

An Overview of the WRF-Solar Ensemble Prediction System

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ICEM 2023

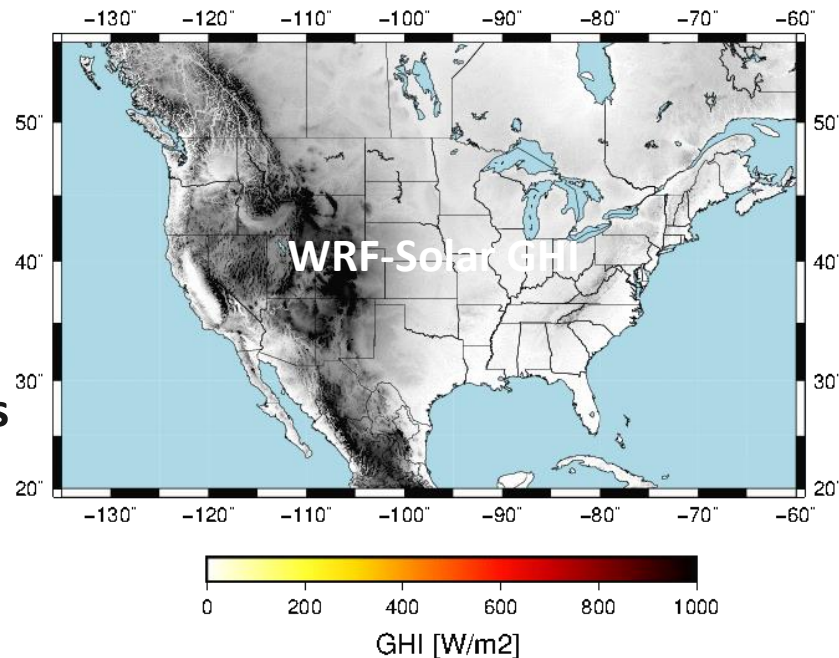
June 29, 2023

Objectives

Develop ensemble prediction system based on WRF-Solar that-

- Provides probabilistic forecasts for the grid with ensemble members tailored for solar forecasts.
- Delivers calibrated forecasts that -
 - Produce unbiased estimation of irradiance. **Goal: GHI bias < 5%; DNI Bias < 10%**
 - Improve the current-state-of-art solar forecasts and reduces uncertainty by **50% from current levels.**

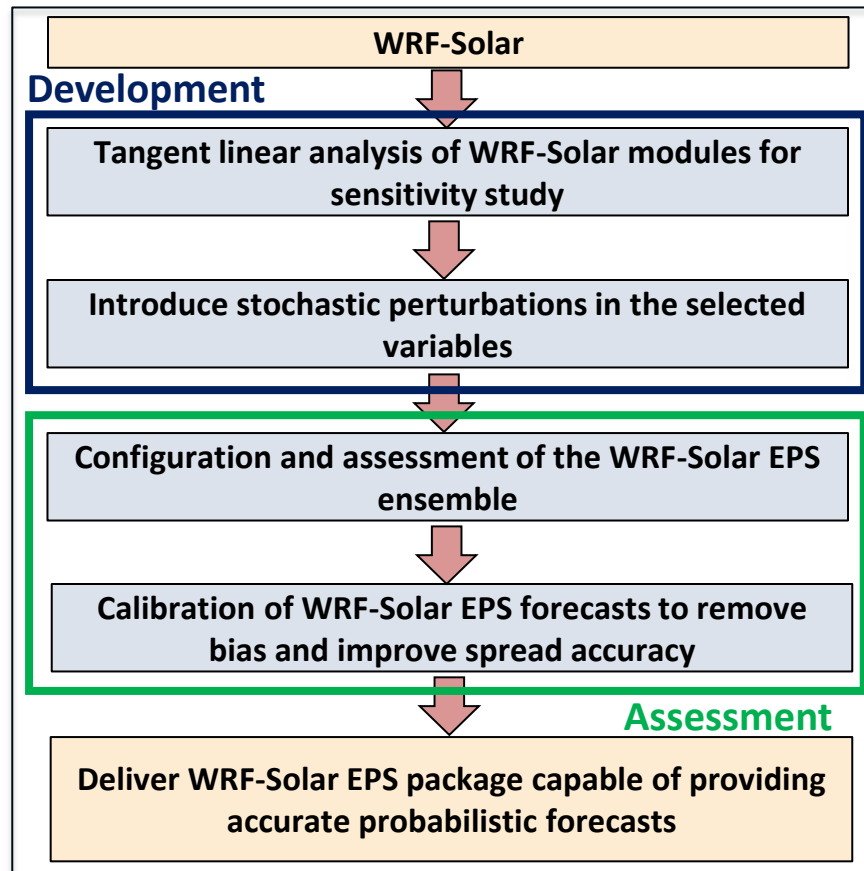
Deliver a publicly available model.



