# Probabilistic Predictions and Uncertainty Quantification with an Analog Ensemble

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# Outline

- Analog Ensemble (AnEn) basic idea
- AnEn for short-term (i.e., 0-48 h) weather predictions
- AnEn for short-term (i.e., 0-72 h) power predictions
- AnEn for 2D/gridded probabilistic predictions
- AnEn for long-term (i.e., multi-year) wind resource assessment
- Summary and future work

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# Weather analogs: basic idea

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**Today**

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**Today**

**One week ago?**

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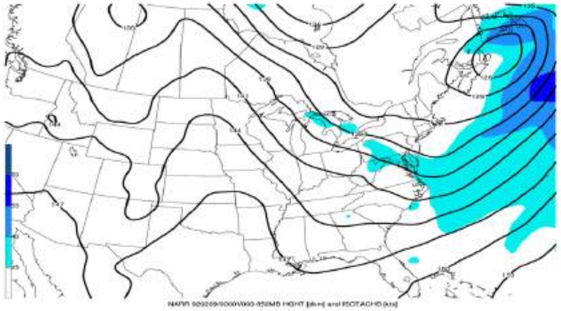
**Today**

**One week ago?**

**5 years ago?!?**

# Weather analogs: basic idea



**Today**

**One week ago?**

**5 years ago?!?**

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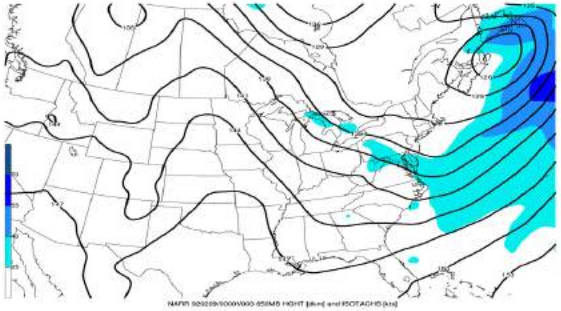

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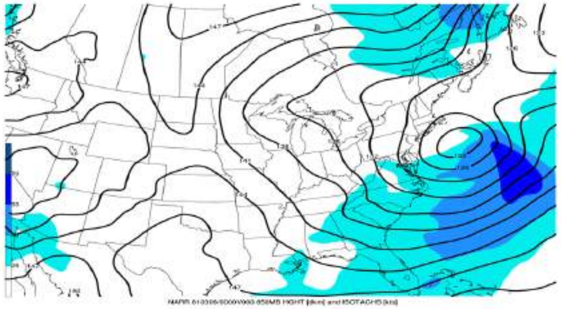

**One week ago?**

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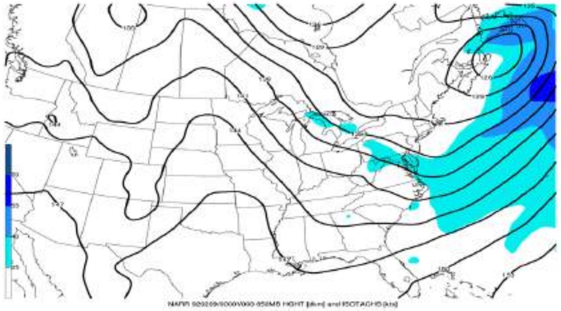
# Weather analogs: basic idea



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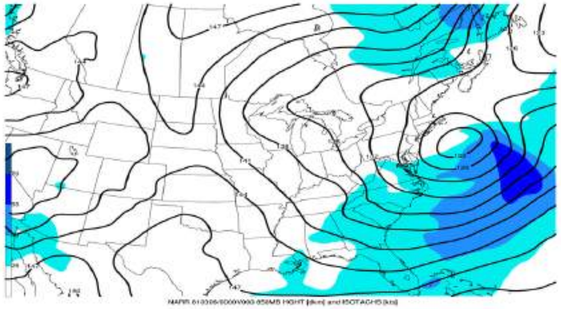

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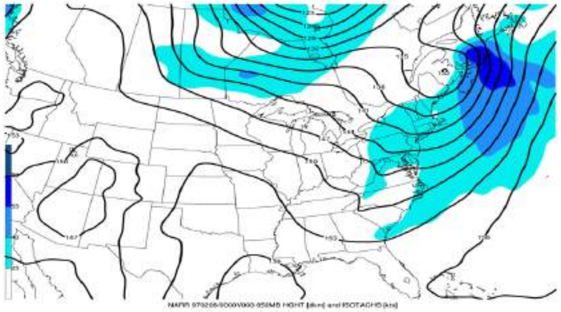
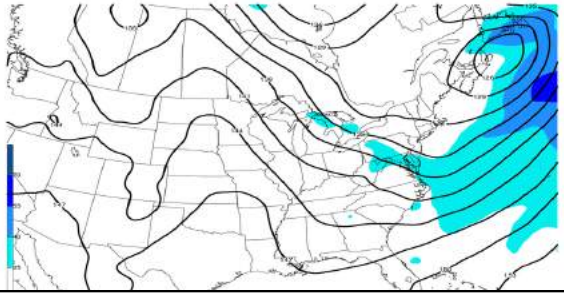


**5 years ago?!?**

# Weather analogs: basic idea



Can we use this information
(i.e., past obs, re-analysis, and forecasts),
to improve forecasts or resource estimates?

**5 years ago?!?**

# There is a problem…

Edward Lorenz, "Atmospheric predictability as revealed by naturally occurring analogues" (JAS 1969):

*…*

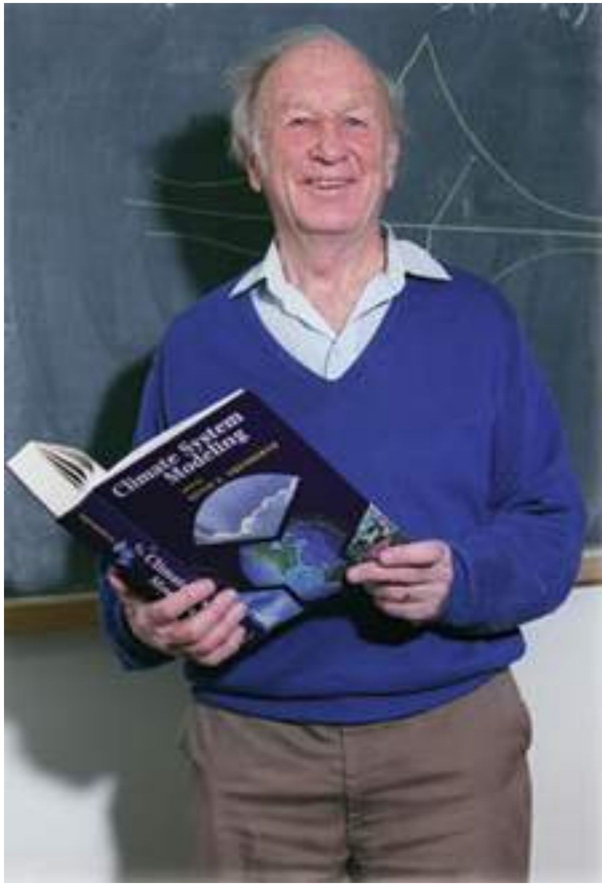
*Five years of twice-daily height values of the 200-, 500-, and 850-mb surfaces at a grid of 1003 points over the Northern Hemisphere*

*…*

*There are numerous mediocre analogues but no truly good ones.*

*…*

*The likelihood of encountering any truly good analogues by processing all existing upper-level data appears to be small.*



# A possible solution?

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Huug van den Dool, “Searching for analogues, how long must we wait?” (Tellus 1994):

*…*

*It is found that it would take a library of order of $10^{30}$ years to find 2 observed flows that match to within current observational error over a large area such as the Northern Hemisphere.*

*…*

*Obviously, with 10-100 years of data, the probability of finding natural analogous is very small, unless one is satisfied with analogy over small areas or in just 2 or 3 degrees of freedom*

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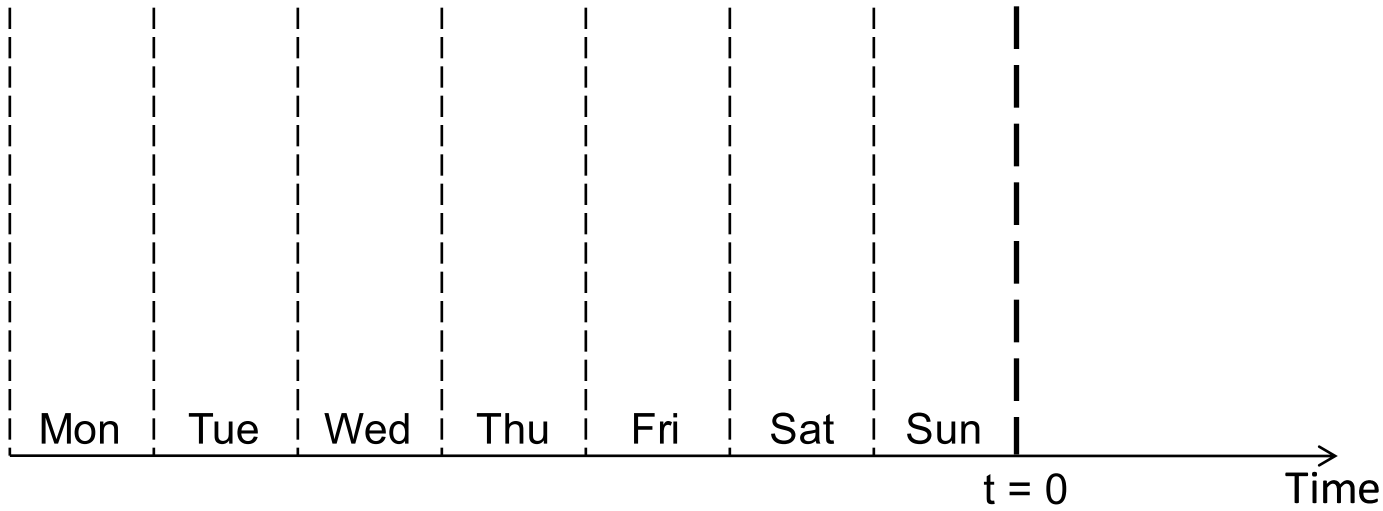
# Analog Ensemble (AnEn)



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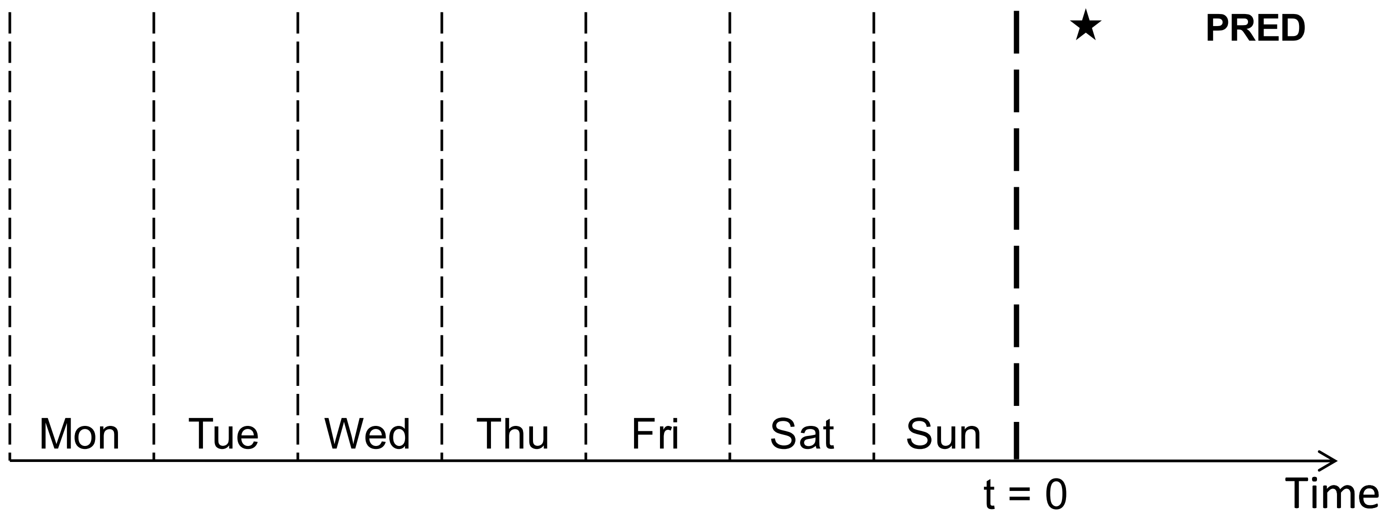

