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Probabilistic Cloud Optimized Day-Ahead Forecasting System Based on WRF-Solar

Award # DE-EE00033503

SETO Workshop on Solar Forecasting

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1. Objectives
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Objectives

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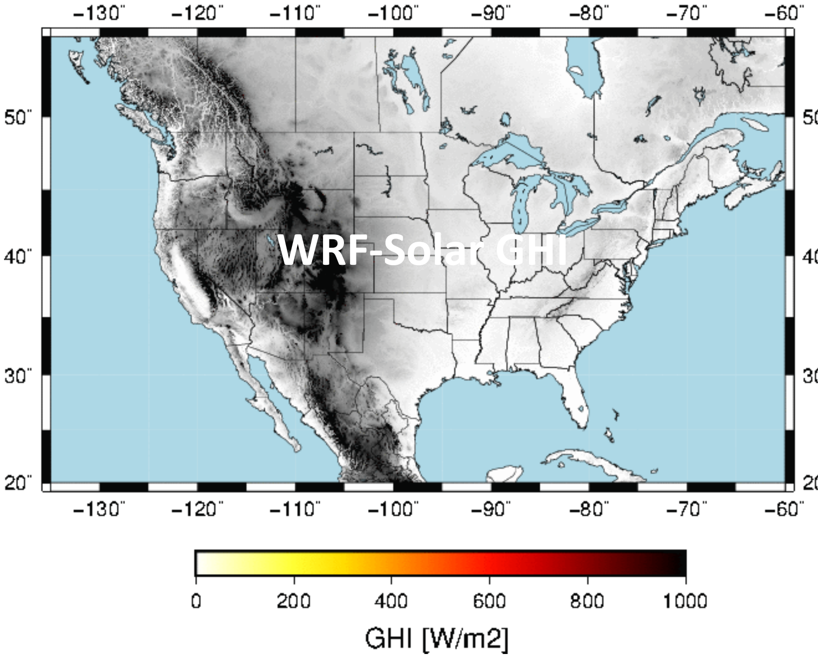
Develop ensemble prediction system based on WRF-Solar that-

- 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

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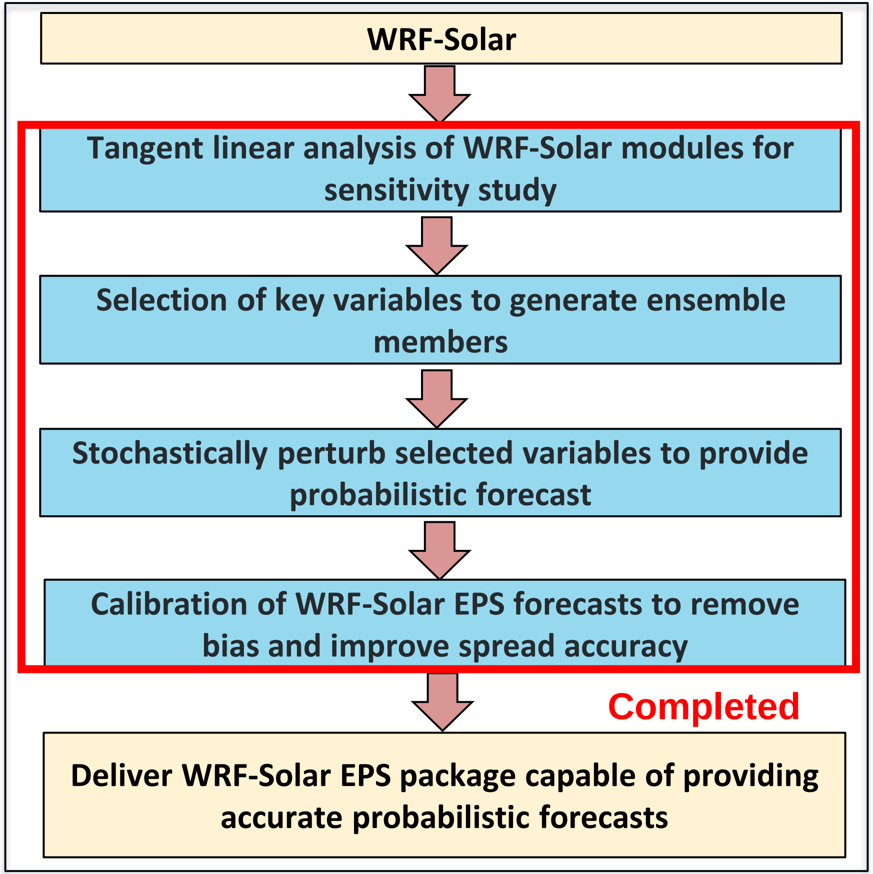
- **Identify variables** that significantly influence the formation and dissipation of clouds and solar radiation.

