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# Assessment of ECMWF Sub-Seasonal Solar Irradiance Forecast over Indo-China Peninsula

**Junyu Cai[1, 2], Bing Ding[3], Veeranjaneyulu Chinta[4, *], Hao Chen[1], Peng Wang[5], Jiangfeng Zhang[1], Mingbo Liu[6], Ning Ding[1, 2], Chen Zeng[7], Wei Zhang[4], Guiting Song[1]**

[1]State Grid Zhejiang Electric Power Co., Ltd, Research Institute, Hangzhou, China

[2]E·Energy Technology Co., Ltd, Hangzhou, China

[3]Human Resource, Westlake University, Hangzhou, China

[4]Marine College, Shandong University, Weihai, China

[5]Zhejiang Branch of China Datang Corporation Co., Ltd, Hangzhou, China

[6]Beijing Branch of State Grid Information and Communication Industry Group Co., Ltd, Beijing, China

[7]Guo Neng (Zhejiang) Energy Development Co., Ltd, Hangzhou, China

## Email address:

veeranjechinta@yahoo.com (Veeranjaneyulu Chinta)

[*]Corresponding author

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**Abstract:** Solar irradiance plays a critical role in Earth's energy balance and climate. Accurate sub-seasonal forecasts of surface solar irradiance are essential for various applications, including renewable energy planning and regional climate research. This study evaluates ensemble forecasts of surface solar irradiance using the ECMWF dataset (EC-ENS) with a 6-hourly time-step. We compare these forecasts with gridded observations from the China Meteorological Agency (CMA) over the Indo-China peninsular region. Solar irradiance, as Earth's primary energy source, is influenced by atmospheric conditions, and even minor fluctuations in the sun's energy output can significantly impact the climate. Hence, understanding and predicting solar irradiance variations are crucial. For the analysis, we utilize the EC-ENS model data and gridded observation data available from June 2021 to May 2022, with hourly and 6-hourly intervals. Performance evaluation metrics, including root mean square error (RMSE), mean absolute error (MAE), and mean bias error (MBE), are employed to assess the accuracy of the EC-ENS model against observations. Results show an RMSE of approximately 414.43 W/m², an MAE of 380.95 W/m², and an MBE of -309.72 W/m², providing insights into forecast deviations. Furthermore, this study focuses on capturing regional variations in solar irradiance. The spatially continuous hourly estimates derived from ensemble forecasts effectively reconstruct sub-seasonal patterns on smaller scales. This precise knowledge is crucial for applications such as site selection for solar power plants and understanding regional climate changes. Accurate assessment of solar irradiance enables informed decision-making for renewable energy planning and enhances our understanding of regional climate dynamics. In summary, performance evaluation metrics provide insights into forecast accuracy. Additionally, spatially continuous estimates capture regional variations, enabling precise predictions for renewable energy planning and climate research. Advancing our understanding of solar irradiance patterns contributes to sustainable energy strategies and enhances knowledge of regional climate dynamics.

**Keywords:** Solar Irradiance, Sub-Seasonal Variability, Forecasting, ECMWF Ensemble Forecast System

# 1. Introduction

In the densely populated Southeast Asian region, accurate sub-seasonal forecasting is critical, particularly during boreal summer and winter solar radiance, wind, and continuous heavy rainfalls. Despite significant interest and progress in sub-seasonal forecasting, it is uncertain how capable dynamical forecasting systems are in Southeast Asia beyond two and six weeks. With the advancement of understanding of sub-seasonal predictability and the improvement of numerical models that produce more skillful sub-seasonal forecasts than in the past [1], there is a great deal of interest across scientific and operational societies in improving sub-seasonal forecasts that bridge the gap between numerical weather forecasts and long-term seasonal perspectives [2, 3]. This increased interest in sub-seasonal forecasting is being driven by an increase in demand from the application groups. Sub-seasonal predictions are particularly valuable in many industries, including energy, agriculture, and water resource management. A useful precipitation forecast on a sub-seasonal forecast, for example, can assist warn of increased flood danger [4, 5].