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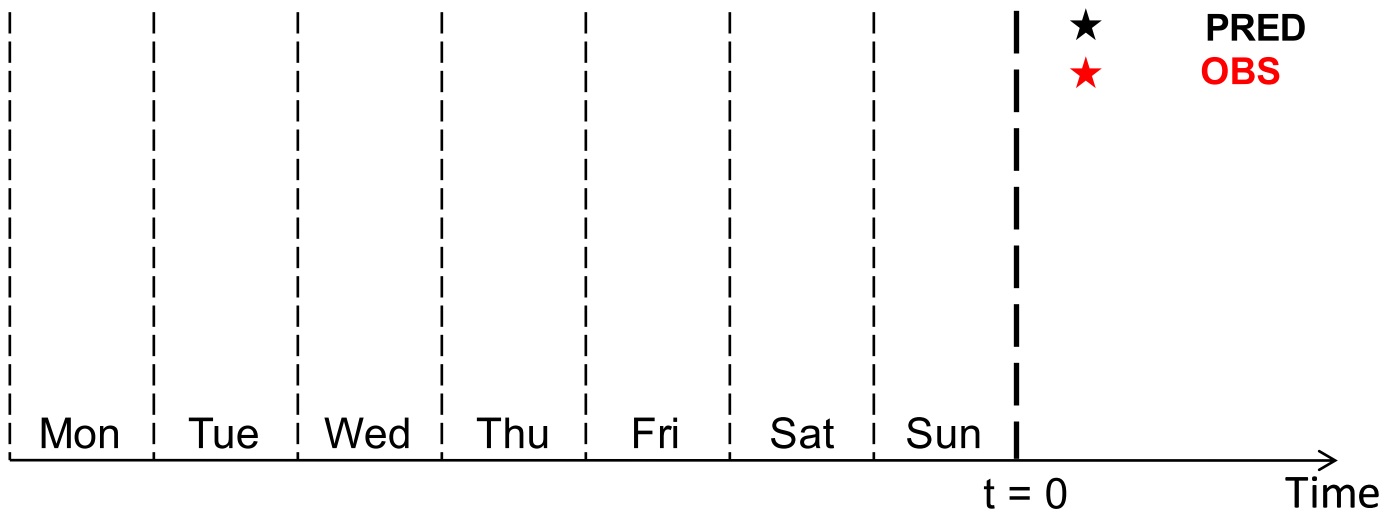

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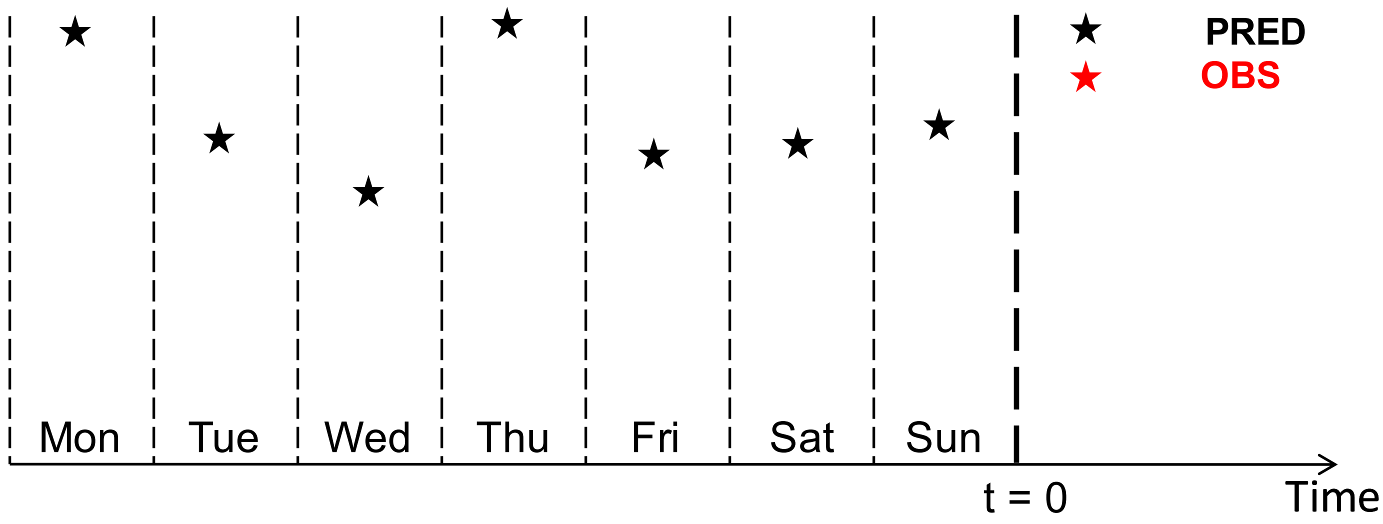

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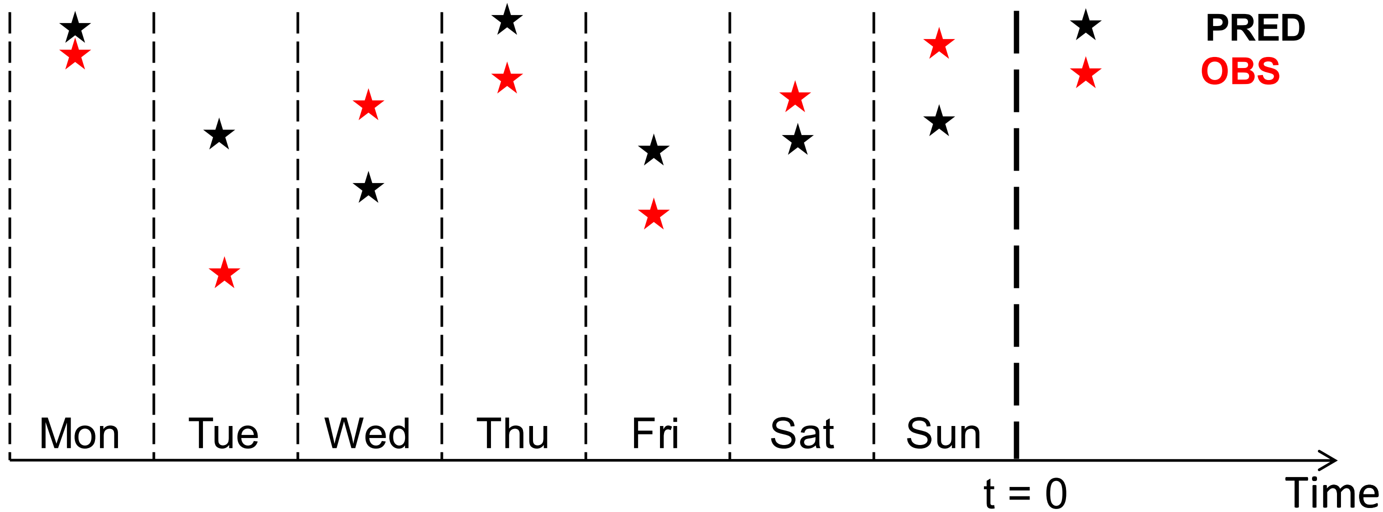

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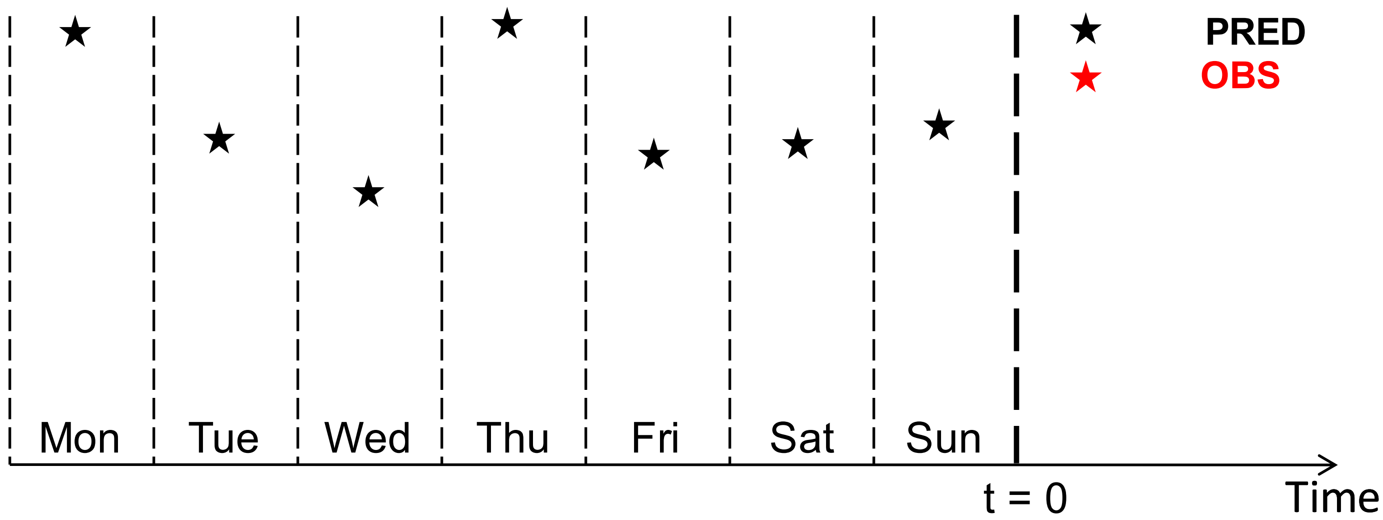

