Short-term Solar Power Forecasting with an Analog Ensemble

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Outline

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- The analog ensemble (AnEn)
- AnEn applications
- AnEn for solar
- Data sets
- Example of probabilistic predictions
- AnEn performance for deterministic and probabilistic predictions
- Summary

The Analog Ensemble

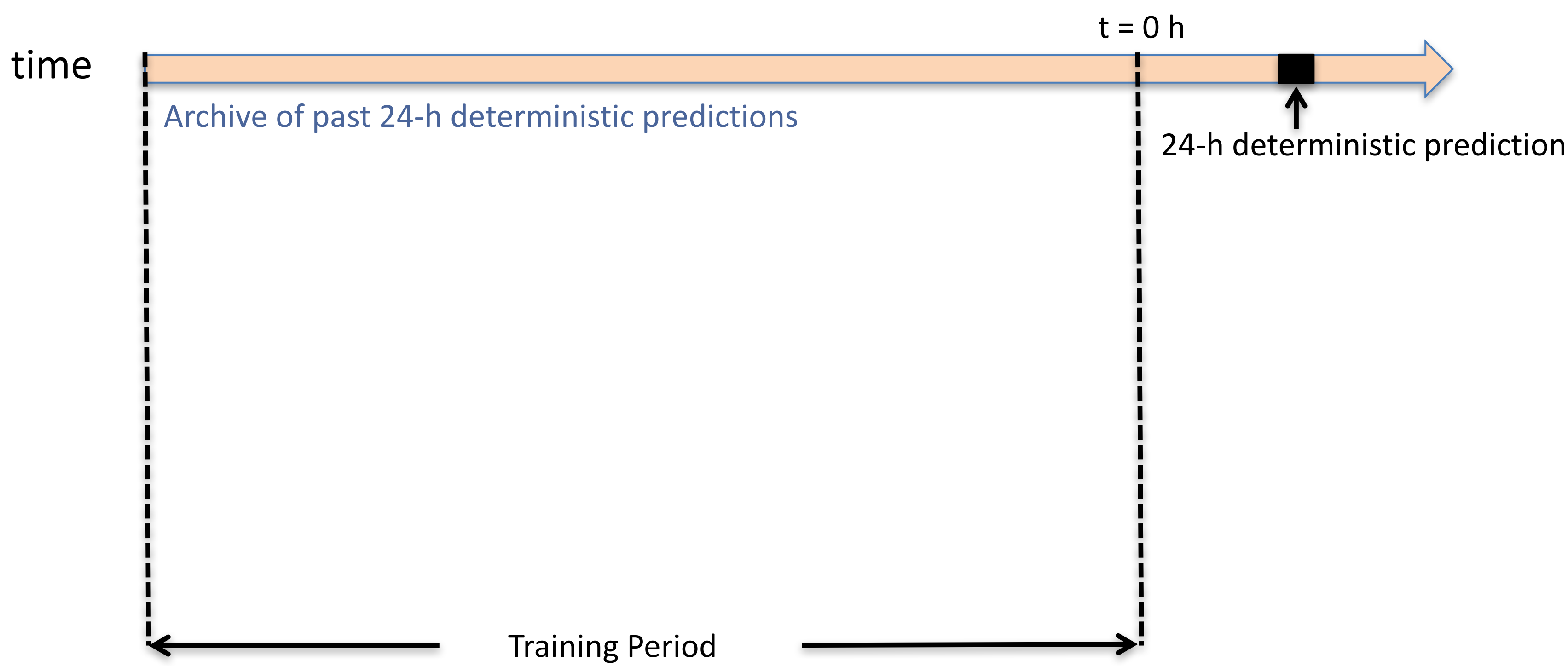

Figure adapted from Delle Monache et al. (2013)

The Analog Ensemble

Find set number of analogs based on certain predictors

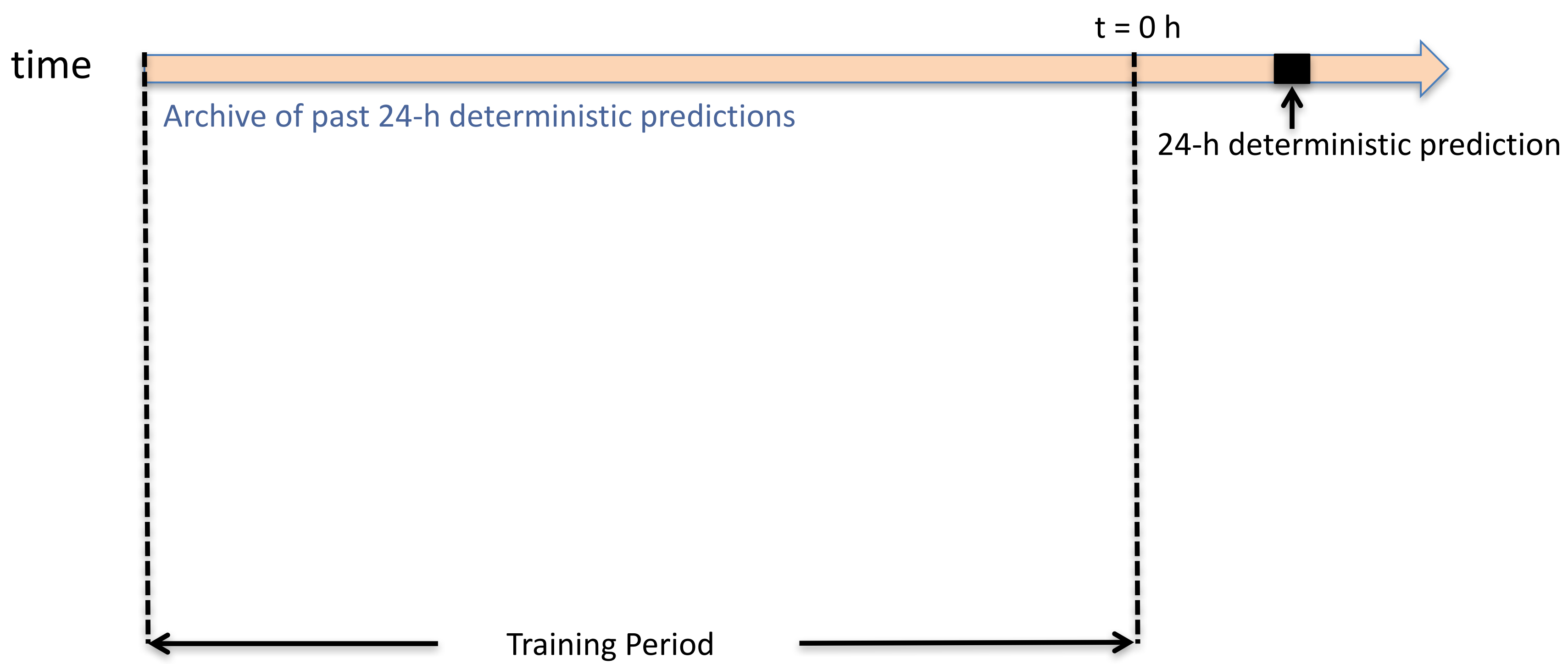

Figure adapted from Delle Monache et al. (2013)

