation and avoid the overestimation problem, it may still have deficiencies in simulating the microphysical structure of cloud systems, resulting in the model's inability to accurately capture the instantaneous fluctuations and detailed variations in irradiance under overcast conditions.

3.3. Random Forest Correction

The total dataset for random forest (RF) modeling includes 15 min WRF-Solar simulations and ground in situ observations from 08:00 to 18:00 daily between 17 June 2022 and 31 December 2023. Data from 14 to 18 June 2023, which were used for WRF microphysics sensitivity tests, were entirely excluded from the total dataset to prevent data overlap between different experimental stages. The RF model directly corrects the global horizontal

irradiance (GHI) output from WRF-Solar, with seven variables from WRF-Solar used as input features: simulated global horizontal irradiance (SWDOWN_WRF), 2 m air temperature (T2), 2 m specific humidity (Q2), surface pressure (PSFC), 10 m zonal wind (U10), 10 m meridional wind (V10), and total cloud fraction (CLDFRA). The target variable was the in situ observed global horizontal irradiance (GHI).

To avoid data leakage in time-series modeling, the dataset was split chronologically rather than randomly: samples from 17 June 2022 to 30 November 2023 formed the training set, and those from 1 December 2023 to 1 January 2024 formed the test set. Four typical days for overcast and high-intermittent conditions were additionally assigned to the test set and not used for model training. The final train–test ratio was approximately 8:2. Feature importance was computed based on Gini impurity reduction (Figure 7). SWDOWN_WRF showed the highest importance (0.442), followed by total cloud fraction (0.119) and surface pressure (0.110). All seven features were retained for the final modeling.