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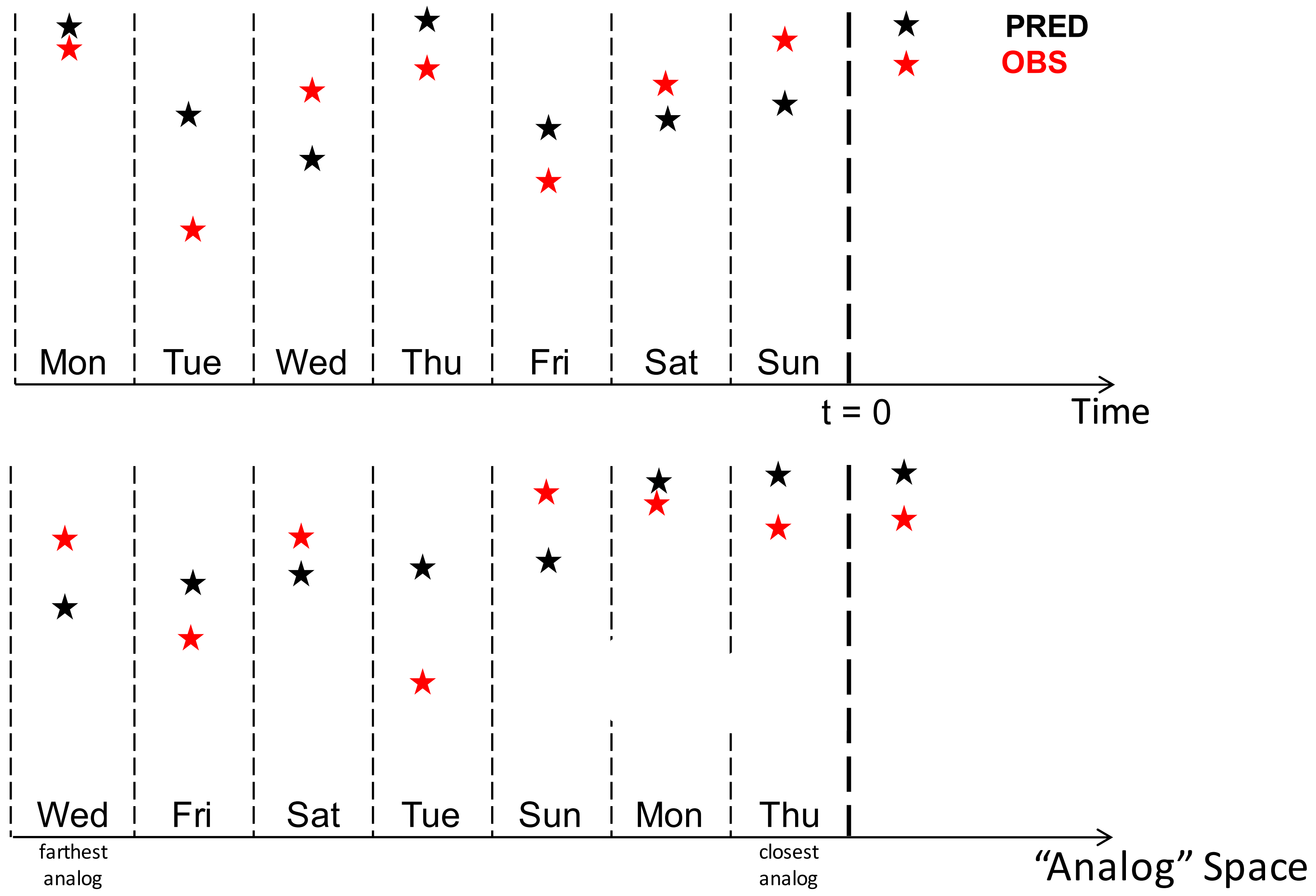

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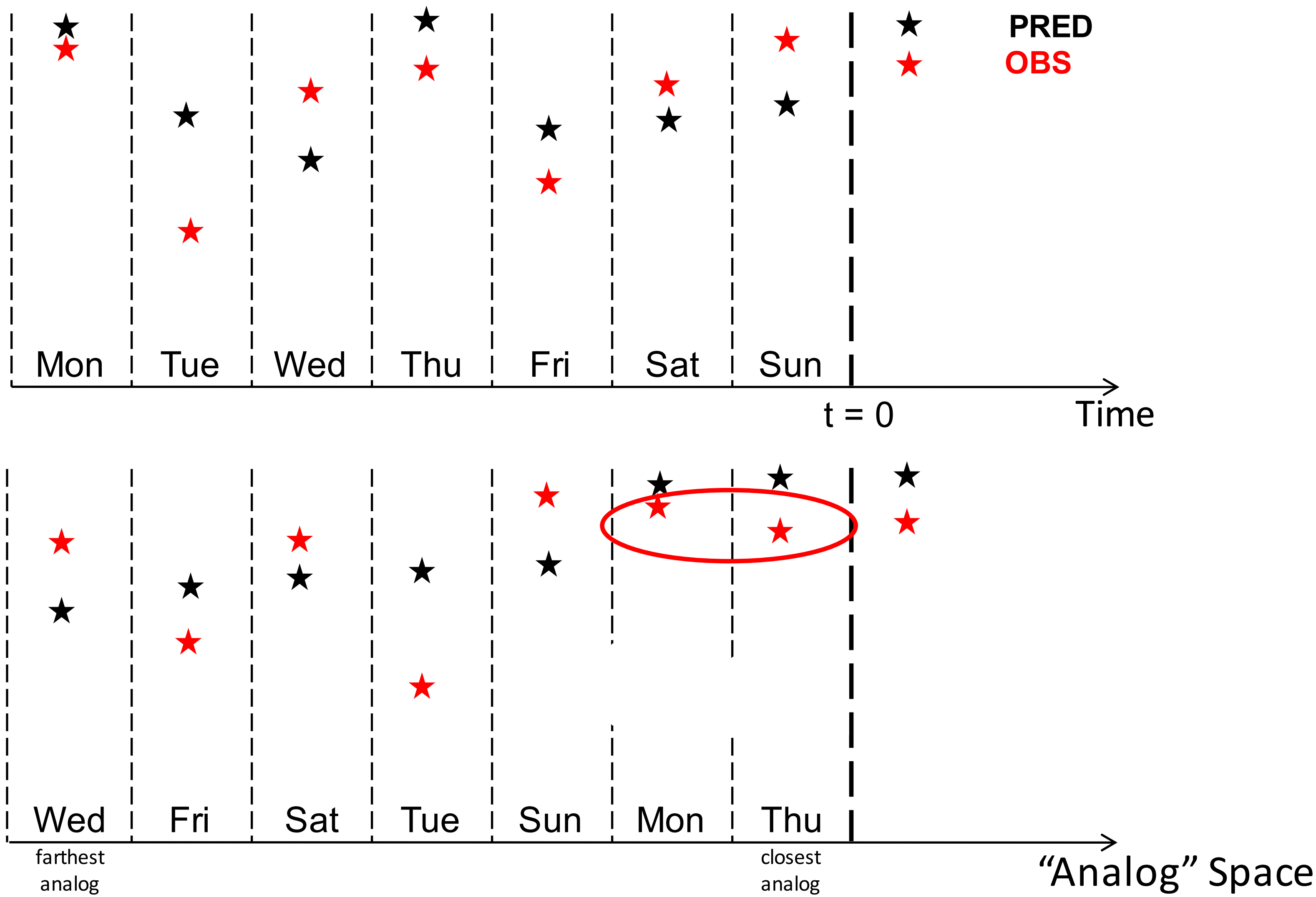

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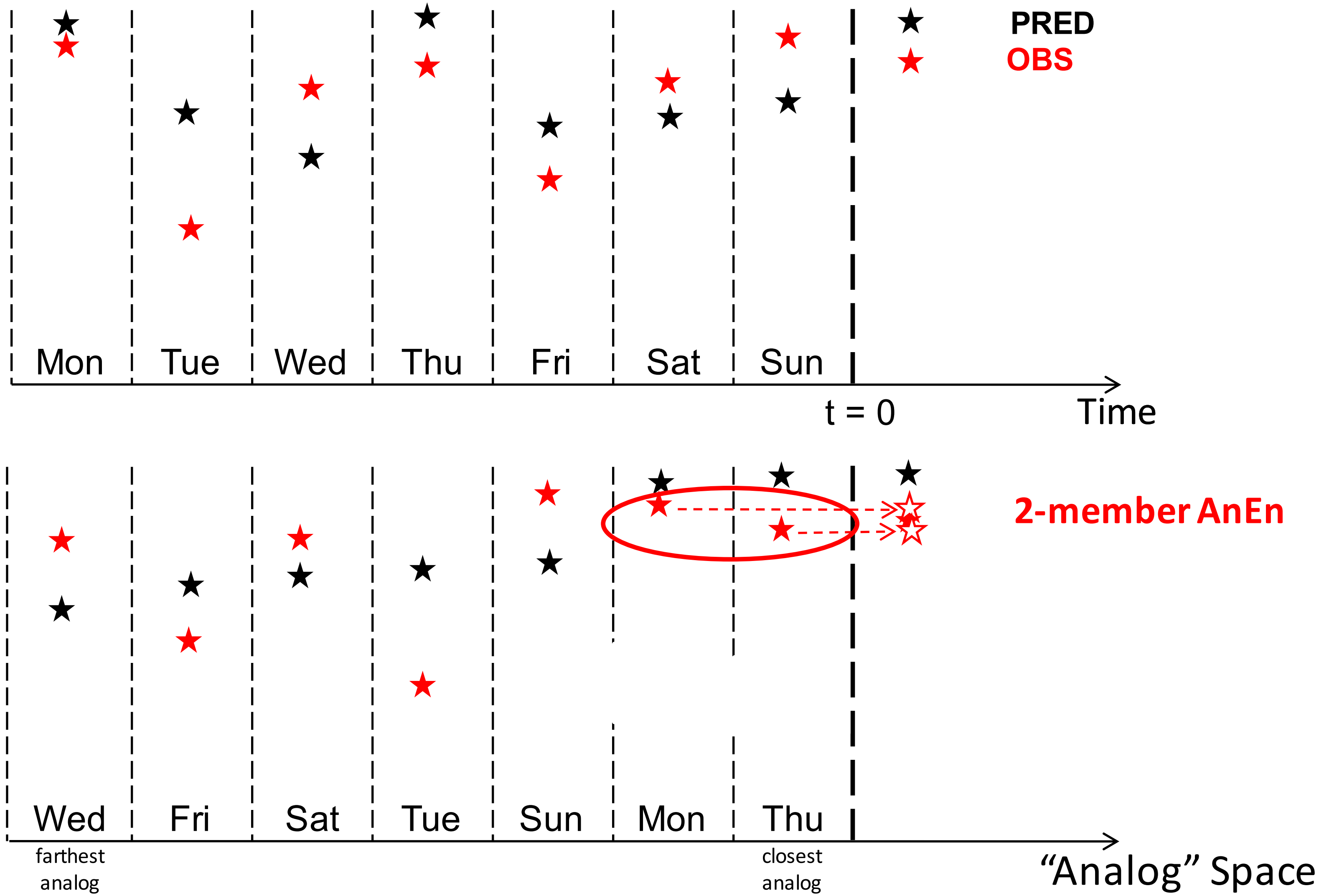


# The metric (1)

Analog strength for a particular forecast lead time *t* is measured by the distance between current and past forecast, over a short window, $2\,\tilde{t}$ wide