- Introduce perturbations in the variables identified in step (a) to develop the **WRF-Solar ensemble prediction system (WRF-Solar EPS)**.

- **Calibrate the WRF-Solar EPS** using measurements 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** delivered by the probabilistic forecasts for the regions and locations identified by Topic Area 1.

- Develop and deliver an **open-source WRF-Solar EPS** for the solar energy community.



WRF-Solar Ensemble Prediction System

1. Selecting Variable for WRF-Solar EPS
2. Development of WRF-Solar EPS
3. Testing of WRF Solar EPS
4. Satellite-derived Datasets for Validation
5. Comparison with WRF-Solar v1

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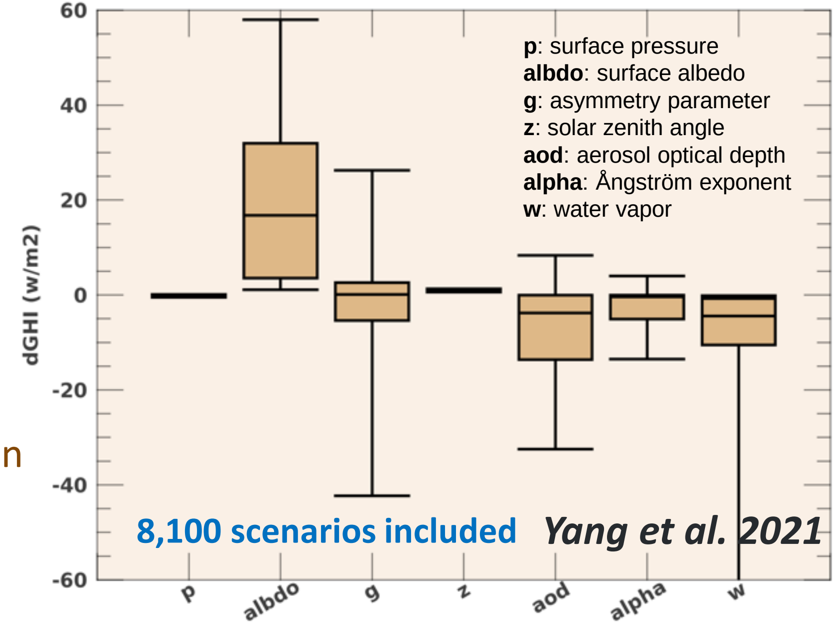
Selecting variables for WRF-Solar EPS

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., Giering, R., An Efficient Method to Identify Uncertainties of WRF-Solar Variables in Forecasting Solar Irradiance Using a Tangent Linear Sensitivity Analysis. Solar Energy, Vol. 220, pp.509-522.

Development of WRF-Solar EPS

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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 tunning 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