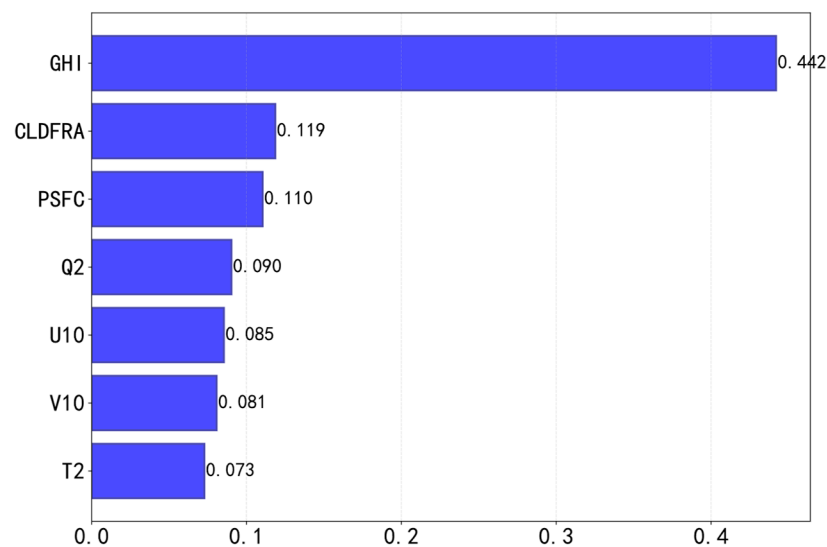


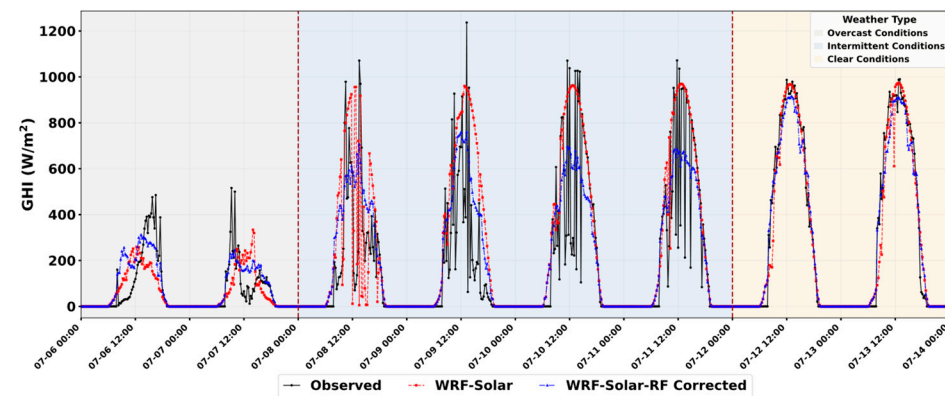
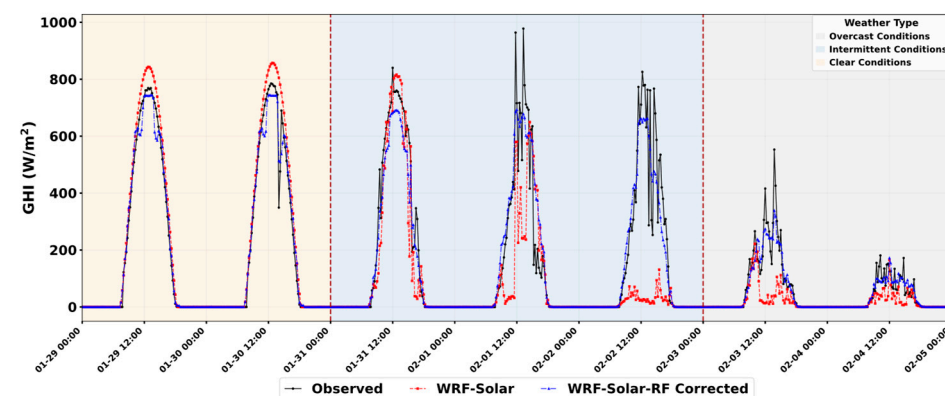
Figure 7. Feature importance of variables.

Separate RF models were built for overcast, intermittent, and clear conditions based on DCI classification. Models were implemented in Python 3.10 with Scikit-learn 1.2.2 using the following hyperparameters: $n_estimators = 200$, $max_depth = 15$, $min_samples_split = 5$, $min_samples_leaf = 2$, $random_state = 42$, and $n_jobs = -1$. These settings balance fitting performance and regularization to mitigate overfitting. Model performance was evaluated on the independent time-series test set. After training, corrected irradiance errors (Table 4) and time-series comparisons (Figures 8 and 9) were obtained.

For the period from 6 to 14 July 2022 (Figure 8), the WRF-Solar-RF correction effectively suppressed the overestimation of irradiance peaks, smoothed the anomalous fluctuations in the time series, and more accurately reproduced the diurnal variation pattern of the observed irradiance under clear conditions, with the corrected results in much closer agreement with the in situ observations. Quantitative error metrics (Table 5) show that after WRF-Solar-RF correction in this period, the root mean square error (RMSE) reached 141.73 W/m^2 , a percentage reduction of 45.88% compared with the original WRF simulation; the mean absolute error (MAE) was 102.26 W/m^2 , with a reduction of 40.02%; the mean bias (Bias) was corrected to -21.91 W/m^2 , with a significantly narrowed systematic bias.

Table 4. Error evaluation metrics for the three weather conditions.

	Clear Conditions	Intermittent Conditions	Overcast Conditions
RMSE (W/m^2)	176.26	21.23	103.94
Bias (W/m^2)	246.53	98.04	166.63
MAE (W/m^2)	280.59	126.17	189.77

**Figure 8.** Global horizontal irradiance (GHI) corrected by WRF-Solar-random forest (RF) model (6–14 July 2022).**Figure 9.** Global horizontal irradiance (GHI) corrected by WRF-Solar-random forest (RF) model (29 January to 5 February 2023).**Table 5.** Comparison of irradiance correction error metrics for the WRF-Solar-random forest (RF) model.