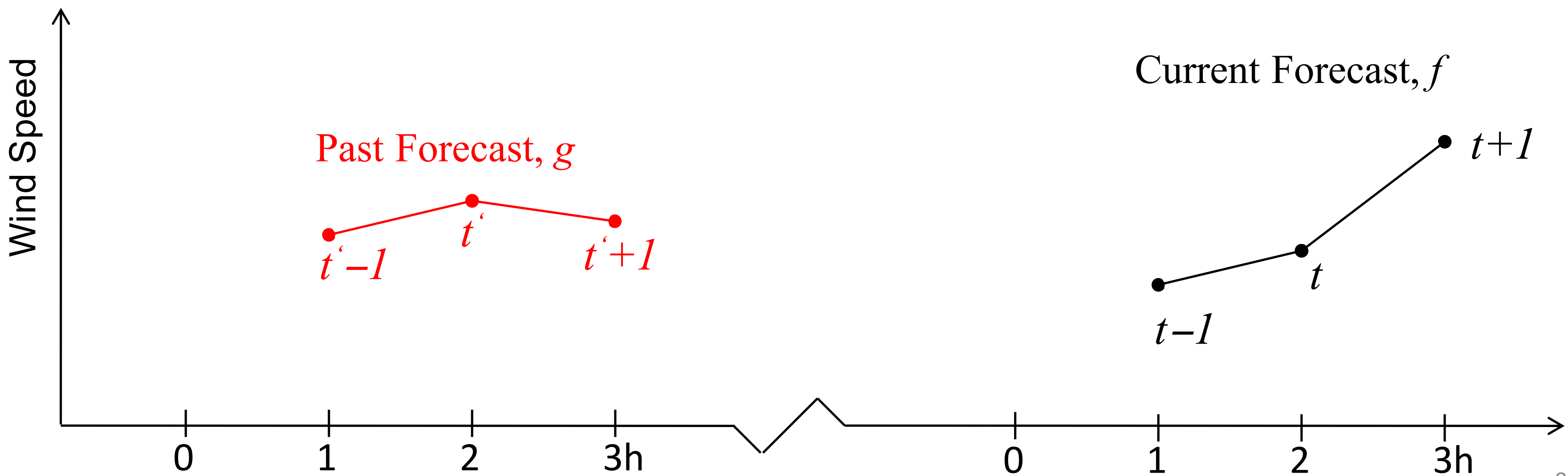
$$\left\| f_t - g_{t'} \right\| = \frac{1}{\sigma_f}\sqrt{\sum_{k=-\tilde{t}}^{+\tilde{t}}\left(f_{t+k} - g_{t'+k}\right)^2}$$

$\sigma_f$ : Forecasts' standard deviation over entire analog training period

Expanded to multiple predictor variables, but still focused on predictand $f$:
(for wind speed, predictors are speed, direction, sfc. temp., sfp pressure, and PBL depth)

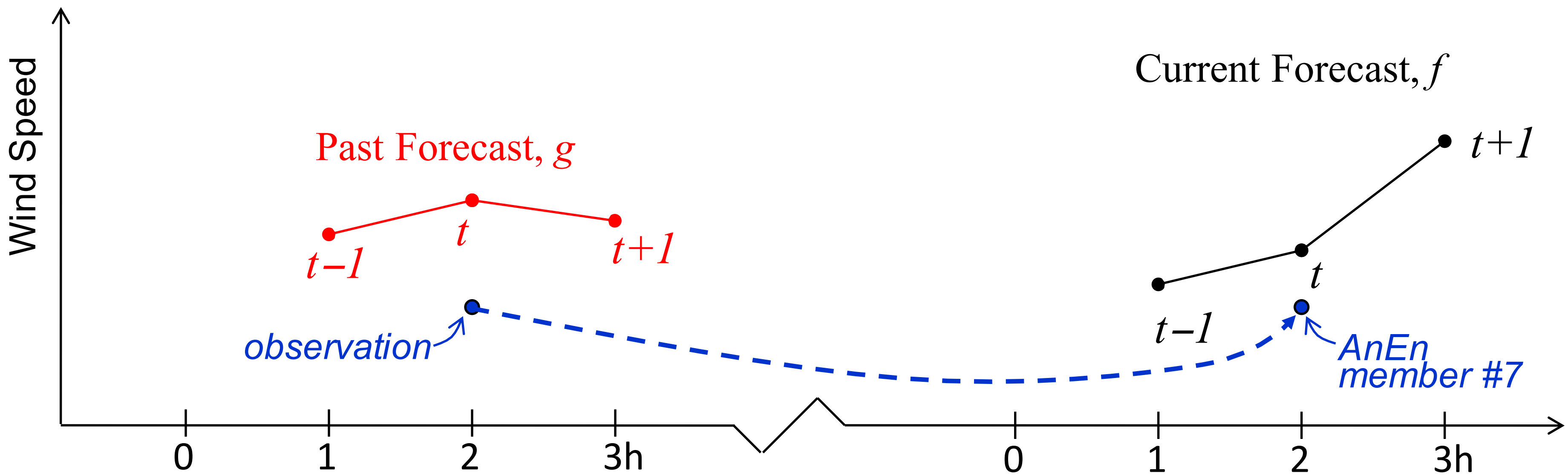
$$\left\| f_t - g_{t'} \right\| = \sum_{v=1}^{N_v}\frac{w_v}{\sigma_{f^v}}\sqrt{\sum_{k=-\tilde{t}}^{+\tilde{t}}\left(f^v_{t+k} - g^v_{t'+k}\right)^2}$$

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



# The metric (2)

After finding the $n$ strongest analogs, each of the $n$ AnEn members is taken as the verifying observation from each analog.



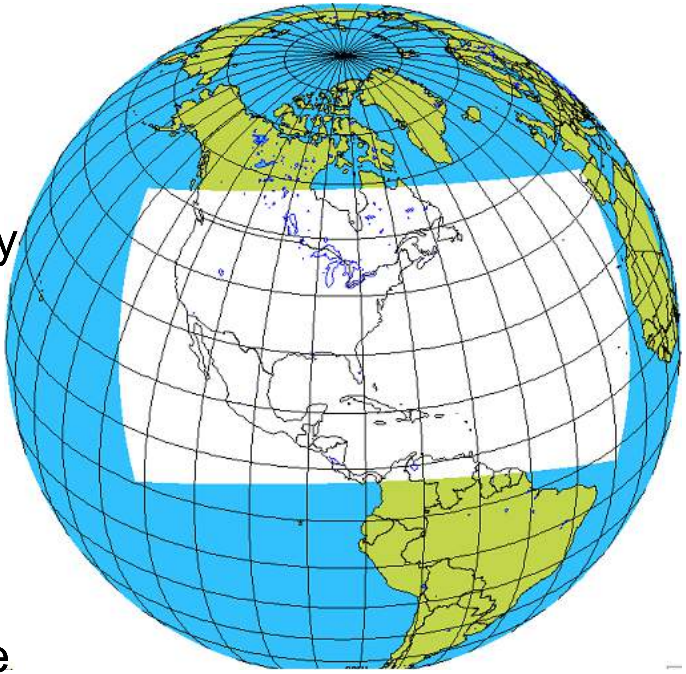
# How skillful is AnEn?

- AnEn generated with Environment Canada GEM (15 km), 0-48 hours
- Comparison with:
  - Environment Canada Regional Ensemble Prediction System (REPS, next slide)
  - Logistic Regression (LR) out of 15-km GEM
  - LR our of REPS, i.e., Ensemble Model Output Statistics (EMOS)
- Period of 15 months (verification over the last 3 months)
- 10-m wind speed
- 550 surface stations over CONUS (in two slides)
- Probabilistic prediction attributes: statistical consistency, reliability, sharpness, resolution, spread-error consistency

Delle Monache et al. (MWR 2013)

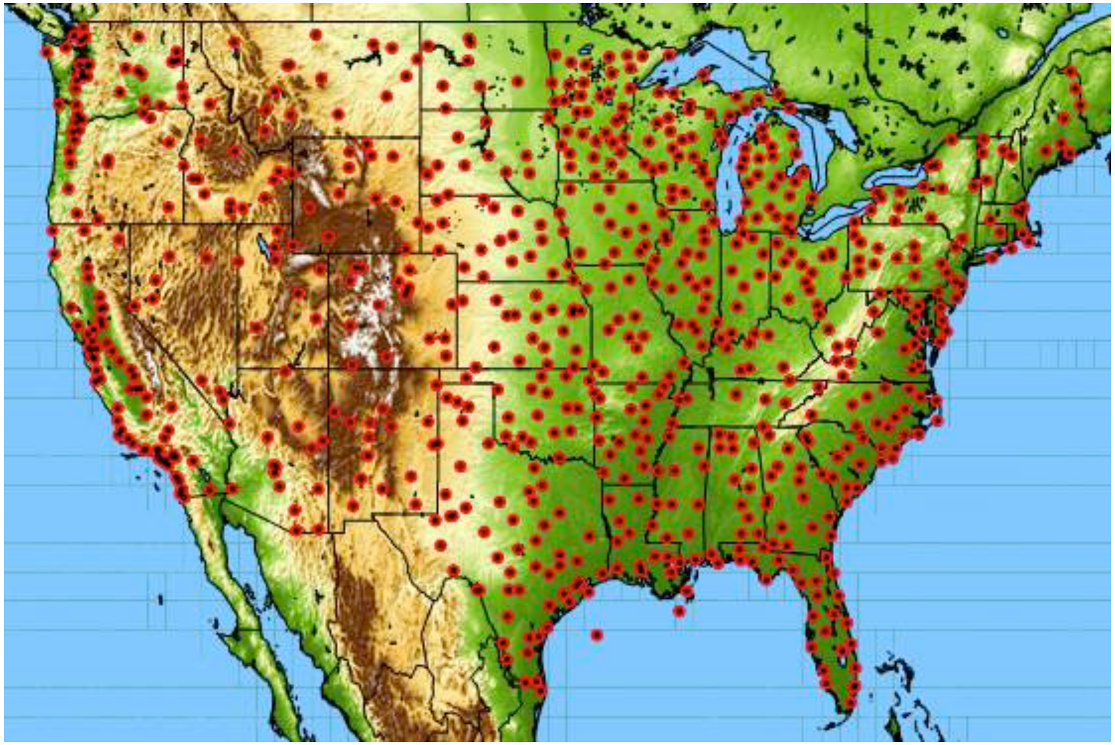
# Regional Ensemble Prediction System (REPS)

- Model: GEM 4.2.0 (vertical staggering)
- 20 members + 1 control run
- 72 hours forecast lead time
- Resolution: ~33 km with 28 levels
- Initial conditions (i.e., cold start) and 3-hourly boundary condition updates from GEPS (EnKF + multi-physics)
- Physics:
  - Kain et Fritsch (1993) for deep convection
  - Li et Barker (2005) for the radiation
  - ISBA scheme (Noilhan et Planton, 1989) for surface
- Stochastic Physics: Markov Chains on physical tendencies



# Ground truth dataset

- 550 hourly METAR Surface Observations
- 1 May 2010 – 31 July 2011, for a total of 457 days
- 10-m wind speed



# Probabilistic forecast attributes: Reliability

Example:

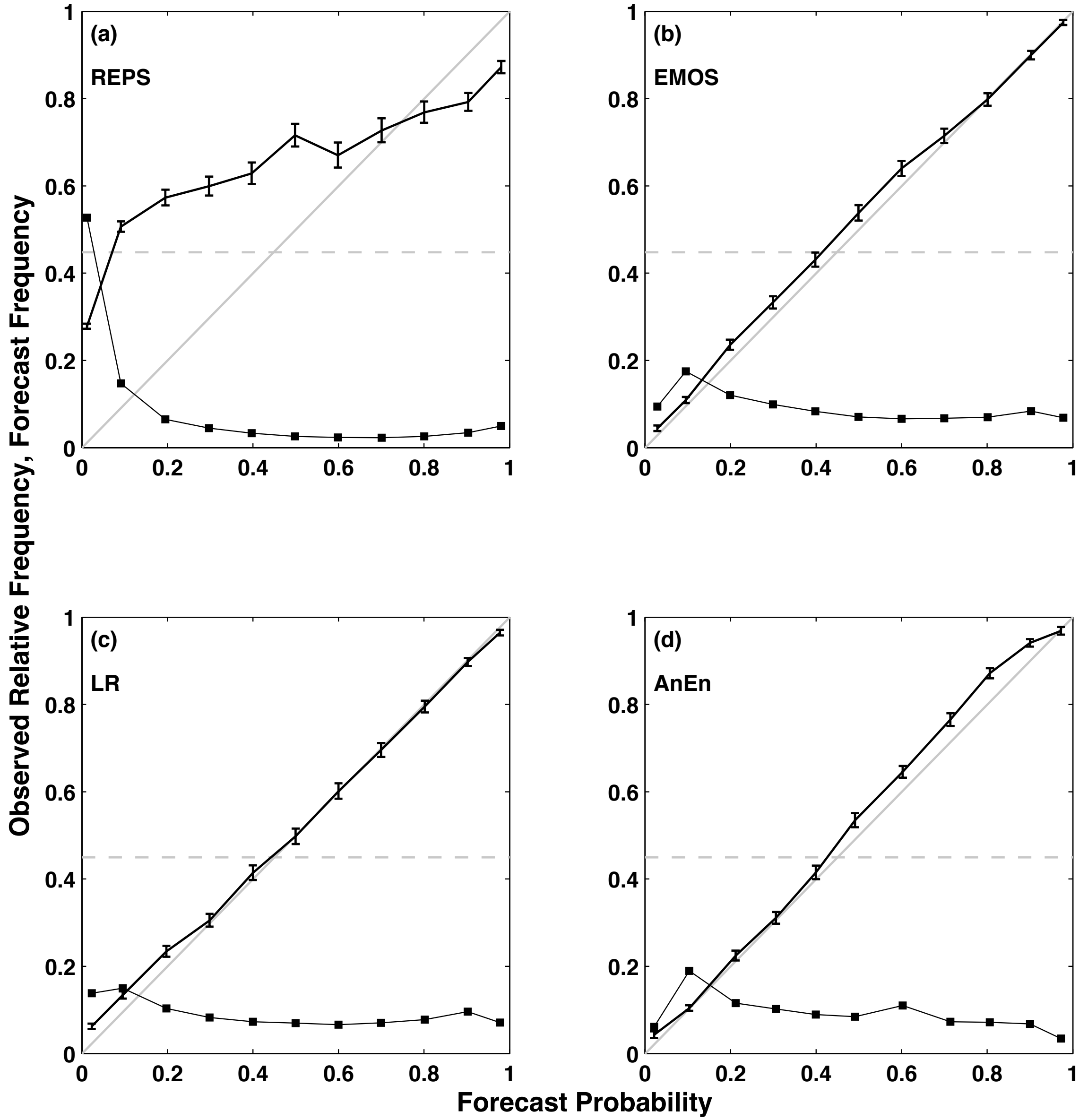
① An event (e.g., wind speed > 5 m/s) is predicted to happen with a 30% probability

② We collect the observations that verified every time we made the prediction in ①

③ If the frequency of the event in the observation collected is 30%, then the forecast is perfectly *RELIABLE*

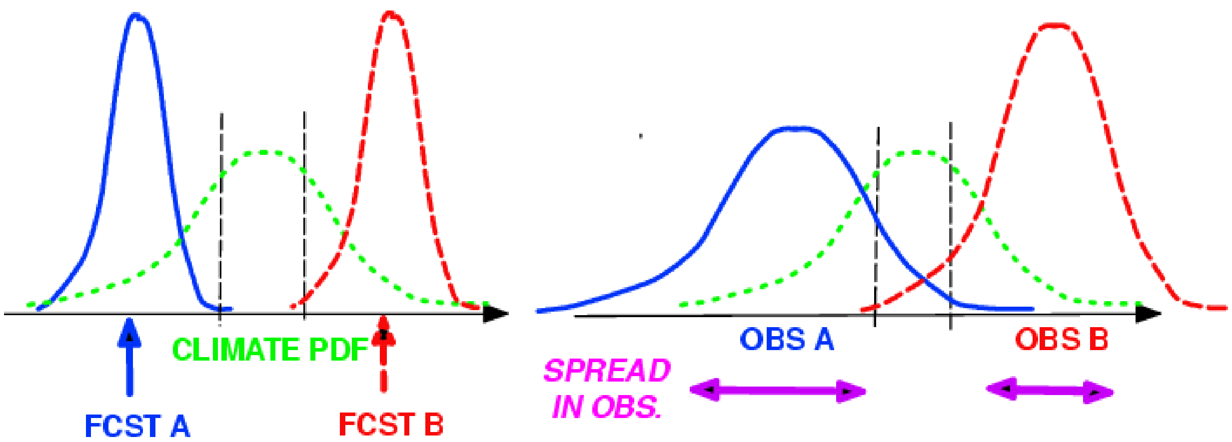
# Analysis of reliability & sharpness

Reliability and sharpness diagram: 10-m wind speed > 5 m $s^{-1}$, 9-h fcst



# Probabilistic forecast attributes: Resolution

NCAR




Consider different classes of forecast events.

If all observed classes corresponds to different forecast classes, then the probabilistic forecast has perfect *RESOLUTION*.

# Analysis of Resolution (1)

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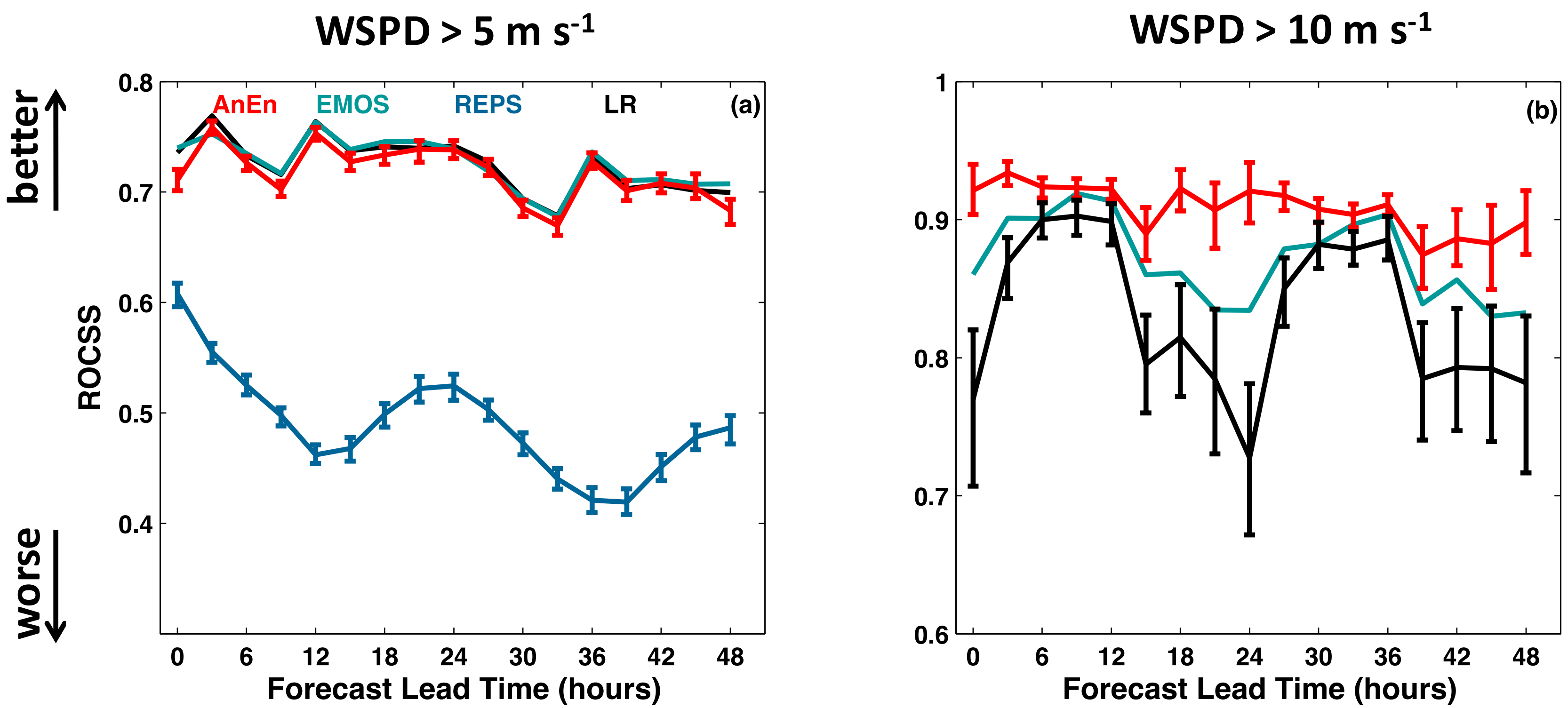
Relative Operating Characteristics skill score, 10-m wind speed ≥ 5, 10 m s$^{-1}$




**AnEn**: Analog Ensemble applied to Environment Canada's 15-km deterministic GEM

**LR**: Logistic Regression applied to Environment Canada's 15-km deterministic GEM

**REPS**: Environment Canada's Regional Ensemble Prediction System

**EMOS**: Ensemble Model Output Statistics applied to REPS

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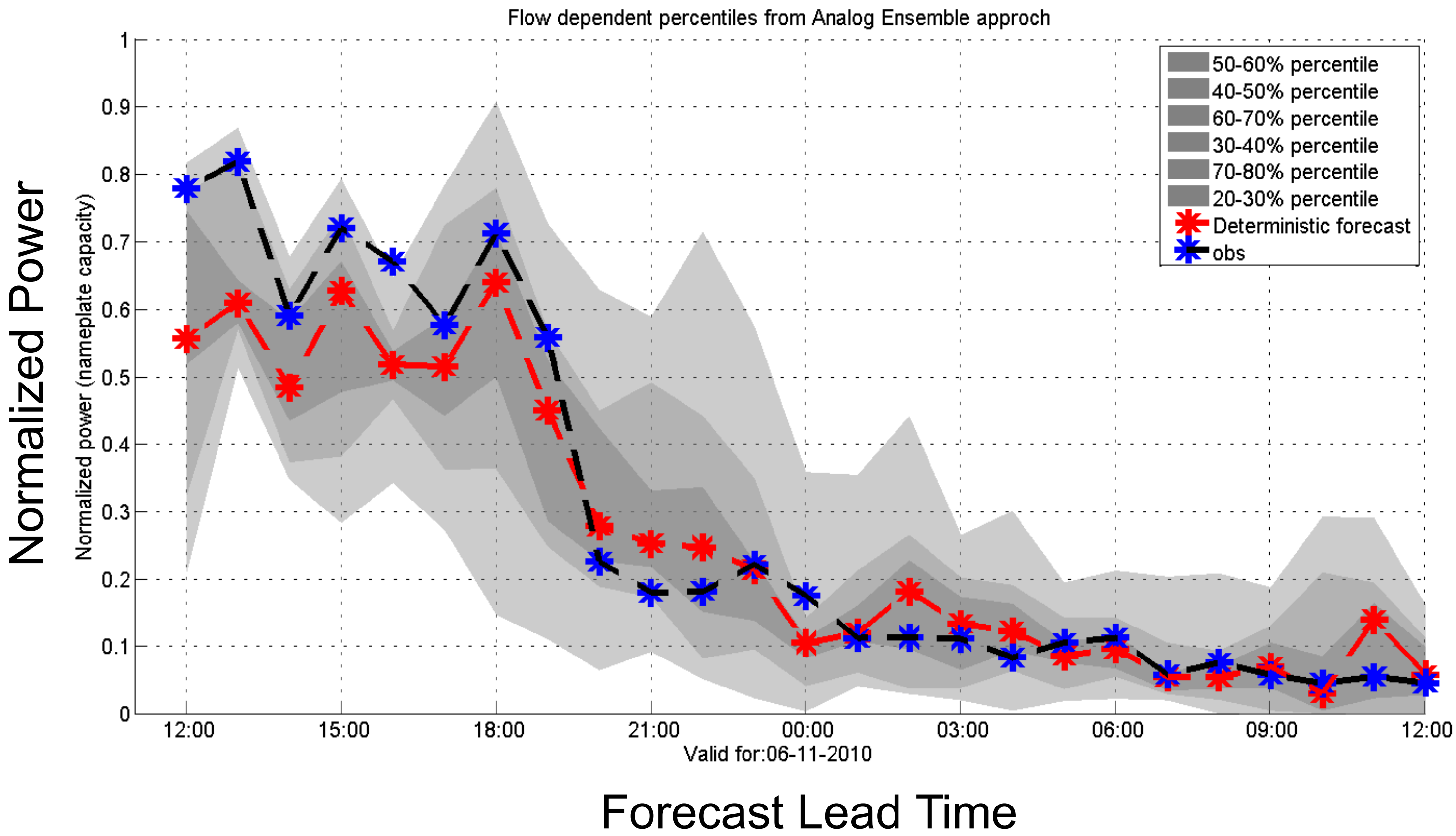
# Power predictions: Experiment design

