Day-ahead forecasting of solar irradiance using WRF-Solar and evaluation using the National Solar Radiation Database

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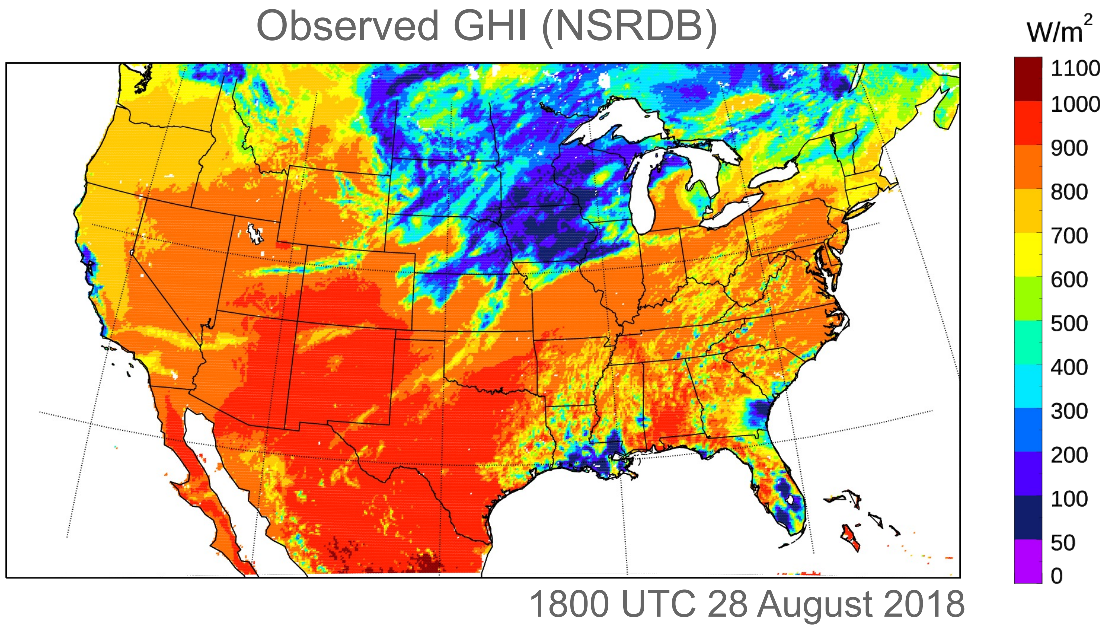
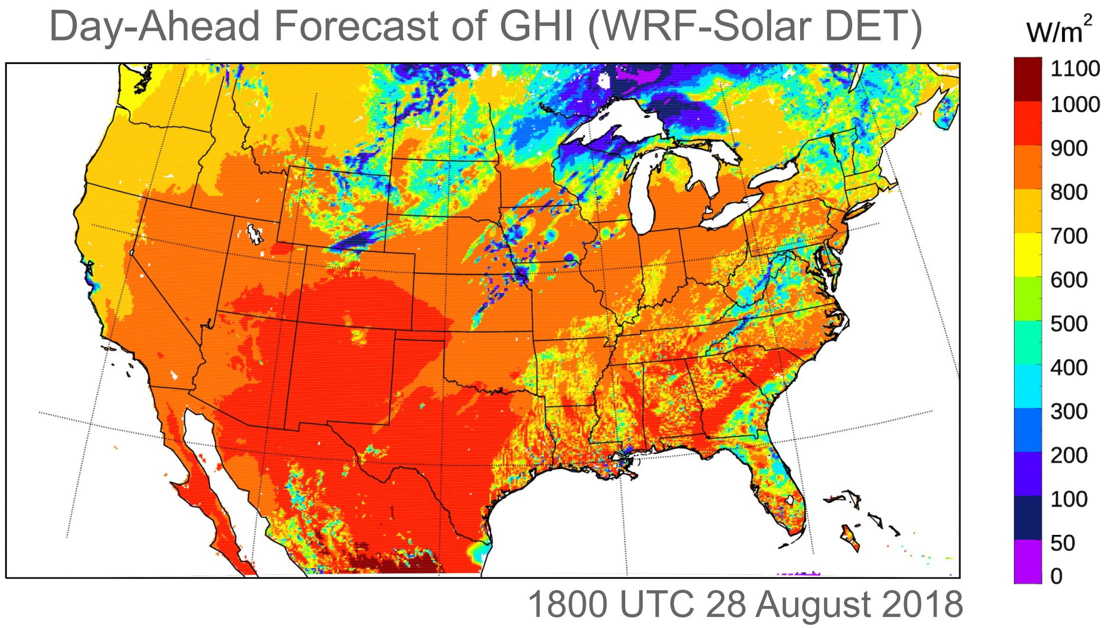
Overview

1. WRF-Solar forecasting systems
2. Experiment design
3. Forecast evaluation results
4. Summary

1. WRF-Solar forecasting systems





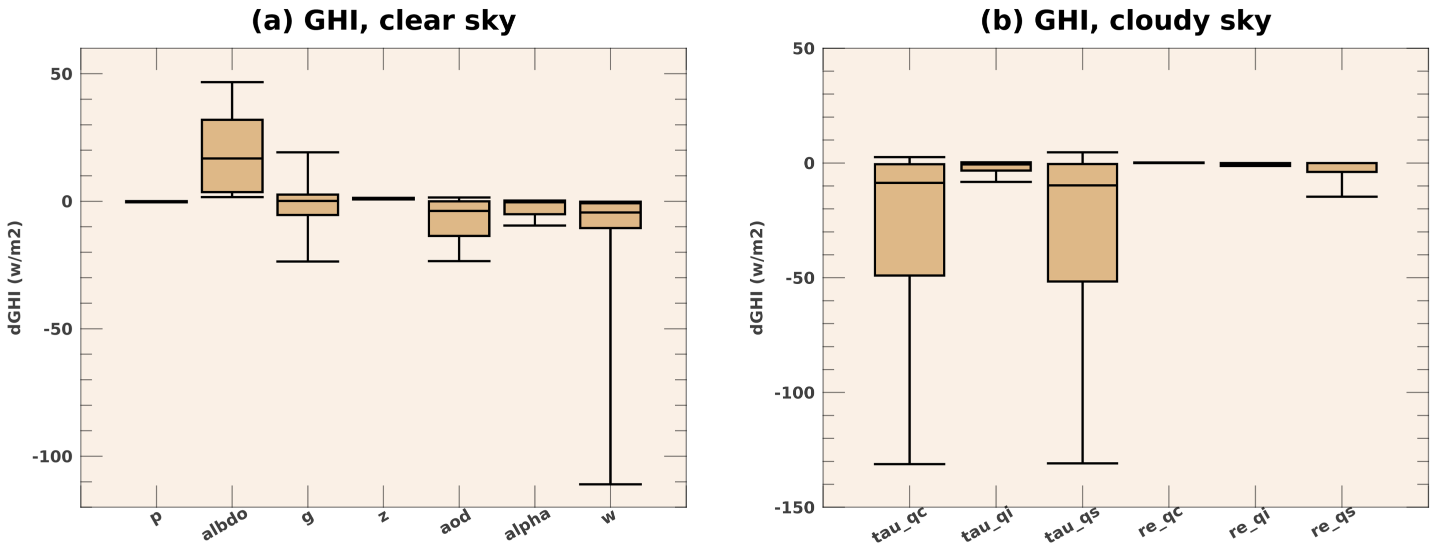
- WRF-Solar forecasting systems focused on the prediction of Global Horizontal Irradiance (GHI) by improving the representation of the cloud-aerosol-radiation feedbacks

