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Preprint

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EVALUATION OF WRF-SOLAR CLOUD FORECAST USING THE NSRDB

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ABSTRACT: The cloud forecast is a crucial component in predicting solar irradiance from numerical weather prediction (NWP) models. Assessing cloud properties from NWP models requires significant work due to the need for high-quality data, spatial analysis covering the model's extent, and detailed analysis of the model's performance for different types of clouds. This study presents an evaluation of the Weather Research and Forecasting (WRF)-Solar cloud forecast using the National Solar Radiation Database (NSRDB). We propose an evaluation framework applied to a single model prediction as well as ensemble-based forecasts. Various cloud detection metrics are calculated for comparison with the satellite-derived data set. The mismatched clouds from WRF-Solar are quantified using nine cloud types classified by cloud top height and cloud optical depth. The results based on the WRF-Solar forecasts covering the entire United States for the full year of 2018 show mismatched cloud frequencies ranging from 8%–46% for thick and high-level (deep convective) to thin and low-level (cumulus) clouds.

1 AIM AND APPROACH

Accurately reproducing clouds in numerical weather prediction (NWP) models is important for predicting solar irradiance because clouds directly influence the solar radiation reaching the surface of the earth; however, cloud forecasts are not easy to evaluate because they require analysis covering a wide range of locations where different types of clouds occur. Due to their coverage at high spatial and temporal resolutions, satellite-derived cloud properties and solar radiation are good sources of data for assessing cloud forecasts if the satellite-based observations are of high enough accuracy to be used for NWP evaluations. The National Solar Radiation Database (NSRDB) [1], [2] has been demonstrated to be of high accuracy when compared to high-quality ground measurements and therefore it is deemed adequate for this evaluation. In this study, we present an evaluation of cloud forecasts simulated from the Weather Research and Forecasting-Solar ensemble prediction system (WRF-Solar EPS) [3]–[5] using the NSRDB. This work aims to investigate which types of clouds are difficult to forecast using WRF-Solar. In addition, we analyze the error and bias of the modeled cloud properties (e.g., cloud optical depth) for each cloud type (this will be included in the extended version of the abstract). The cloud forecasts covering the entire contiguous United States (CONUS) are used to analyze the ability of WRF-Solar EPS to represent cloud properties for various cloud types.

2 SCIENTIFIC INNOVATION AND RELEVANCE

2.1 Data

WRF-Solar EPS is a state-of-the-art ensemble model developed for solar energy applications. In this study, the model is employed to simulate day-ahead forecasts covering 2018. WRF-Solar EPS is configured with 9-km horizontal grid spacing (Fig. 1) and initialized at 6 UTC for each set of day-ahead forecasts (48 hours). The National Centers for Environmental Prediction Global Forecast System (0.25°×0.25°; 3-hour intervals) forecast data are used to provide the initial and boundary conditions for the model. The NSRDB is used to evaluate the cloud forecasts from WRF-Solar EPS. The native NSRDB data sets (2-km spatial resolution) are reprocessed to produce data for originally excluded parts over the ocean and then spatially interpolated to the 9-km WRF-Solar EPS model grid. The 9-km NSRDB data used in this work have been evaluated against surface observations by [6] and have been validated to be sufficient for use in the WRF-Solar model assessment.

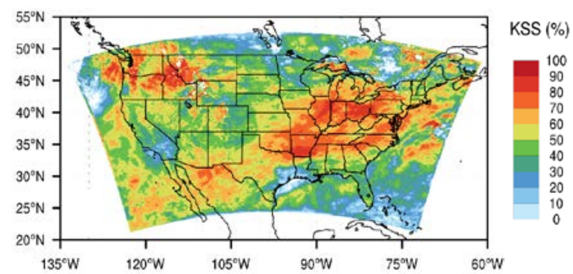

Figure 1. KSS (see Eq. (9)) calculated for the entire domain of WRF-Solar EPS.

2.2 Methodology

To analyze the cloud mask forecasts from WRF-Solar EPS, we build a methodology to filter the pixels from the NSRDB and WRF-Solar EPS data sets for clear and cloudy conditions. First, an absolute difference between all-sky global horizontal irradiance (GHI) and clear-sky GHI is calculated for both data sets as follows:

$$\Delta GHI = \left|GHI_{all-sky} - GHI_{clear-sky}\right| \qquad (1)$$

Here, ΔGHI is calculated at each grid point and time step. Second, each pixel is filtered using the criteria for ΔGHI specified in Table 1. For the NSRDB data, if ΔGHI is less than 1.0 W/m^2, the pixel is treated as clear sky; otherwise, the pixel is regarded as cloudy sky. The method can be applied to forecasts comprising a single member as well as ensemble members. In the case of a single forecast, a method similar to that applied to the NSRDB can be used. For ensemble forecasts, an additional criterion is considered. To filter the ensemble data sets comprising ensemble members, if more than 50% of the ensemble members satisfy the case of $\Delta GHI \geq 1.0\ W/m^2$, that pixel is regarded as cloudy sky.