The Analog Ensemble

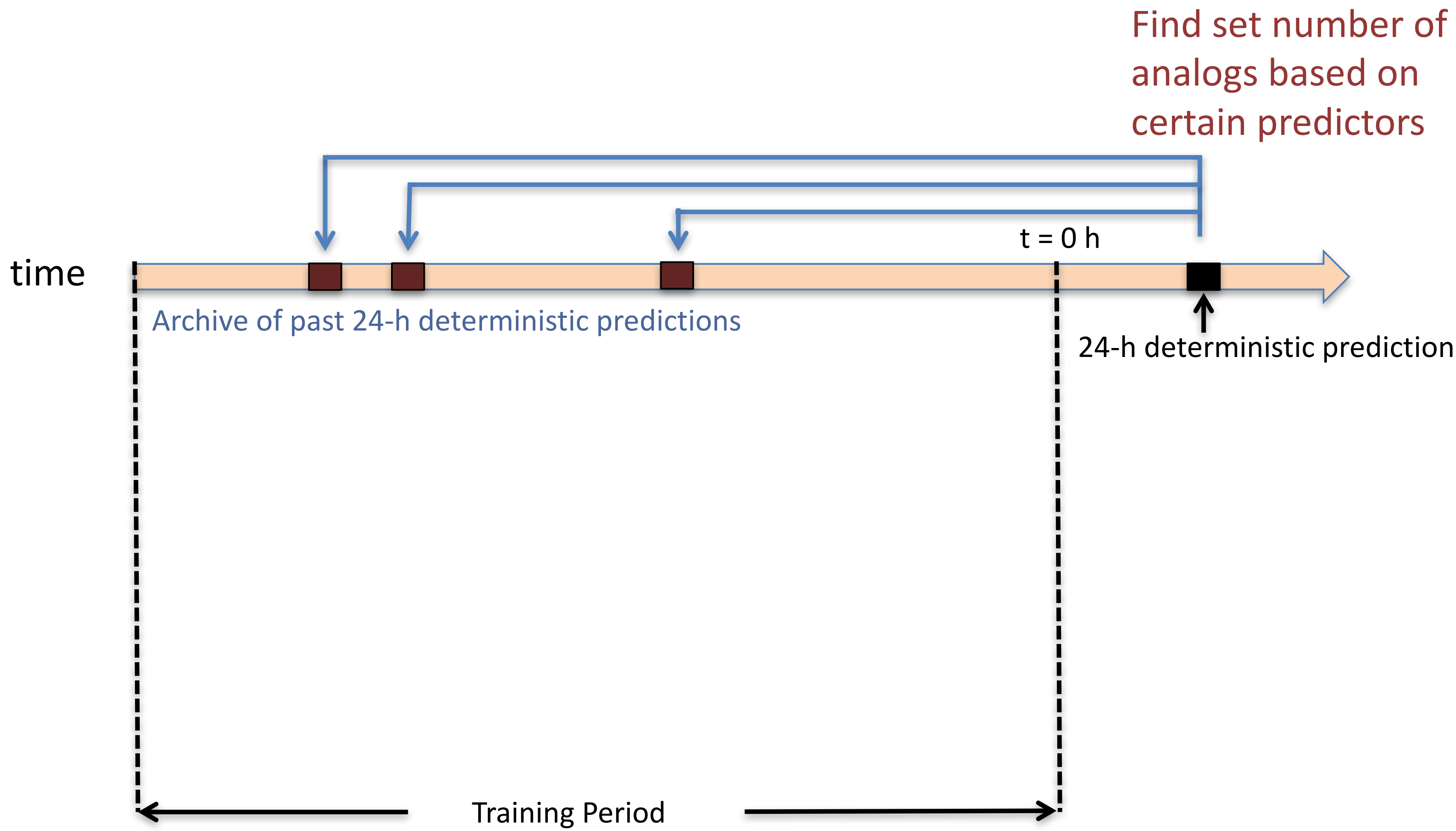

Figure adapted from Delle Monache et al. (2013)

The Analog Ensemble

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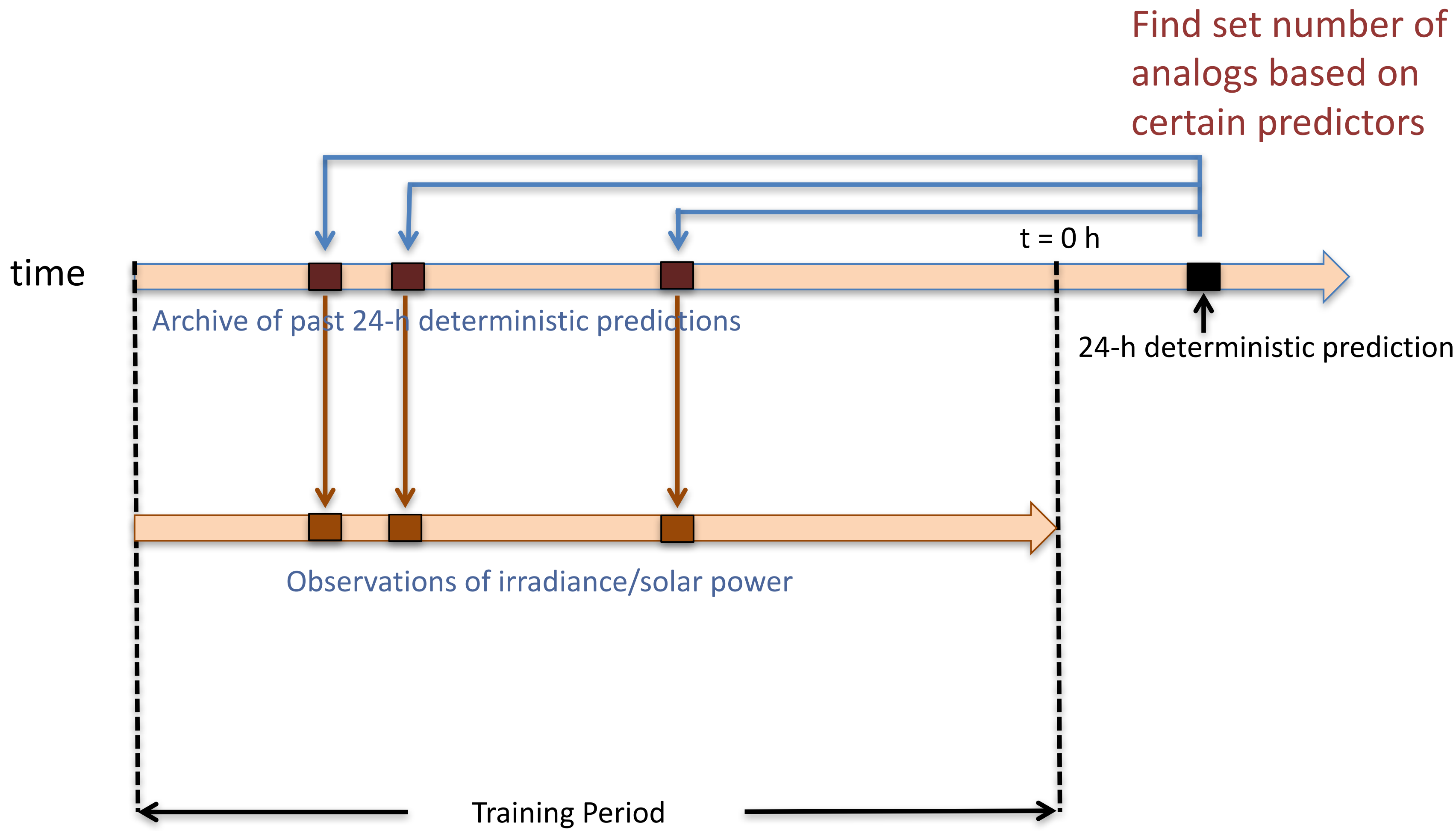


Figure adapted from Delle Monache et al. (2013)

The Analog Ensemble

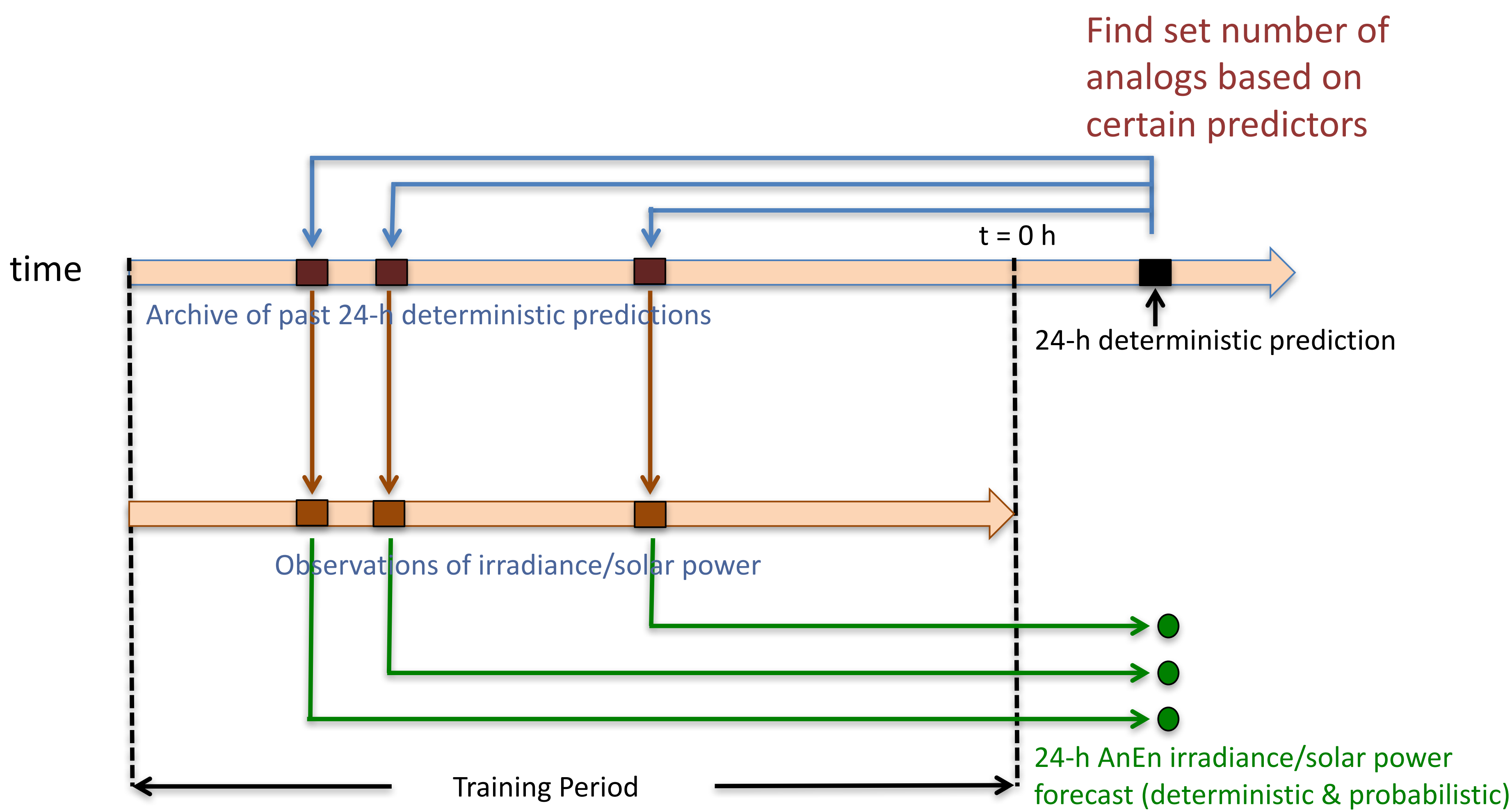
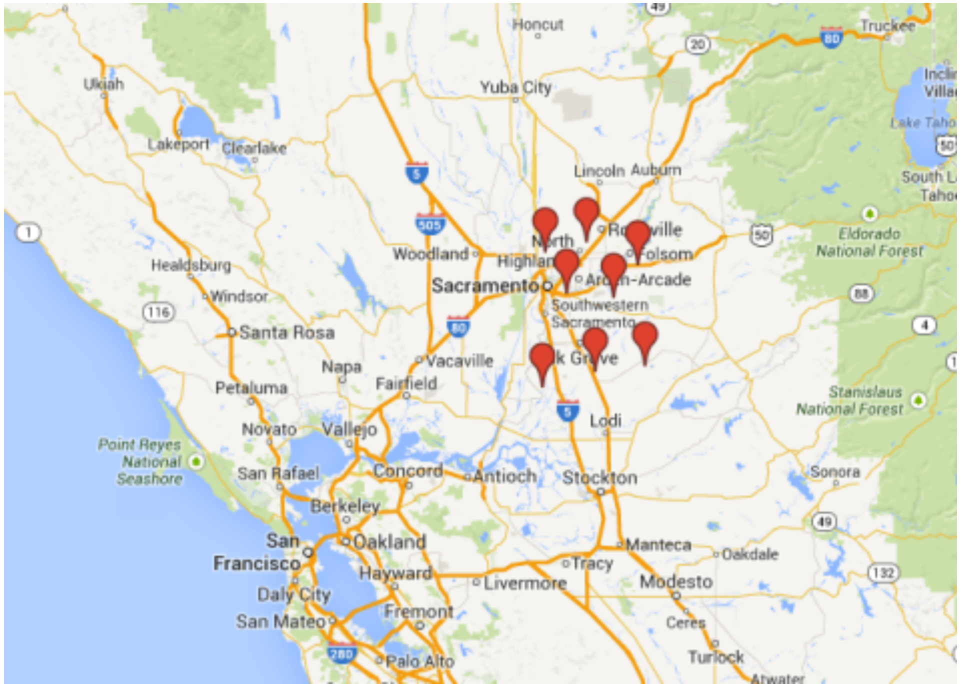


