An Irradiance Probabilistic Prediction System based on WRF-Solar EPS and the Analog Ensemble

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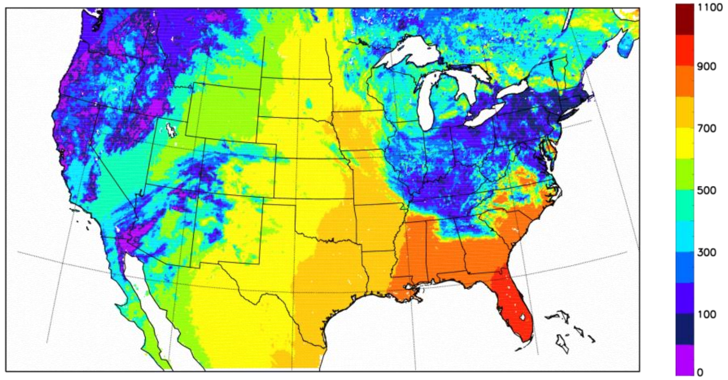
1. WRF-Solar Forecasting systems

NSRDB OBS

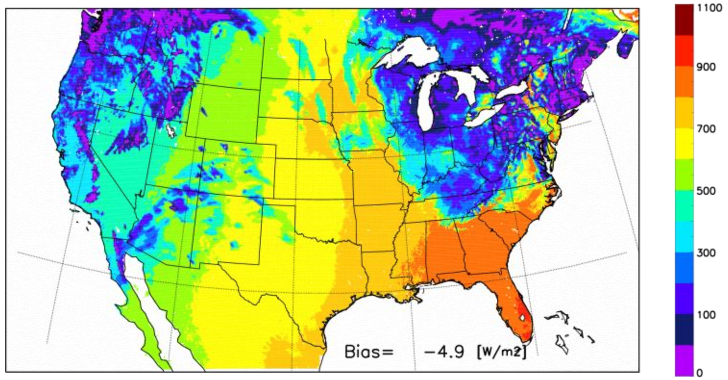
- National Solar Radiation Data Base (https://nsrdb.nrel.gov)
- 4-km horizontal resolution, 30-min interval (1998 to 2018)
- Sengupta et al. (2018)



NSRDB (GHI) at 1530 UTC 16 April 2018

WRF-Solar

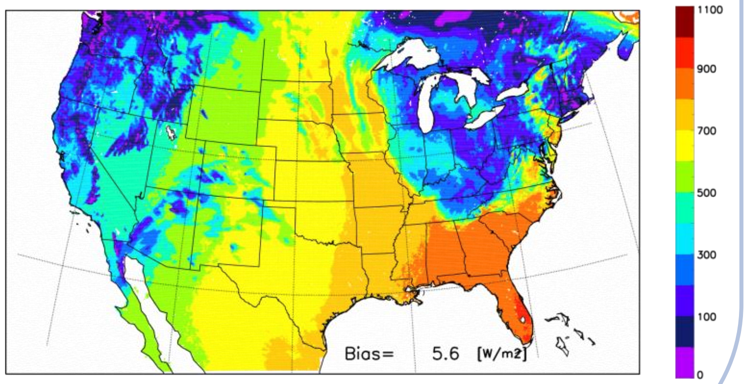
- Deterministic prediction system
- Jimenez et al. (2016)
- FARMS radiation scheme
- Deng shallow cumulus scheme



GHI forecast from WRF-Solar

WRF-Solar EPS

- Ensemble prediction system
- Adding stochastic perturbation to six physics schemes in WRF-Solar
- 10 ensemble members



GHI forecast from WRF-Solar EPS

WRF-Solar EPS

- Six parameterizations affecting solar irradiance and cloud processes are selected:

