Using High-Resolution NSRDB Data to Evaluate Cloud Mask Forecast from WRF-Solar EPS

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1. INTRODUCTION

- Accurately forecasting clouds in numerical weather prediction models is key to accurately predicting solar irradiance.
- However, validating cloud forecasts is challenging because this requires high-quality cloud-property observations at significantly high spatial and temporal resolution for long periods of time.
- In this study, we evaluate ensemble cloud-mask forecasts from the WRF-Solar ensemble prediction system (WRF-Solar EPS) (Yang et al. 2021, 2022; Kim et al. 2021, 2022; Jiménez et al. 2022; Alessandrini et al. 2023) using the high-resolution cloud data from the National Solar Radiation Database (NSRDB) (Sengupta et al. 2018).
- Cloud-mask forecast of WRF-Solar EPS (9-km) is evaluated against NSRDB (2-km) based on two scenarios:
  - ✓ Consider the presence of any clouds from 2-km NSRDB domain (referred to as EM_{All}).
  - ✓ Use a minimum 50 % cloud fraction threshold to classify a pixel as cloudy (EM_{P50}) => Because the NSRDB data is available at 2-km resolution, we can compute cloud fraction over the 9-km WRF-Solar EPS grid.

2. APPROACH

1) Data-processing for two sky conditions

Step 1. Calculate Δ_{GHI} for each pixel:

$$\Delta_{GHI} = \left| GHI_{clear-sky} - GHI_{all-sky} \right|$$

Step 2. Classify the pixel in to the two sky conditions satisfied with:

Night times are excluded by SZA < 85°

Evaluation method	Classification	$NSRDB_{9km}$ (observation)	WRF-Solar EPS (prediction)
EM_{All}	Clear sky	Δ_{GHI} < 1.0 W/m^2	> 50 % of ensemble members are: Δ_{GHI} < 1.0 W/m^2
	Cloudy sky	Δ_{GHI} ≥ 1.0 W/m^2	≥ 50 % of ensemble members are: Δ_{GHI} ≥ 1.0 W/m^2
EM_{P50}	Clear sky	COD = 0	Same with EM_{All}
	Cloudy sky	COD > 0	Same with EM_{All}

9-km GHI: spatially averaged 2-km pixels
9-km cloud optical depth (COD): calculated based on 2-km cloud types

- By using EM_{All}, the low-resolution cloud masks from WRF-Solar EPS are directly evaluated against the cloud-resolving scale gridded observations from NSRDB.
- In EM_{P50}, we assume that scenes with < 50 % cloudiness from the 2-km NSRDB are clear scenes. Therefore, this evaluation method enables a fair comparison with WRF-Solar EPS resolved for a 9-km grid.

2) Contingency table for NSRDB and WRF-Solar EPS and equations for cloud detection metrics (Yang et al. 2022)

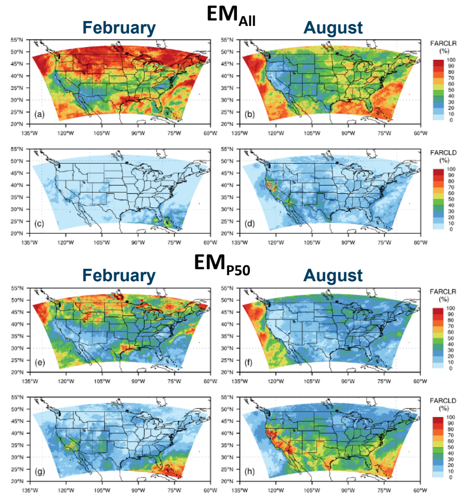
Observation \ Prediction	WRF-Solar EPS		
NSRDB	**Scenario**	Clear sky	Cloudy sky
	Clear sky	A	B
	Cloudy sky	C	D