Figure adapted from Delle Monache et al. (2013)

AnEn has been successfully applied for:

- Short-term predictions of:
  - 10- and 80-m wind speed, 2-m temperature, etc.
    Delle Monache et al. MWR 2011, 2013, Junk et al. MZ 2015
  - Wind power
    Alessandrini et al. RE 2015, Davo et al. SE 2016
  - Load
    Alessandrini et al. ICEM 2015
  - Air quality predictions (ground level ozone, surface $PM_{2.5}$)
    Djalalova et al. AE 2015, Delle Monache et al. JGR 2017
  - Tropical cyclones intensity
    Alessandrini et al. MWR 2016
  - Gridded/2D probabilistic predictions
    Sperati et al. QJRMS 2017
- Downscaling, resource assessment:
  Vanvyve et al. RE 2015, Zhang et al. AE 2015, Keller et al. JAMC 2017
  - Wind speed, precipitation
  - Computationally efficient dynamical downscaling

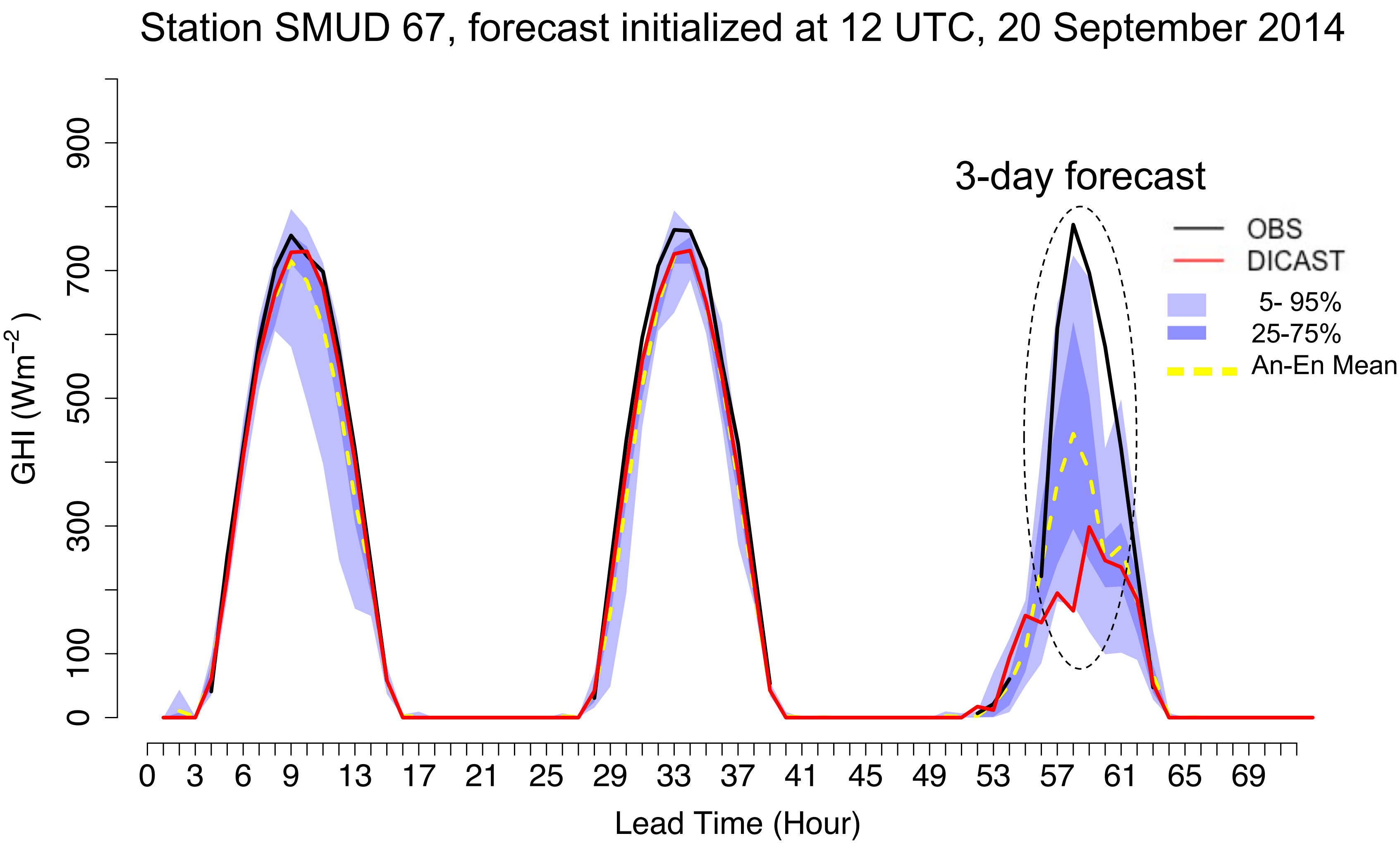
Data sets



- 8 Sacramento Municipal Utility District (SMUD) stations with global horizontal irradiance (GHI) observations
- GHI data over ~7 months (3-month verification period)
- Analog predictors (from NCAR's DICast): GHI, direct normal irradiance (DNI), and cloud cover (CC)

- 3 stations with solar power data
- Milano: 1 1/2 years, Calabria: 2 years, Catania: 2 years (1-year verification period)
- Analog predictors (from Regional Atmospheric Modeling System – RAMS): GHI, CC, DNI, 2-m temperature, azimuth, solar elevation
- Alessandrini et al. (*Applied Energy*, 2015)

