Assessment of Cloud Mask Forecasts from the WRF-Solar Ensemble Prediction System

Preprint

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ASSESSMENT OF CLOUD MASK FORECASTS FROM THE WRF-SOLAR ENSEMBLE PREDICTION SYSTEM

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ABSTRACT:
Numerical weather prediction (NWP) models are important tools used by government agencies and the renewable energy enterprise to forecast solar radiation. Cloud prediction, a key process of NWP models, has the highest impact on the accuracy of solar forecasting. This study uses satellite observations from the National Solar Radiation Database (NSRDB) to evaluate the cloud mask forecast by the Weather Research and Forecasting-Solar Ensemble Prediction System (WRF-Solar EPS). Preliminary analysis of the data in 2018 demonstrates the need for further improvement in predicting thin and low-level clouds. The information obtained from this work will be used to enhance WRF-Solar EPS in reproducing the cloud field over the contiguous U.S. and reducing solar forecasting errors.

1 Aim and Approach

The main purpose of this study is to develop a method to evaluate cloud forecasts from numerical weather prediction (NWP) models. The limitation in the current verification of gridded solar forecasts, which focus only on the evaluation of NWP outputs for the prediction of solar irradiance using simple statistical metrics, has motivated a new approach in this study to assess the prediction accuracy of solar irradiance. Forecasting of clouds in NWP is the key factor in predicting solar irradiance because that directly impacts the solar irradiance under overcast or partial cloudy-sky conditions (i.e., solar irradiance forecasts are influenced by errors stemming from the cloud forecasts); thus, it is essential to implement an evaluation of cloud forecasts from NWP models.

In addition, forecast developers and users need information for model performance at arbitrary locations on the NWP model grid. If we use only ground observations for the model evaluations, it is not possible to acquire the spatial distribution of forecast errors on the model grid. In this case, satellite-derived solar radiation data offer the opportunity for an in-depth analysis to assess gridded forecasts over a wide range of regions.

In this study, we suggest a method for validating cloud products from the Weather Research and Forecasting-Solar Ensemble Prediction System (WRF-Solar EPS), which is an enhanced version of WRF-Solar [1], to provide grid operators with high-quality probabilistic solar forecasts. This work includes three objectives:

- Assessment of cloud mask forecasts from WRF-Solar against the National Solar Radiation Database (NSRDB)
- Analysis of cloud detection metrics (e.g., hit rate, false alarm rate, Kuiper's skill score)
- Development of evaluation techniques to verify WRF-Solar EPS using the cloud detection metrics.

2 Scientific Innovation and Relevance

2.1 WRF-Solar EPS

WRF-Solar (https://ral.ucar.edu/projects/wrf-solar) [1] is the state-of-the-art NWP model that provides prediction of solar irradiance with global horizontal irradiance (GHI), direct normal irradiance, and diffuse horizontal irradiance specialized for solar power applications. Recently, WRF-Solar EPS) [2] was developed through a collaboration between the National Renewable Energy Laboratory and the National Center for Atmospheric Research under a U.S. Department of Energy project to provide probabilistic forecast information on solar irradiance. WRF-Solar EPS generates ensemble members by using a technique to stochastically perturb key forecasting variables identified through the tangent linear sensitivity analysis [3] for six WRF-Solar modules, controlling the solar irradiance and the formation and dissipation of clouds.

2.2 Satellite Observations

The NSRDB [4] is used for the evaluation of cloud mask forecasts from WRF-Solar EPS. The NSRDB is a publicly available data set of satellite-derived observations that provides meteorological data in North and Central America (https://nsrdb.nrel.gov/). Because the domain of WRF-Solar EPS covers the contiguous United States (CONUS) as well portions of the Pacific and Atlantic oceans, we reprocessed the currently available NSRDB to produce additional data over the ocean. This work aims to evaluate the forecasts of WRF-Solar EPS for its full extent, including the ocean and CONUS. In addition, the NSRDB has been aggregated from the native NSRDB grid (2-km or 4-km resolution based on year) to the WRF-Solar grid (9 km) to efficiently handle the two big data sets (Fig. 1).

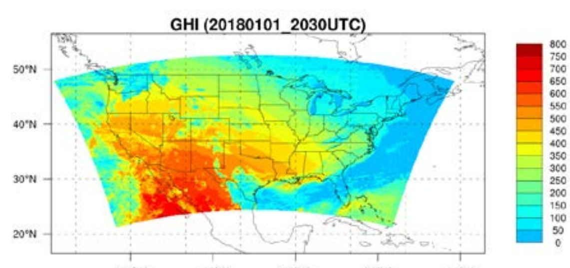

Figure 1. GHI from 9-km NSRDB aggregated to WRF-Solar EPS grid (20:30 UTC 01 January 2018).