- Having a probabilistic forecast is necessary to be able to provide uncertainty estimations. WRF-Solar was lacking a ensemble prediction system specifically tailored for solar applications

Development of WRF-Solar Ensemble Prediction System

Stochastic Ensemble Prediction System

- The most relevant variables for the largest uncertainties in predicting surface solar irradiance and clouds have been identified with tangent linear models of selected parameterizations (Yang et al., 2021).

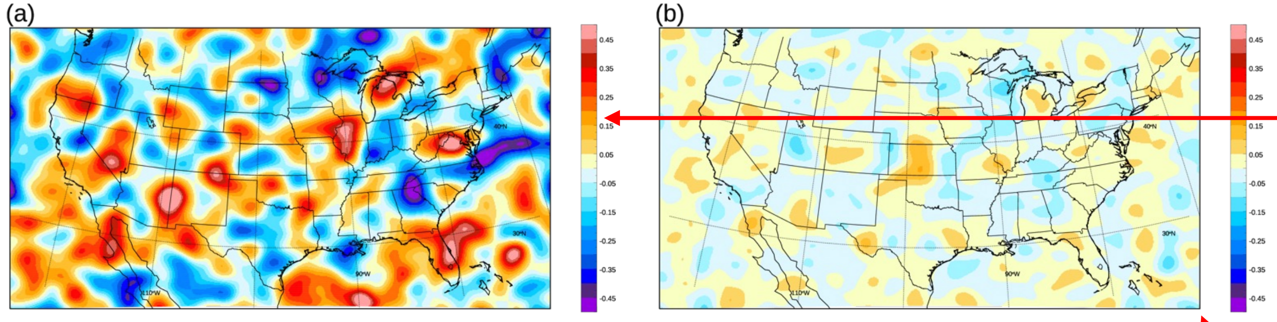


Summary of the characteristics of 14 stochastic perturbations in WRF-Solar EPS.

n	Variable name	Selected modules	σ	λ [m]	τ [s]	ω
1	Albedo	FARMS	0.10	100 000	86 400	0
2	Aerosol optical depth	FARMS	0.25	100 000	3 600	0
3	Ångström wavelength exponent	FARMS	0.10	100 000	3 600	0
4	Asymmetry factor	FARMS	0.05	100 000	3 600	0
5	Water vapor mixing ratio	FARMS, MYNN-PBL, Thompson microphysics, Noah LSM, Deng shallow cumulus, and CLD3	0.05	100 000	3 600	1
6	Cloud water mixing ratio	FARMS, MYNN-PBL, Thompson microphysics, and Deng shallow cumulus	0.10	100 000	3 600	1
7	Ice mixing ratio	Thompson microphysics	0.10	100 000	3 600	1
8	Snow mixing ratio	FARMS and Thompson microphysics	0.10	100 000	3 600	1
9	Ice number concentration	Thompson microphysics	0.05	100 000	3 600	1
10	Potential temperature	MYNN, Noah, Deng shallow cumulus, and CLD3	0.001	100 000	3 600	1
11	Turbulent kinetic energy	MYNN-PBL	0.05	80 000	600	1
12	Soil moisture content	Noah LSM	0.10	80 000	21 600	1
13	Soil temperature	Noah LSM	0.001	80 000	21 600	1
14	Vertical velocity	Deng shallow cumulus	0.10	80 000	21 600	1

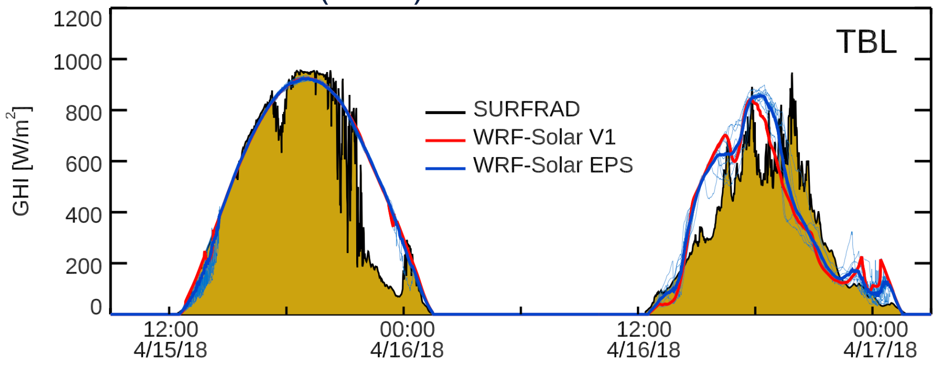
- Multiple stochastic perturbations are added to the selected variables to six physics schemes in WRF-Solar.

$$X_n' = [1 + f(\sigma_n, \lambda_n, \tau_n)]X_n$$



Instantaneous pattern of stochastic perturbations for the (a) Aerosol Optical Depth (AOD) and (b) Turbulent Kinetic Energy (TKE).