Probabilistic prediction: an example



Probabilistic prediction: an example

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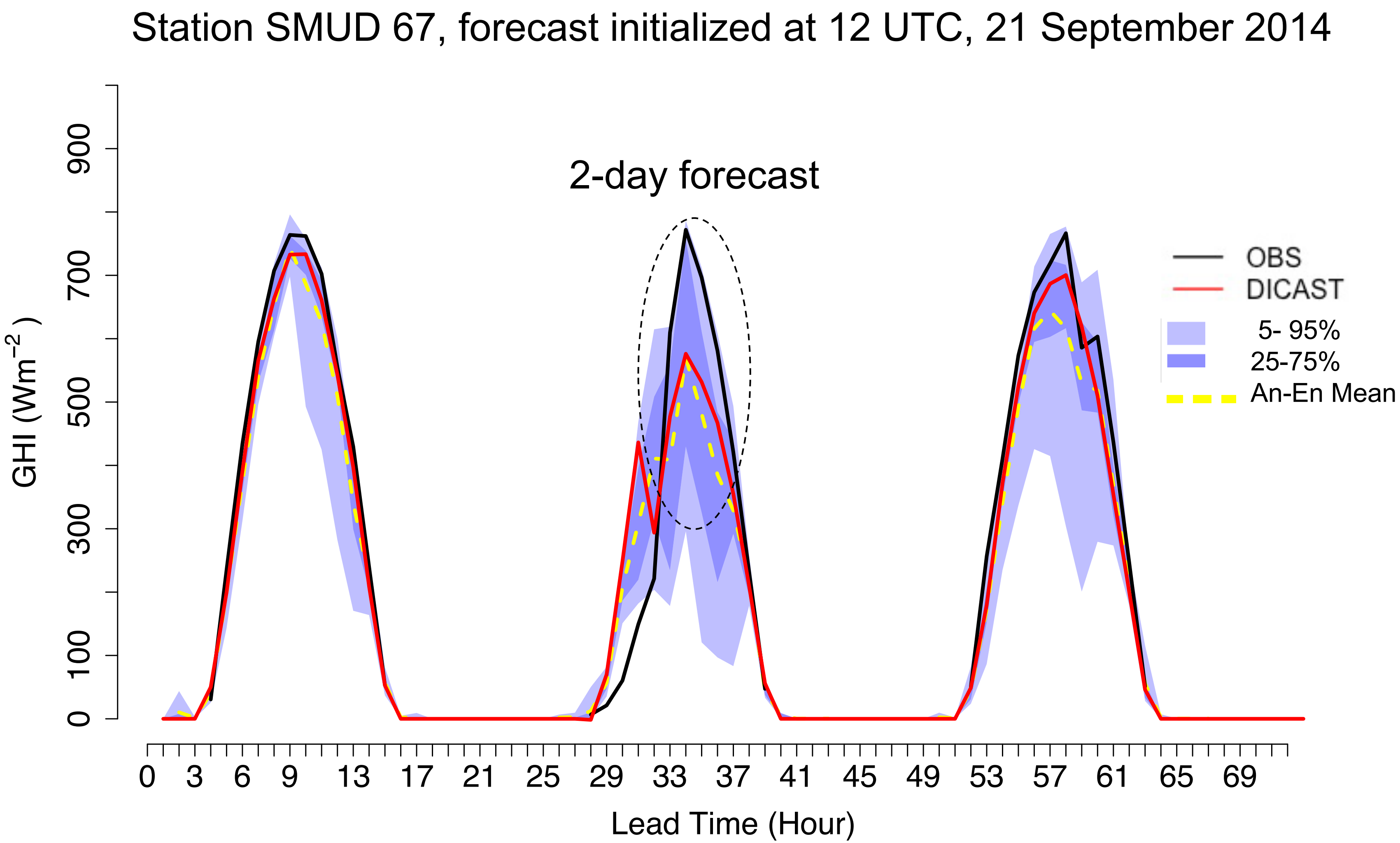

Probabilistic prediction: an example

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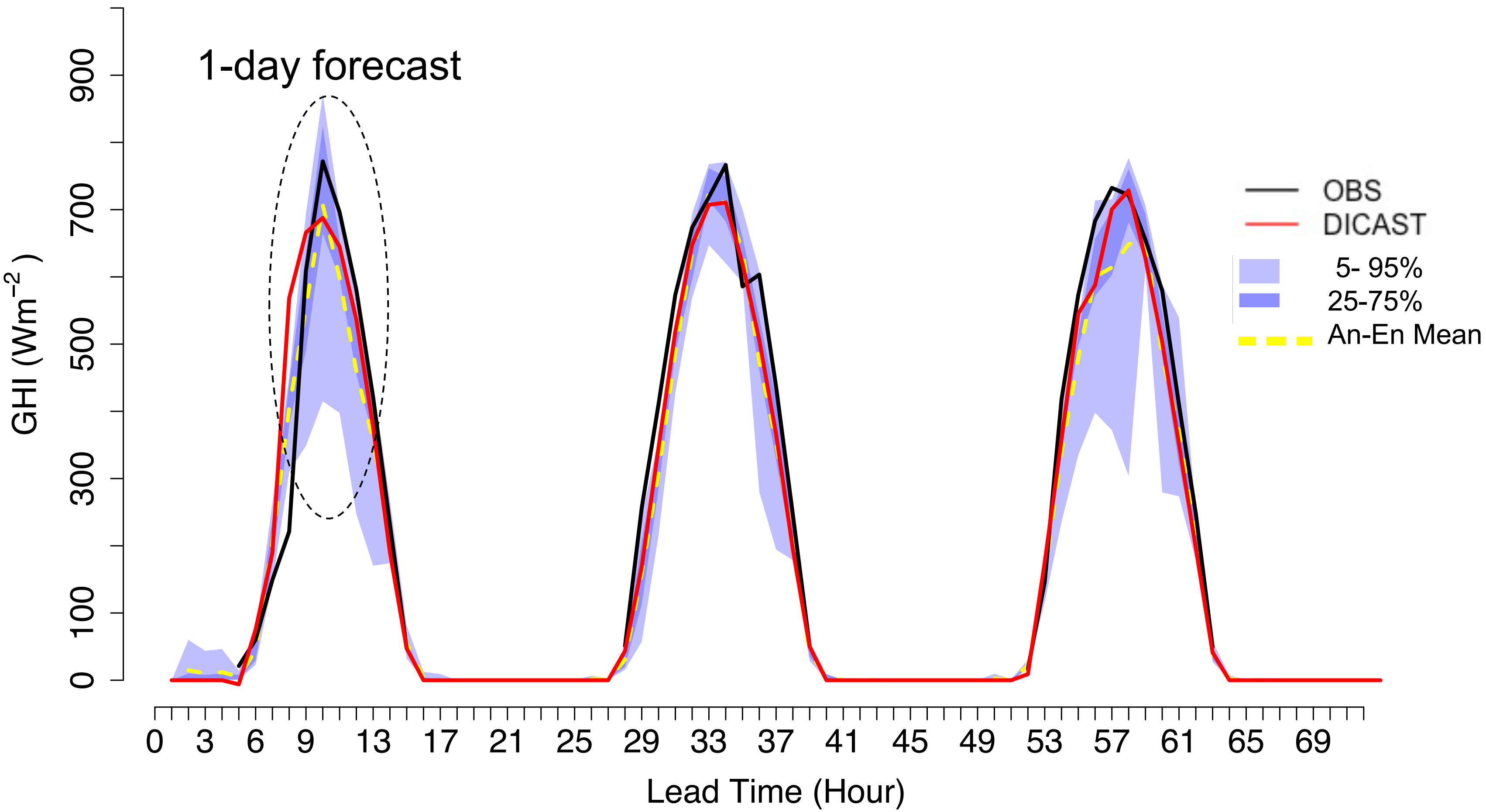
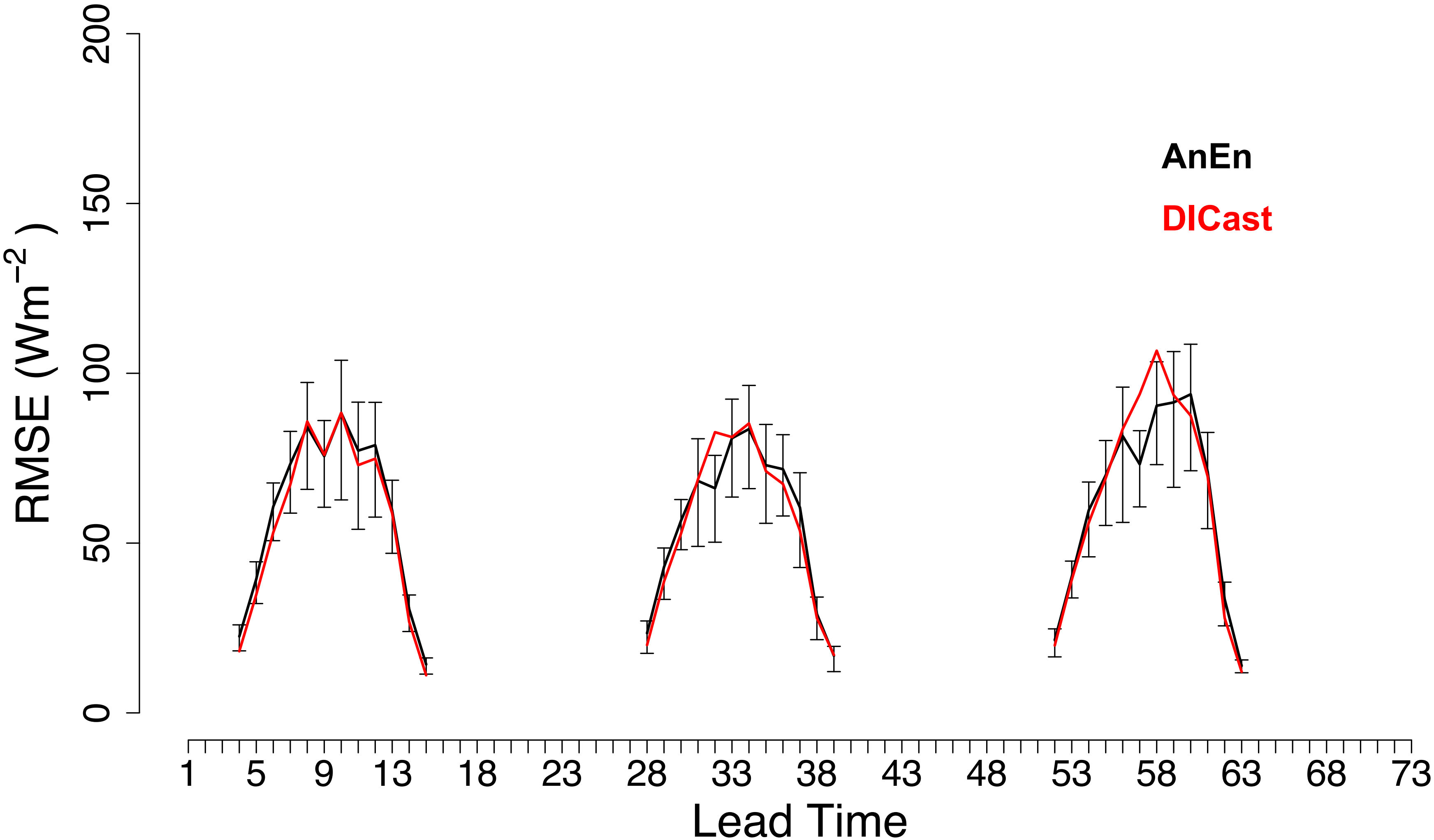
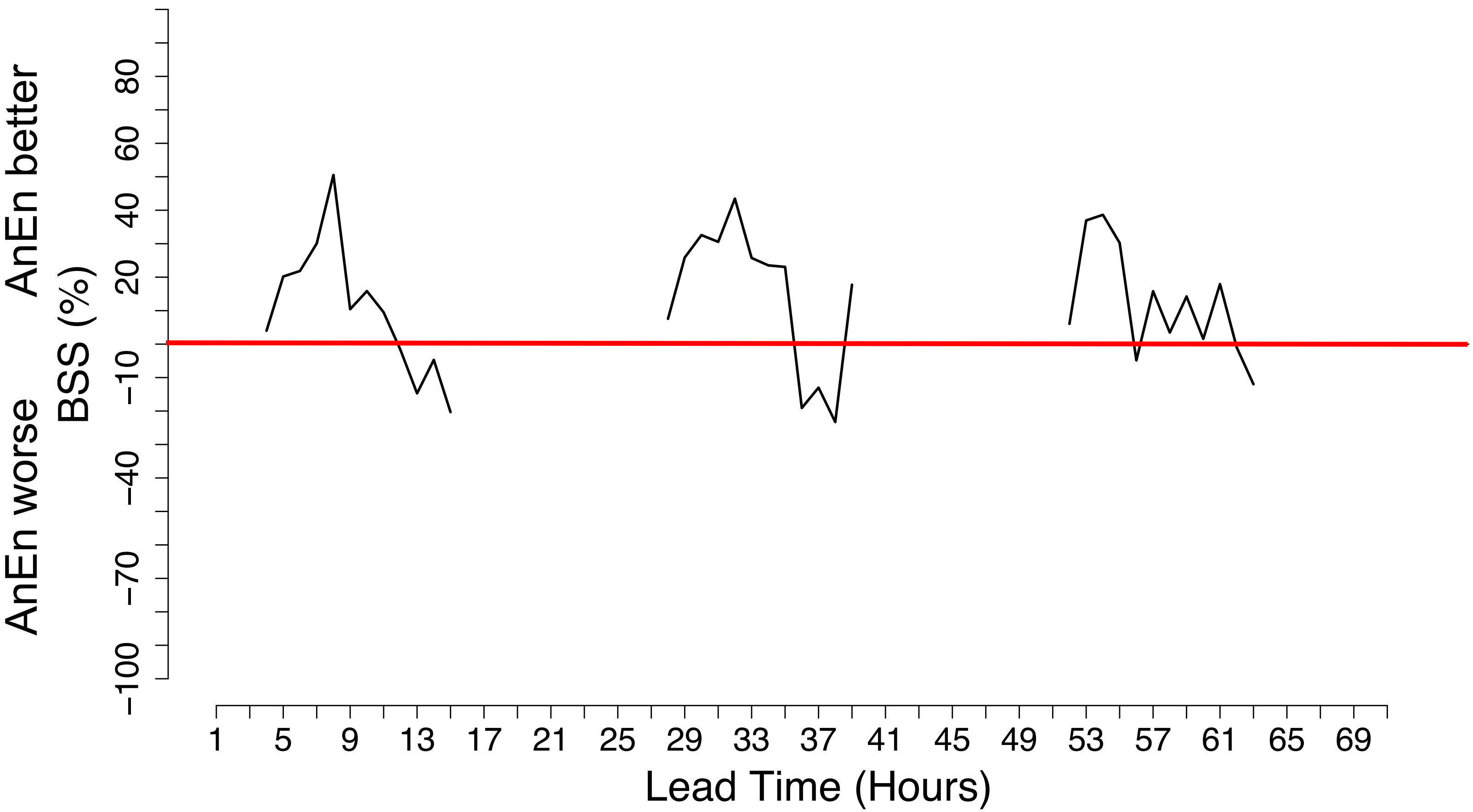
Station SMUD 67, forecast initialized at 12 UTC, 22 September 2014