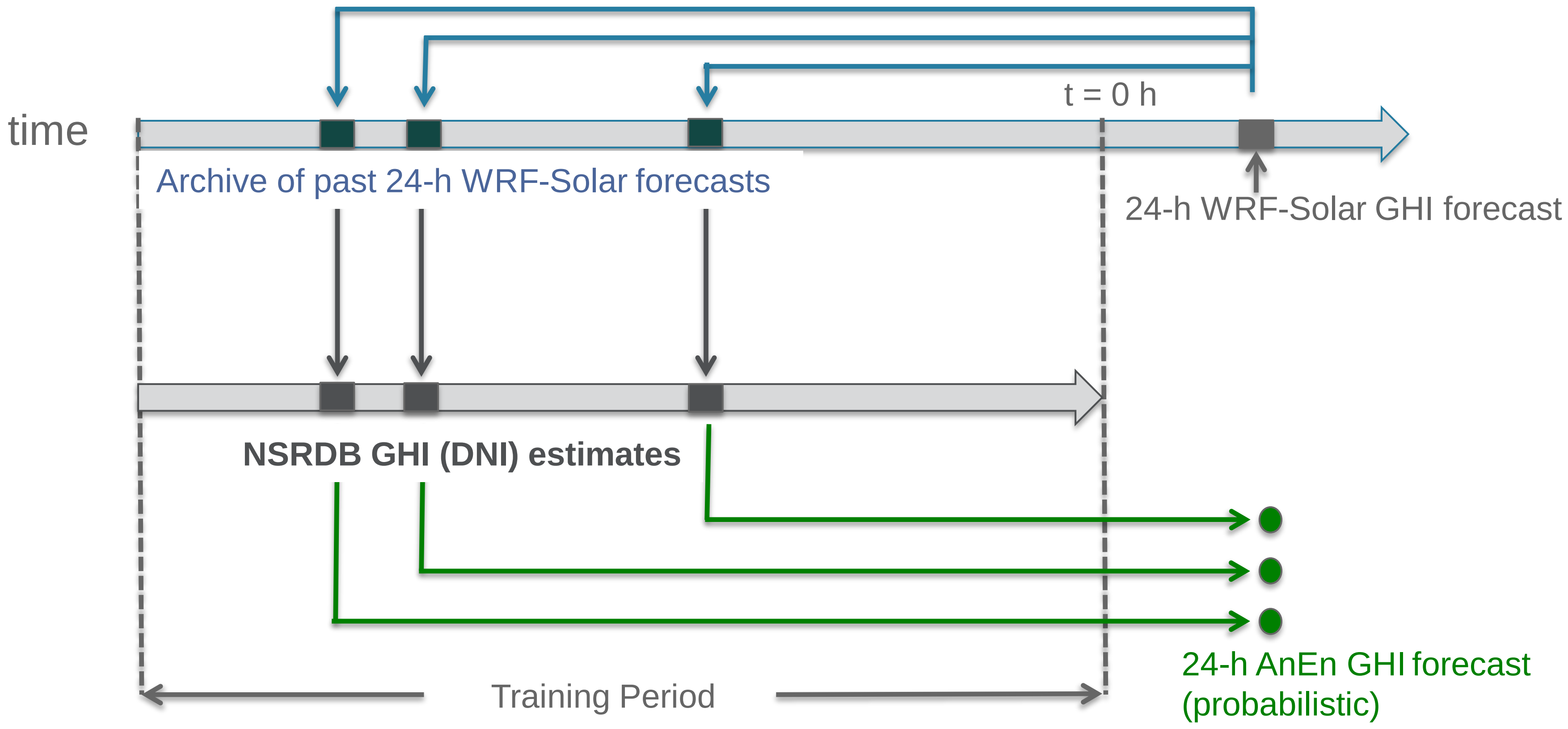
(1) Thompson microphysics,
(2) Mellor–Yamada–Nakanishi–Niino planetary boundary layer parameterization,
(3) The Noah land surface model,
(4) Deng's shallow cumulus parameterization,
(5) the Fast-All-sky Radiation Model for Solar applications,
(6) a parameterization of the effects of unresolved clouds based on relative humidity.

- Tangent linear models of these parameterizations to quantify sensitivities of the input variables to the parameterizations and select the ones introducing the most significant uncertainties in the output variables

- As a result of this analysis, we selected 14 state variables. In the final step, we introduced stochastic perturbations to these variables during the model integration in order to create the WRF-Solar EPS component

2. Analog ensemble method

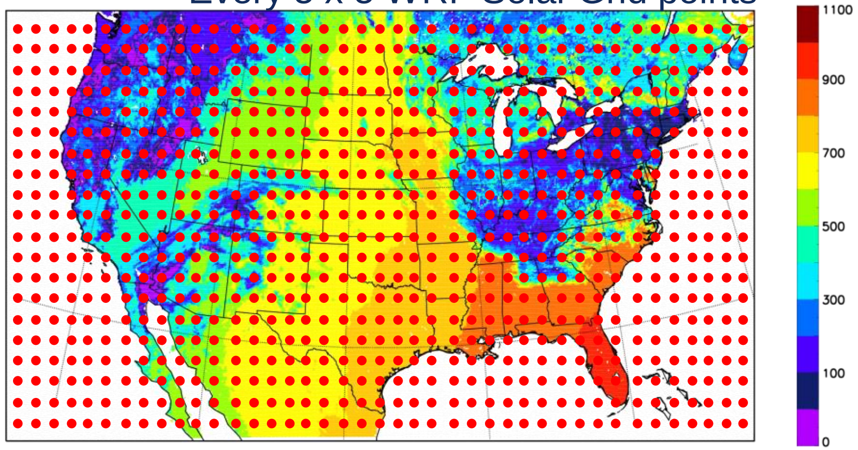
WRF-Solar predictors used for GHI (DNI):GHI and DNI equally weighted
WRF-Solar EPS predictors used for GHI (DNI): GHI (DNI) and GHI spread (DNI spread), equally weighted