	2022-07-06–2022-07-14		2023-01-29–2023-02-05	
	WRF-SOLAR	WRF-SOLAR-RF	WRF-SOLAR	WRF-SOLAR-RF
RMSE (W/m^2)	261.86	141.73	214.974	63.89
Bias (W/m^2)	−63.33	−21.91	79.17	−3.58
MAE (W/m^2)	170.48	102.26	135.83	40.86

For the period from 29 January to 5 February 2023 (Figure 9), the WRF-Solar-RF correction eliminated the peak irradiance deviation under clear and high-intermittent cloudy conditions, and narrowed the gap with the observed values under overcast conditions, with the overall trend of the corrected curve in better agreement with the observed time series. Quantitative error metrics further confirm (Table 5) that after WRF-Solar-RF correction in this period, the RMSE reached 63.89 W/m^2 , a percentage reduction of 70.26% compared with the original simulation; the MAE was 40.86 W/m^2 , with a reduction of 69.92%; the

bias was corrected to -3.58 W/m^2 , which effectively reduced the systematic bias of the WRF simulation.

4. Discussion

In this study, we systematically improved the irradiance simulation accuracy for a photovoltaic (PV) plant in Guangdong Province through weather classification, optimization of WRF-Solar parameterization schemes, and weather-type-based random forest (RF) correction. Our findings align with recent international studies that use post-processing techniques to improve the performance of the WRF-Solar model, while also revealing the applicable conditions and limitations of different methods, providing deeper insights into the integrated application of physical models and statistical/machine learning methods.

First, this study found that even after the optimization of the microphysics scheme, the WRF-Solar model still exhibited significant simulation deviations under overcast conditions, with a root mean square error (RMSE) as high as 328.07 W/m^2 and a mean bias (Bias) of 226.05 W/m^2 . This finding is highly consistent with the core conclusion of Prasad and Kay [26], that the inaccurate representation of clouds in the model is the fundamental factor leading to poor irradiance simulation under overcast and intermittent conditions. Both independent studies identified a systematic underestimation of cloud fraction by the model in different geographical regions, manifested as over-smoothed simulated curves and a general overestimation of actual irradiance. This consensus finding clearly indicates that although the optimization of parameterization schemes can bring marginal improvements, advancing the representation of cloud physical processes is the universal key to enhancing the performance of the WRF-Solar model.

Second, the weather classification method based on the Daily Variability Index (DVI) and Daily Clear-sky Index (DCI) adopted in this study builds on and extends the research framework of Huang et al. [27]. We not only verified the fundamental law regarding DVI peaks under intermittent cloud conditions, but more importantly, developed this method into an effective tool for diagnosing the sources of model errors. Based on this classification method, the RF correction model introduced in this study showed excellent correction performance, significantly reducing the bias to 44.97 W/m^2 under intermittent conditions and 20.75 W/m^2 under overcast conditions, respectively. This result strongly confirms the conclusion of Huang et al. that the random forest model has unique advantages in capturing the complex nonlinear relationships related to solar irradiance variability. The success of the RF model is attributed to its ability to learn the complex mapping relationship between multiple input features (including meteorological elements such as cloud fraction, air pressure, and humidity) and irradiance errors, which provides new empirical support for the application of machine learning in the field of solar energy meteorology. The decaying average method adopted by Cheng-Liang Huang et al. [42] achieved a 22% improvement in irradiance prediction, while this study used the RF method to correct irradiance under complex intermittent cloudy conditions, reducing the bias from 217.20 W/m^2 to 44.97 W/m^2 .

Both studies jointly reveal a key phenomenon: any single post-processing method has inherent limitations. This study observed a performance degradation of the RF model under clear conditions, while the study by Huang et al. also found that the decaying average method failed in specific regions (e.g., winter in Taoyuan). This consensus demonstrates that the effectiveness of post-processing methods is significantly constrained by local weather conditions and climatic characteristics.