AnEn mean vs. DICast



AnEn vs. DICast (Brier Skill Score)

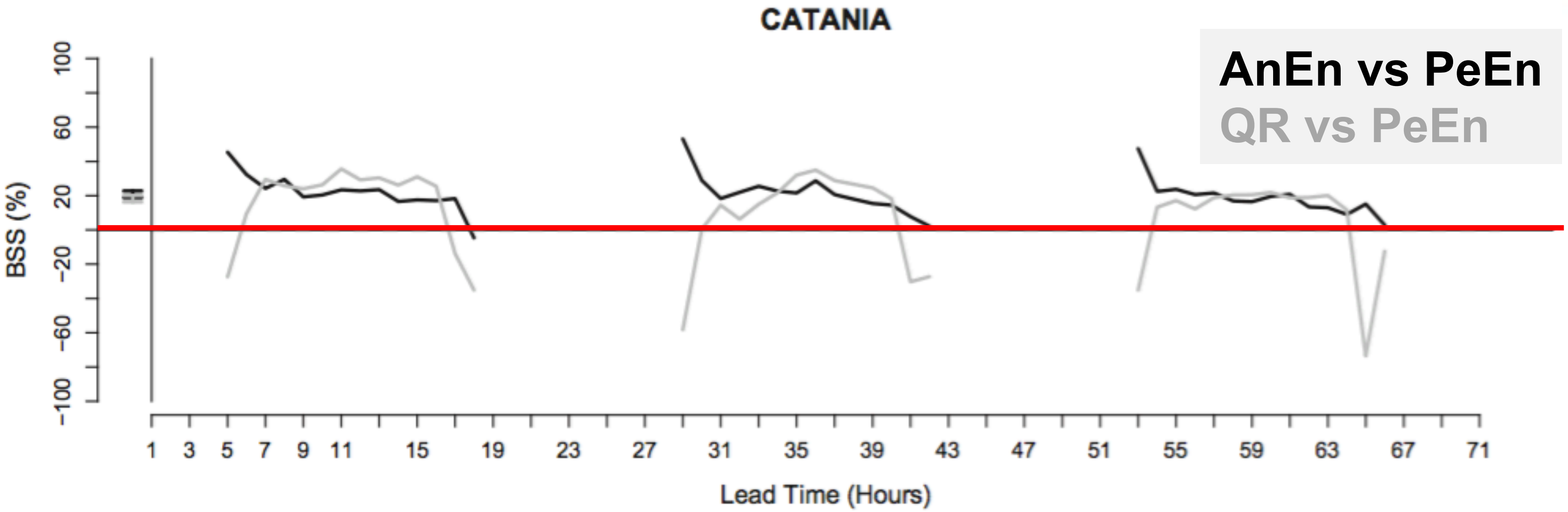


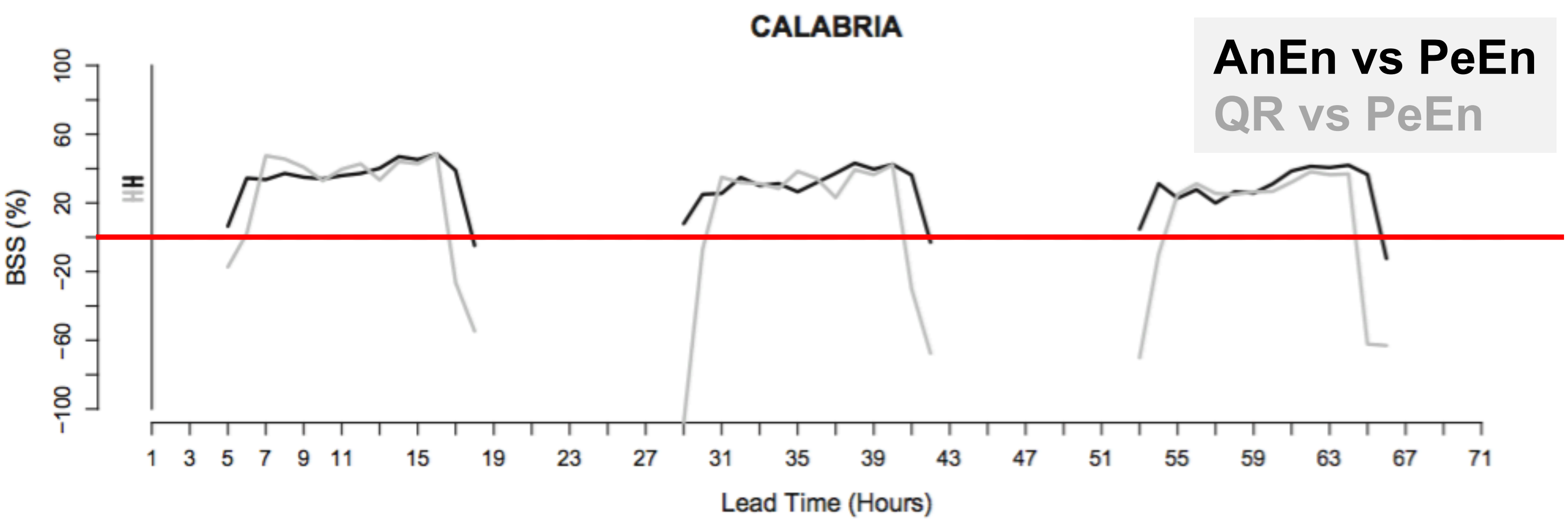
$$BSS = 1 - \frac{BS_{\mathrm{mod}1}}{BS_{\mathrm{mod}2}} \qquad BS = \frac{1}{N}\sum_{t=1}^{N}\left(f_t - o_t\right)^2$$

f_t : probability that the event was forecasted
O_t: actual outcome (equal 0 if it does not happen and 1 if it does)
N: number of forecast-observation pairs

