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)

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

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

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**NSRDB (GHI) at 1530 UTC 16 April 2018**

**GHI forecast from WRF-Solar**

**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

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

![Every 5 x 5 WRF Solar Grid points](image_url)
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).
4. Results: RMSE maps for GHI forecast over CONUS

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

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)

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

- 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).

<table>
<thead>
<tr>
<th>1P</th>
<th>GHI_M</th>
</tr>
</thead>
<tbody>
<tr>
<td>2P</td>
<td>GHI_M, GHI_S</td>
</tr>
<tr>
<td>4P</td>
<td>GHI_M, GHI_S, DNI_M, DNI_S</td>
</tr>
<tr>
<td>4P_T</td>
<td>GHI_M, GHI_S, 2m_T_M, 2m_T_S</td>
</tr>
<tr>
<td>4P_W</td>
<td>GHI_M, GHI_S, W_M, W_S</td>
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