The limitations of this study are mainly reflected in the following aspects, which also point out the direction for future improvements. First, the model validation in this study is based on observation data from a single PV plant site, so the universality of the conclu-

sions needs further verification. There are significant differences in climatic characteristics, topographic conditions, and atmospheric environments in different geographical regions. Especially under different underlying surface conditions, such as coastal vs. inland, and plain vs. mountainous areas, the cloud formation mechanism and radiative transfer characteristics may show obvious regional features. Second, the black-box nature of the RF model limits its interpretability in practical operational applications. Although we identified key influencing factors such as irradiance, cloud fraction, and surface pressure through feature importance analysis, the specific decision-making process and internal mechanism of the model are still not transparent enough. This lack of interpretability may lead to the following problems: (1) when the model produces abnormal predictions, it is difficult to trace the source of errors and implement targeted corrections; and (2) under extreme weather conditions, the model's prediction behavior lacks physical constraints, which may lead to abnormal outputs that do not conform to the laws of atmospheric physics.

5. Conclusions

This study systematically investigated the irradiance simulation for a photovoltaic plant in Guangdong Province using a combination of numerical simulation, statistical analysis, and machine learning methods, with the main conclusions drawn as follows.

- (1) This study introduced the Daily Variability Index (DVI) and Daily Clear-sky Index (DCI) to achieve effective classification of clear conditions, intermittent conditions, and overcast conditions during the simulation period. This classification method, based on radiation observation data and theoretical clear-sky radiation calculation, lays a foundation for subsequent model evaluation and correction under different weather conditions, and can be extended to other regions and PV plants.
- (2) Through sensitivity experiments on the microphysics and radiative transfer parameterization schemes in the WRF-Solar model, combined with comparative analysis against in situ observation data, this study determined the optimal combination of parameterization schemes suitable for the study area: the Kessler microphysics scheme and the RRTMG radiation scheme. This scheme improved the model's ability to simulate the radiation trend and fluctuations under overcast conditions to a certain extent, but also revealed the limitations of the model in characterizing cloud processes, pointing out the direction for subsequent model improvement.
- (3) This study introduced the random forest (RF) method to correct the irradiance simulated by WRF-Solar. The results show that the RF correction can significantly improve the simulation accuracy and reduce both systematic and random errors under intermittent and overcast conditions. However, under clear conditions, the simulation results from the original WRF-Solar model are more accurate. This correction strategy can give full play to the advantages of both the WRF-Solar model and the RF model, thereby improving the overall accuracy and reliability of solar radiation prediction.

In summary, this study effectively improved the irradiance simulation accuracy for a PV plant in Guangdong Province through weather condition classification, model parameter optimization, and RF correction. Future research can further explore methods to improve the performance of the RF model under clear conditions, develop correction methods more suitable for clear conditions, and conduct in-depth research on cloud microphysical processes to fundamentally improve the accuracy of solar radiation prediction.