- Brier Skill Score (BSS) > 0 indicate that AnEn has more skill than DICast
- Event considered being GHI > mean(observed GHI at the given lead time)

An-En vs PeEn, QR

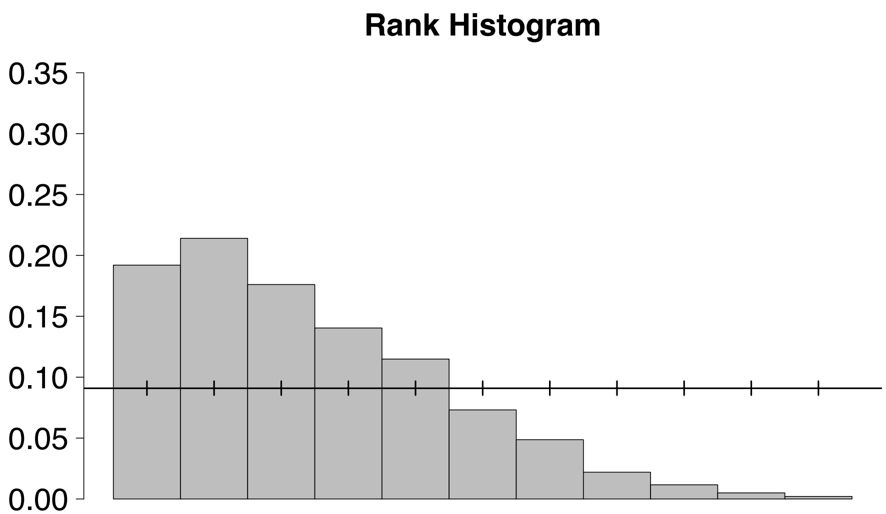




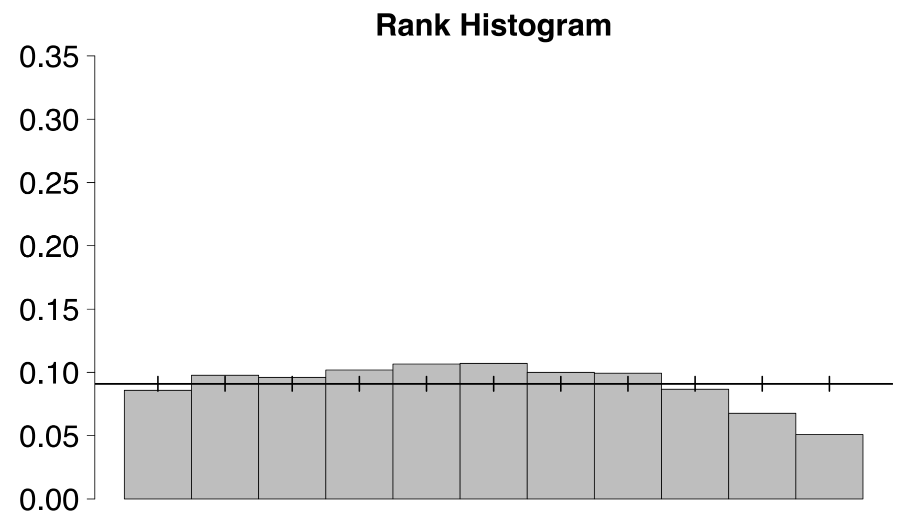
Persistence Ensemble (PeEn): most recent 20 measurements at the same hour of the day

Quantile Regression (QR): quantiles of PDF defined independently with different regression coefficients on past predicted and observed PV values

AnEn sensitivity to time shift in analog search

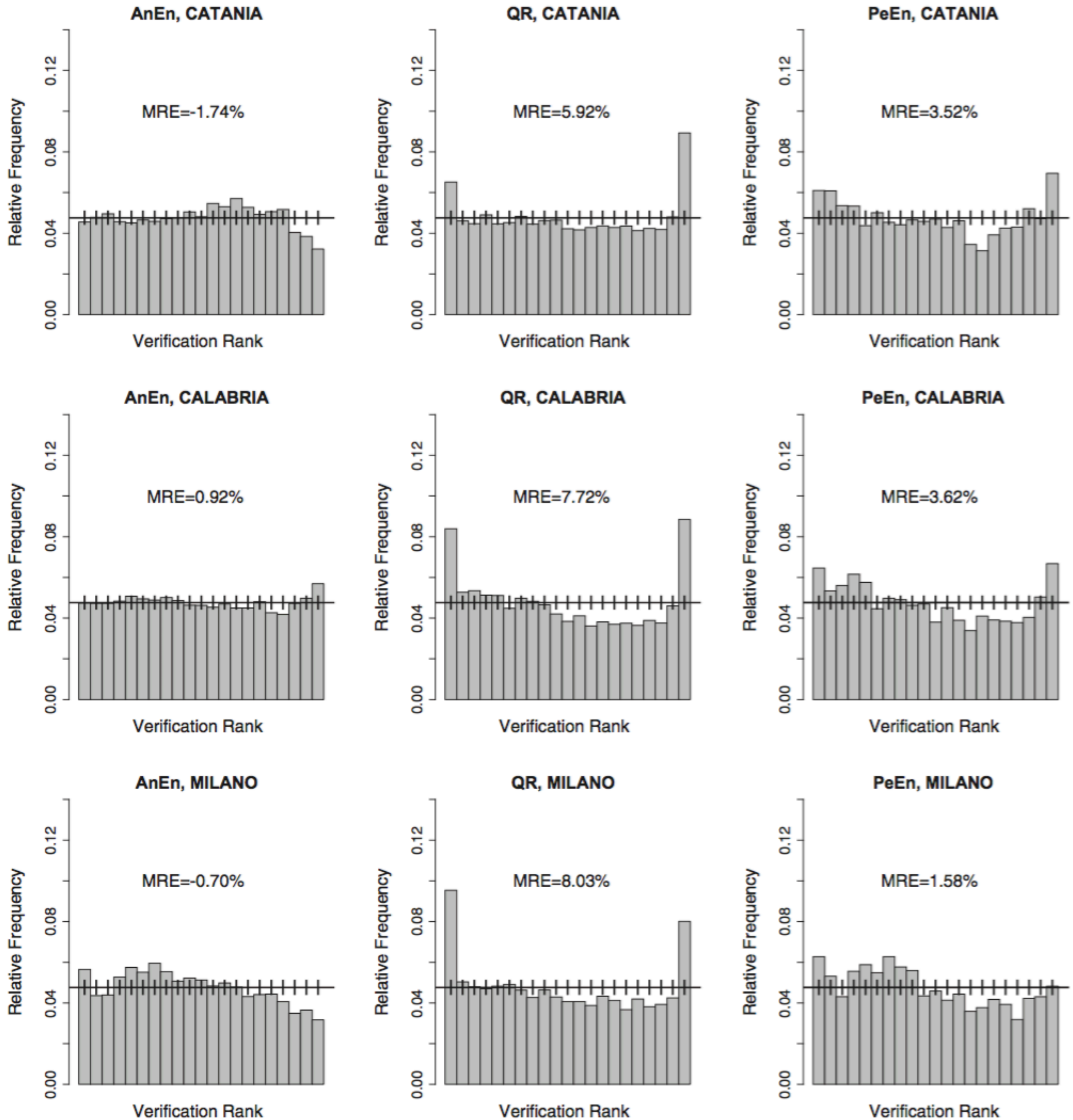


Time shift = 0 hours



Time shift = 3 hours

Searching for analog in lead times before or after the lead time of interest extends the training data set, and it improves AnEn statistical consistency


AnEn, CATANIA
MRE=-1.74%
QR, CATANIA
MRE=5.92%
PeEn, CATANIA
MRE=3.52%
AnEn, CALABRIA
MRE=0.92%
QR, CALABRIA
MRE=7.72%
PeEn, CALABRIA
MRE=3.62%
AnEn, MILANO
MRE=-0.70%
QR, MILANO
MRE=8.03%
PeEn, MILANO
MRE=1.58%
Relative Frequency
Verification Rank
0.00
0.04
0.08
0.12