Kim et al. (2022)



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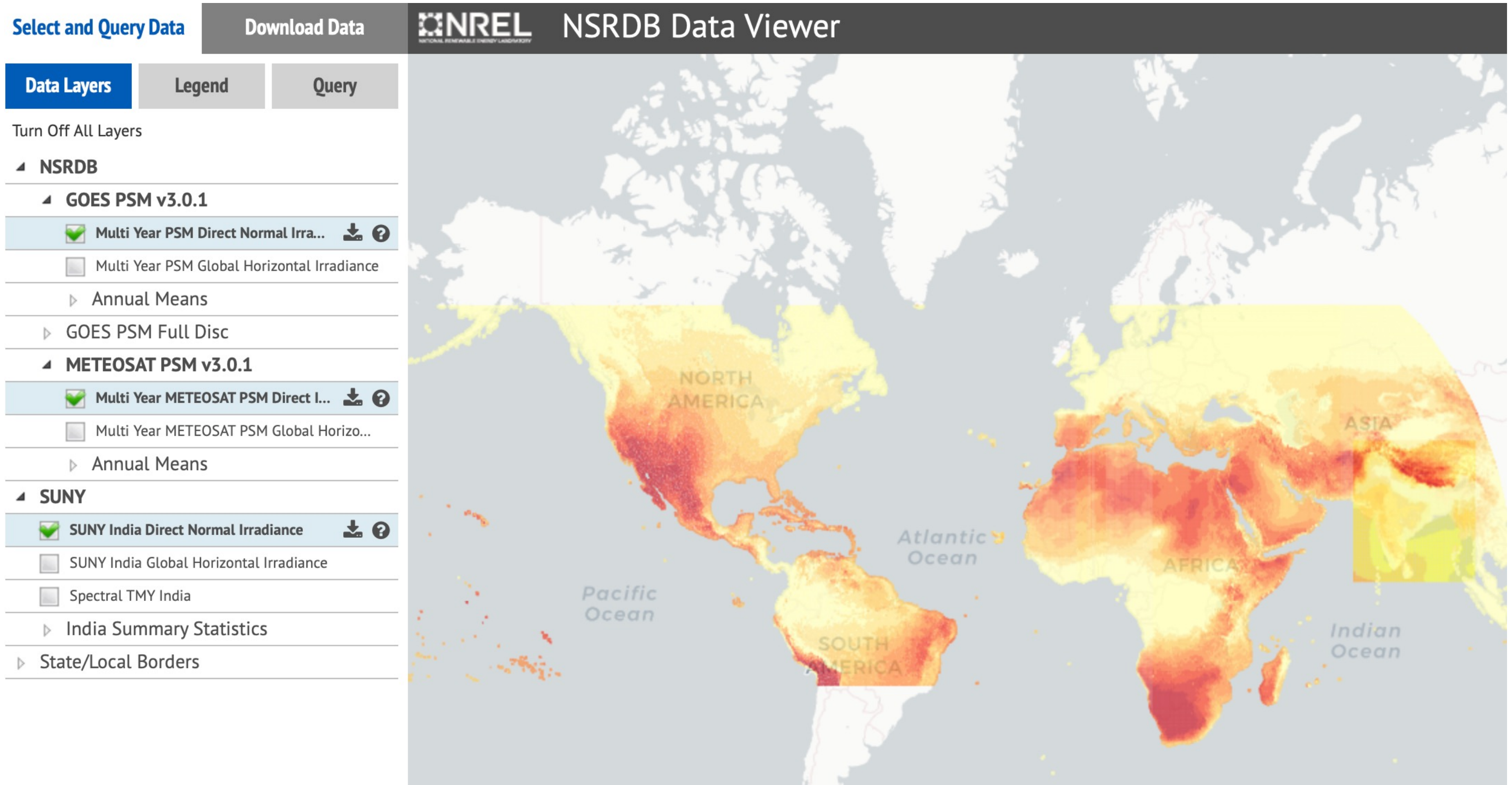
National Solar Radiation Data Base (NSRDB)

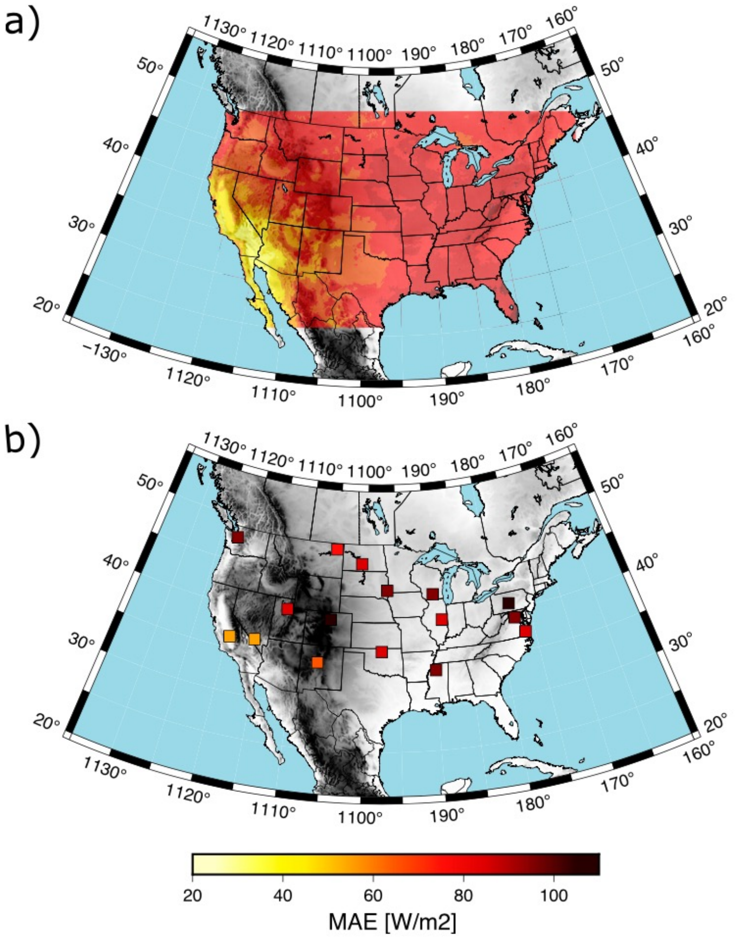


https://nsrdb.nrel.gov

- ❑ Global horizontal irradiance (GHI) and Direct normal irradiance (DNI)
- ❑ 4-km horizontal resolution, 30-min interval (1998 to 2019)
- ❑ This data is known as to show 5% (10%) bias in GHI (DNI) against surface site observations
- ❑ Sengupta et al. (2018)

In this study, this data was regridded to 9-km resolution WRF-Solar Domain for 2018 for validation of prediction results.

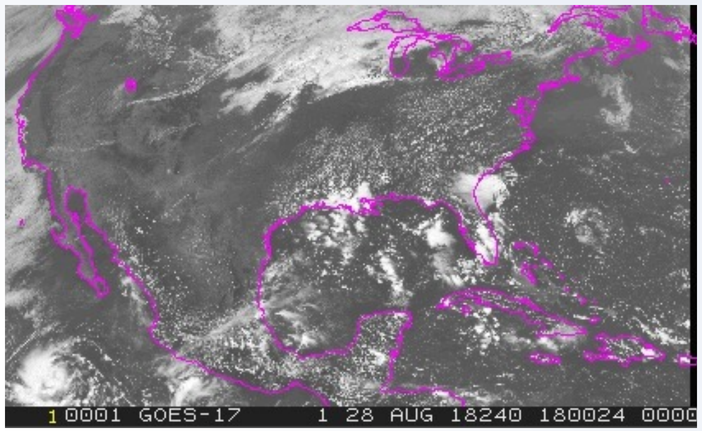
Why NSRDB?