Table 1. Criteria for data-filtering the NSRDB (observation) and WRF-Solar (prediction) for clear/cloudy sky conditions

	NSRDB (observation)	Prediction from a single member	Prediction from ensemble members
Clear sky	$\Delta_{GHI} < 1.0$ W/m^2	$\Delta_{GHI} < 1.0$ W/m^2	> 50% of ens. members are: $\Delta_{GHI} < 1.0$ W/m^2
Cloudy sky	$\Delta_{GHI} \geq 1.0$ W/m^2	$\Delta_{GHI} \geq 1.0$ W/m^2	≥ 50% of ens. members are: $\Delta_{GHI} \geq 1.0$ W/m^2

To quantify the results, we calculate cloud detection metrics [7], [8] based on a 2 × 2 contingency table (Table 2), which represents the population of occurrences for each category "A" – "D". An important analysis in this work is to confirm the model's capability to predict different cloud types classified by cloud top height (CTH) and cloud optical depth (COD). To enable this analysis, we filter the occurrences in Table 2 by CTH and COD obtained from the NSRDB.

Table 2. Contingency table for NSRDB (observation) and WRF-Solar EPS (prediction)

Prediction / Observation	WRF-Solar EPS		
NSRDB	Scenario	Clear sky	Cloudy sky
	Clear sky	A	B
	Cloudy Sky	C	D

The frequency of clouds and seven additional metrics—including probability of detection in clear sky (PODCLR), probability of detection in cloudy sky (PODCLD), false alarm rate in clear sky (FARCLR), false alarm rate in cloudy sky (FARCLD), hit rate, Kuiper's skill score (KSS), and mismatched cloud frequency (MCF)—are used to assess the accuracy of clouds produced by WRF-Solar EPS [Eqs. (2)–(10)].

$$FOC_{NSRDB} = \frac{C+D}{A+B+C+D} \times 100\% \tag{2}$$

$$FOC_{WRF-Solar} = \frac{B+D}{A+B+C+D} \times 100\% \tag{3}$$

$$PODCLR = \frac{A}{A+B} \times 100\% \tag{4}$$

$$PODCLD = \frac{D}{C+D} \times 100\% \tag{5}$$

$$FARCLR = \frac{C}{A+C} \times 100\% \tag{6}$$

$$FARCLD = \frac{B}{B+D} \times 100\% \tag{7}$$

$$Hit\ rate = \frac{A+D}{A+B+C+D} \times 100\% \tag{8}$$

$$(where\ 0 \leq HR \leq 100\%)$$

$$KSS = \frac{A \cdot D - B \cdot C}{(A+B) \cdot (C+D)} \times 100\% \tag{9}$$

$$(where\ -100\% \leq KSS \leq 100\%)$$

$$MCF = \frac{C}{C+D} \times 100\% \tag{10}$$

3 RESULTS

We quantify the overall performance of WRF-Solar EPS in terms of forecasting skills for nine cloud types. MCF is calculated and used as an adequate metric to estimate how many cloudy occurrences are missed by the model. Figure 2 shows the averaged MCF across all seasons for CONUS in 2018. The MCF scores for WRF-Solar EPS show that the ensemble model performs better for high-level and thick clouds than for low-level and thin clouds. For three CTH levels, WRF-Solar EPS exhibits scores ranging from 8%–27%, 16%–33%, and 19%–46% for high- (7 km < CTH), middle- (3 km < CTH ≤ 7km), and low-level (CTH ≤ 3 km) clouds. In terms of MCF classified in three COD ranges, the model shows MCFs ranging from 8%–19%, 13%–34%, and 27%–46% for thick (20.0 < COD), middle-thickness (3.0 < COD ≤ 20.0), and thin (COD ≤ 3.0) clouds.

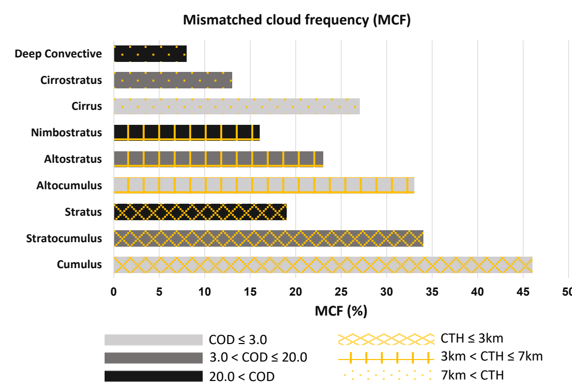

Figure 2. Averaged MCF of WRF-Solar EPS calculated over CONUS for 2018.

4 CONCLUSIONS

In this study, we present an evaluation approach for NWP cloud forecasts using satellite information from the NSRDB. Day-ahead cloud mask forecasts are simulated from WRF-Solar EPS on a 9-km grid. To assess the performance of WRF-Solar EPS in forecasting clouds over the ocean as well as for CONUS, the NSRDB data sets are newly processed and aggregated to the 9-km model grid. We quantify the model's cloud mask forecast by using cloud detection metrics and MCFs classified in different COD and CTH. Preliminary results indicate that WRF-Solar EPS provides accurate forecasts for thick (MCF: 8%–19%) and high-level (MCF: 8%–27%) clouds, whereas thin (MCF: 27%–46%) and low-level (MCF: 19%–46%) clouds cause difficulties for the model in predicting cloud masks. This analysis produces useful information about types of clouds that are not adequately reproduced by the model. This information eventually enables model developers with information that can lead to further model improvements. An evaluation of WRF-Solar models with increased spatial resolution, different settings in the physics options, and long-term simulations will be further considered in a future study.

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