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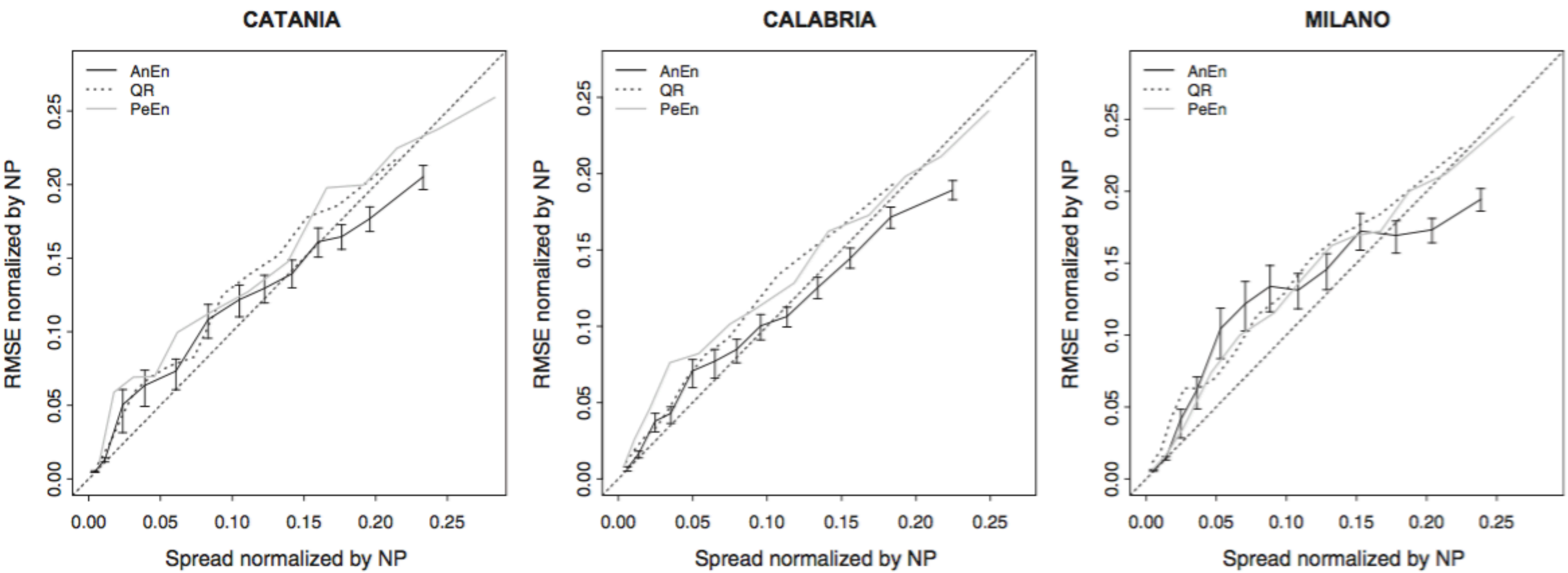
Spread-skill Relationship



Summary

- AnEn successfully tested for solar irradiance and solar power short-term predictions
- With AnEn, only one real-time deterministic forecast needed to generate probabilistic predictions
- No need for initial condition and model perturbation strategies to generate an ensemble
- Improves deterministic forecast as well as provides probabilistic information
- General algorithm, implemented for several applications
- Superior skill in predicting rare events when compared to state-of-the-science post-processing methods

Thanks!

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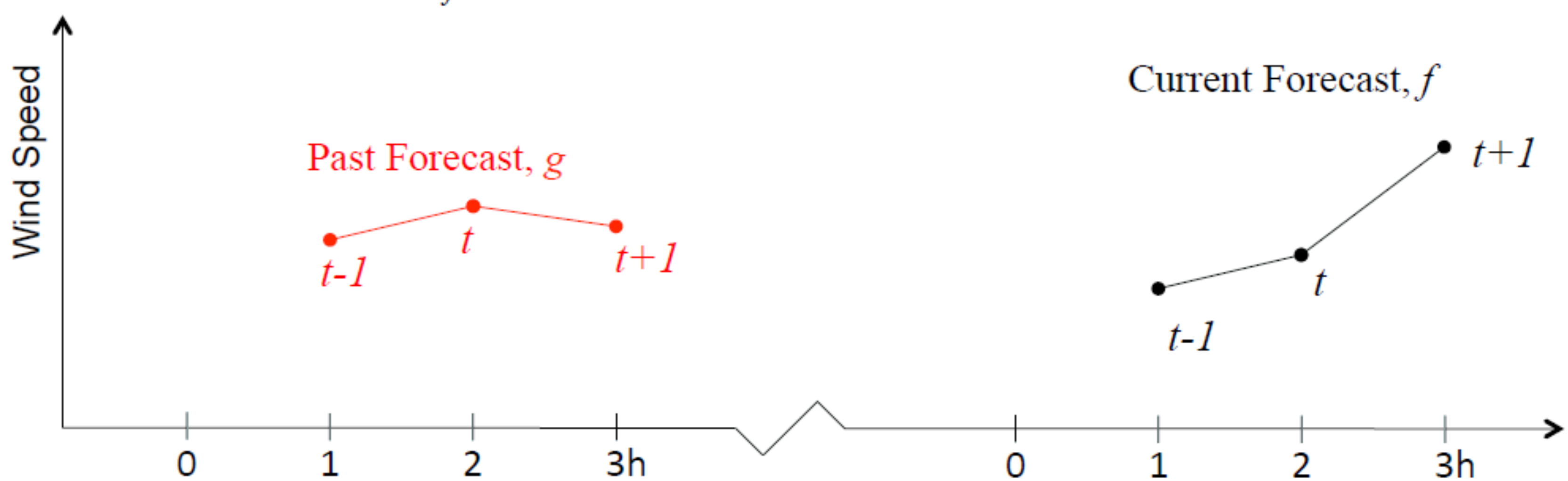
Analog Ensemble (AnEn)

Similarity criterion to search and sort the past analog forecast

$$d_t = \| f_t - g_t \| = \sum_{v=1}^{N_v} \frac{w_v}{\sigma_{f^v}} \sqrt{\sum_{k=-\tilde{t}}^{+\tilde{t}} \left(f_{t+k}^v - g_{t+k}^v \right)^2}$$

N_v : Number of predictor variables
w_v : Weight given to each predictor

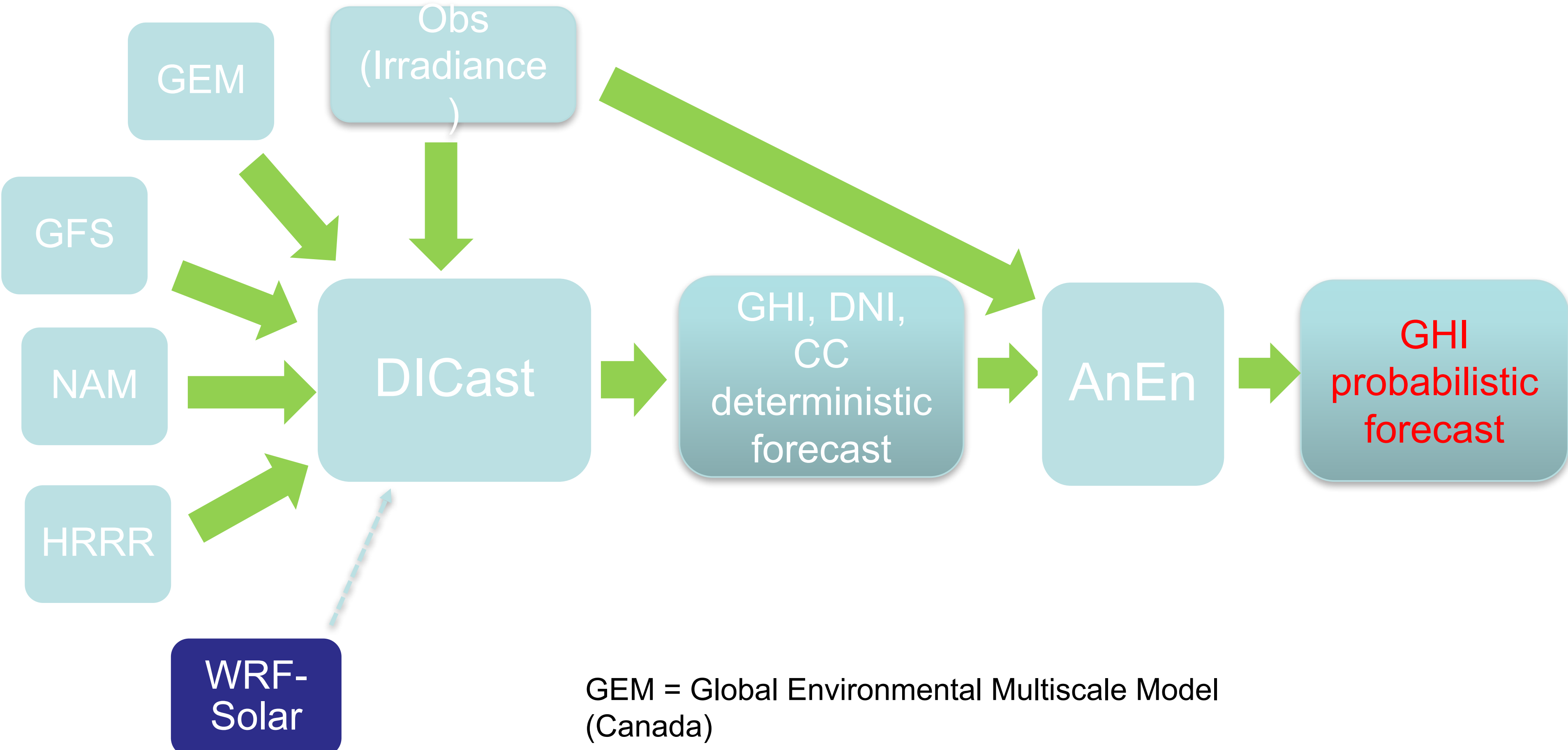


Delle Monache et al. *MWR* (2013

Dynamic Integrated foreCast (DICast)

- NCAR technology (circa 2000)
- Weather engine for a large portion of on-line wx forecasts
- “Lay” forecasts, transportation, wind power, now solar
- State-of-the-art consensus forecast system
- Optimally combines Numerical Weather Prediction (NWP) model data
- Creates ‘tuned’ forecasts using observations
- For SunCast system, hourly GHI forecasts to 3 days
- For details see: Mahoney et al. 2012 or contact Sue Haupt, haupt@ucar.edu