3. Experiment design

Prediction systems	WRF-Solar forecasting systems Reference configuration is in the WRF-Solar web site. (https://ral.ucar.edu/projects/wrf-solar)
Observation	NSRDB
Forecast variable	GHI and DNI
Lead time	24 hours of the second day forecast
Training	1 January 2016 to 31 December 2017
Forecast period (verification)	2018
Experiments	1) Verification over 8520 points over CONUS domain (Every 5 x 5 WRF Grid points)

Every 5 x 5 WRF Solar Grid points



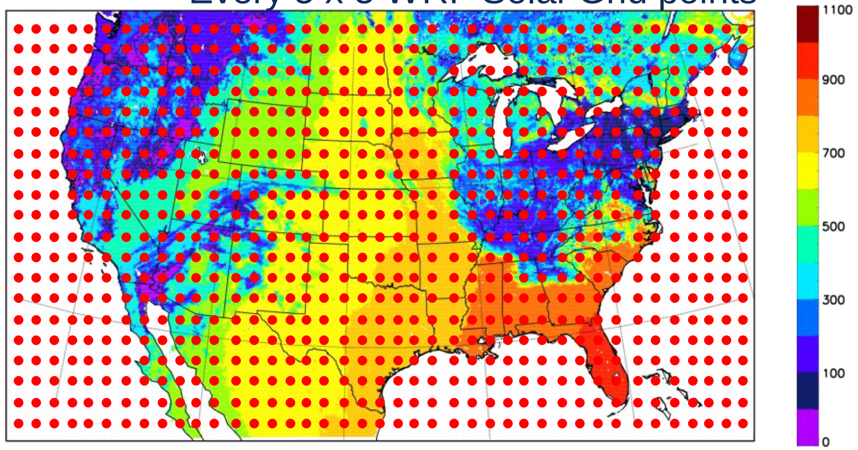
3. Experiment design: Goals

1. To assess and compare **WRF-Solar** and **WRF-Solar EPS** performances in different climatic regions of the US in terms of deterministic GHI and DNI predictions.

2. To compare the performance of the computationally cheaper ensemble, the **WRF-Solar AnEn**, against the more expensive **WRF-Solar EPS.**

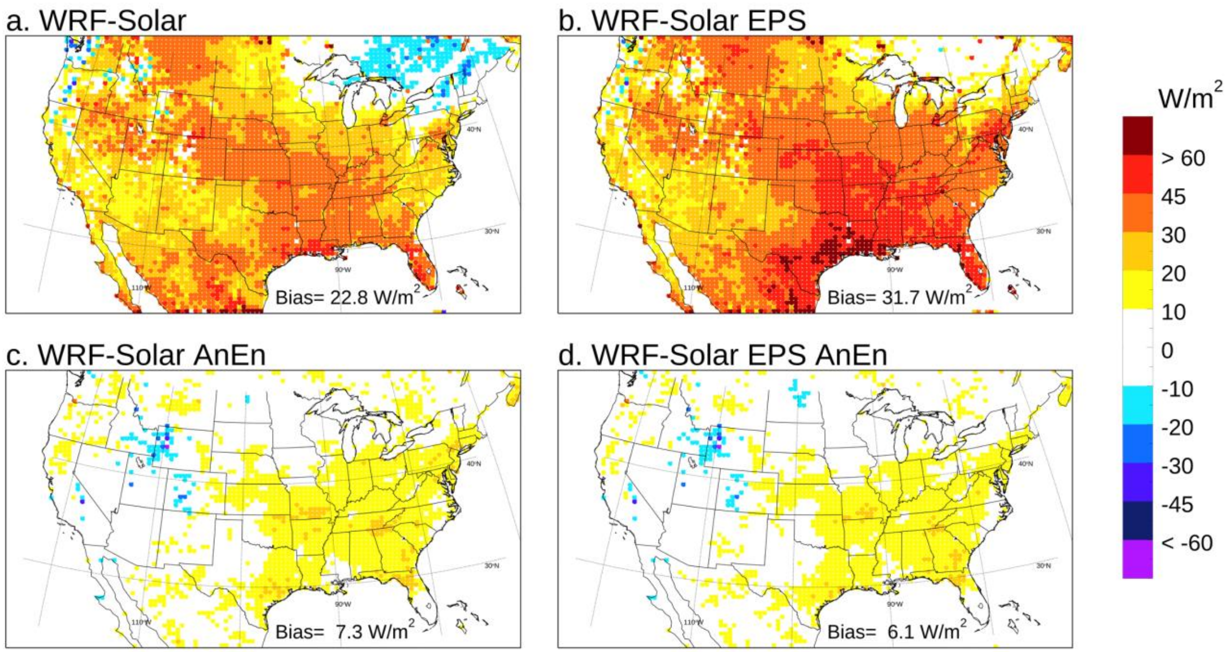
3. To quantify the improvements obtained by the **AnEn** with respect to the raw models to which it is applied (**WRF-Solar** and **WRF-Solar EPS**).