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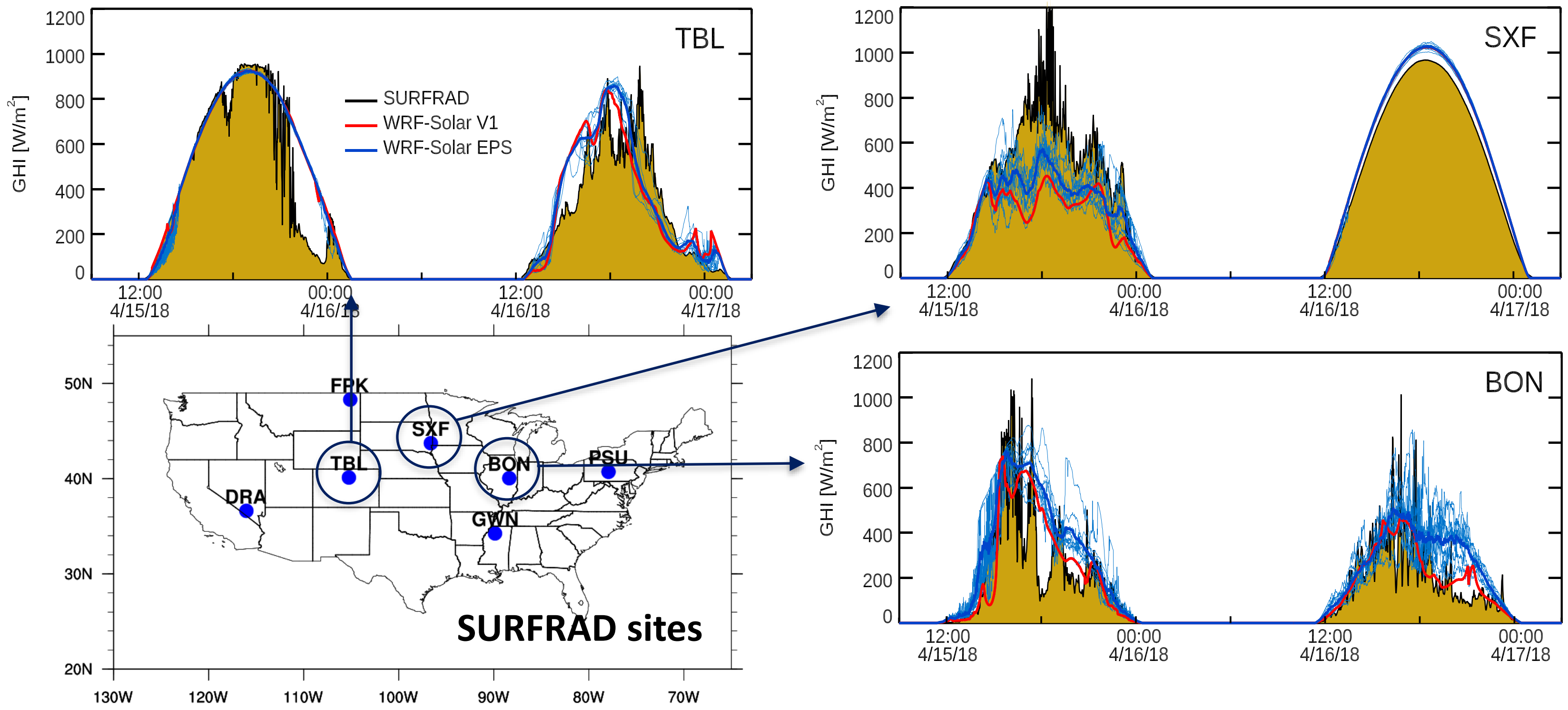
Timeseries of predicted GHI from the WRF-Solar EPS



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

Satellite-derived Datasets for Validation

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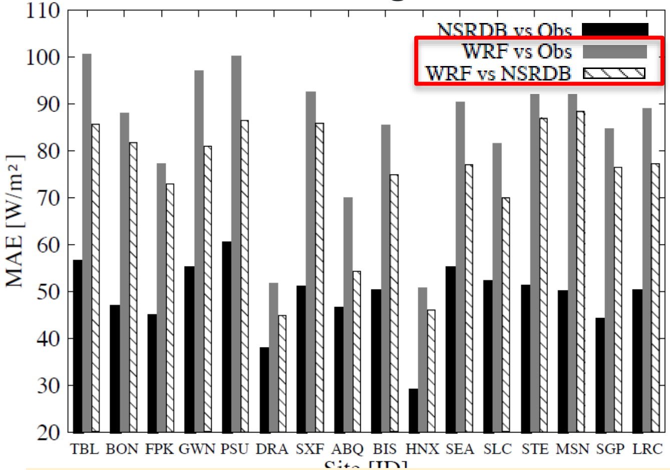
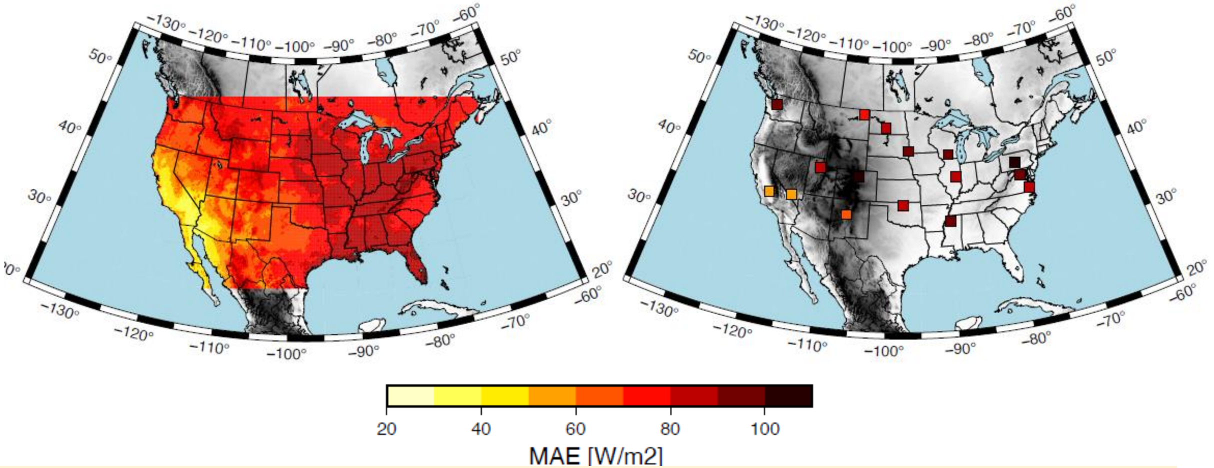
NSRDB compared with surface observations and deterministic WRF-Solar day ahead forecasts (2018).