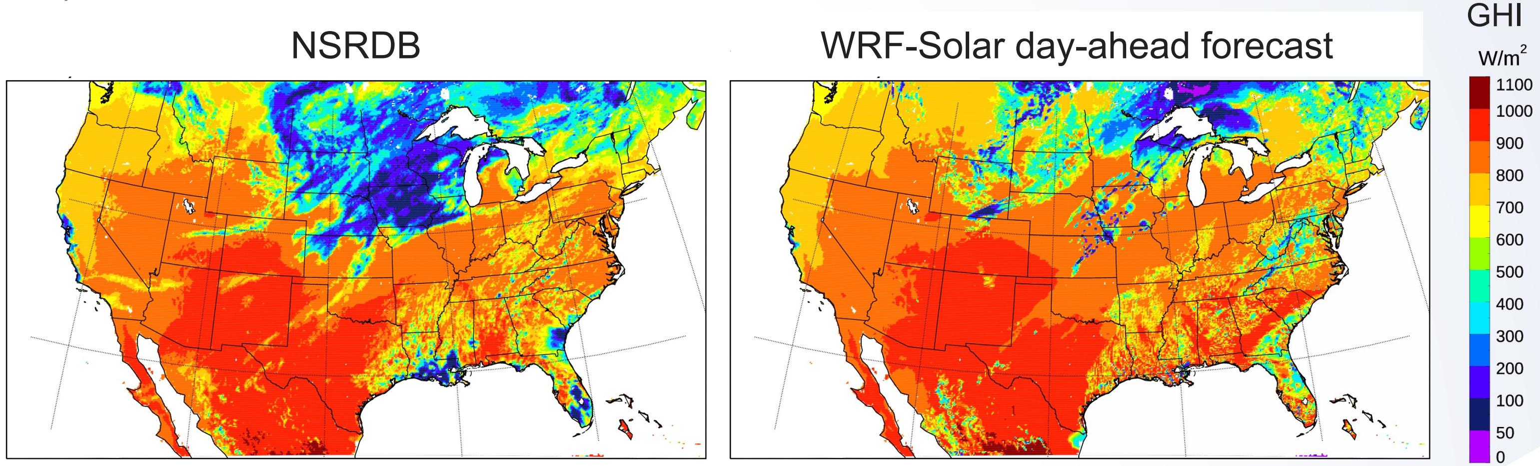


MAE calculated with (a) NSRDB and (b) ground observations and WRF-Solar REF_1D experiment. (Jimenez et al. 2022)

- ✓ *Ground observations provide a limited spatial coverage of the surface irradiance!*
- ✓ *“NSRDB tends to provide slightly better statistics than those obtained with high-quality ground observations on the seasonal or annual time scales!” (Jimenez et al. 2022)*

GOES-17 Channel 1



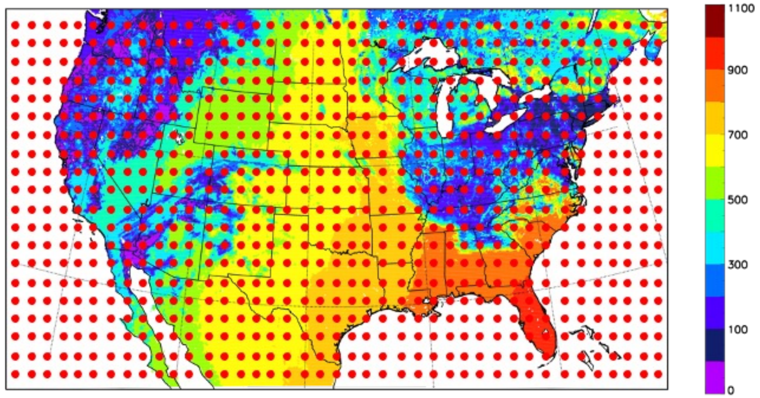


at 1800 UTC 28 August 2018

2. Experiment design

Prediction results	1. WRF-Solar DET – Deterministic WRF-Solar 2. WRF-Solar EPS - WRF-Solar Ensemble Prediction System (10 members) 3. SKEBS - Stochastic Kinetic Energy Backscatter Scheme (10 members) 4. WRF-Solar PHYS - WRF-Solar multi-physics ensemble (10 members)
Observation	NSRDB
Forecast period	From 1 January to 29 December 2018 by every day
Grid spacing	9-km (600 x 354)
Forecast lead time	• 48-hour forecasts initialized at every 06 UTC • Evaluation- 24 hours of the second day forecast
Physics configuration	• Thompson microphysics • MYNN PBL • Loah LSM • Deng shallow cumulus • FARMS radiation • RRTMG SW/LW radiation