Despite various efforts to operationalize sub-seasonal forecasting and build or show the potential values of applications and vital information [3], the sub-seasonal timescale remains a distinct horizon for predictability research. Forecast accuracy, as well as associated modeling design issues such as initialization procedures, initial conditions, ocean-atmosphere interaction, and so on, remain unresolved [2]. Sub-seasonal forecasts must be validated in order to assess their accuracy, identify their strengths and weaknesses, and improve forecasting systems [6].

The assessment of surface solar irradiance as a resource is an important field of research in renewable energy. Such methods are utilized in research to better understand the characteristics of surface solar irradiance, notably regional and seasonal variations [7]. The findings of such studies may be useful for investing in solar power projects and maintaining grid networks. The intensity of surface solar irradiance is a major research issue in the renewable energy business. Many studies have also been conducted to investigate the dynamics of this irradiance's variation [8, 9, 10]. Numerous additional articles have focused on the daily or single-day characteristics of global solar irradiance, direct normal irradiation, and clear-sky solar radiation at the surface.

Although the use of short-term weather forecasts is increasingly prevalent in the energy industry, and there has been substantial academic study in this area [11, 12], there has been comparably less emphasis paid to the use of sub-seasonal forecasts. This might be connected to the perceived difficulties in obtaining reliable signals from long-term forecasts [13]. Recent breakthroughs in forecasting, however, have begun to produce more accurate long-term estimates for European demand [14]. Production of wind energy [15], solar energy production [16], and hydroelectric [17].

The remainder of this paper is arranged as follows: Section 2 discusses the research data and methods. Section 3 examines the solar irradiance variability seen in the Indo-China peninsula region under study. Finally, Section 4 Summary and conclusions.

# 2. Data and Methodology

### 2.1. Observations

The China Meteorological Agency provides ground radiation data (CMA). Total surface solar irradiation from 202106 to 202205 is one of three important physical variables measured by the CMA. The DFY-4 and TBQ-2 total radiation meters, the DFY-3 and TBS-2 direct radiation meters (both with solar tracking frames), the DFP-1 shade ring, and the RYJ-4 automated radiation recorder are among the station's instruments. The radiation meters described above are all electro thermal, having two components: the induction surface and the thermopile. The website, http://data.cma.cn/site/index.html has detailed instrument information for CMA stations. The regional distribution of in this investigation is depicted in Figure 1.

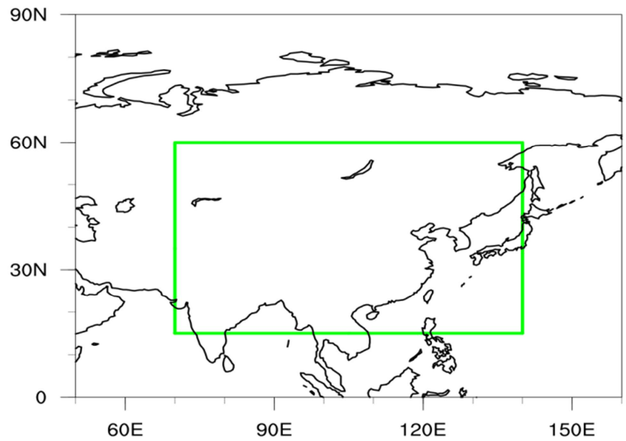


*Figure 1. Study region of Indo-China peninsular over green box over 15 °N - 60 °N, 70 °E - 140 °E.*

### 2.2. Model Data Sets

The ECMWF's Integrated Forecasting System (IFS) is a global-scale NWP system that generates both reanalysis and operational forecasts at various time scales and resolutions using a collection of models such as the global atmospheric model or the wave ocean model. Sub-seasonal projections from the ECMWF operational ensemble's four ocean-atmosphere coupled models [EC-ENS; 18]. Atmospheric model Ensemble 45-day prediction for sub-seasonal, which corresponds to a forecast horizon of up to 16-45 days. To illustrate the uncertainty in that best-guess forecast, ENS publishes a 50-member ensemble forecast rather than a single best guess. In other words, the ensemble contains fifty perturbed predictions and one control forecast. ENS runs four times each day at various base times, 00Z, 06Z, 12Z, and 18Z, producing predictions up to 45 days in advance. The resolution for the following horizons is 6-hourly. The 6-hourly predictions are only available from the 00Z and 12Z runs, not the 06Z and 18Z runs.