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 ~10% of high-quality ground observations and reproduces the spatial variability of the error (r = 0.96).

Accuracy of NSRDB is sufficient for WRF-EPS validation.

WRF-Solar v1 vs WRF-Solar EPS

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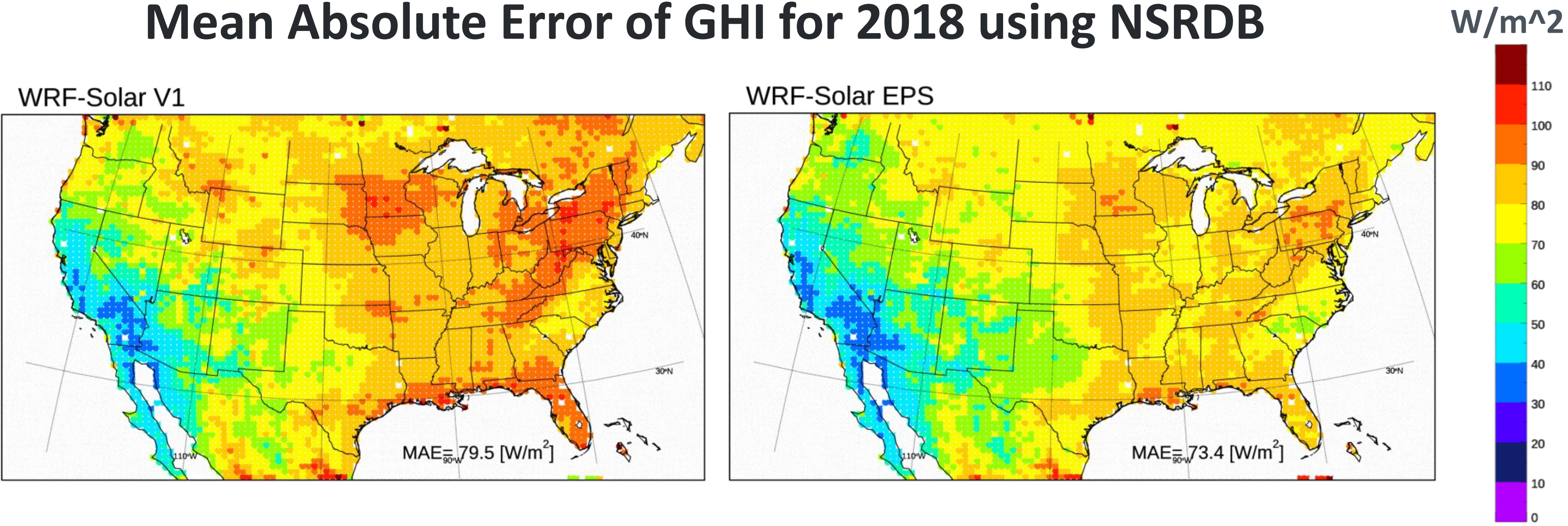
Mean Absolute Error of GHI for 2018 using NSRDB



MAE of GHI was reduced by 8% when using WRF-Solar EPS and comparing the day-ahead forecast to baseline WRF-Solar V1.

Calibration and Evaluation of the Probabilistic Forecasts

1. Ensemble Calibration: Methodology
2. Ensemble Calibration: Results
3. Ensemble Verification Metrics
   a) Error: Continuous Rank Probability Score
   b) Uncertainty: Spread-skill
   c) Consistency: Rank Histogram

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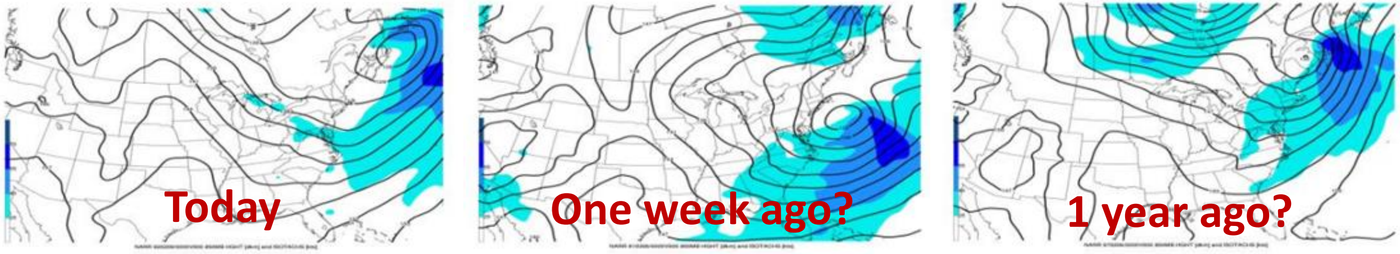
Ensemble Calibration: Methodology