Every 5 x 5 WRF Solar Grid points



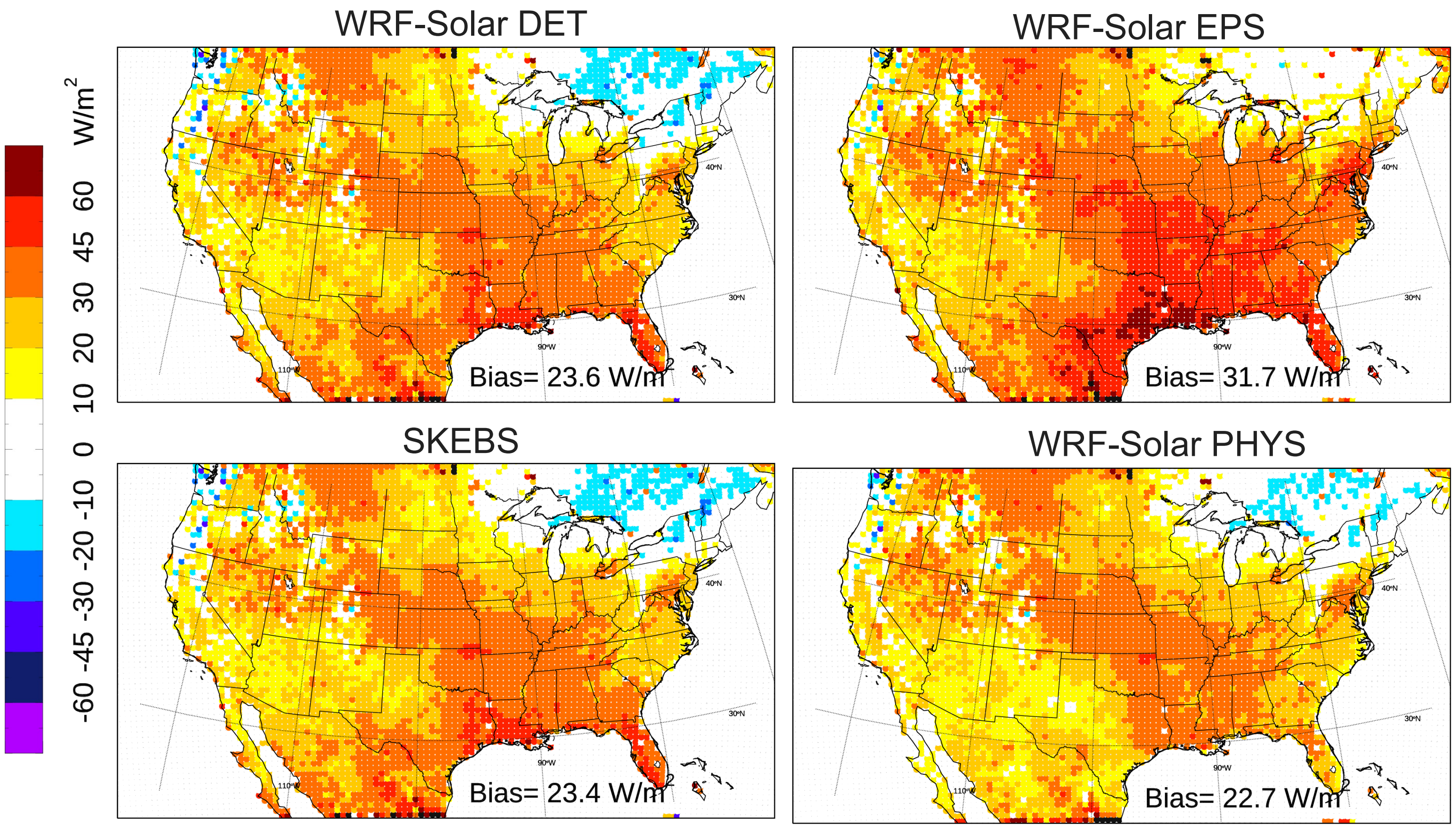
We compare forecast results of ***four prediction systems,*** focusing on the impact of the stochastic perturbations in WRF-Solar EPS!

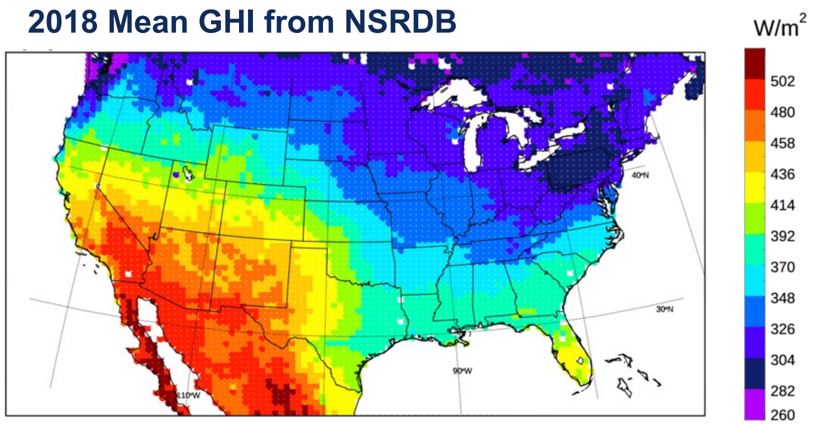
Table 2. Summary of multiphysics ensemble configuration.

	Microphysics	Cumulus	Shallow Cumulus	Aerosol	LSM	Albedo	radiation
1	Thompson	no	Deng	Tegen (1997)	Unified Noah	Monthly albedo	RRTMG
2	Thompson aerosol awareness	no	Deng	Thompson and Eidhammer (2014)	Unified Noah	Monthly albedo	RRTMG
3	Thompson	GF	MYNN (icloud_bl=1, ishallow=0)	Tegen (1997)	Unified Noah	Monthly albedo	RRTMG
4	Thompson	GF	Grell (Icloud_bl=0, ishallow=1 Edmf=0)	Tegen (1997)	Unified Noah	Monthly albedo	RRTMG
5	Thompson	no	Deng	Tegen (1997)	Noah MP	Table	RRTMG
6	Thompson	no	Deng	Ruiz-Arias et al. (2014)	Unified Noah	Monthly albedo	Goddard
7	Goddard	no	Deng	Tegen (1997)	Unified Noah	Monthly albedo	RRTMG
8	Goddard	no	Deng	Ruiz-Arias (2014)	Unified Noah	Monthly albedo	Goddard
9	Thompson	KF	icloud_bl=0, ishallow=1 Edmf=0	Tegen (1997)	Unified Noah	Monthly albedo	RRTMG
10	Thompson	Modified Tiedtke	icloud_bl=0, ishallow=1 Edmf=0	Tegen (1997)	Unified Noah	Monthly albedo	RRTMG