2.3 Data Processing for NSRDB and WRF-Solar EPS

To analyze the capability of WRF-Solar EPS in predicting the cloud mask, we need to filter the NSRDB and the forecasts of WRF-Solar EPS for clear- and cloudy-sky conditions. The following are the main steps of the filtering algorithm:

- Step 1: An absolute difference between clear-sky GHI and all-sky GHI is calculated for each individual pixel and time step:

$$DIFF = \left| GHI_{Clear} - GHI_{All\ Sky} \right| \quad (1)$$

- Step 2: Each pixel is filtered by the conditions in Table 1. If DIFF from Eq. (1) is smaller than 1 W/m^2, the pixel is treated as clear sky; otherwise, the pixel is treated as cloudy sky. For ensemble forecasts simulated from WRF-Solar EPS, additional criteria are employed. For example, if more than 50% of the ensemble members satisfy the condition of DIFF ≥ 1.0 W/m^2, that pixel is treated as cloudy sky. Note that nighttime data are excluded by filtering with a threshold for inclusion (0° < solar zenith angle < 85°) in this analysis.

Table 1. Criteria for data-processing of NSRDB and WRF-Solar EPS for clear-/cloudy-sky conditions

	NSRDB	**WRF-Solar EPS**
Clear sky	DIFF < 1.0 W/m^2	> 50% of ensemble members are: DIFF < 1.0 W/m^2
Cloudy sky	DIFF ≥ 1.0 W/m^2	≥ 50% of ensemble members are: DIFF ≥ 1.0 W/m^2

After filtering is completed, the cloud detection metrics are calculated based on a contingency table (Table 2). The four categories in Table 2 indicate binary representations for the cloud occurrences for the NSRDB and WRF-Solar EPS. We compute the total number of frequencies that corresponded to each category (i.e., a, b, c, and d) and then calculate the following metrics [5] to quantify the results:

$$POD_{clear} = \frac{a}{a+b} \times 100\% \quad (2)$$

$$POD_{cloudy} = \frac{d}{c+d} \times 100\% \quad (3)$$

$$FAR_{clear} = \frac{c}{a+c} \times 100\% \quad (4)$$

$$FAR_{cloudy} = \frac{b}{b+d} \times 100\% \quad (5)$$

$$HR = \frac{a+d}{a+b+c+d} \times 100\% \quad (where\ 0 \le HR \le 100\%) \quad (6)$$

$$KSS = \frac{a \cdot d - c \cdot b}{(a+b) \cdot (c+d)} \times 100\% \quad (where\ -100\% \le KSS \le 100\%) \quad (7)$$

Table 2. Contingency matrix for WRF-Solar EPS and NSRDB.

	WRF-Solar EPS		
NSRDB	Scenario	Clear	Cloudy
	Clear	a	b
	Cloudy	c	d

3 Results

We analyze the hit rate (HR) to quantify the performance of the cloud mask forecasts from 10 stochastic-based ensemble members simulated from WRF-Solar EPS. The monthly variation of hit rate computed with all pairs of observations and predictions for 2018 is presented in Fig. 1. Figure 1a shows that the hit rates are smaller in summer than in the other seasons. Two examples of spatial distribution of hit rate in February and July are shown in Figs. 1b and 1c. In February 2018, some regions show high hit rates (>80%), which can be attributed to winter storms on the east part of CONUS (Fig. 1b). Apparently, WRF-Solar EPS accurately represents nonconvective events, as shown from the high hit rates in February 2018, compared to the low hit rates over the central part of the U.S. unrepresented events in July 2018 (Fig. 1c). The unrepresented events are apparently related to the higher uncertainty in predicting the location and timing of the occurrence of convection in summer.

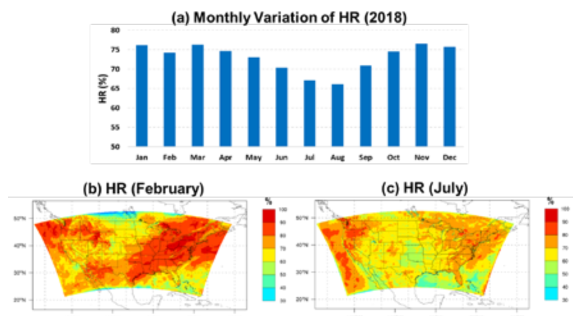

Figure 2. (a) Monthly variation of hit rate for 2018 and spatial distribution of hit rate in (b) February and (c) July.