Every 5 x 5 WRF Solar Grid points

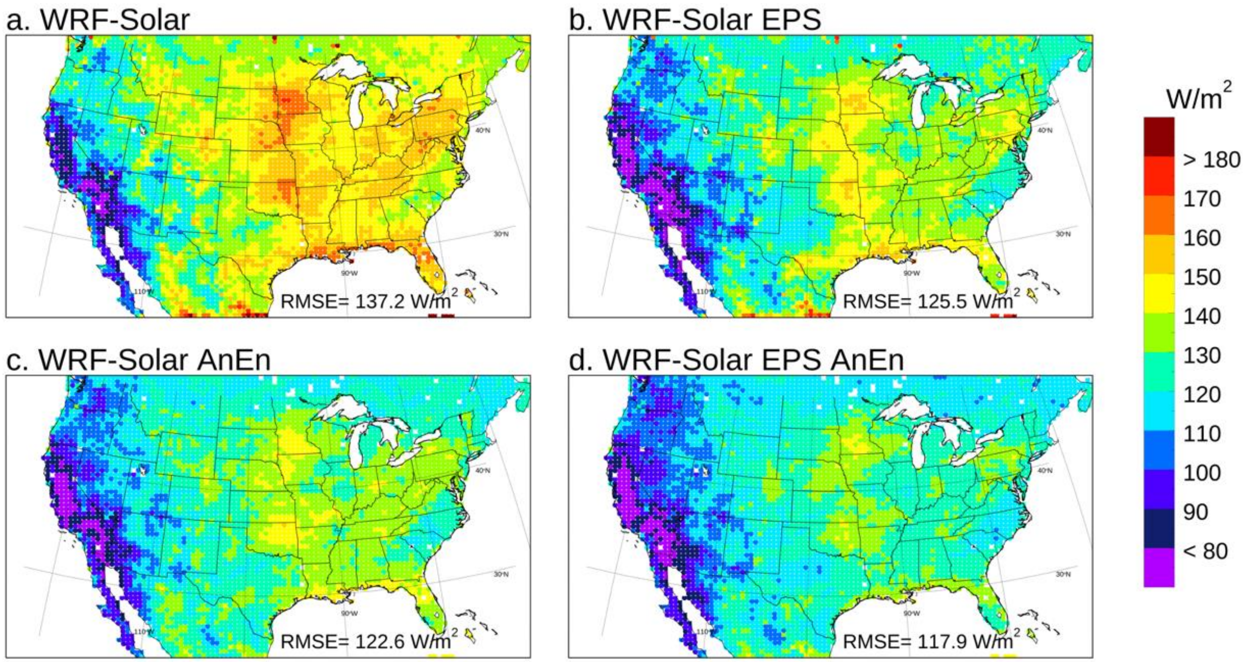


4. Results: RMSE maps for GHI forecast over CONUS

BIAS



RMSE



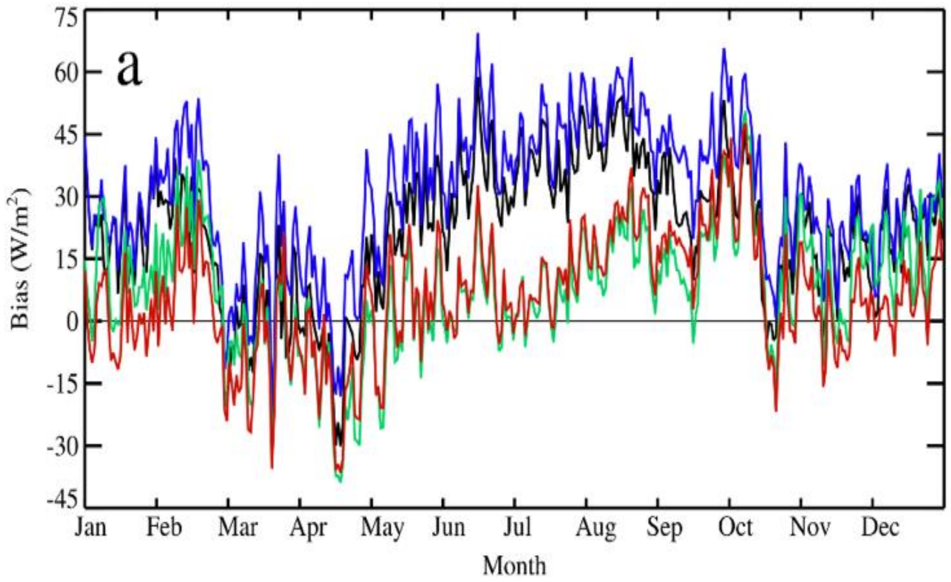
1. WRF-Solar EPS reduces the RMSE compared to WRF-Solar by ~8% in GHI prediction

2. AnEn reduces the RMSE in WRF-Solar EPS by ~6% in GHI prediction.

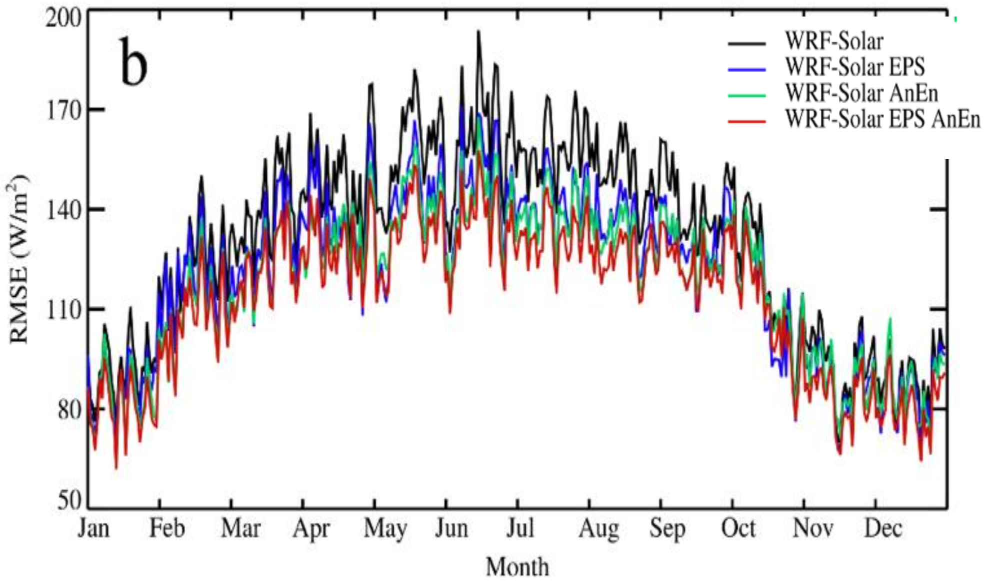
3. WRF-Solar AnEn (ensemble) very competitive even if not the best model in terms of RMSE