Approach

- Identify variables that significantly influence the formation and dissipation of clouds and solar radiation through a **tangent linear analysis** of WRF-Solar modules that influence cloud processes.
- Introduce stochastic perturbations in the variables identified in previous step to develop **WRF-Solar ensemble prediction system (WRF-Solar EPS)**.
- **Calibrate WRF-Solar EPS** using observations to ensure that the forecasts' trajectories are unbiased and provide accurate estimates of forecast uncertainties under a wide range of meteorological regimes.
- **Demonstrate the improvements of WRF-Solar EPS.**
- Incorporate WRF-Solar EPS in the **WRF** community model as an **open-source probabilistic framework**.

WRF-Solar EPS is the first NWP ensemble model specifically designed to provide probabilistic irradiance forecast.



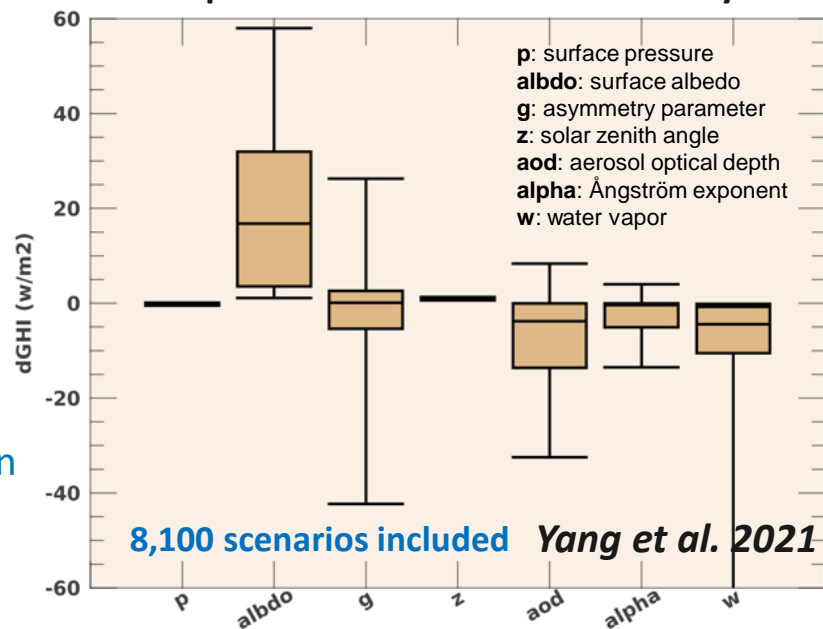
Selecting Variables for WRF-Solar EPS

Developed tangent linear (TL) models to quantify the impact of the uncertainty of input variables on the output when forecasting clouds and irradiance.

WRF-Solar parameterizations selected:

- Fast All-sky Radiation Model for Solar applications
- Thompson microphysics
- Mellor–Yamada–Nakanishi–Niino (MYNN) for PBL
- Deng shallow cumulus system
- Unresolved clouds parameterization module based on relative humidity (CLD3)
- Noah land surface model (Noah LSM)

Impact of uncertainty of FARMS input variables on GHI in clear-sky



Innovative approach that can cover all possible ranges of input parameters efficiently.

Yang, J., Kim, J.H., Jimenez, P.A., Sengupta, M., Dudhia, J., Xie, Y., Golnas, A. and Giering, R., 2021. An efficient method to identify uncertainties of WRF-Solar variables in forecasting solar irradiance using a tangent linear sensitivity analysis. *Solar Energy*, 220, pp.509-522. (**Best paper award from Solar Energy Journal**).

Development of WRF-Solar EPS

Selected 14 WRF-Solar variables to be stochastically perturbed to generate ensemble members for solar forecasts

#	Variable Name	σ	λ (m)	τ (s)
1	Albedo	0.1	100000	86400
2	Aerosol optical depth	0.25	100000	3600
3	Ångström wavelength exponent	0.1	100000	3600
4	Asymmetry factor	0.05	100000	3600
5	Water vapor mixing ratio	0.05	100000	3600
6	Cloud water mixing ratio	0.1	100000	3600
7	Ice mixing ratio	0.1	100000	3600
8	Snow mixing ratio	0.1	100000	3600
9	Ice number concentration	0.05	100000	3600
10	Potential temperature	0.001	100000	3600
11	Turbulent kinetic energy	0.05	80000	600
12	Soil moisture content	0.1	80000	21600
13	Soil temperature	0.001	80000	21600
14	Vertical velocity	0.1	80000	21600

Characteristics of the perturbation

σ : Standard deviation which is used as tuning parameter to control the amplitude of the perturbation

λ : Length scale [m]

τ : Time scale [s]