Metric	Calculation
Frequency of cloud for NSRDB	$FOC_{NSRDB} = \frac{C+D}{A+B+C+D} \times 100\%$
Frequency of clouds for WRF-Solar	$FOC_{WRF-Solar} = \frac{B+D}{A+B+C+D} \times 100\%$
Probability of detection in clear sky	$PODCLR = \frac{A}{A+B} \times 100\%$
Probability of detection in cloudy sky	$PODCLD = \frac{D}{C+D} \times 100\%$
False alarm rate in clear sky	$FARCLR = \frac{C}{A+C} \times 100\%$
False alarm rate in cloudy sky	$FARCLD = \frac{B}{B+D} \times 100\%$
Hit rate	$HR = \frac{A+D}{A+B+C+D} \times 100\%$ $(where\ 0 \le HR \le 100\%)$
Kuiper's skill score	$KSS = \frac{A \cdot D - B \cdot C}{(A+B) \cdot (C+D)} \times 100\%$ $(where\ -100\% \le KSS \le 100\%)$
Mismatched cloud frequency	$MCF = \frac{c}{c+d} \times 100\%$

We used the metrics to quantify the performance of WRF-Solar EPS in forecasting cloud mask.

3. SPATIAL ANALYSIS (EM_{All} vs. EM_{P50})

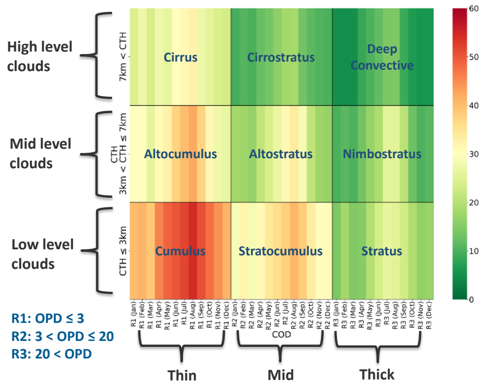
False alarm rate (FAR) in clear-/cloud-sky calculated for each pixel in February and August 2018



- For EM_{All}, WRF-Solar EPS shows high FARCLRs and low FARCLDs for CONUS because a large portion of the cloud-free-pixels in WRF-Solar EPS is missed clouds (when directly comparing with 2-km NSRDB clouds).
- EM_{P50} does not penalize the FARCLR and FARCLD from WRF-Solar EPS. Especially, improved FARCLR by the EM_{P50} is reasonable given that the model usually represents clear-sky pixels with high accuracy.
- A cloud-resolving scale model grid (1-4 km) might be required for future WRF-Solar EPS enhancements to resolve the biases in cloud occurrences resulting from the selected WRF configuration (from a point of view in EM_{All}), and EM_{P50} is needed in order to a fair comparison with the current 9-km WRF-Solar EPS.

4. ANALYSIS FOR DIFFERENT CLOUD TYPES

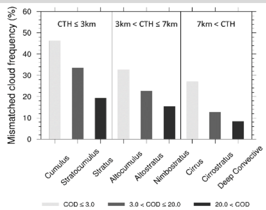
Mismatched cloud frequency (MCF, %)



- We used EM_{P50} and analyzed MCF classified in different cloud optical depth (COD) and cloud top height (CTH).
- Given the MCF, WRF-Solar EPS provides accurate forecasts for high-level and thick clouds, whereas low-level and thin clouds cause difficulties in predicting cloud masks from the WRF-Solar EPS.
- There are notable high MCF values for 'Cumulus' category in summer.
- This might be a result of the representation of shallow cumulus clouds using the Deng parameterization in WRF-Solar EPS.
- But note that there are also difficulties in detecting thin and low-level clouds from satellite.

5. SUMMARY

- Cloud-mask forecast of WRF-Solar EPS (9-km) is evaluated against high-resolution NSRDB (2-km) through EM_{All} and EM_{P50} based on two scenarios.
- Cloud detection metrics are used to quantify and evaluate ensemble cloud mask forecasts from the WRF-Solar EPS.
- WRF-Solar EPS shows high mismatched cloud frequency in predicting thin clouds (27%–46%) and low-level clouds (19%–46%).



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