Author Contributions: Conceptualization, Z.G.; Methodology, Y.H.; Formal analysis, Z.L.; Investigation, F.Z.; Data curation, Y.H. and F.Z.; Writing—original draft, Y.H.; Writing—review & editing, Z.G.; Supervision, Z.L. and Z.G.; Project administration, Y.H., Z.L. and Z.G.; Funding acquisition, Z.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study were derived from the following public domain resources: the Moderate Resolution Imaging Spectroradiometer (MODIS) dataset, available at the NASA Earthdata platform (<https://earthdata.nasa.gov/>, accessed on 16 April 2026); and the Global Forecast System (GFS) dataset, available at the NOAA National Centers for Environmental Information (<https://www.ncei.noaa.gov/products/weather-climate-models/global-forecast>, accessed on 16 April 2026). No new proprietary data were generated in this study.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Dai, H.; Su, Y.; Kuang, L.; Liu, J.; Gu, D.; Zou, C. Contemplation on China's Energy-Development Strategies and Initiatives in the Context of Its Carbon Neutrality Goal. *Engineering* **2021**, *7*, 1684–1687. [CrossRef]
2. Hayat, M.B.; Ali, D.; Monyake, K.C.; Alagha, L.; Ahmed, N. Solar energy—A look into power generation, challenges, and a solar-powered future. *Int. J. Energy Res.* **2019**, *43*, 1049–1067. [CrossRef]
3. Kannan, N.; Vakeesan, D. Solar energy for future world:—A review. *Renew. Sustain. Energy Rev.* **2016**, *62*, 1092–1105. [CrossRef]
4. Li, H.; Sun, X.; Li, L. The Enlightenment of the European Energy Crisis for China's Development of Nuclear Energy. *Chin. Energy* **2022**, *44*, 57–68. (In Chinese)
5. Xu, X. Evolutionary Game Analysis of China's Energy Structure Transition. Master's Thesis, Anhui University of Science and Technology, Huainan, China, 2022. (In Chinese)
6. Kabir, E.; Kumar, P.; Kumar, S.; Adelodun, A.A.; Kim, K.-H. Solar energy: Potential and future prospects. *Renew. Sustain. Energy Rev.* **2018**, *82*, 894–900. [CrossRef]
7. Ahmed, R.; Sreeram, V.; Mishra, Y.; Arif, M.D. A review and evaluation of the state-of-the-art in PV solar power forecasting: Techniques and optimization. *Renew. Sustain. Energy Rev.* **2020**, *124*, 109792. [CrossRef]
8. Zhao, Z.; Liu, D.; Guo, W.; Zhang, Q.; Song, M.; Liu, B.; Cui, S.; Wang, F.; Liu, L.; Tian, J. The Impact of Aerosol Optical Depth on Irradiance Forecasting. *Sol. Energy* **2018**, 52–59. (In Chinese) [CrossRef]