4. Results: RMSE timeseries for GHI forecast over CONUS

BIAS



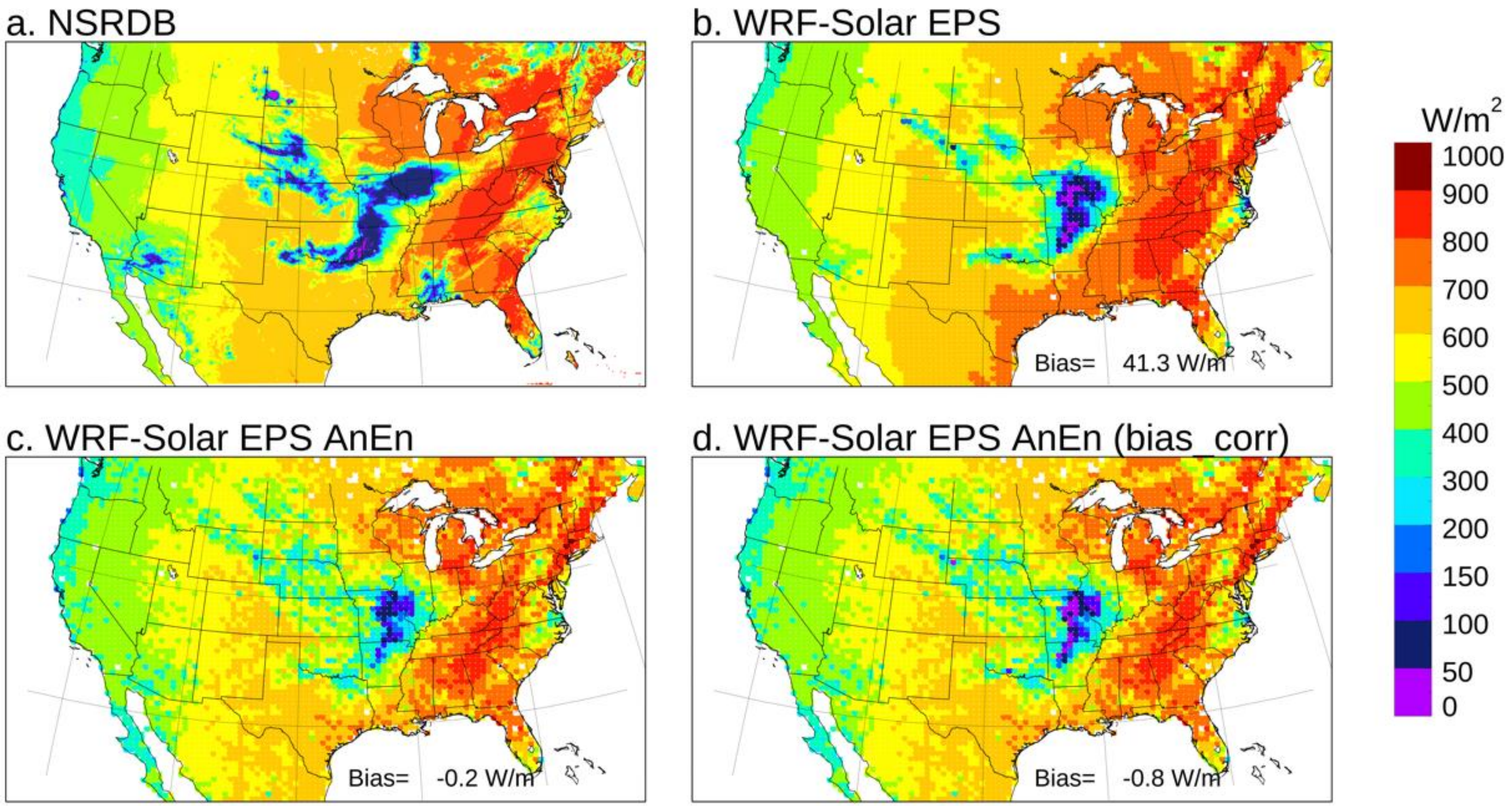
RMSE



Largest biases (GHI overestimated) during summer related to