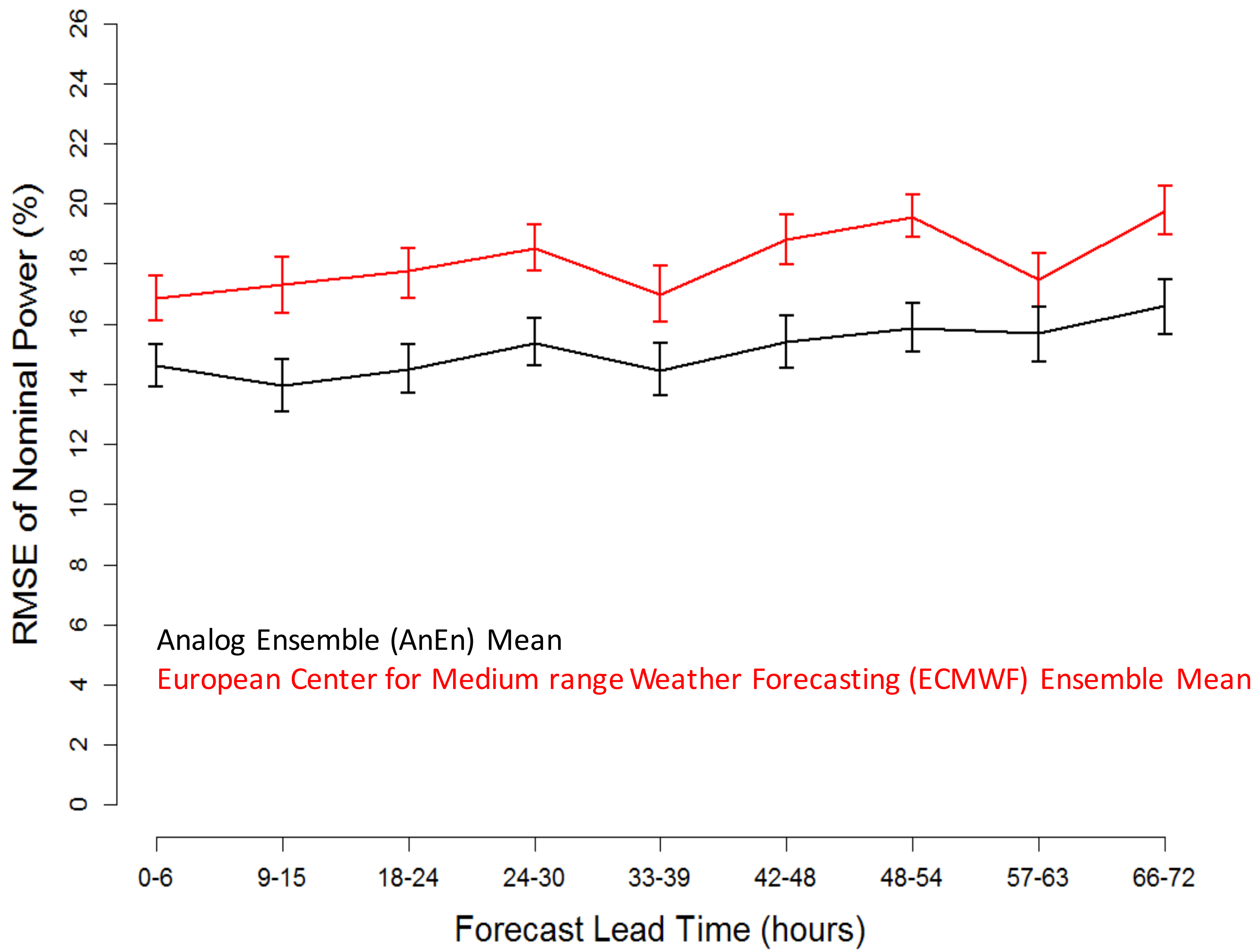
- Test site: Wind farm in northern Sicily − 9 turbines, 850 kW Nominal Power (NP)
- Training period: November 2010 - October 2012
- Verification period: November 2011 – October 2012
- Probabilistic prediction systems: ECMWF EPS, COSMO LEPS, AnEn

Alessandrini et al. (RE 2015)

# Power predictions



# RMSE of ensemble means

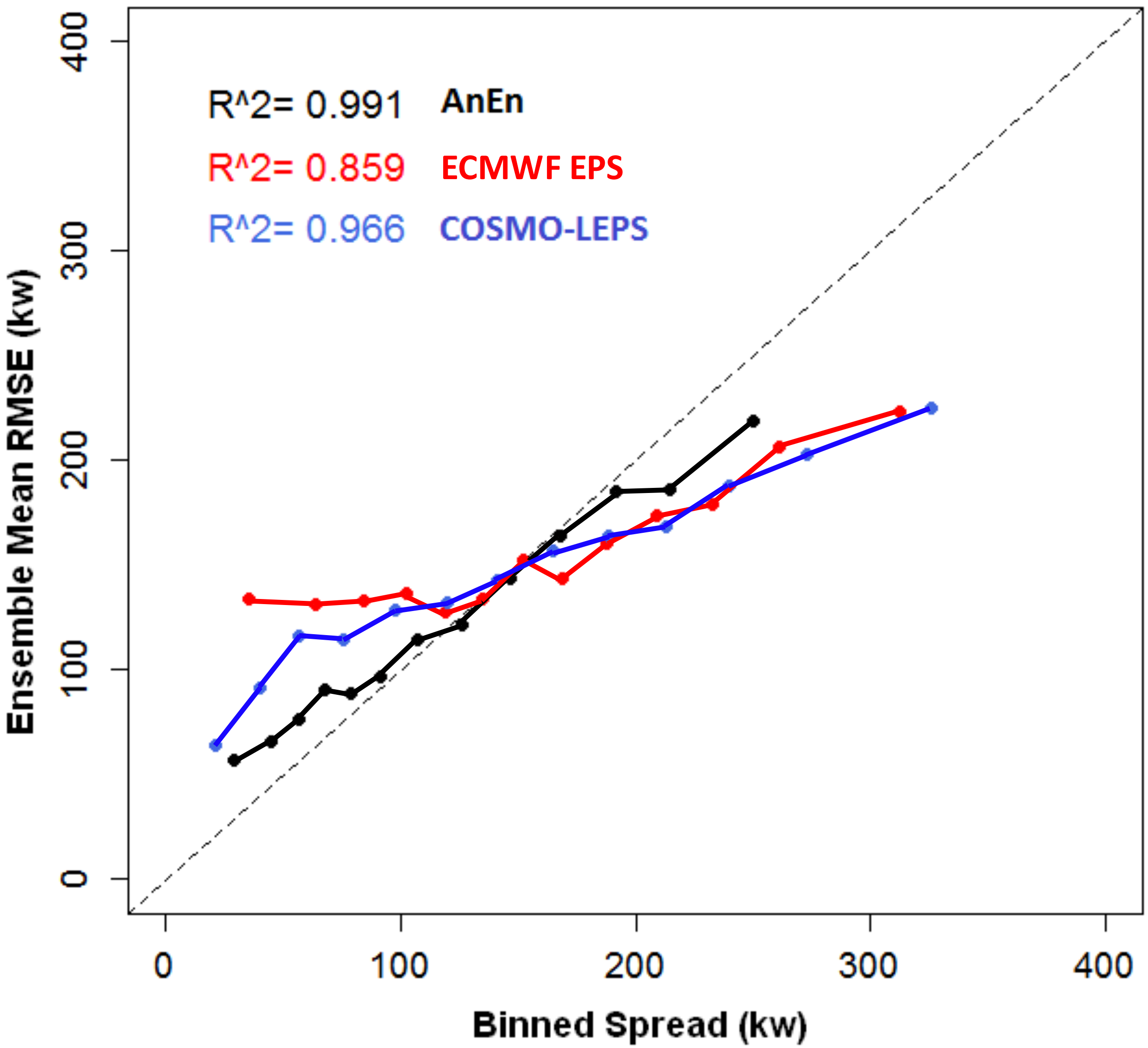


# Probabilistic forecast attributes: Statistical and spread-error consistency

① The ensemble spread tell us how uncertain a forecast is. Ideally, large spread should be associate with larger uncertainties, low spread should indicate higher accuracy

① If an ensemble is perfect, than the observations are indistinguishable from the ensemble members