**Main parameters to control
WRF-Solar EPS**

A user-friendly interface

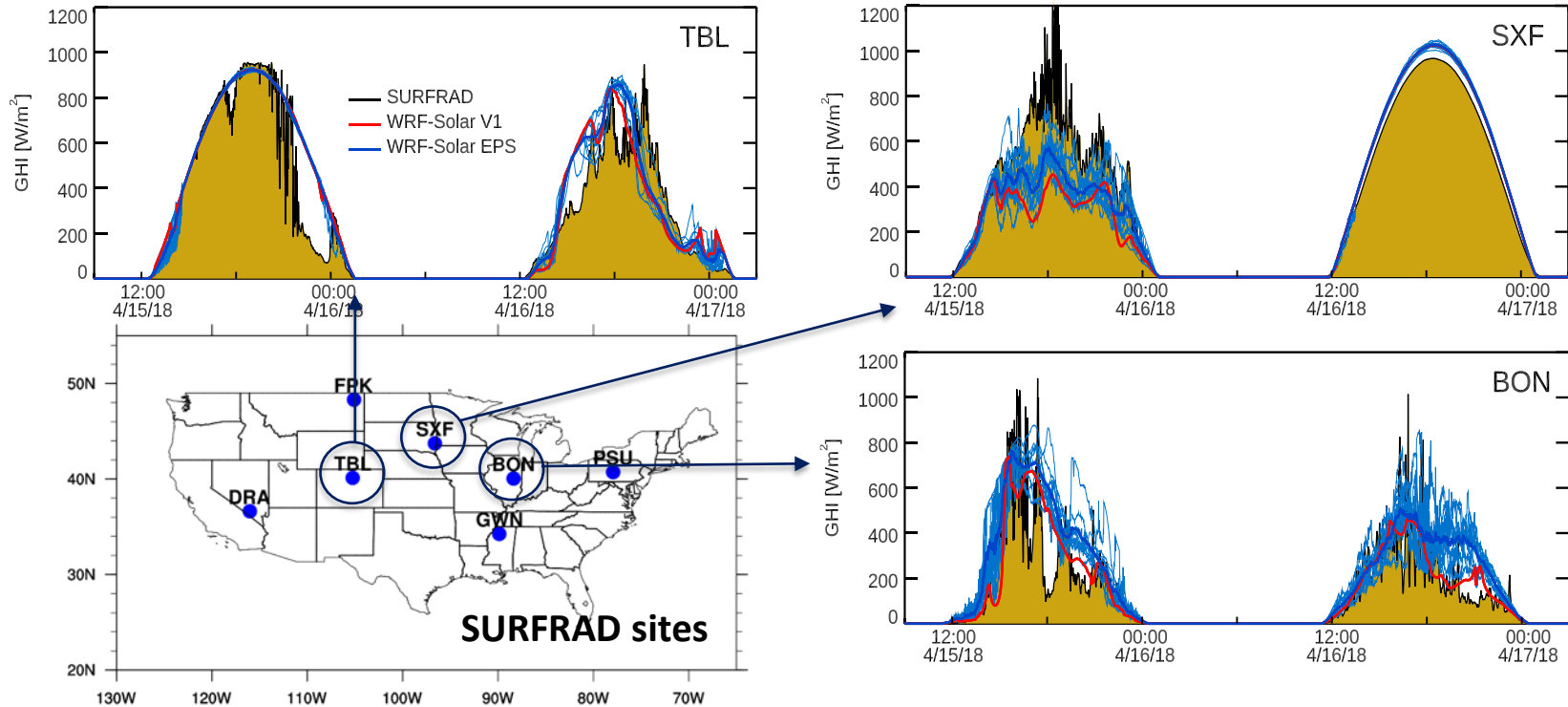
```
&stoch
multi_perturb           = 1
num_ensemble            = 10

pert_farms              = .true.
pert_farms_albedo       = 1.0
pert_farms_aod          = 1.0
pert_farms_angexp       = 1.0
pert_farms_aerasy       = 1.0
pert_farms_qv           = 1.0
pert_farms_qc           = 1.0
pert_farms_qs           = 1.0
```

- We specify the characteristics of the stochastic perturbations for each variable using a configuration file.
- Preliminary user's guide for WRF-Solar EPS:
<https://ral.ucar.edu/projects/wrf-solar-eps>

Testing of WRF-Solar EPS

Timeseries of predicted GHI from the WRF-Solar EPS

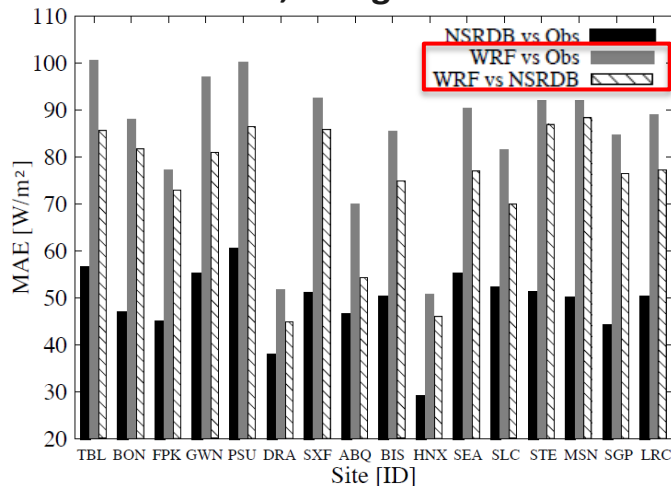


The impact of perturbations on 10 ensemble members is pronounced in cloudy-sky.

