An Overview of the WRF-Solar Ensemble Prediction System

Presenter: Manajit Sengupta (NREL)
Pedro A. Jimenez (NCAR), Ju-Hye Kim (NCAR), Jaemo Yang (NREL), Jimy Dudhia (NCAR), Yu Xie (NREL), Stefano Alessandrini (NCAR)
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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.

WRF-Solar

Development

Tangent linear analysis of WRF-Solar modules for sensitivity study

Introduce stochastic perturbations in the selected variables

Configuration and assessment of the WRF-Solar EPS ensemble

Calibration of WRF-Solar EPS forecasts to remove bias and improve spread accuracy

Assessment

Deliver WRF-Solar EPS package capable of providing accurate probabilistic forecasts
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.

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

<table>
<thead>
<tr>
<th>#</th>
<th>Variable Name</th>
<th>$\sigma$</th>
<th>$\lambda$ (m)</th>
<th>$\tau$ (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Albedo</td>
<td>0.1</td>
<td>100000</td>
<td>86400</td>
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<tr>
<td>2</td>
<td>Aerosol optical depth</td>
<td>0.25</td>
<td>100000</td>
<td>3600</td>
</tr>
<tr>
<td>3</td>
<td>Ångström wavelength exponent</td>
<td>0.1</td>
<td>100000</td>
<td>3600</td>
</tr>
<tr>
<td>4</td>
<td>Asymmetry factor</td>
<td>0.05</td>
<td>100000</td>
<td>3600</td>
</tr>
<tr>
<td>5</td>
<td>Water vapor mixing ratio</td>
<td>0.05</td>
<td>100000</td>
<td>3600</td>
</tr>
<tr>
<td>6</td>
<td>Cloud water mixing ratio</td>
<td>0.1</td>
<td>100000</td>
<td>3600</td>
</tr>
<tr>
<td>7</td>
<td>Ice mixing ratio</td>
<td>0.1</td>
<td>100000</td>
<td>3600</td>
</tr>
<tr>
<td>8</td>
<td>Snow mixing ratio</td>
<td>0.1</td>
<td>100000</td>
<td>3600</td>
</tr>
<tr>
<td>9</td>
<td>Ice number concentration</td>
<td>0.05</td>
<td>100000</td>
<td>3600</td>
</tr>
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<td>10</td>
<td>Potential temperature</td>
<td>0.001</td>
<td>100000</td>
<td>3600</td>
</tr>
<tr>
<td>11</td>
<td>Turbulent kinetic energy</td>
<td>0.05</td>
<td>80000</td>
<td>600</td>
</tr>
<tr>
<td>12</td>
<td>Soil moisture content</td>
<td>0.1</td>
<td>80000</td>
<td>21600</td>
</tr>
<tr>
<td>13</td>
<td>Soil temperature</td>
<td>0.001</td>
<td>80000</td>
<td>21600</td>
</tr>
<tr>
<td>14</td>
<td>Vertical velocity</td>
<td>0.1</td>
<td>80000</td>
<td>21600</td>
</tr>
</tbody>
</table>

Characteristics of the perturbation

$\sigma$: Standard deviation which is used as tuning parameter to control the amplitude of the perturbation

$\lambda$: Length scale [m]

$\tau$: Time scale [s]

Main parameters to control WRF-Solar EPS

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](https://ral.ucar.edu/projects/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).

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-Solar EPS validation.

Mean bias of **GHI** for 2018 using NSRDB

- 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.


An ensemble calibration technique used in this work: **analog ensemble (AnEn)**.
Total improvement of 14% is attained by calibrated WRF-Solar EPS for GHI forecasts (WRF-Solar V1 vs. 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)**

- **Underspread:** when ensemble doesn’t spread out enough
- **Overspread:** when ensemble spreads out too much

**Perfect statistical consistency is the 1:1 line.**

**RMSE (W/m²) vs. Spread (W/m²)**

- WRF-Solar EPS
- Calibrated WRF-Solar EPS

**Rank Histogram (for consistency)**

- **WRF-Solar EPS**
  - MRE=46.25%
  - Overconfident

- **Calibrated WRF-Solar EPS**
  - MRE=-1.41%

- 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.
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

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

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

3. **Overview of WRF-Solar EPS development:**

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

5. **Intercomparison between three different ensemble systems:**

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

**Paper in preparation:**
The best WRF-Solar configuration to produce high-quality solar irradiance forecast
Thank you

www.nrel.gov

Contact:
Manajit.Sengupta@nrel.gov
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.