### 2.3. Measuring Forecast Accuracy

Four metrics were used to compare the output of the combination model to the observations: define Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Bias Error (MBE) [19].

These measurements are as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum(I_{Pred} - I_{Obs})^2}\,, \tag{1}$$

$$\mathrm{MAE} = \frac{1}{N}\sum|I_{Pred} - I_{Obs}| \tag{2}$$

$$\mathrm{MBE} = \frac{1}{N}\sum(I_{Pred} - I_{Obs}) \tag{3}$$

Where $I_{pred}$ is the model's forecast solar irradiance, $I_{obs}$ is the observed CMA data, and $(I_{obs})$ is the expected value of the observations, or the average. When the observations and model values were determined, and these times were not included in the MAE, RMSE, and MBE computations.

## 3. Results

Here we show plots and a table of the errors between the EC-ENS and observational data of the solar irradiance sub-seasonal forecast. Figure 2 depicts the RMSE, MAE, and MBE performance metrics generated for the ECMWF-ENS and observations in the Indo-China Peninsula area; these well-known connections are frequently used to evaluate forecasting approaches in similar prediction challenges. The sub-seasonal solar irradiance rise in forecast time and the monthly variability of RMSE and MAE minimums in December, at the same time MBE is at its maximum, are all indicators of a sub-seasonal solar irradiance error increase. Maximum RMSE and MAE are displayed in April-May; however, MBE is the minimum value of the sub-seasonal irradiance forecast. RMSE and MAE increase in the spring while MBE drops; in the fall, RMSE and MAE decrease while MBE increases.

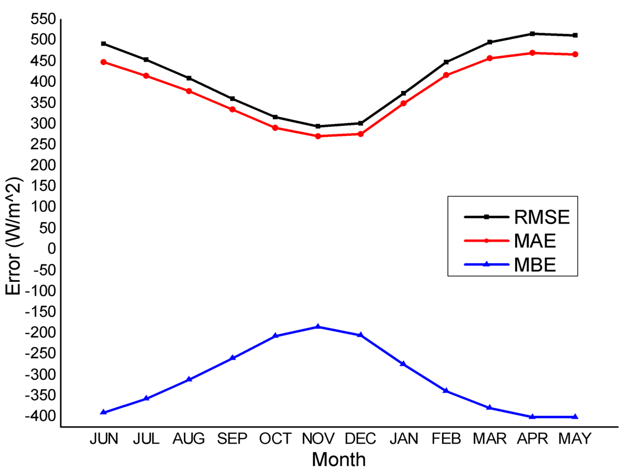


***Figure 2.*** *RMSE, MAE and MBE errors of monthly solar irradiance sub-seasonal forecast during June 2021-May 2022.*

Figure 3 depicts the total errors for the sub-seasonal period. All months increased forecast time with the observations with the lowest and greatest RMSE (193.82 $W/m^2$ and 756.46 $W/m^2$) for EC-ENS, since solar irradiance is lower in the autumn-winter season than in the spring-summer sub-seasonal irradiance across the Indo-China peninsula region. Due to the high intensity of solar irradiation, small RMSEs are likely to occur throughout the summer season. Although the MAE and MBE show that errors rise with increasing irradiance intensity throughout the day, the results are still encouraging because the RMSEs are all below. Because the amounts of received surface irradiation are initially extremely low in the morning and at night, RMSE values during the corresponding hours are substantial despite the comparatively tiny RMSE. These variations in the time dimension might be caused by a divergence between the observation and the model. If the clouds move quickly, the ground stations will be hidden by cloud shadows for a while but will eventually be clear when the sensor scans, resulting in ground readings that are significantly less than observation-based inversion values.