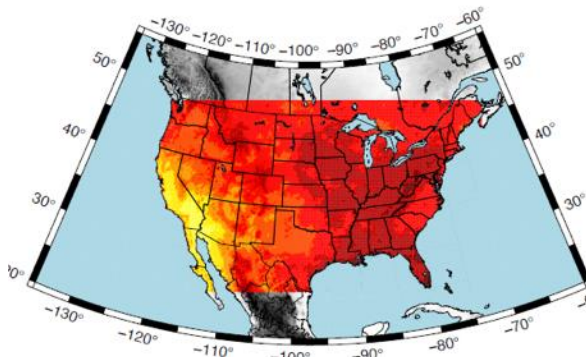
Satellite-derived Data sets for Model Validation and Calibration

NSRDB compared with surface observations and deterministic WRF-Solar day ahead forecasts (2018).

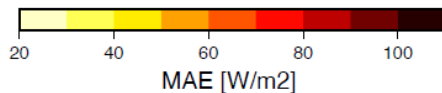
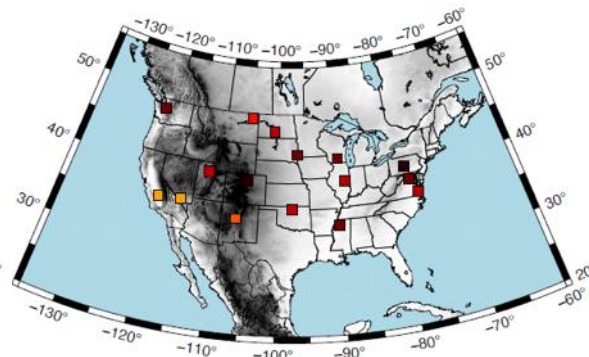
MAE comparison of WRF-Solar, NSRDB, and ground Obs.



MAE of WRF-Solar GHI calculated with NSRDB.



MAE of WRF-Solar GHI calculated with ground Obs.



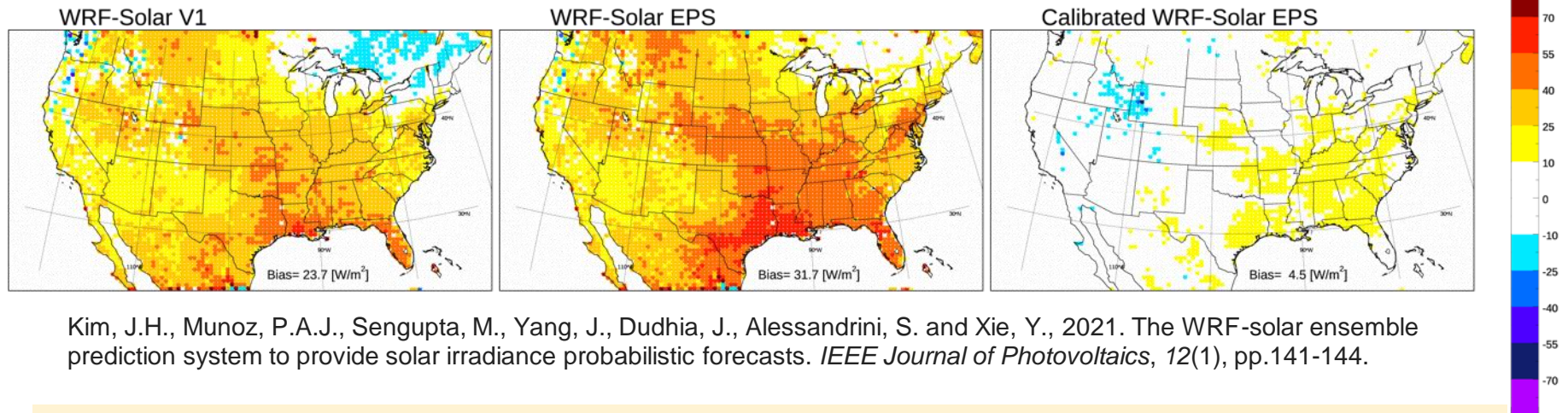
The MAE calculated with NSRDB is within $\sim 10\%$ of high-quality ground observations and reproduces the spatial variability of the error ($r = 0.96$).

Accuracy of NSRDB is sufficient for WRF-Solar EPS validation.