under-estimation of convective clouds

AnEn post-processing improves positive BIAS in summer

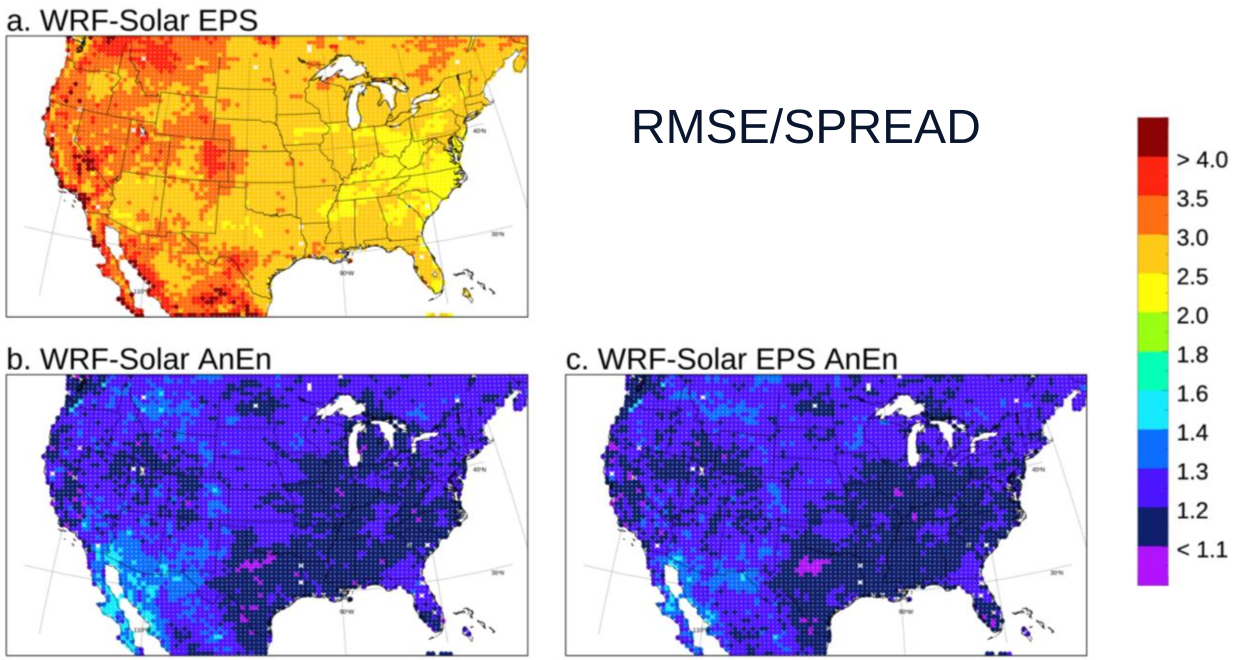
4. Results: Rare events (high cloudiness)