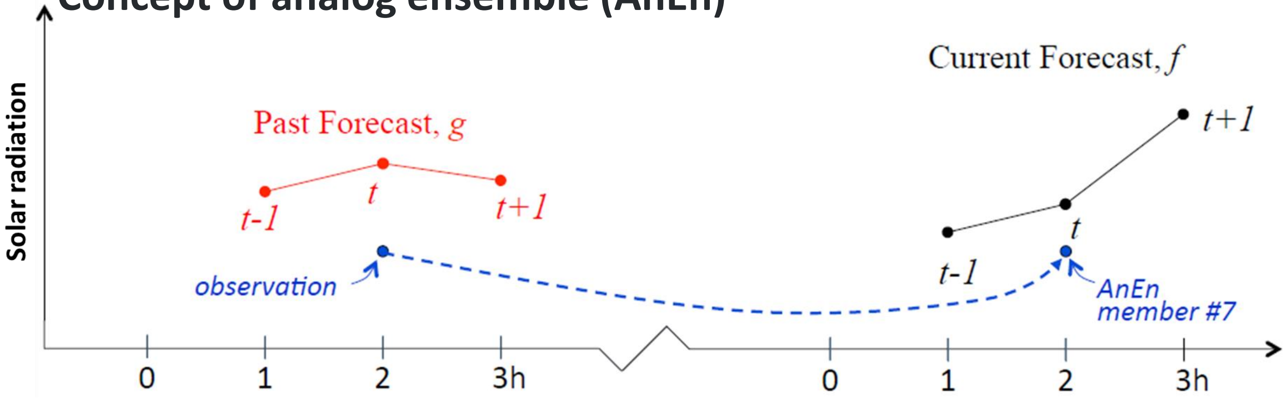
We implemented an analog technique as an ensemble post-processing method to improve the performance of WRF-Solar EPS. High-quality observations are essential to improve solar forecasts.

Basic idea of weather analogs



Can we use this information to improve NWP forecast?

Concept of analog ensemble (AnEn)



We used **the NSRDB** to calibrate the ensemble forecasts.

Delle Monache et al. 2013

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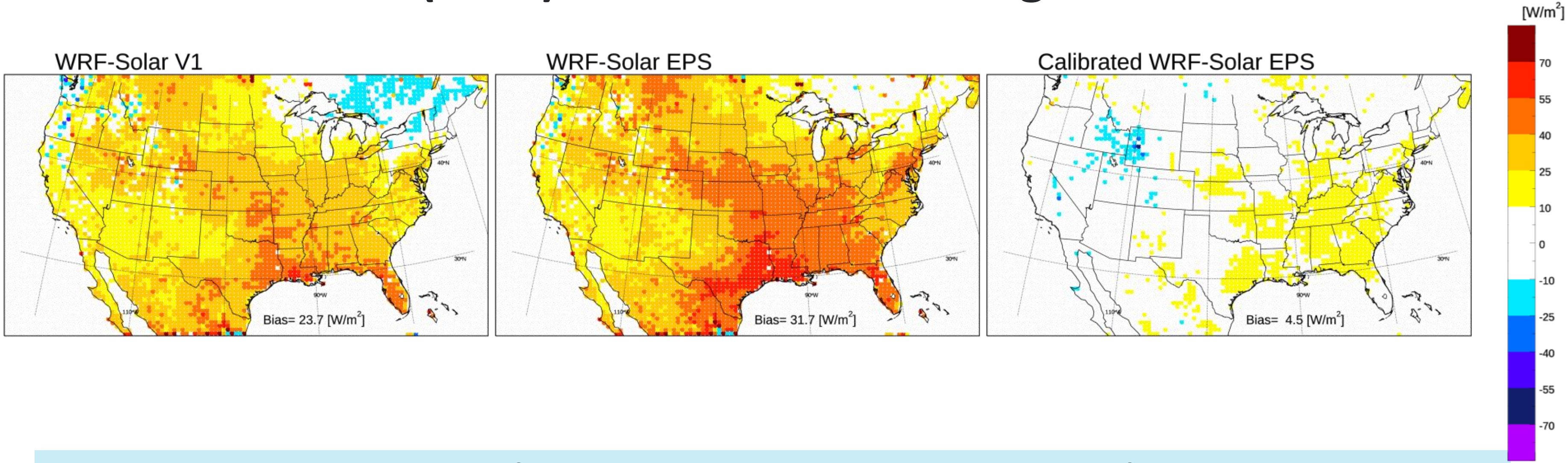
Ensemble Calibration: Results

Mean Bias Error (MBE) of GHI for 2018 using NSRDB



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

Ensemble Verification Metrics

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We used three metrics to assess ensemble-based probabilistic solar forecasts from WRF-Solar EPS and calibrated WRF-Solar EPS.