Ensemble Calibration Results

Mean bias of GHI for 2018 using NSRDB

An ensemble calibration technique used in this work: analog ensemble (AnEn)

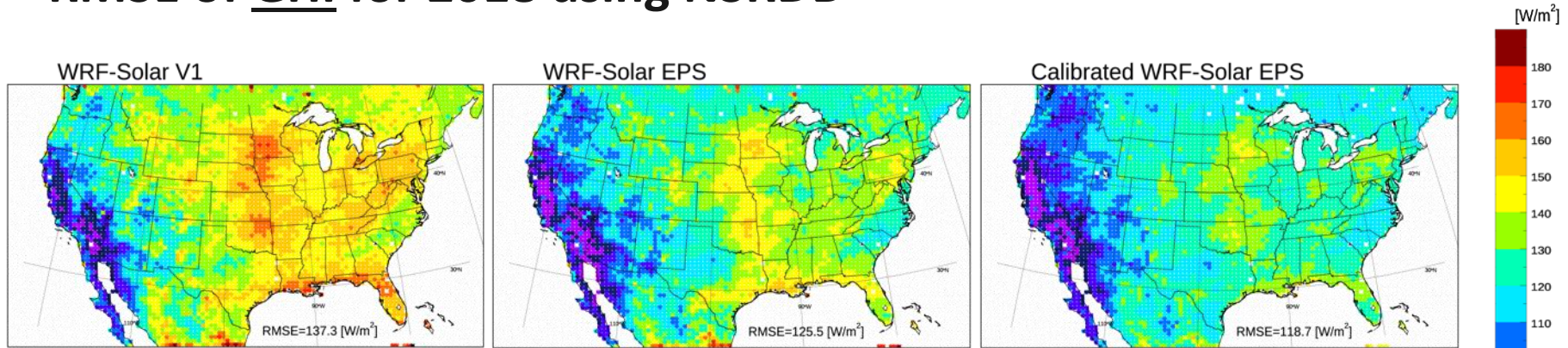


Kim, J.H., Munoz, P.A.J., Sengupta, M., Yang, J., Dudhia, J., Alessandrini, S. and Xie, Y., 2021. The WRF-solar ensemble prediction system to provide solar irradiance probabilistic forecasts. *IEEE Journal of Photovoltaics*, 12(1), pp.141-144.

- GHI bias was reduced by 81% (WRF-Solar V1 vs. calibrated WRF-Solar EPS).
- GHI bias is approximately 1% compared to NSRDB (Milestone: 5% for GHI).
- Forecast bias was reduced for all regions.