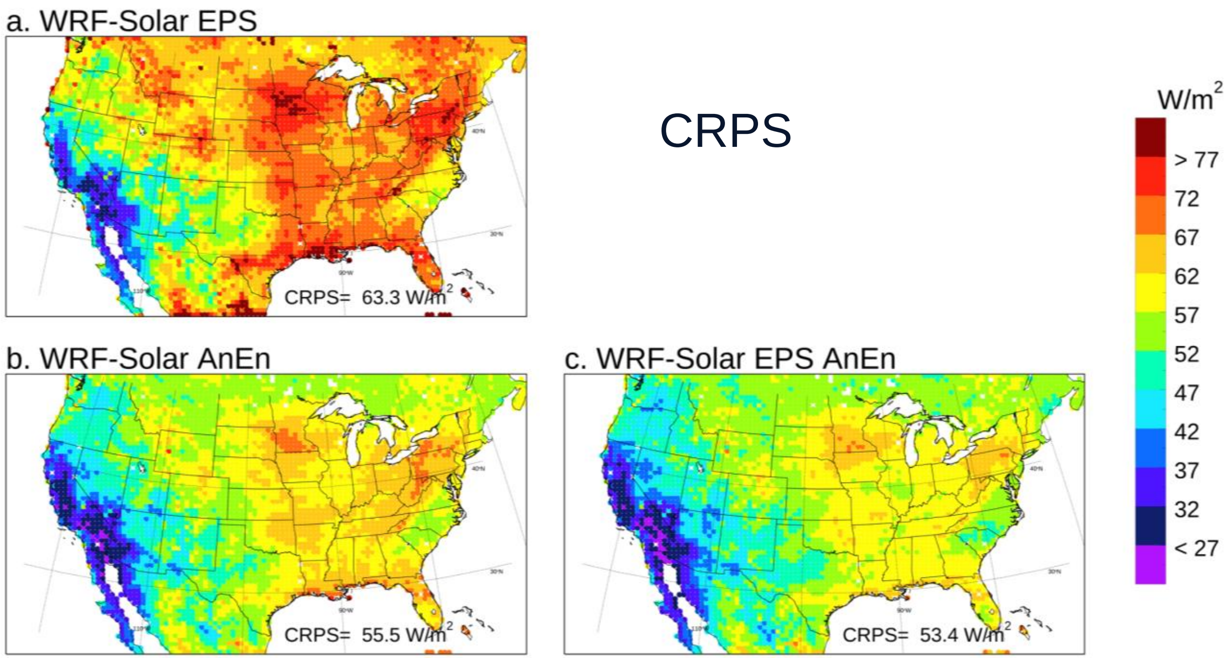


NSRDB GHI map **(a)** at 1530 UTC on July 29, 2018. Model predictions from the ensemble mean of WRF-Solar EPS **(b)**, WRF-Solar EPS AnEn **(c)**, and WRF-Solar EPS AnEn with bias correction **(d)**.

1. Algorithm for addressing AnEn negative bias for rare events is applied as in Alessandrini 2022 *Solar Energy*
2. When comparing with the NSRDB map (a), a positive bias is introduced by the AnEn calibration (c) over the area with a GHI lower than 100 W/m^2 (GHI values under 50 W/m^2 are missing).
3. By using the bias correction for rare events (d) values under 50 W/m^2 are introduced back in the forecast, consistently with the NSRDB and WRF-Solar EPS, while still keeping the overall improvement in terms of bias reduction (−0.8 W/m^2) very similar to that of the AnEn without the correction for rare events (c).