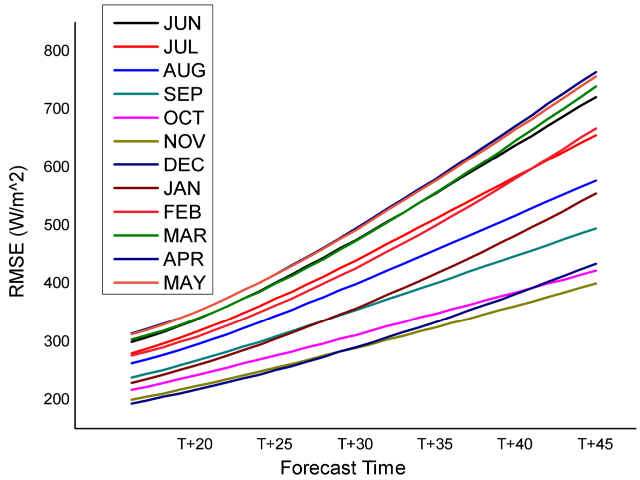


***Figure 3.*** *RMSE time series of sub-seasonal solar irradiance forecast during June 2021-May 2022.*

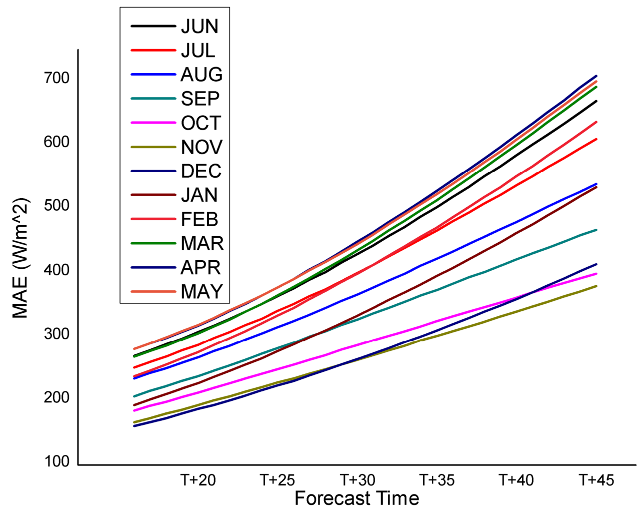


***Figure 4.*** *MAE time series of sub-seasonal solar irradiance forecast during June 2021-May 2022.*

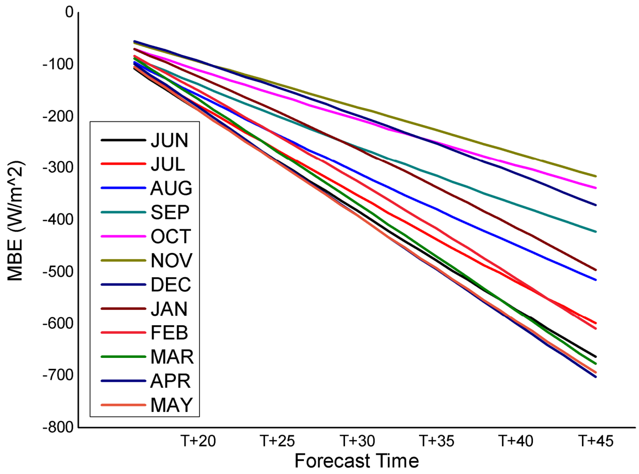


***Figure 5.*** *MBE time series of sub-seasonal solar irradiance forecast during June 2021-May 2022.*

Figures 4 and 5. Overall, it gives adequate estimates for daily irradiance at the regional scale, with a minimum and maximum MAE of 160.82 W/m$^2$ and 708.73 W/m$^2$, respectively, and a MBE of -54.82 W/m$^2$ and -701.98 W/m$^2$ for ECMWF-ENS. The negative MBE values suggest that the forecast understates surface radiation to some extent, which may explain the relative higher values owing to urbanization impacts [20].