Ensemble Calibration Results

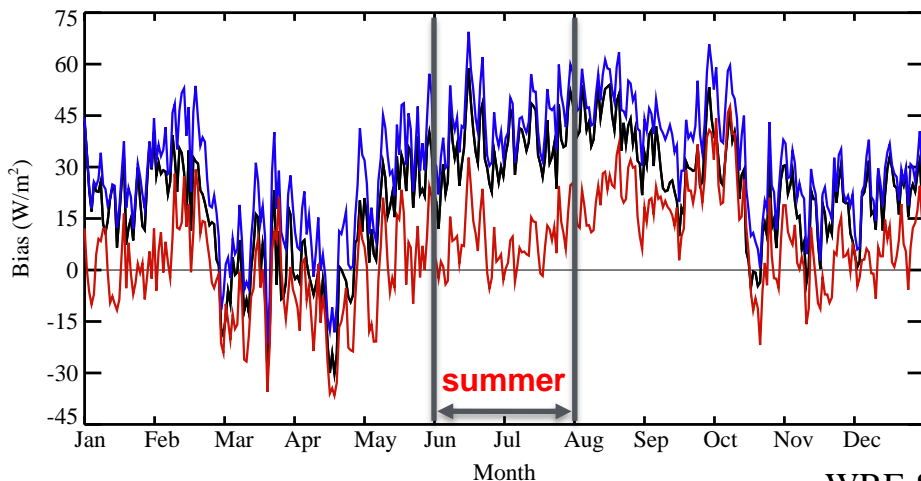
RMSE of GHI for 2018 using NSRDB



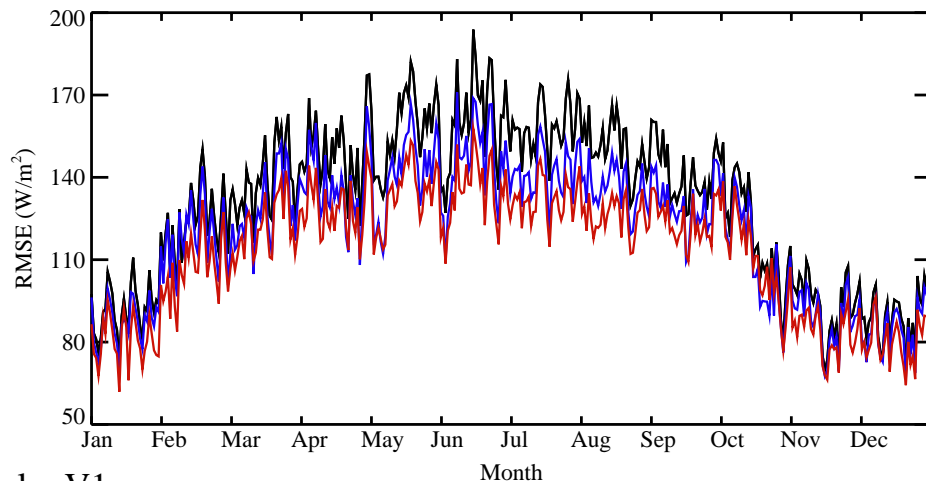
- Total improvement of 14% is attained by calibrated WRF-Solar EPS for GHI forecasts (WRF-Solar V1 vs. calibrated WRF-Solar EPS).

Monthly Variation of Bias and RMSE (2018)

Mean bias of GHI



RMSE of GHI

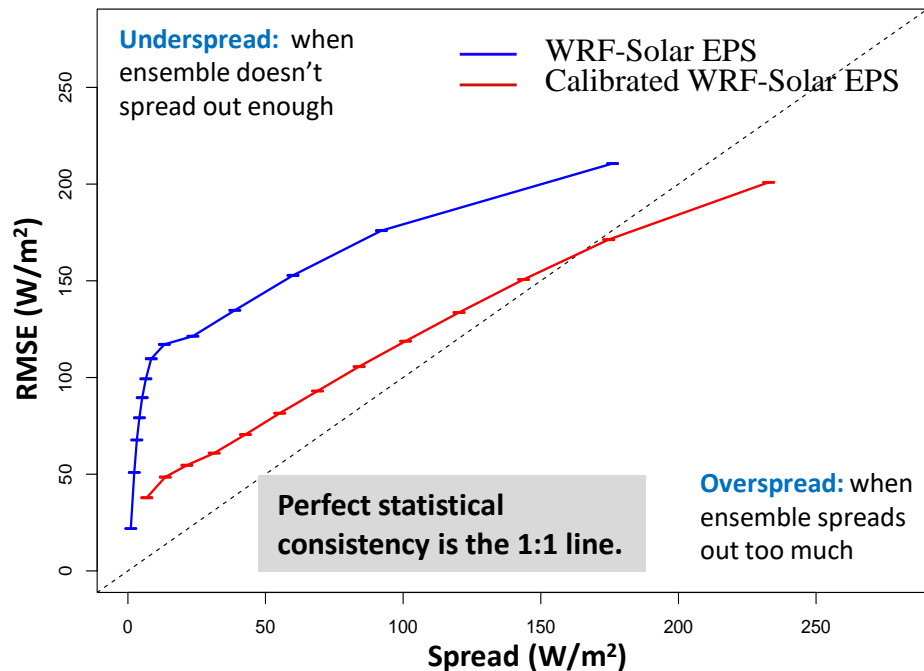


— WRF-Solar V1
— WRF-Solar EPS
— Calibrated WRF-Solar EPS

- Both 1) magnitude of GHI and 2) occurrence of convection are high across CONUS in summer. => WRF-Solar models show higher bias and RMSE in summer than in the other seasons.
- The calibration technique (AnEn) effectively reduces the bias and error, especially in summer.
- The calibrated WRF-Solar EPS shows the smallest RMSEs across all months of 2018.

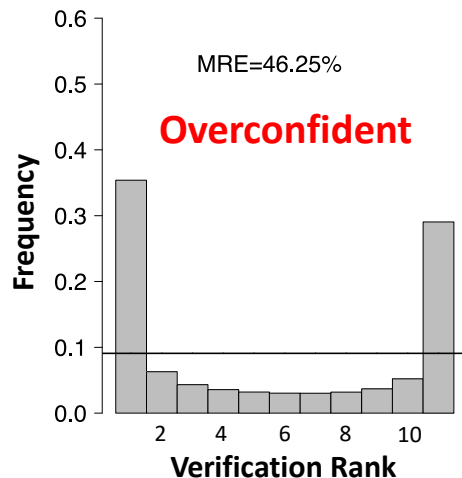
Evaluation of Probabilistic Forecasts

Binned spread-skill plot (for uncertainty)

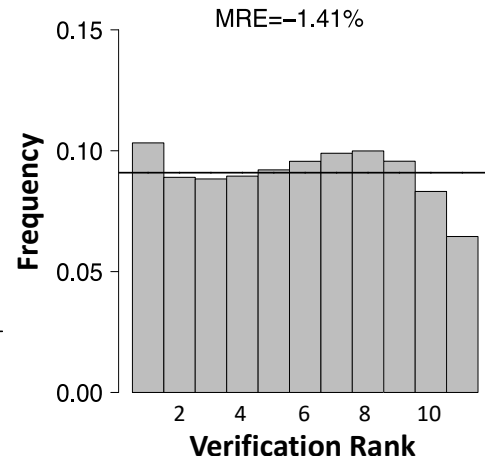


Rank Histogram (for consistency)

WRF-Solar EPS



Calibrated WRF-Solar EPS



The black line indicates perfect, uniform probability of for the 10 ensemble members.