1) Continuous Rank Probability Score (CRPS) - is a metric to evaluate overall accuracy of probabilistic forecasts (**equivalent to MAE** in assessment of deterministic forecast). **This metric summarizes the error of the forecasts.**

2) Binned spread-skill Diagram – quantifies how good the uncertainty estimations are by comparing ensemble spread to RMSE of the ensemble mean. **This metric summarizes the uncertainty of the forecasts.**

3) Rank Histogram - answers the question *"Do the observations belong to the distribution of the ensemble forecasts?"*. **This metric summarizes the consistency of the ensemble: if the ensemble captures the distribution of the uncertainties, the observations are one more member of the ensemble.**

Error: Continuous Rank Probability Score

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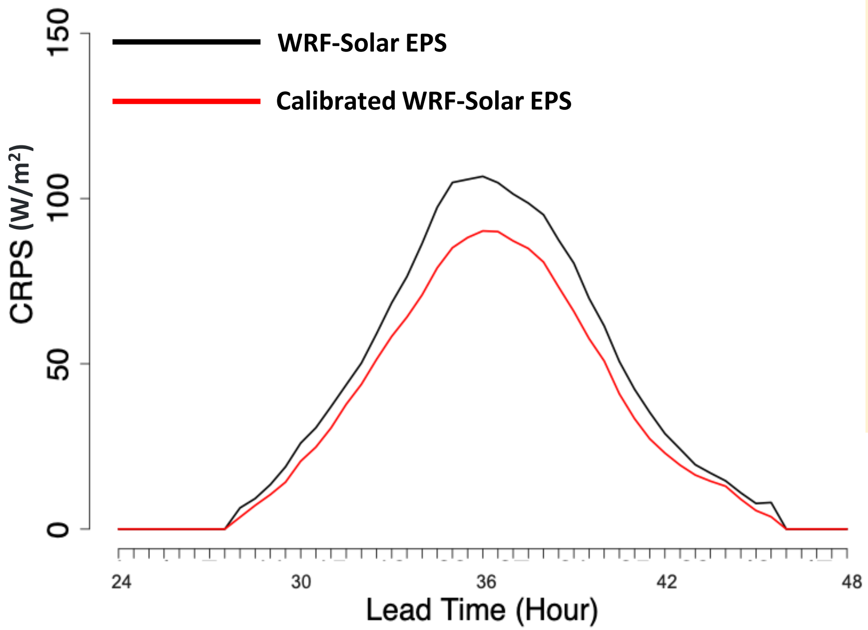
The error of probabilistic forecasts for locations from Topic Area 1

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.**
- **Calibrated WRF-Solar shows reduced CRPS when compared to WRF-Solar EPS.**
- **CRPS of GHI was improved by 18% approximately.**

- **Training period:** 2017
- **Evaluation period:** 2018
- **AnEn Predictors:** Mean_GHI, Std_GHI, Mean_DNI, Std_DNI
- **Metrics calculation:** all available data for each hour of the day ahead forecasts for locations determined by Topic Area 1
- **Observation:** NSRDB

Uncertainty: Spread-skill

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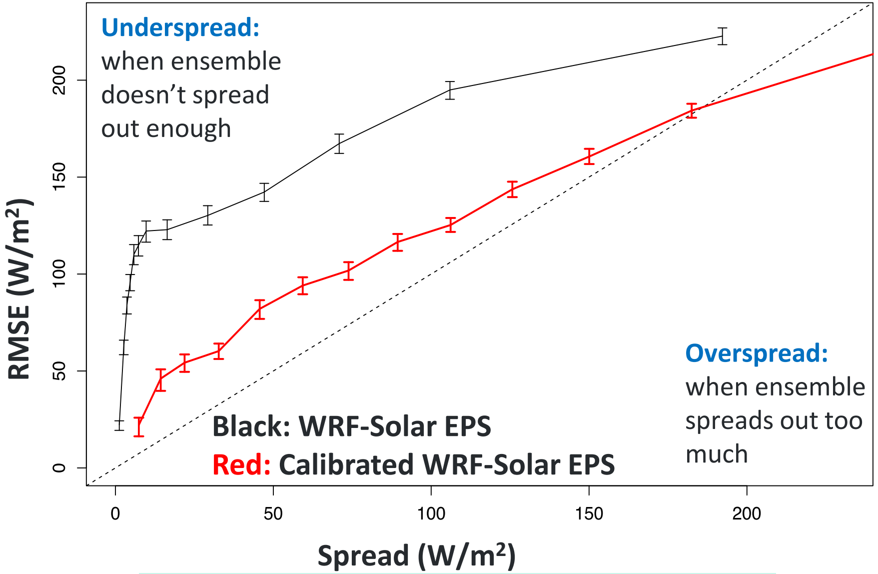
Binned spread-skill plot