# Spread-skill relathionship



# Analog predictor weight optimization

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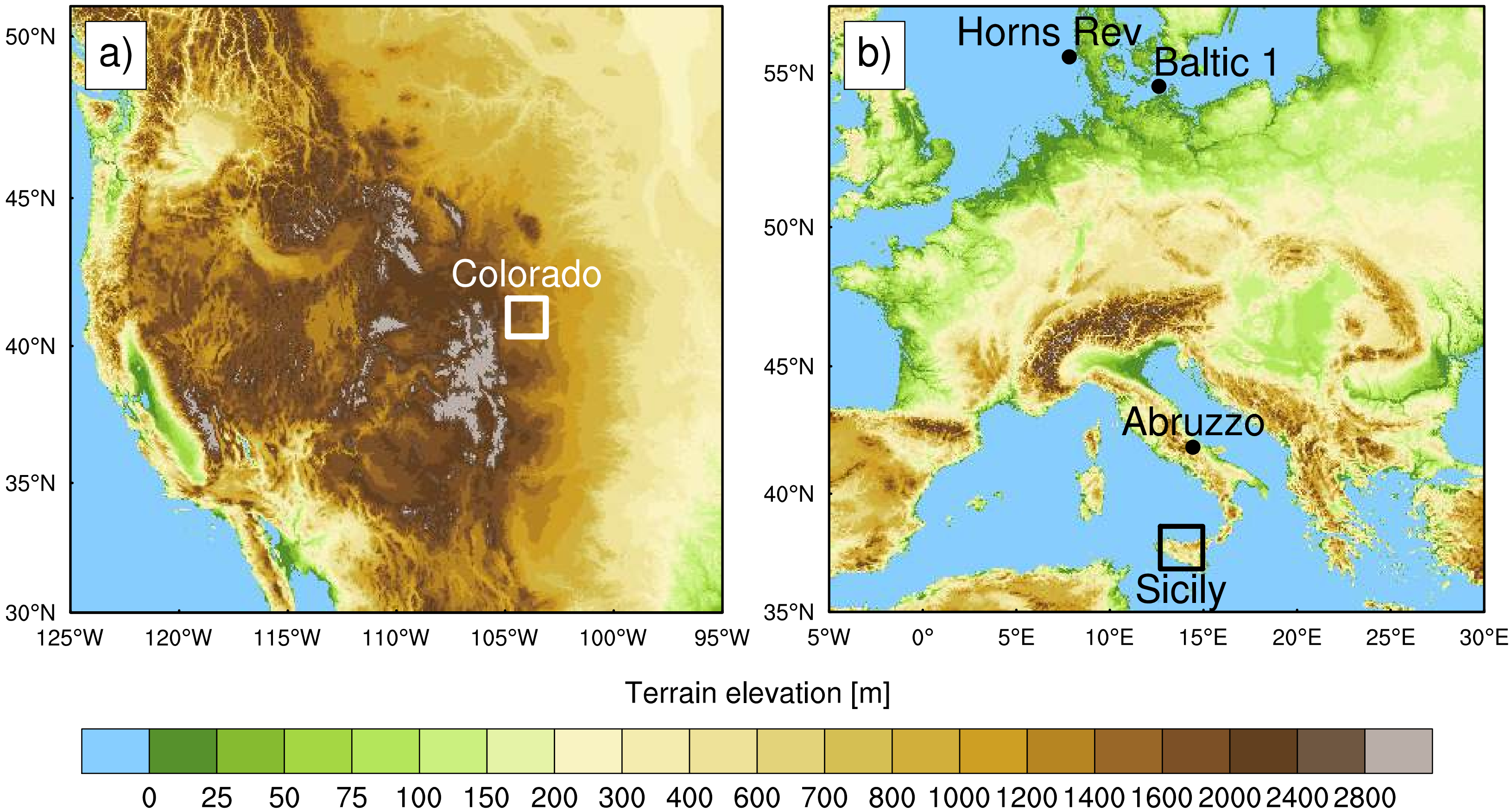
$$\left\| f_t - g_{t'} \right\| = \sum_{v=1}^{N_v} \frac{w_v}{\sigma_{f^v}} \sqrt{\sum_{k=-\tilde{t}}^{+\tilde{t}} \left( f_{t+k}^{v} - g_{t'+k}^{v} \right)^2}$$

$N_v$ : Number of predictor variables

$w_v$ : Weight given to each predictor

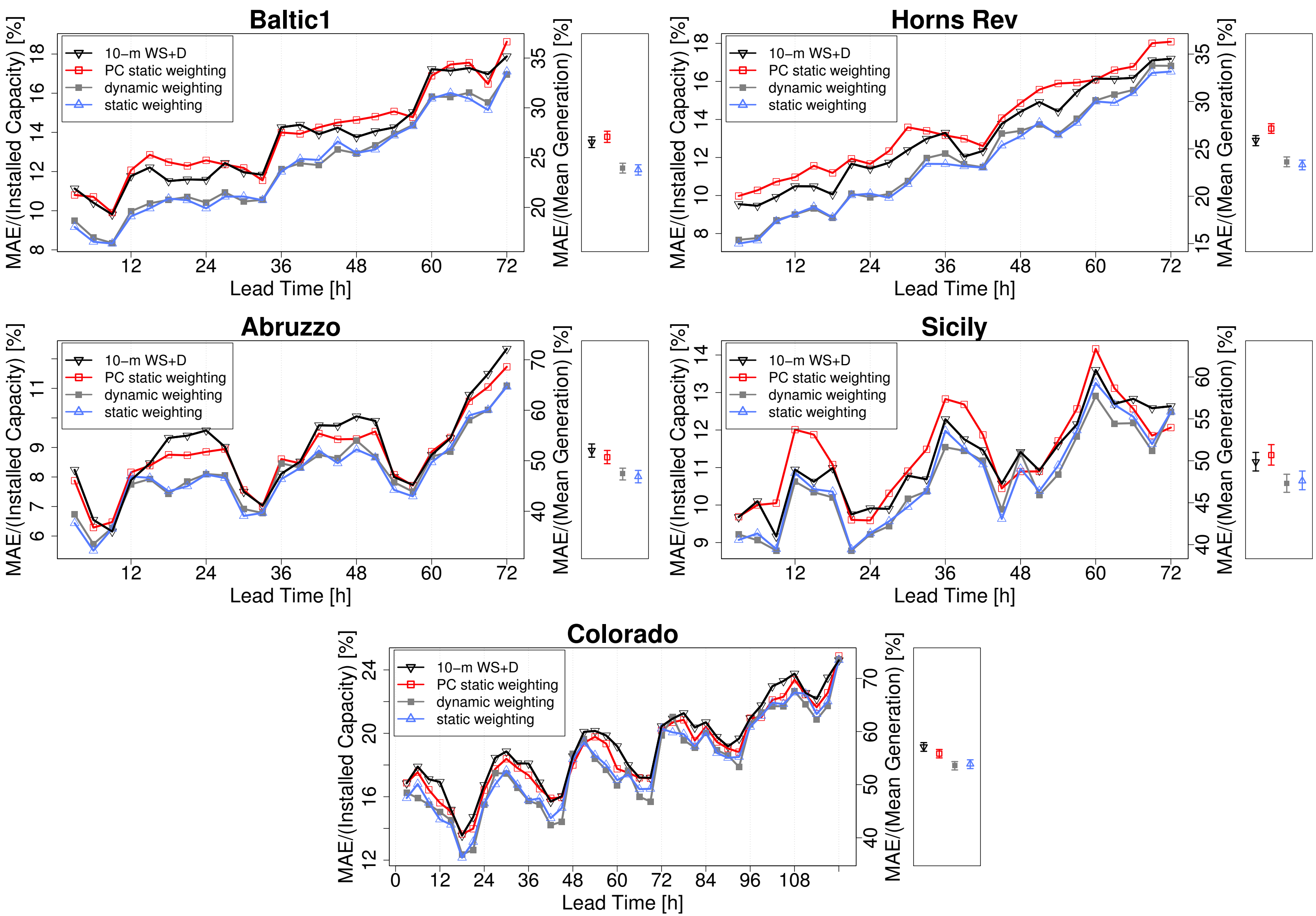
$\sigma_f$ : Forecasts' standard deviation over entire analog training period

# Analog predictors weighting strategies: Data locations




Junk et al. (WE 2015)

# Analog predictors weighting strategies: Impact on deterministic prediction



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# Data sets

- Variable: 10-m wind speed (WS)
- Period: March 2012 – March 2015
- Domain (right): Northern Italy, 500 km x 500 km (0.25° horizontal resolution, 513 grid points)
- "Ground-truth": European Centre for Medium-Range Weather Forecasts (ECMWF) Analysis (0.125° horizontal resolution; 0, 6, 12, 18 UTC)
- ECMWF deterministic forecast (DET)
- (0.125° horizontal resolution; +144 h lead time; 3-hourly forecasts)
- ECMWF Ensemble Prediction System (EPS)

 (0.25° horizontal resolution; 51 members; +144 h lead time; 3-hourly forecasts)
- AnEn also generated using EPS Control Run

 (AnEn CR vs AnEn DET)


Source: Google Earth

Sperati et al. (2016, in preparation)

# Experiment set-up

- Methods:
  - **Calibrated EPS**: calibrated ECMWF EPS
  - **AnEn DET**: AnEn generated from ECMWF deterministic run

    NOTE: DA + forecast generation ~**6-8 times** cheaper than EPS calibrated
  - **AnEn CR**: AnEn generated from ECMWF EPS control run

    NOTE: forecast generation **51 times** cheaper than EPS calibrated
- Training: March 2012 – February 2014
  - Search of analogs for AnEn
  - Variance Deficit calibration for ECMWF EPS (Buizza et al. *Q. J. Roy. Meteor. Soc.* 2003; Alessandrini et al. *Appl. Energy* 2013)
- Verification: March 2014 – March 2015
- Several deterministic and probabilistic metrics

# Metrics for ensemble means

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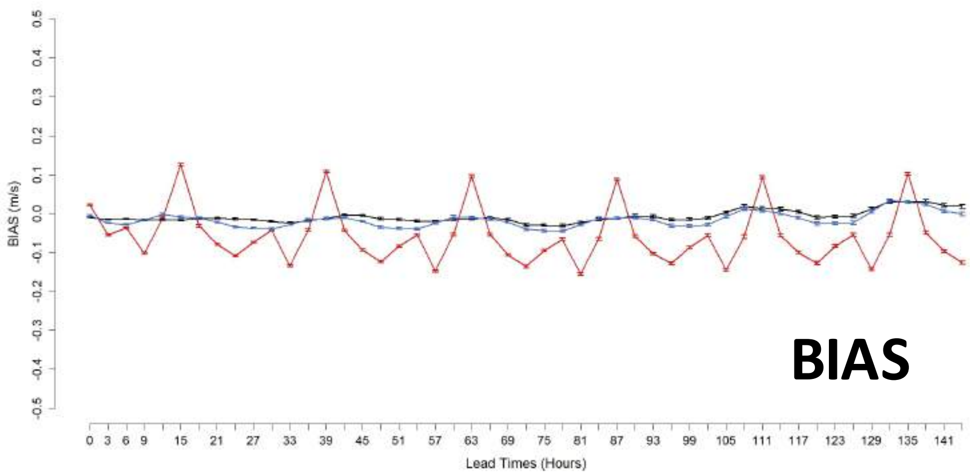
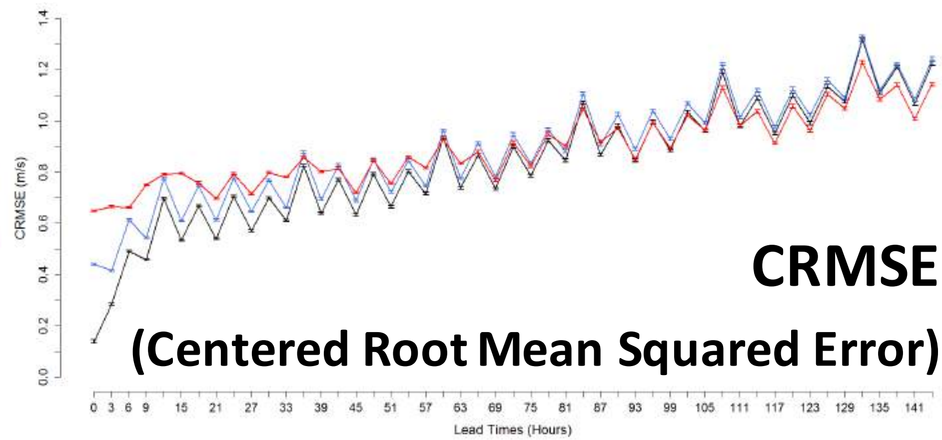
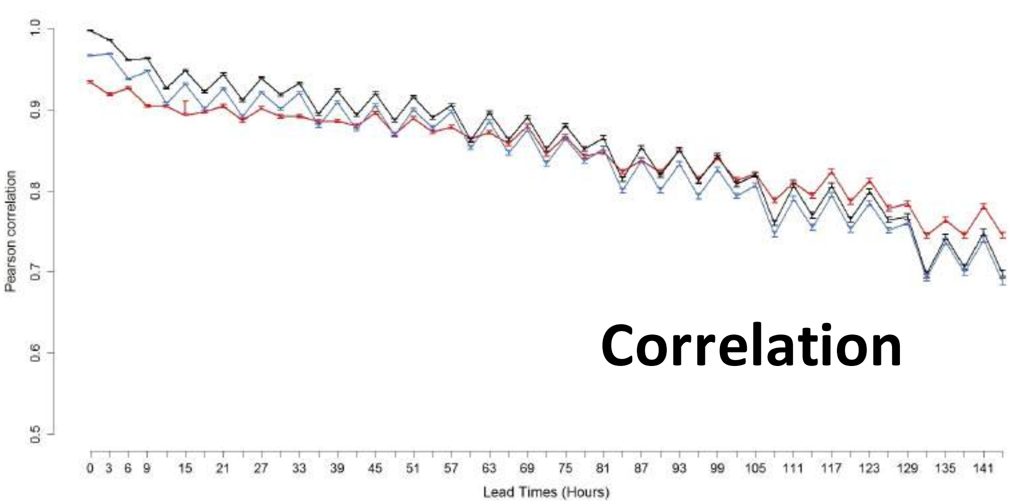