9. Jimenez, P.A.; Hacker, J.P.; Dudhia, J.; Haupt, S.E.; Ruiz-Arias, J.A.; Gueymard, C.A.; Thompson, G.; Eidhammer, T.; Deng, A. WRF-SOLAR: Description and Clear-Sky Assessment of an Augmented NWP Model for Solar Power Prediction. *Bull. Am. Meteorol. Soc.* **2016**, *97*, 1249–1264. [CrossRef]
10. Verbois, H.; Huva, R.; Rusydi, A.; Walsh, W. Solar irradiance forecasting in the tropics using numerical weather prediction and statistical learning. *Sol. Energy* **2018**, *162*, 265–277. [CrossRef]
11. Gueymard, C.; Jiménez, P. Validation of Real-Time Solar Irradiance Simulations Over Kuwait Using WRF-Solar. In Proceedings of the EuroSun 2018—International Conference on Solar Energy for Buildings and Industry, Rapperswil, Switzerland, 10–13 September 2018. [CrossRef]
12. Dasari, H.P.; Desamsetti, S.; Langodan, S.; Attada, R.; Kunchala, R.K.; Viswanadhapalli, Y.; Knio, O.; Hoteit, I. High-resolution assessment of solar energy resources over the Arabian Peninsula. *Appl. Energy* **2019**, *248*, 354–371. [CrossRef]
13. Blaga, R.; Sabadus, A.; Stefu, N.; Dughir, C.; Paulescu, M.; Badescu, V. A current perspective on the accuracy of incoming solar energy forecasting. *Prog. Energy Combust. Sci.* **2019**, *70*, 119–144. [CrossRef]
14. Wang, C.; Shen, Y.; Zhai, Z.; Qiu, K. Verification and Correction of FY-4A Surface Solar Radiation Products: A Case Study of Anhui Province. *Acta Energetica Solaris Sin.* **2021**, *42*, 159–169. (In Chinese) [CrossRef]
15. Jia, D.; Li, K.; Yang, L.; Gao, X.; Zhao, C. Projection of Solar Radiation Variation over the Next 30 Years Using CMIP5 Climate Models. *J. Acta Energetica Solaris Sinica* **2020**, *41*, 199–205. (In Chinese)
16. Liu, B.; Ma, L.; Rong, X.; Su, J.; Yan, Y.; Hua, L.; Tang, Y. High-Resolution Model for Seasonal Prediction of Surface Shortwave Radiation over China. *J. Appl. Meteor. Sci.* **2022**, *33*, 341–352. (In Chinese) [CrossRef]
17. Kwon, Y.; Kwasinski, A.; Kwasinski, A. Solar Irradiance Forecast Using Nave Bayes Classifier Based on Publicly Available Weather Forecasting Variables. *Energies* **2019**, *12*, 1529. [CrossRef]
18. Sansine, V.; Ortega, P.; Hissel, D.; Hopuare, M. Solar Irradiance Probabilistic Forecasting Using Machine Learning, Metaheuristic Models and Numerical Weather Predictions. *Sustainability* **2022**, *14*, 15260. [CrossRef]
19. Bin, L.; Yi, D.; Zhe, B.; Yu, S.; Wei, L. A Short-Term Photovoltaic Forecasting Model Coupling WRF-Solar and Irradiance Correction. *J. Electr. Power Sci. Technol.* **2025**, *40*, 110–118. (In Chinese) [CrossRef]
20. Yang, C.; Han, W.; Gao, Z. Short-Term Forecasting of Solar Irradiance Based on GRU Neural Network. *Chin. Sci. Tech. Pap.* **2020**, *15*, 8–14. (In Chinese)