Perfect statistical consistency is the 1:1 line.

The uncertainty of forecasts from ensemble members

- **Uncalibrated WRF-Solar EPS forecasts (black) are highly underspread for all spread values.**
- **Calibrated ensemble (red) exhibits improved spread-skill relationship compared to uncalibrated ensemble (calibrated ensemble is close to 1:1 line).**

- **Traning period:** 2017
- **Evaluation period:** 2018
- **AnEn Predictors:** Mean_GHI, Std_GHI, Mean_DNI, Std_DNI
- **Metrics calculation:** all available data for the day ahead forecasts for locations determined by Topic Area 1
- **Observation:** NSRDB

The uncertainty of day-ahead forecast was reduced by >50% (exceeds milestone)

Consistency: Rank Histogram

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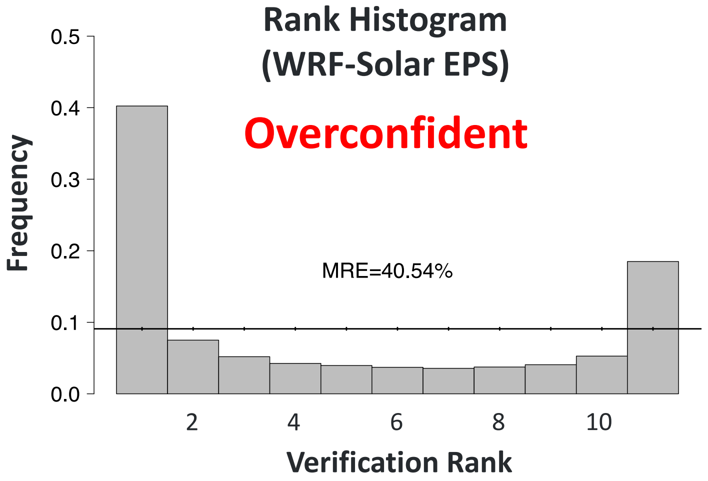
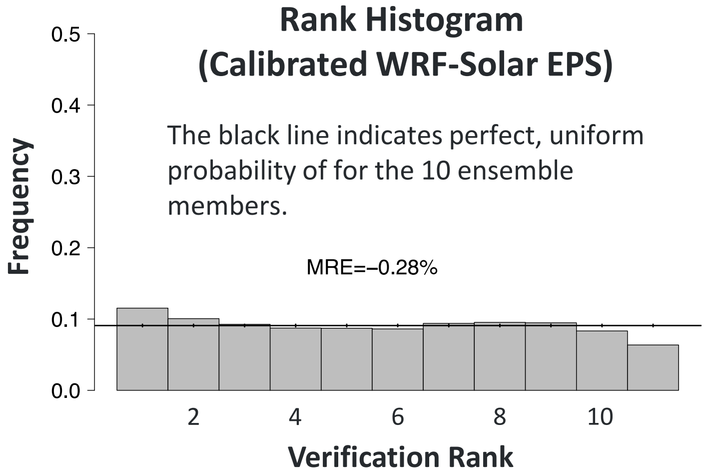
The consistency of the forecasts from ensemble members





- **Training period:** 2017
- **Evaluation period:** 2018
- **AnEn Predictors:** Mean_GHI, Std_GHI, Mean_DNI, Std_DNI
- **Metrics calculation:** all available data for the day ahead forecasts for locations determined by Topic Area 1
- **Observation:** NSRDB

- **Highest consistency: Rank histogram will be flat and match the 0.1 line (in this case with 10 ensemble members).**
- **The shape of rank histogram will be skewed or concave (convex) when the ensemble forecasts are biased or underspread (overspread).**

The flatter rank histogram (reduction in MRE by nearly 100%) after calibration demonstrates the improvement in the consistency of the results.