Modeling System



GEM = Global Environmental Multiscale Model (Canada)
GFS = Global Forecast System (US NWS)
NAM = North American Model (US NWS)
HRRR = High Resolution Rapid Refresh (ESRL)

Verification Plan

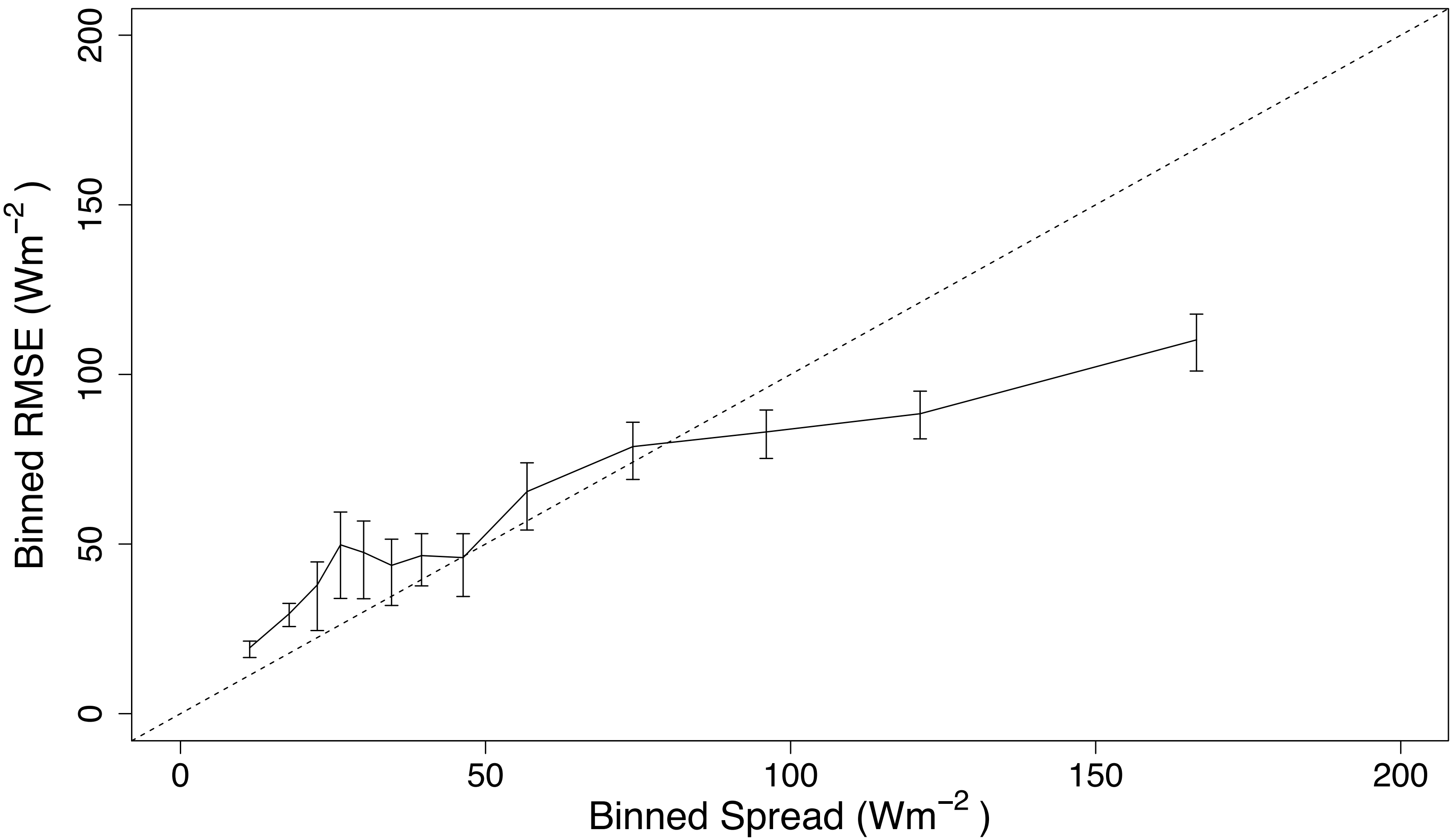
- **Training:** Method requires concurrent observations and forecasts for a sufficient time history to train
  - Use 136 days of concurrent observations and DICast predictions
  - DICAST daily forecasts initialized at 12 UTC over the 226-day period, lead times from 0 to 72 hours
  - Available variables (i.e., *analog predictors*): GHI, direct normal irradiance (DNI), and cloud cover (CC)
- **Preliminary Testing:** 90 days, from 04 September-2 December, 2014, forecast lead times from 0 to 72 hours
- **Prediction:** GHI (Global Horizontal Irradiation, Wm^{-2})

Analog Ensemble (AnEn) Configuration

- 10 historic analog ensemble members
- 3 predictors with different weighting
  (GHI, DNI and Cloud Cover)
- Analog-predictor weights obtained by an optimization algorithm (minimizing RMSE) over the period (5 August-03 September 2014) performed independently at each station

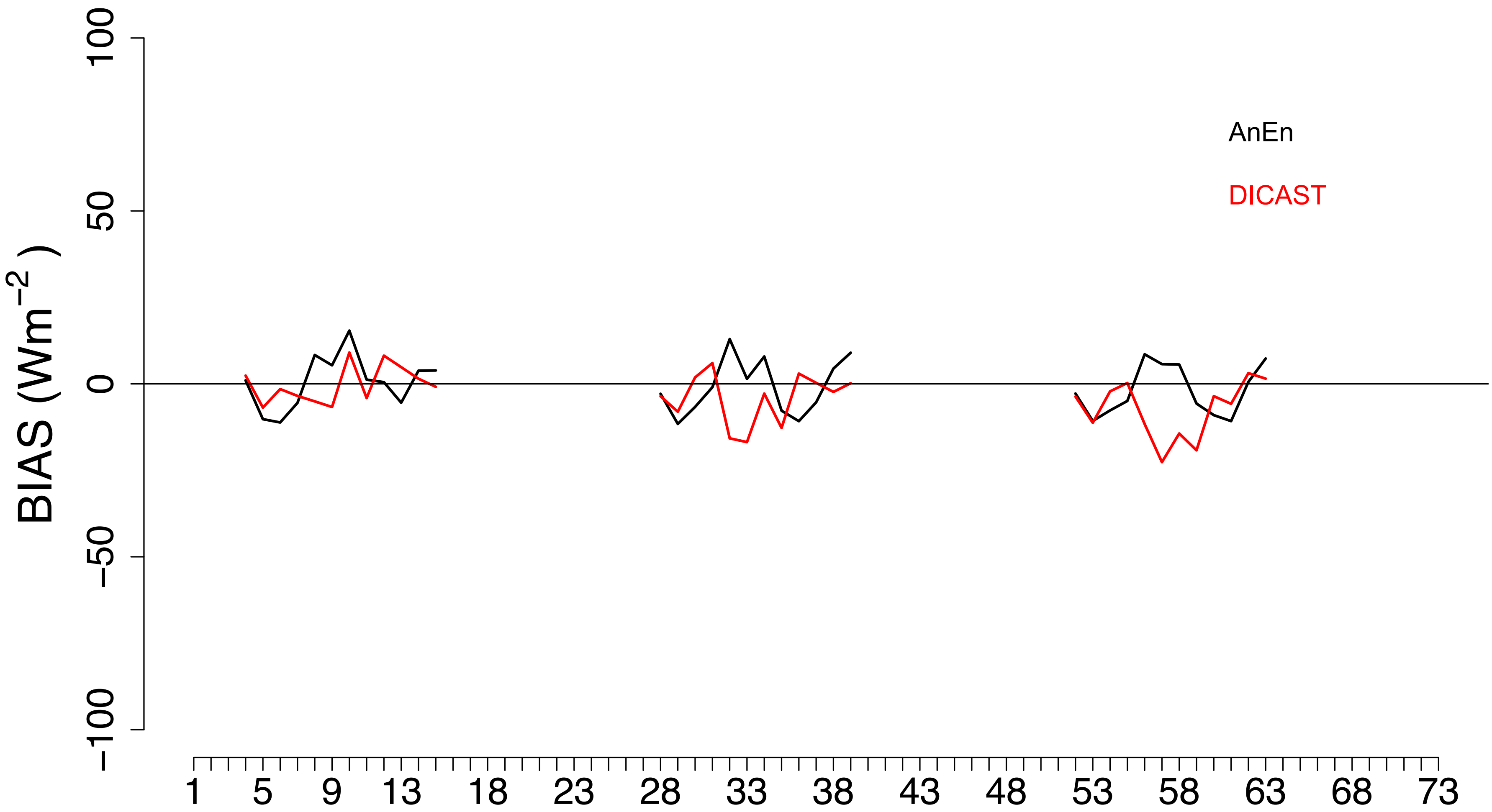
- Possible weights: 1, 0.9, 0.8,…..0.1, 0. (66 possible combinations)
- Different time shift lengths tested for analog searching (3 hours, optimal)

AnEn: spread skill



Conclusion: AnEn provides probabilistic information that provides skill, even for the short training period

AnEn vs. DICAST (BIAS)



NOTE:
Average BIAS over 3 stations and daylight lead times: -1.08 Wm^{-2} (AnEn), -4.21 Wm^{-2} (DICast)
Therefore: AnEn improves on the DICast bias calibration for this short verification period