3. Forecast Results

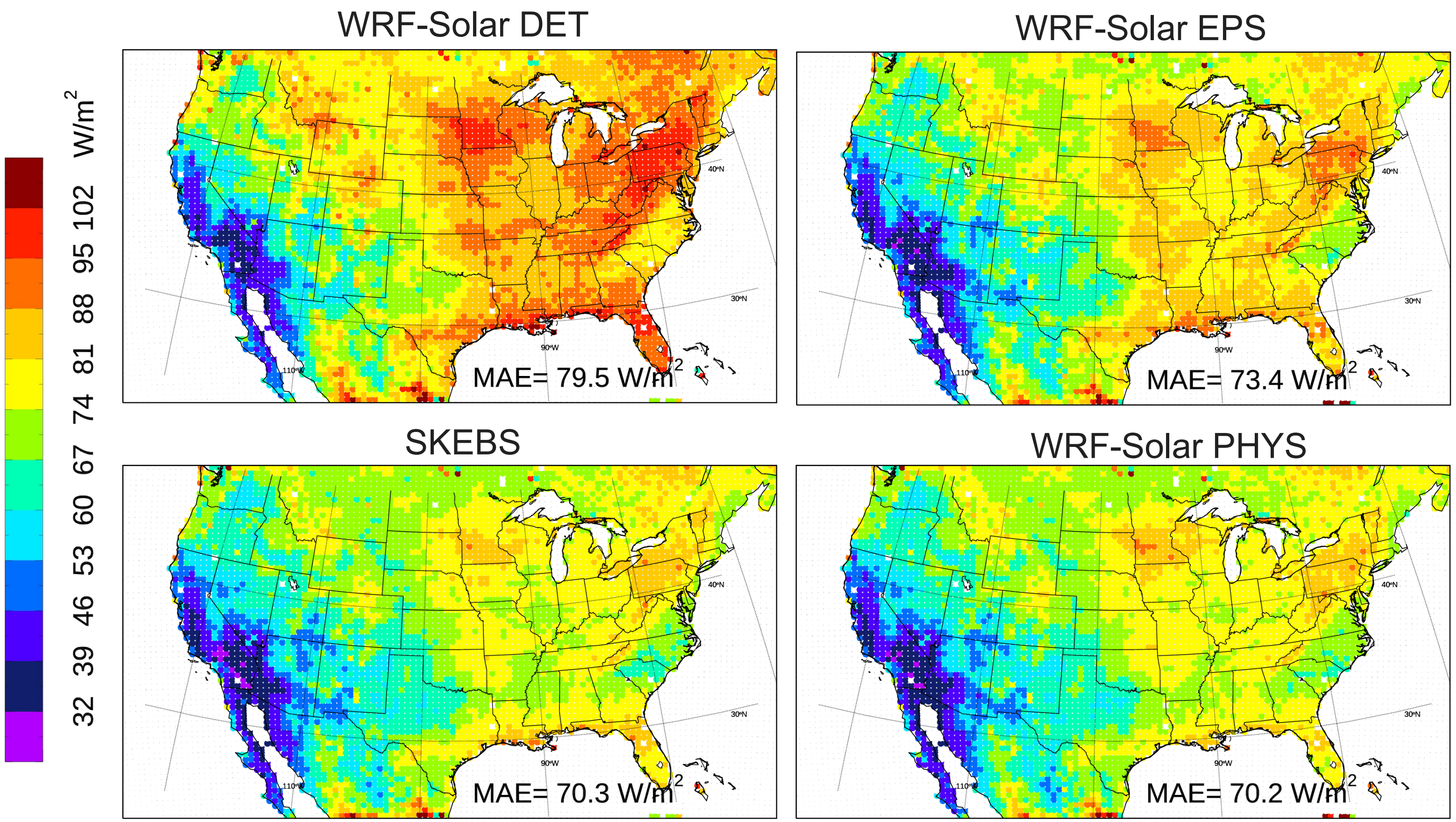
Bias Maps for 2018 GHI Forecast



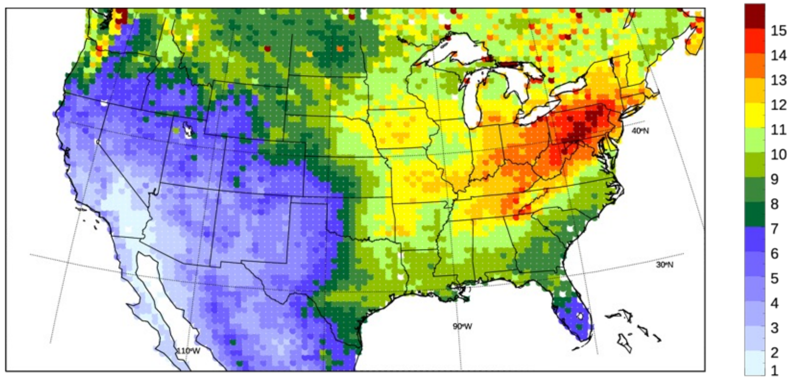


- WRF-Solar DET, WRF-Solar EPS, and SKEBS show similar patterns of the bias with the largest positive bias in the southeastern United States, but the WRF-Solar EPS shows a slightly more positive bias
- WRF-Solar PHYS shows a different pattern, with the largest bias in the central United States and reduced bias in southern areas