Next Steps

1. WRF-Solar EPS Website
2. Publications
3. Summary
4. Future Extension of Research

WRF-Solar EPS Website

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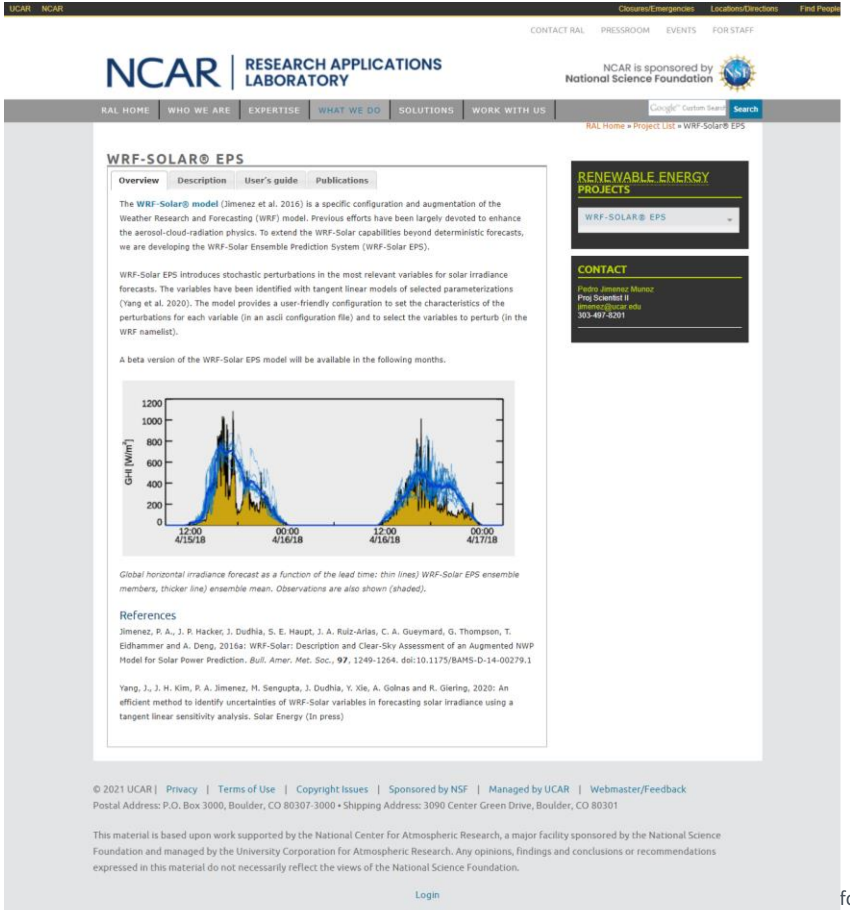
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WRF-SOLAR® EPS

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, P. A., J. P. Hacker, J. Dudhia, S. E. Haupt, J. A. Ruiz-Arias, C. A. Gueymard, G. Thompson, T. Eidhammer 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, P. A. Jimenez, M. Sengupta, J. Dudhia, Y. Xie, A. Golnas 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)

RENEWABLE ENERGY PROJECTS

WRF-SOLAR® EPS

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

- This website includes a preliminary overview of WRF-Solar EPS:

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

Publications

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Yang, J., J.H. Kim, P.A. Jimenez, M. Sengupta, J. Dudhia, Y. Xie, A. Golnas and R. Giering, 2021: **An Efficient Method to Identify Uncertainties of WRF-Solar Variables in Forecasting Solar Irradiance Using a Tangent Linear Sensitivity Analysis**. *Solar Energy*, Vol. 220, pp.509-522.

Yang, J., Sengupta, M., Xie, Y., Jimenez, P.A. and Kim, J.H., 2019. **Adjoint Sensitivity of FARMS to the Forecasting Variables of WRF-Solar**. In *36th European Photovoltaic Solar Energy Conference and Exhibition.*

Kim, J.H., Jimenez, P.A., Dudhia, J., Yang, J., Sengupta, M., Xie, Y., 2020, "**Probabilistic Forecast of All-sky Solar Radiation Using Enhanced WRF-Solar**", In *37th European Photovoltaic Solar Energy Conference and Exhibition.*

6 presentations at AMS Annual Meetings in 2019-2021.

Ongoing:

- Description of WRF-Solar EPS
- Value of NSRDB to evaluate WRF-Solar performance
- Characterization of the strengths/limitations of WRF-Solar cloud forecasts

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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 website has been developed.
- WRF-Solar EPS will be publicly available as part of the official WRF Git repository by the end of the project.

Future Extension of Research

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- Improve cloud representation and its coupling with radiation in WRF-Solar.
- Efficient algorithms to improve cloud initialization for short term forecasts.
- Understand the behavior of different ensemble approaches and their combinations to improve day-ahead predictions.
- Characterize the strengths of different post-processing methodologies.

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Thank you

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