Because the hit rate represents an overall efficiency of the model performance for both clear- and cloudy-sky conditions, the probability of detection (POD) is analyzed separately for the two sky conditions. Figure 3 exhibits an example of POD_{clear} and POD_{cloudy} analyzed for July 2018. As expected, WRF-Solar EPS provides high POD_{clear} scores (>80%) for CONUS in July (Fig. 3a). On the other hand, there are POD_{cloudy} values that are lower than 40% in the central parts of the United States (Fig. 3b). As stated previously, we found that a large portion of mismatched clouds under cloudy-sky conditions, indicated by the low POD_{cloudy}, resulted in the the regions of low hit rates in Figure 2c.

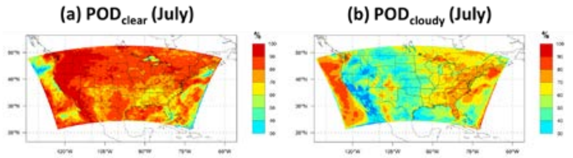

Figure 3. Spatial distribution of POD in (a) clear-sky and (b) cloudy-sky conditions in July 2018.

As shown in Fig. 3, WRF-Solar EPS produces more mismatched pixels for cloud mask forecasts in cloudy-sky than clear-sky conditions; therefore, we need to investigate which types of clouds cause difficulties in predicting cloud masks from WRF-Solar EPS. To further assess the cloud mask forecasts of WRF-Solar EPS, we analyzed POD_{cloudy} classified into various cloud optical depth ranges with data obtained from the NSRDB (Fig. 4a). In terms of the capability of WRF-Solar EPS in predicting clouds, POD_{cloudy} increases as optical depth increases, and this pattern occurs for all seasons. This indicates that we will need to focus on further improvements in the prediction of thin clouds in WRF-Solar EPS. Because the cloud types can be grouped by altitude of occurrence, we additionally analyzed the performance of WRF-Solar separately for low-, middle- and high-level clouds. For this analysis, we calculated false alarm rate (FAR) in cloudy conditions as a metric to evaluate cloud mask forecasts for the three levels of cloud heights. The cloud top height (CTH) extracted from the WRF-Solar runs was used to classify the clouds into three groups: CTH less than 2 km are classified as low-level clouds, CTH between 2 km and 6 km are classified as middle-level clouds, and the rest are classified as high-level clouds. WRF-Solar produces higher FAR_{cloudy} when predicting low-level clouds compared to FAR_{cloudy} for high-level clouds (Fig. 4b). Consistent with the results of POD_{cloudy} shown in Fig. 4a, patterns of the classified FAR_{cloudy} for different CTHs are similar throughout the seasons, while noting that WRF-Solar produces lower POD_{cloudy} and higher FAR_{cloudy} in summer than winter.

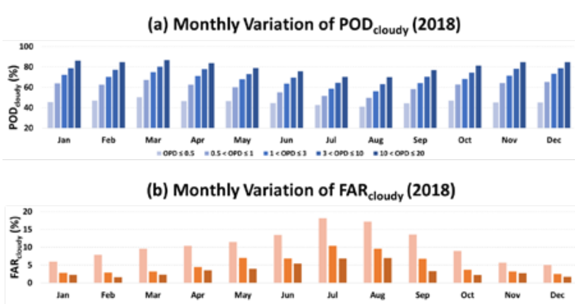

Figure 4. Monthly variation of (a) POD_{cloudy} classified in different cloud optical depths and (b) FAR_{cloudy} classified in three cloud levels for 2018.

4 Conclusions

In this research, we present a new approach for evaluating cloud mask forecasts simulated from WRF-Solar EPS. The newly processed NSRDB data sets, which were aggregated to the 9-km WRF-Solar grid, are used to assess the model performance in predicting clouds over the ocean as well as for CONUS. Preliminary results indicate that we will need further development in WRF-Solar to improve the prediction skills for low-level and thin clouds. Future studies will be needed to consider the lack of skill in detecting thin and low-level clouds from satellites. The proposed evaluation method is proven to be useful when assessing cloud mask forecasts from WRF-Solar EPS and when quantifying its performance by using satellite-derived observations, and it can be extended to forecast evaluations in general.

Acknowledgments

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