MAE Maps for 2018 GHI Forecast

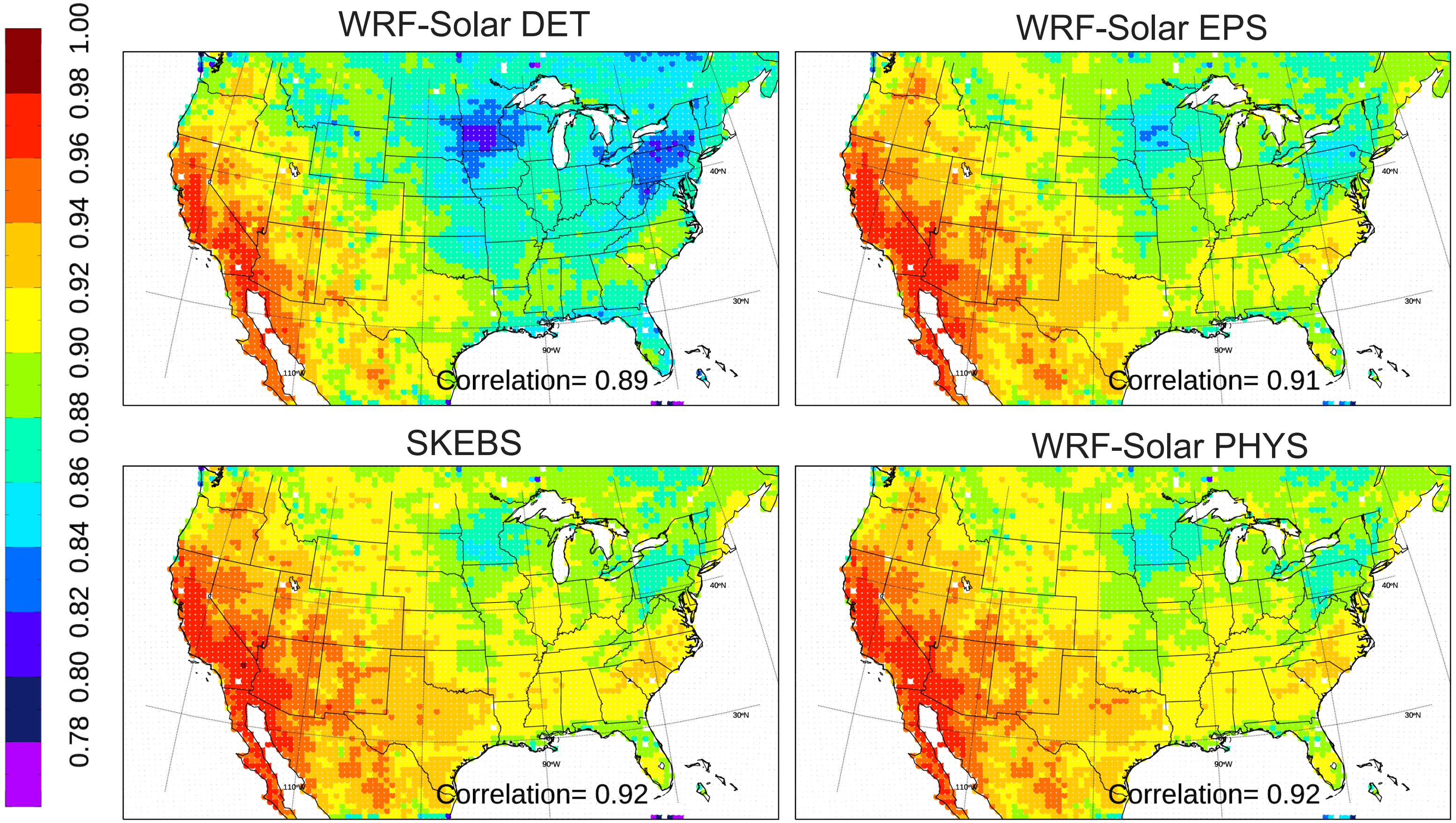


2018 Mean cloud optical depth from NSRDB

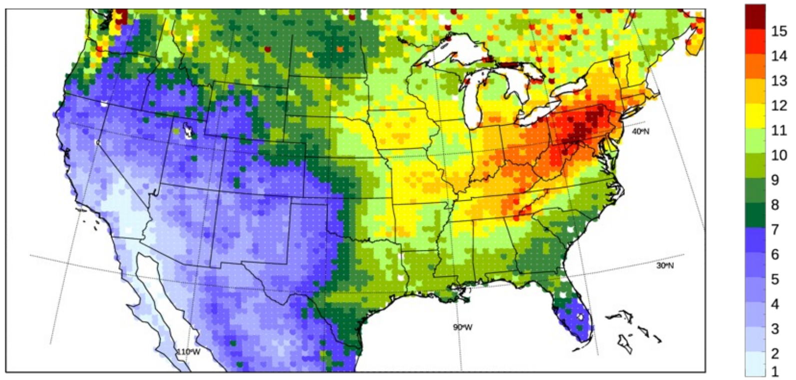


- All forecasts show the largest MAE in the eastern United States, and the regions with large errors are highly correlated (0.77-0.80) with the cloudy regions
- The ensemble forecast improve predictability in most regions, especially in the eastern United States, compared to WRF-Solar DET
- WRF-Solar EPS reduces the MAE in WRF-Solar DET by 7.5 % in GHI prediction

Correlation Maps for 2018 GHI Forecast

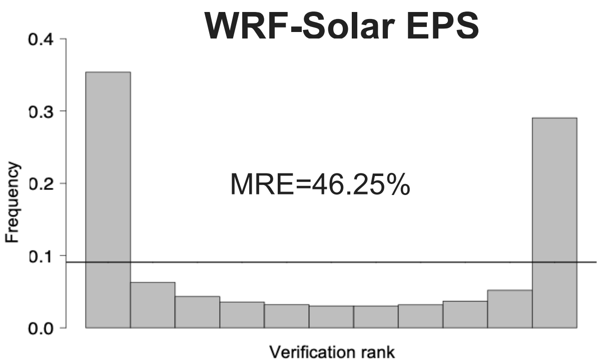


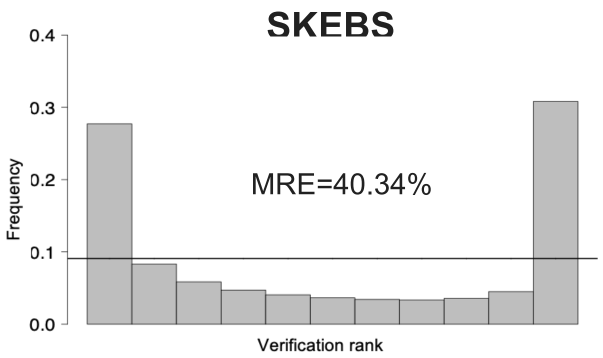
2018 Mean cloud optical depth from NSRDB

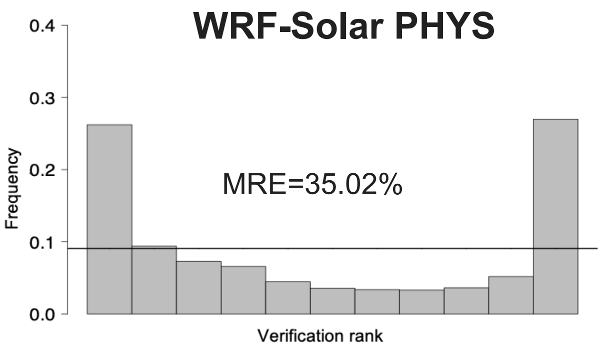


- The correlation coefficient shows high values in the western United States (0.94-0.98) and lower values (0.82-0.90) in the eastern region
- The ensemble forecasts show a higher overall correlation than the deterministic forecast in most regions, especially the eastern region

Rank Histogram and Missing Rate Error

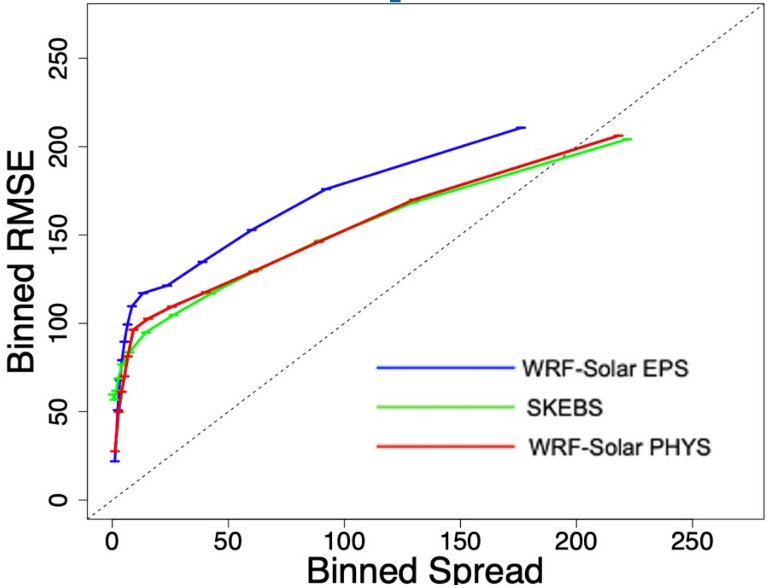






An ensemble is perfectly statistically consistent when its rank histogram is flat!

Binned Spread-Skill



- The three ensembles show U-shape histograms revealing under dispersion in a very similar way.
- WRF-Solar PHYS has a relatively better dispersion relationship (MRE = 35.02%), followed by SKEBS (MRE = 40.34%), and WRF-Solar EPS (MRE = 46.25%)
- In Binned Spread-Skill, SKEBS and WRF-Solar PHYS are a bit closer to the 1:1 line compared to WRF-Solar EPS.
- But all experiments show under-dispersive ensembles.