The aforementioned RMSE, MAE, and MBE values are comparable to those in previous models; for example, Shamim, M. A. et al produced a testing RMSE of solar irradiation of roughly 110.83 W/m$^2$ [21], while [22] obtained RMSE values of solar radiation ranging from 131.39 to 142.22 W/m$^2$ over the East Asian region. The global model provides the most fascinating estimation of six-hourly irradiation due to the adequate modeling of dynamic cloud shape and non-linear connections between inputs and outputs. The performance on solar radiation estimation at daily total and monthly-averaged daily total scales is likewise much better than earlier research, with RMSEs of 47.24 W/m$^2$ and 28.08 W/m$^2$, respectively. For example, the testing RMSE of daily total solar radiation from [23] was 66.75 W/m$^2$ and 63.29 W/m$^2$ from [24]; the validation RMSE of monthly averaged daily total solar radiation was 86.27 W/m$^2$ from [25] and 42.48 W/m$^2$ from [23]. The six-hourly solar radiation from the EC-ENS model exhibited the most inaccuracy relative to every other performance metric, with the highest RMSE, MAE, and MBE errors (see table 1).

***Table 1.*** *Performance metrics for ECMWF-ENS model of sub-seasonal solar irradiance forecast from July 2021- May 2022.*

| RMSE | MAE | MBE |
|---|---|---|
| 414.43 | 380.95 | -309.72 |

Figure 6 depicts the total errors of seasonal variations in sub-seasonal irradiance. Because of the high intensity of solar irradiation, large MBEs are more likely to develop in the afternoon. However, the MBE and RMSE show that mistakes increase throughout the summer due to the increased intensity of solar radiation compared to other seasons. Since the levels of received surface radiation are initially quite low in the fall and winter on the temporal dimension, these differences might be attributed to the fact that the model represents an instantaneous state of the atmosphere, whereas ground measurements provide the average state over a certain time period.

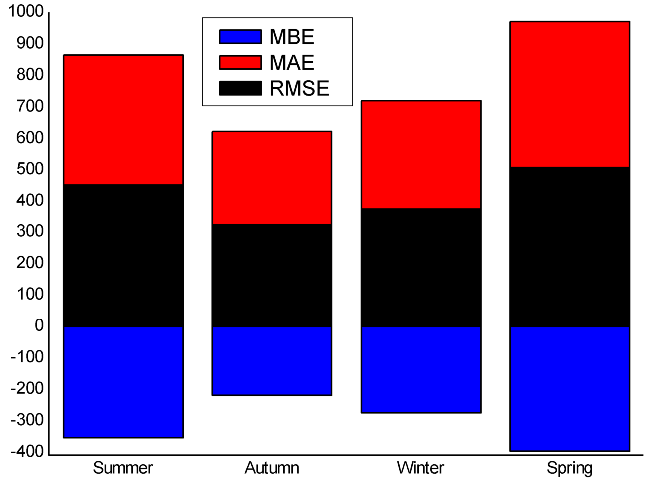


***Figure 6.*** *Bar plot of sub-seasonal solar irradiance errors of seasonal time scales.*

## 4. Summary and Conclusion

Sub-seasonal solar irradiance is critical for detecting global dimming and brightening, quantifying the Earth's surface energy budget, developing sustainable biological ecosystems, simulating regional climate models, and assessing solar resources for solar power generation. In this study, we compared for the irradiance prediction for the Indo-China peninsula (15 °N - 60 °N, 70 °E - 140 °E) using hourly data from June 2021 to May 2022 and solar irradiance input from EC-ENS and CMA.

Our results showed that the EC-ENS model had the greatest inaccuracy compared to any other performance metric, with RMSE, MAE, and MBE error values of 414.43 W/m$^2$, 380.95 W/m$^2$, and -309.72 W/m$^2$ after one year. However, the EC-ENS model reduced these summer and winter seasons with RMSE values of 452.16 W/m$^2$ and 373.77 W/m$^2$, MAE values of 413.94 W/m$^2$ and 347.11 W/m$^2$, and MBE values of -353.15 W/m$^2$ and -273.10 W/m$^2$, respectively.

Our analysis also suggests that ECMWF-ENS model data information from sub-seasonal solar irradiance accuracy and advances in simulating the sub-seasonal variability of solar irradiance. Future research should focus on deploying the generated models for various climatic zones in the Southeast Asian region and assessing their performance in diverse climatic zones.

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