21. Duan, J.; Zuo, H.; Bai, Y.; Chang, M.; Chen, X.; Wang, W.; Ma, L.; Chen, B. A multistep short-term solar radiation forecasting model using fully convolutional neural networks and chaotic aquila optimization combining WRF-Solar model results. *Energy* **2023**, *271*, 126980. [\[CrossRef\]](#)
22. Frimane, Â.; Munkhammar, J.; van der Meer, D. Infinite hidden Markov model for short-term solar irradiance forecasting. *Sol. Energy* **2022**, *244*, 331–342. [\[CrossRef\]](#)
23. Alfadda, A.; Rahman, S.; Pipattanasomporn, M. Solar irradiance forecast using aerosols measurements: A data driven approach. *Sol. Energy* **2018**, *170*, 924–939. [\[CrossRef\]](#)
24. Hu, Y. An Irradiance-Based Interval Prediction Method for Solar Resources. *China Sci. Technol. Inf.* **2023**, *6*, 76–79. (In Chinese)
25. Yu, L. Study on the Variation and Influencing Factors of Clear-Sky Surface Solar Radiation over China. Master's Thesis, China University of Geosciences, Wuhan, China, 2020. (In Chinese)
26. Prasad, A.A.; Kay, M. Assessment of Simulated Solar Irradiance on Days of High Intermittency Using WRF-Solar. *Energies* **2020**, *13*, 385. [\[CrossRef\]](#)
27. Chen, H.; Jin, K.; Zhao, W. Correction Technique for ERA5 Surface Downward Total Solar Irradiance Based on Routine Surface Meteorological Observation Data. *Desert Oasis Meteorol.* **2025**, *19*, 92–99. (In Chinese) [\[CrossRef\]](#)
28. Dhar, P.; De, B.K.; Banik, T.; Gogoi, M.M.; Babu, S.S.; Guha, A. Atmospheric aerosol radiative forcing over a semi-continental location Tripura in North-East India: Model results and ground observations. *Sci. Total Environ.* **2017**, *580*, 499–508. [\[CrossRef\]](#)
29. Zhang, J.; Shen, Y.; Zhao, Z.; Mo, J.; Wang, X. Study on the Impact of Dust Weather on Surface Solar Radiation and Forecast Correction in the Eastern Foothills of the Taihang Mountains. *Desert Oasis Meteorol.* **2025**, *19*, 19–27. (In Chinese) [\[CrossRef\]](#)
30. Cao, H.; Ma, T.; Chen, Q. Impact of Dust Weather on Air Quality and Solar Radiation. In Proceedings of the 35th Annual Meeting of the Chinese Meteorological Society, Hefei, China, 24–26 October 2018; p. 3. (In Chinese)
31. Gao, R.; Zuo, H.; An, X.; Gao, N. Study on Spatial Distribution Characteristics of Total Solar Radiation in Ningxia Based on FY-4A Data. *Meteorol. Res. Appl.* **2025**, *46*, 67–75. (In Chinese) [\[CrossRef\]](#)
32. Xu, L.; Sun, Y.; Li, Z.; Yu, H. Bias Correction Scheme for FY-4A SSI Products at Locations with Sparse Radiation Observations. *Plateau Meteorol.* **2022**, *41*, 1051–1061. (In Chinese) [\[CrossRef\]](#)
33. Cheng, K.; Wei, L.; Li, Y.; Sun, R.; Zhang, F. Machine Learning-Based Correction Method for Shortwave Radiation Numerical Weather Prediction in Henan Province. *Meteorology* **2025**, *51*, 941–953. (In Chinese)
34. Shang, Y.; Guo, J.; Song, Y.; Liu, W.; Ma, W.; Li, W. A Study on Short-Term Irradiance Forecasting Based on WRF-Solar Model and SCA Correction. *J. Sol. Energy* **2023**, *44*, 274–279. (In Chinese) [\[CrossRef\]](#)
35. Dong, X.; Chen, Y.; Meng, X. Evaluation of WRF-Solar Model Simulation Performance for Global Solar Radiation in Shandong. *J. Mar. Meteorol.* **2021**, *41*, 36–51. (In Chinese) [\[CrossRef\]](#)
36. Xu, L.; Shen, Y.; Li, Z.; Ye, H. Correction of FY-4A Surface Incident Solar Radiation Based on Probability Density Matching Method. *Plateau Meteorol.* **2021**, *40*, 932–942. (In Chinese) [\[CrossRef\]](#)
37. Yu, E.; Bai, R.; Chen, X.; Shao, L. Impact of physical parameterizations on wind simulation with WRF V3.9.1.1 under stable conditions at Planetary Boundary Layer gray-zone resolution: A case study over the coastal regions of North China. *Geosci. Model Dev.* **2022**, *15*, 8111–8134. [\[CrossRef\]](#)
38. Salvação, N.; Bentamy, A.; Soares, C.G. Developing a new wind dataset by blending satellite data and WRF model wind predictions. *Renew. Energy* **2022**, *198*, 283–295. [\[CrossRef\]](#)
39. Jiménez, P.A.; Dudhia, J.; Thompson, G.; Lee, J.A.; Brummet, T. Improving the cloud initialization in WRF-Solar with enhanced short-range forecasting functionality: The MAD-WRF model. *Sol. Energy* **2022**, *239*, 221–233. [\[CrossRef\]](#)
40. Yang, J.; Kim, J.-H.; Jiménez, P.A.; Sengupta, M.; Dudhia, J.; Xie, Y.; Golnas, A.; Giering, R. An efficient method to identify uncertainties of WRF-Solar variables in forecasting solar irradiance using a tangent linear sensitivity analysis. *Sol. Energy* **2021**, *220*, 509–522. [\[CrossRef\]](#)
41. Yang, J.; Sengupta, M.; Jiménez, P.A.; Kim, J.-H.; Xie, Y. Evaluating WRF-Solar EPS cloud mask forecast using the NSRDB. *Sol. Energy* **2022**, *243*, 348–360. [\[CrossRef\]](#)
42. Huang, C.L.; Wu, Y.K.; Tsai, C.C.; Hong, J.S.; Li, Y.Y. Revolutionizing Solar Power Forecasts by Correcting the Outputs of the WRF-SOLAR Model. *Energies* **2024**, *17*, 88. [\[CrossRef\]](#)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.