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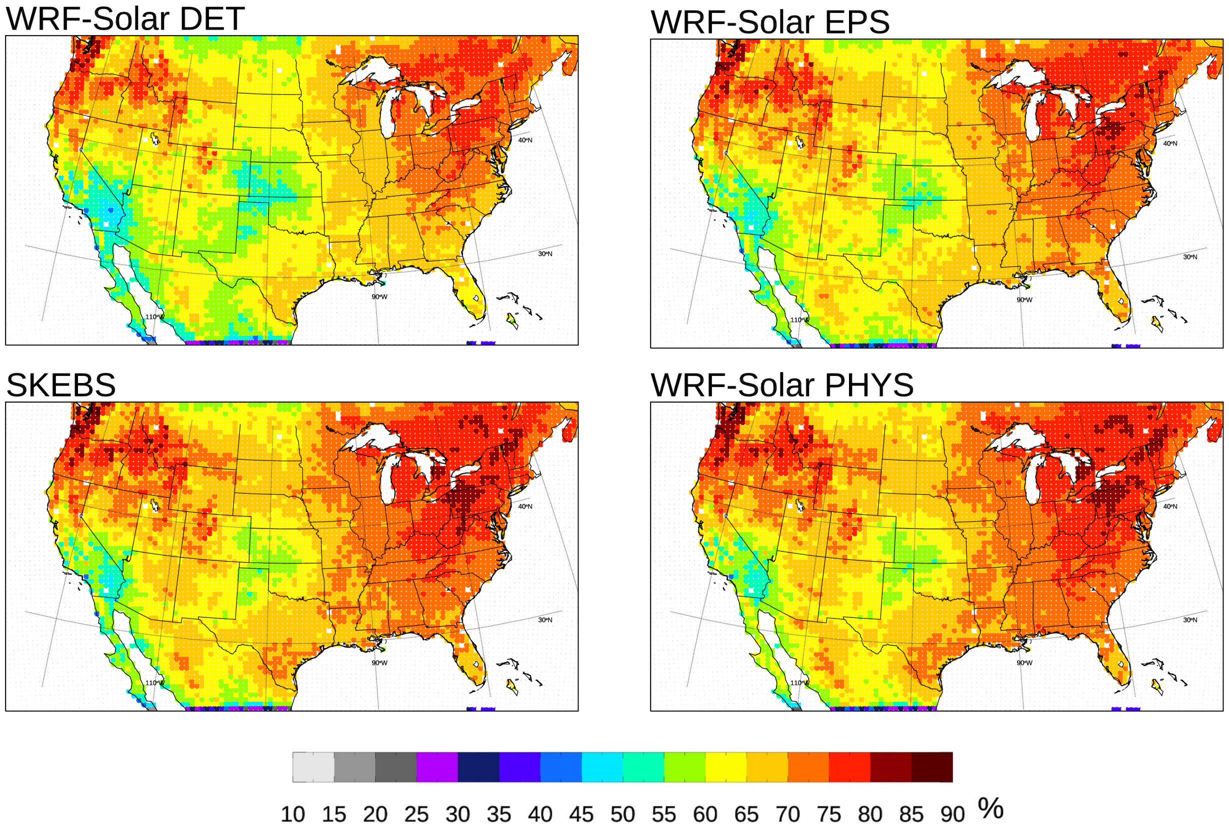
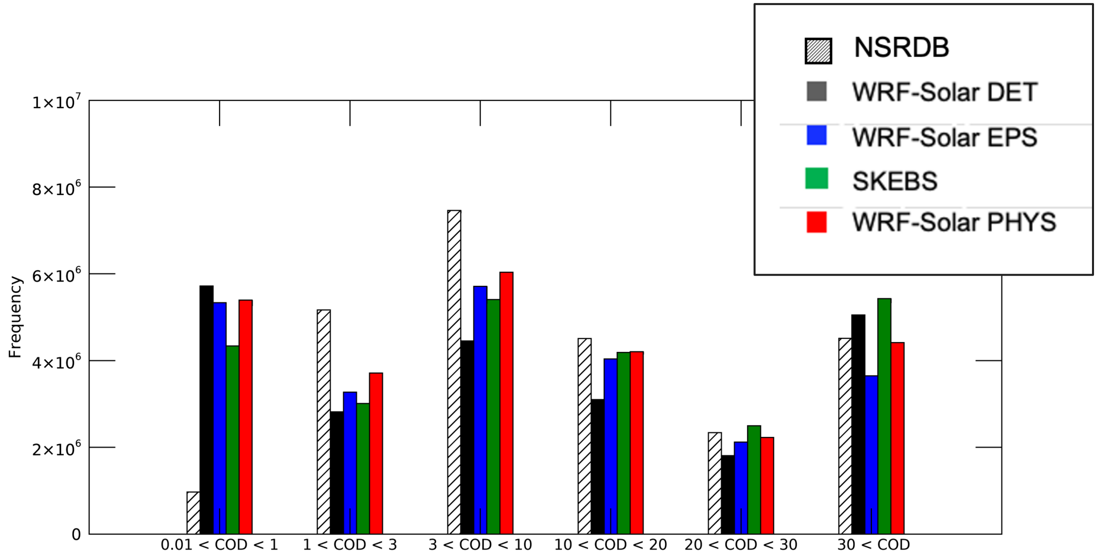
Peirce Skill Score (PSS) of Cloud Detection



	Forecasting		
NSRDB	Scenario	Cloudy	Cloud-free
	Cloudy	CC	CN
	Cloud-free	NC	NN

$$PSS = \frac{CC \times NN - CN \times NC}{(CC + CN)(NC + NN)}$$

Frequency of Cloud Optical Depth



- SKEBS and WRF-Solar PHYS show slightly superior performance over WRF-Solar EPS in detecting clouds
- Models tend to produces optically thin clouds (COD <1) more frequently and medium thickness clouds (1<COD<10) less frequently than observations. WRF-Solar EPS produces less optically thick clouds (30 < COD) than other predictions

4. Summary

- Day-ahead forecasts of solar irradiance were conducted by WRF-Solar DET, WRF-Solar EPS, SKEBS, and WRF-Solar PHYS for 2018. Using NSRDB as observation data set enables evaluations of the spatial distribution of the error reduction over the CONUS.
- WRF-Solar EPS shows slightly higher positive bias than WRF-Solar DET, SKEBS, and WRF-Solar PHYS in the GHI forecast, but the MAE decreases by 7.5% compared to WRF-Solar DET with increasing spatial correlation to observations.
- SKEBS and WRF-Solar PHYS shows slightly superior performance over WRF-Solar EPS in general, but all of the three ensemble systems produce under-dispersive, unreliable, and overconfident ensembles.
- The results provide guidelines for improving the performance of WRF-Solar EPS in the future: 1) Considering a non-linear relationship of changed cloud amounts and surface irradiance, 2) Adding perturbation to momentum as well, and 3) Selecting different combinations of physics schemes.

Prepare to submit (Kim et al. 2022)