- Calibrated ensemble (red) exhibits improved spread-skill relationship compared to uncalibrated ensemble.
- The uncertainty of day-ahead forecast was reduced by >50%.
- The flatter rank histogram (reduction in MRE by nearly 100%) after calibration demonstrates the improvement in the consistency of the results.

WRF-Solar EPS Website and Distribution

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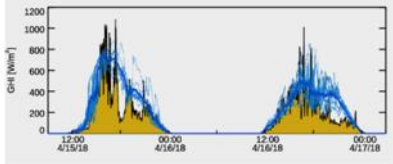
WRF-SOLAR® EPS

Overview Description User's guide Publications

The WRF-Solar® model (Jimenez et al. 2016) is a specific configuration and augmentation of the Weather Research and Forecasting (WRF) model. Previous efforts have been largely devoted to enhance the aerosol-cloud-radiation physics. To extend the WRF-Solar capabilities beyond deterministic forecasts, we are developing the WRF-Solar Ensemble Prediction System (WRF-Solar EPS).

WRF-Solar EPS introduces stochastic perturbations in the most relevant variables for solar irradiance forecasts. The variables have been identified with tangent linear models of selected parameterizations (Yang et al. 2020). The model provides a user-friendly configuration to set the characteristics of the perturbations for each variable (in an ascii configuration file) and to select the variables to perturb (in the WRF namelist).

A beta version of the WRF-Solar EPS model will be available in the following months.



Global horizontal irradiance forecast as a function of the lead time: thin lines) WRF-Solar EPS ensemble members, thicker line) ensemble mean. Observations are also shown (shaded).

References

Jimenez, R. A., J. P. Hacker, J. Dudhia, S. E. Haupt, J. A. Ruiz-Arias, C. A. Gueymard, G. Thompson, T. Edhammer and A. Deng, 2016a: WRF-Solar: Description and Clear-Sky Assessment of an Augmented NWP Model for Solar Power Prediction. Bull. Amer. Met. Soc., 97, 1249-1264. doi:10.1175/BAMS-D-14-00279.1

Yang, J., J. H. Kim, R. A. Jimenez, M. Sengupta, J. Dudhia, Y. Xie, A. Golias and R. Giering, 2020: An efficient method to identify uncertainties of WRF-Solar variables in forecasting solar irradiance using a tangent linear sensitivity analysis. Solar Energy (in press)

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Login

- We have created the website for WRF-Solar EPS (<https://ral.ucar.edu/projects/wrf-solar-eps>).

- This website includes an overview of WRF-Solar EPS:

- ✓ Description of WRF-Solar EPS
- ✓ User's guide
- ✓ Publications

WRF-Solar EPS is publicly available from **WRF Version 4.4** (<https://github.com/wrf-model/WRF/releases>).

Summary

- The WRF-Solar ensemble prediction system (WRF-Solar EPS) has been developed.
- First NWP model with an ensemble capability tailored for solar energy applications.
- Project objectives have been met: Day-Ahead Forecast Bias < 5%, uncertainty reduced by > 50%.
- WRF-Solar EPS is publicly available as part of the official WRF Git repository.

Technical report:

Sengupta, M., Jimenez, P.A., Kim, J.H., Yang, J. and Xie, Y., 2022. Final Report on Probabilistic Cloud Optimized Day-Ahead Forecasting System Based on WRF-Solar (No. NREL/TP-5D00-81904). National Renewable Energy Lab.(NREL), Golden, CO (United States). <https://doi.org/10.2172/1855782>

Publications (Peer-reviewed Journal)

1. Tangent linear analysis for WRF-Solar EPS development:

Yang, J., Kim, J.H., Jimenez, P.A., Sengupta, M., Dudhia, J., Xie, Y., Golnas, A. and Giering, R., 2021. An efficient method to identify uncertainties of WRF-Solar variables in forecasting solar irradiance using a tangent linear sensitivity analysis. *Solar Energy*, 220, pp.509-522.

2. Validation of NSRDB for WRF-Solar performance assessment:

Jiménez, P.A., Yang, J., Kim, J.H., Sengupta, M. and Dudhia, J., 2022. Assessing the WRF-Solar model performance using satellite-derived irradiance from the National Solar Radiation Database. *Journal of Applied Meteorology and Climatology*, 61(2), pp.129-142.