4. Results: RMSE/SPREAD and CRPS maps for GHI forecast over CONUS





1. RMSE/SPREAD ratio is significantly underestimated by WRF-Solar EPS even in less cloudiness (overconfident)

2. There is not enough variability (in terms of cloudiness) across the members

3. AnEn improves RMSE/SPREAD consistency in WRF-Solar EPS

4. WRF-Solar AnEn ensemble is again very competitive in terms of statistical consistency and overall performance (CRPS)

5. Summary

- Both WRF-Solar and the WRF-Solar EPS overestimate GHI and DNI, which indicates that cloudiness is generally underestimated.

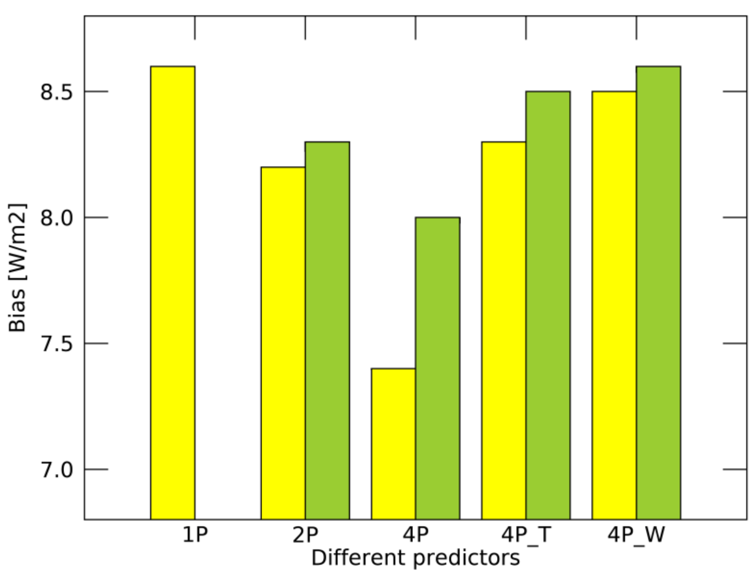
- For RMSE, the WRF-Solar EPS improves upon WRF-Solar both for DNI and GHI with a reduction in RMSE in many areas.

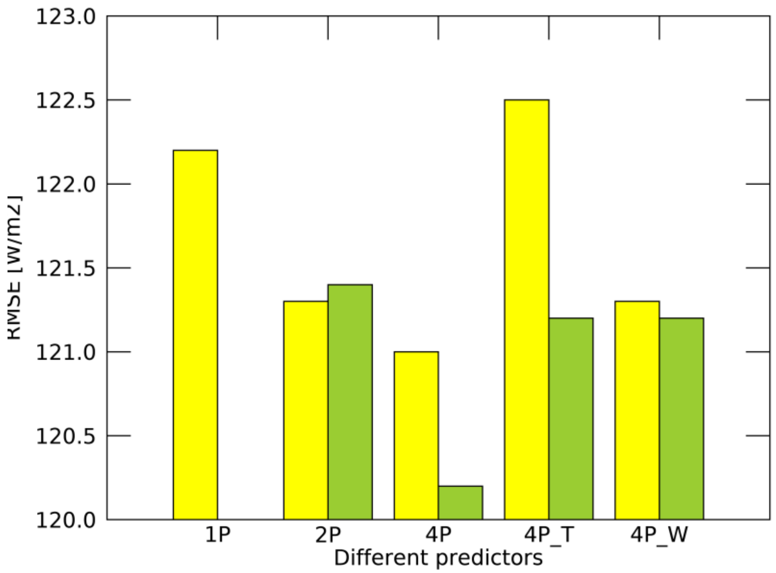
- The WRF-Solar AnEn (computationally cheaper) outperforms the WRF-Solar EPS both in terms of deterministic scores (lower bias and better RMSE) and probabilistic scores with improved statistical consistency and overall lower CRPS.

- The benefit of the AnEn calibration is evident for both models (WRF-Solar and WRF-Solar EPS).

- The full benefit of using the WRF-Solar EPS is evident only after the AnEn calibration process, allowing better performances than the WRF-Solar AnEn in all three metrics (bias, RMSE, and correlation) for both GHI and DNI.

4.1 Results: Training period and predictors





wo weights optimization

wh weights optimization

1P	GHI_M
2P	GHI_M, GHI_S
4P	GHI_M, GHI_S, DNI_M, DNI_S
4P_T	GHI_M, GHI_S, 2m_T_M, 2m_T_S
4P_W	GHI_M, GHI_S, W_M, W_S

- ✓ We tested mean and standard deviation of GHI, DNI, 2-m temperature, and total column of water vapor from WRF-Solar as predictors
- ✓ RMSE and Bias shows the best results when mean and standard deviation of GHI and DNI are used as predictors (4P)