3. Overview of WRF-Solar EPS development:

Kim, J.H., Munoz, P.A.J., Sengupta, M., Yang, J., Dudhia, J., Alessandrini, S. and Xie, Y., 2021. The WRF-solar ensemble prediction system to provide solar irradiance probabilistic forecasts. *IEEE Journal of Photovoltaics*, 12(1), pp.141-144.

4. Evaluation of WRF-Solar EPS cloud forecast using NSRDB:

Yang, J., Sengupta, M., Jiménez, P.A., Kim, J.H. and Xie, Y., 2022. Evaluating WRF-Solar EPS cloud mask forecast using the NSRDB. *Solar Energy*, 243, pp.348-360.

5. Intercomparison between three different ensemble systems:

Kim, J.H., Jiménez, P.A., Sengupta, M., Dudhia, J., Yang, J. and Alessandrini, S., 2022. The Impact of Stochastic Perturbations in Physics Variables for Predicting Surface Solar Irradiance. *Atmosphere*, 13(11), p.1932.

6. Calibration of WRF-Solar EPS forecast using NSRDB and AnEn:

Alessandrini, S., Kim, J.H., Jimenez, P.A., Dudhia, J., Yang, J. and Sengupta, M., 2023. A Gridded Solar Irradiance Ensemble Prediction System Based on WRF-Solar EPS and the Analog Ensemble. *Atmosphere*, 14(3), p.567.

Paper in preparation:

The best WRF-Solar configuration to produce high-quality solar irradiance forecast

Thank you

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Contact:

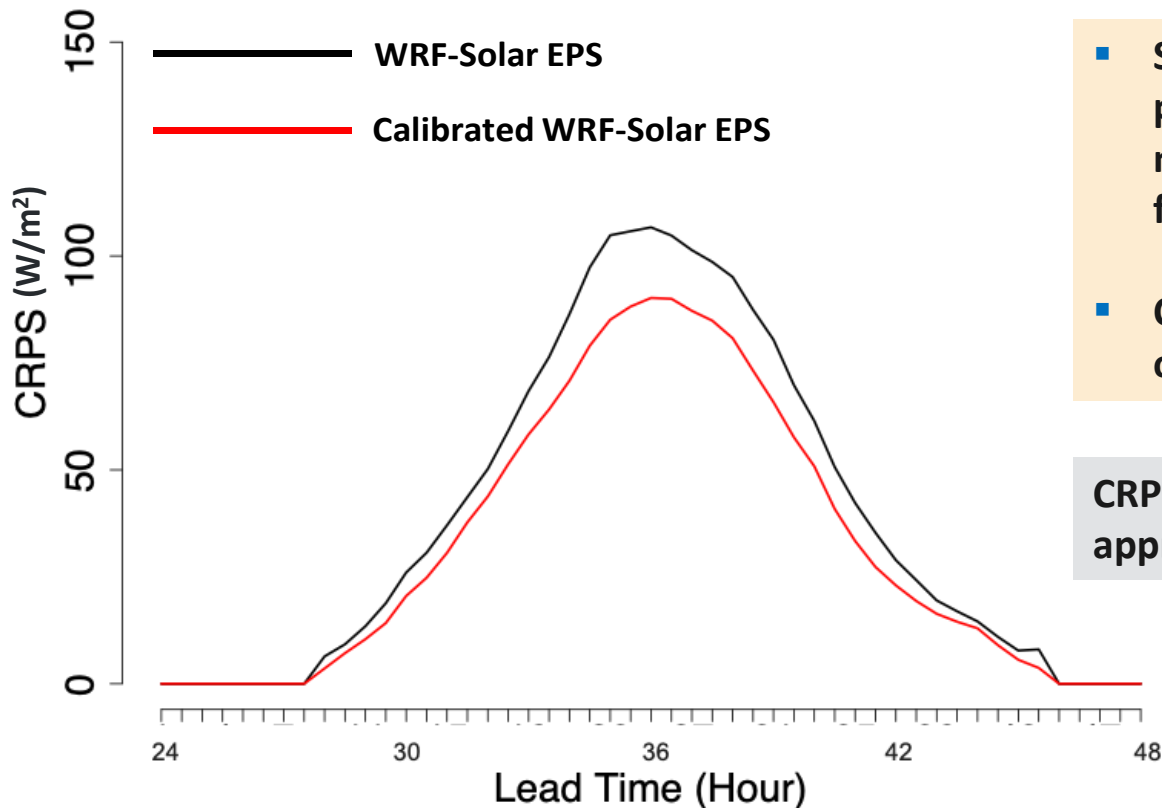
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Evaluation of Probabilistic Forecasts

Continuous Rank Probability Score (CRPS)



- Statistical metrics for deterministic prediction such as RMSE and MAE are not directly applicable to probabilistic forecasts.
- CRPS generalizes the MAE to the case of probabilistic forecasts.

CRPS of GHI was improved by 18% approximately.