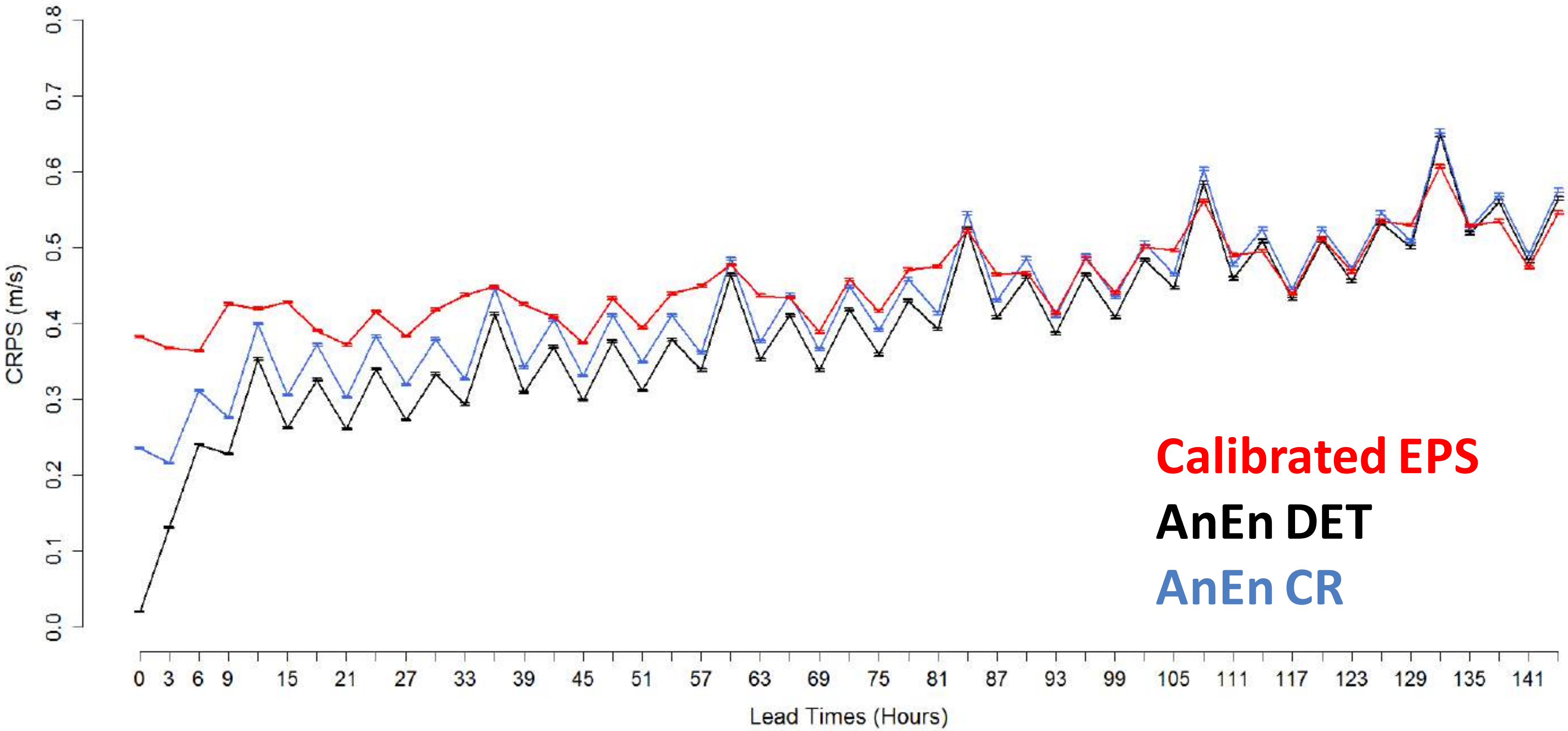




Calibrated EPS

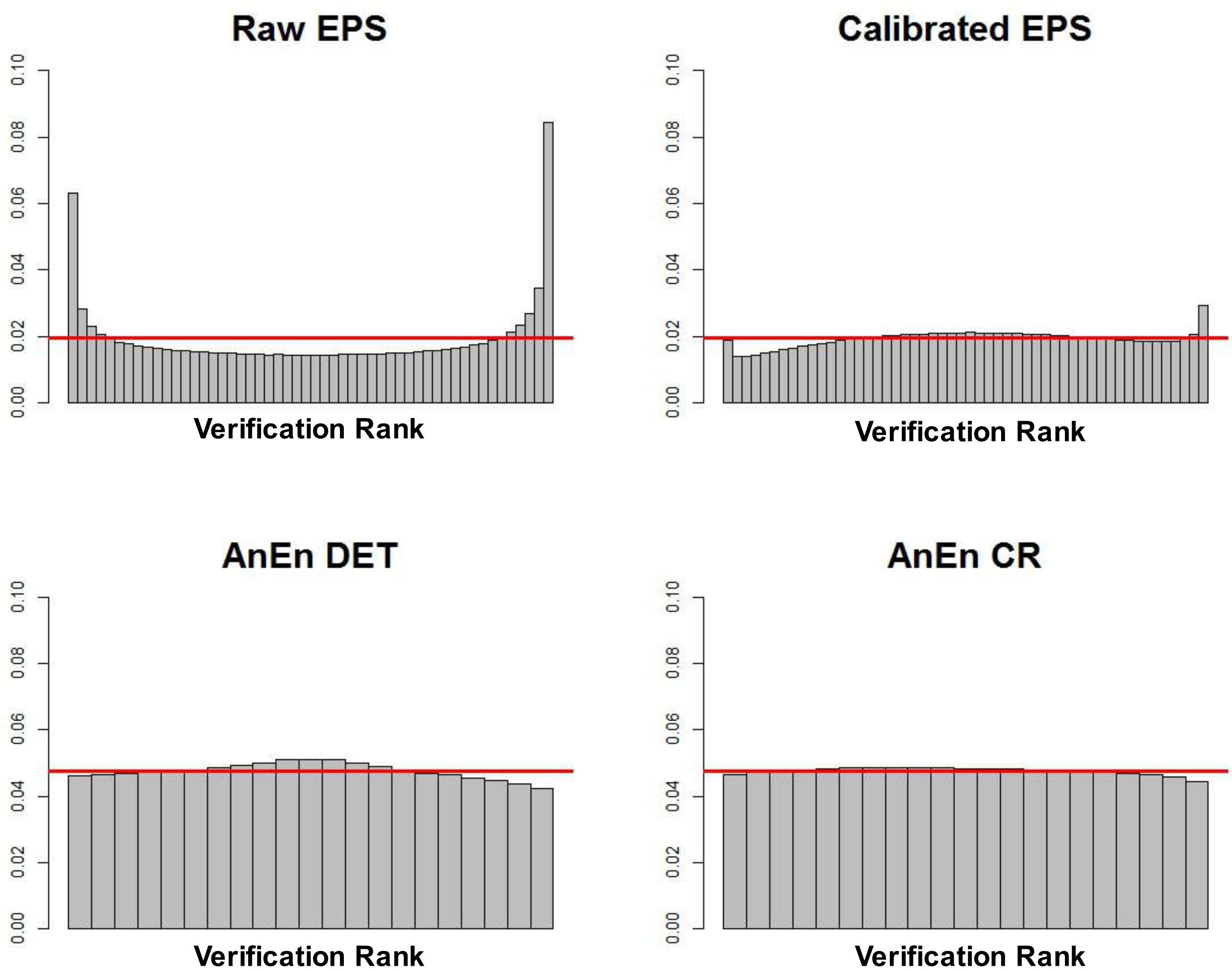
AnEn DET

AnEn CR

# Continuous Ranked Probability Score

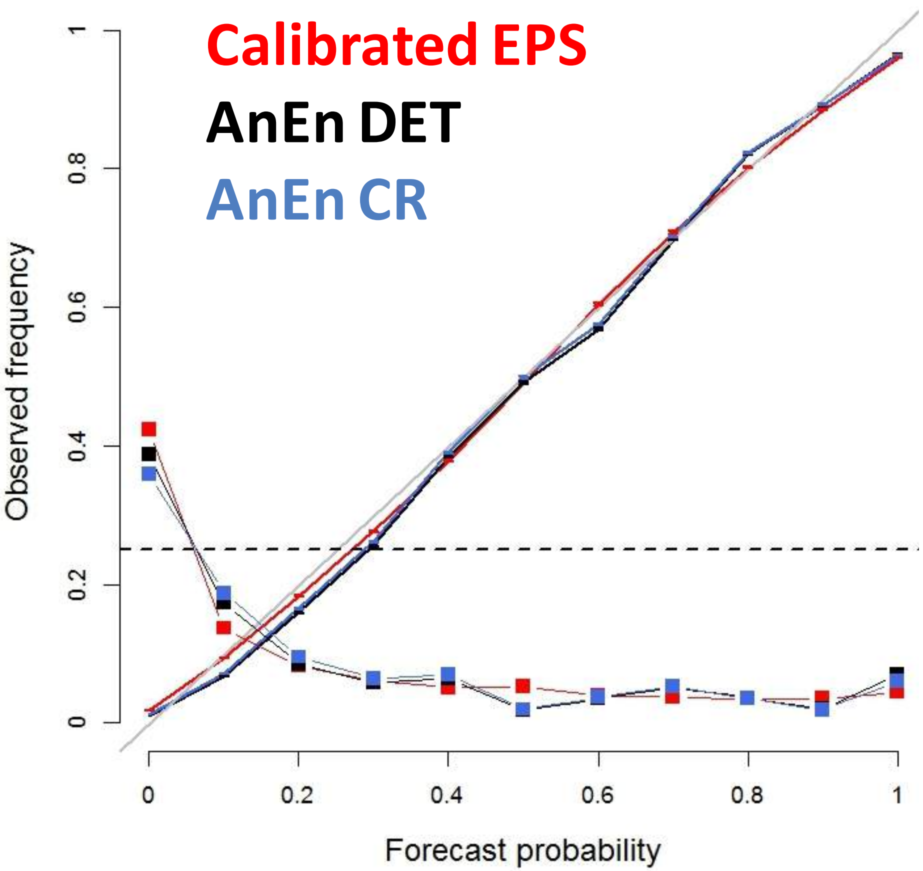


# Rank histograms

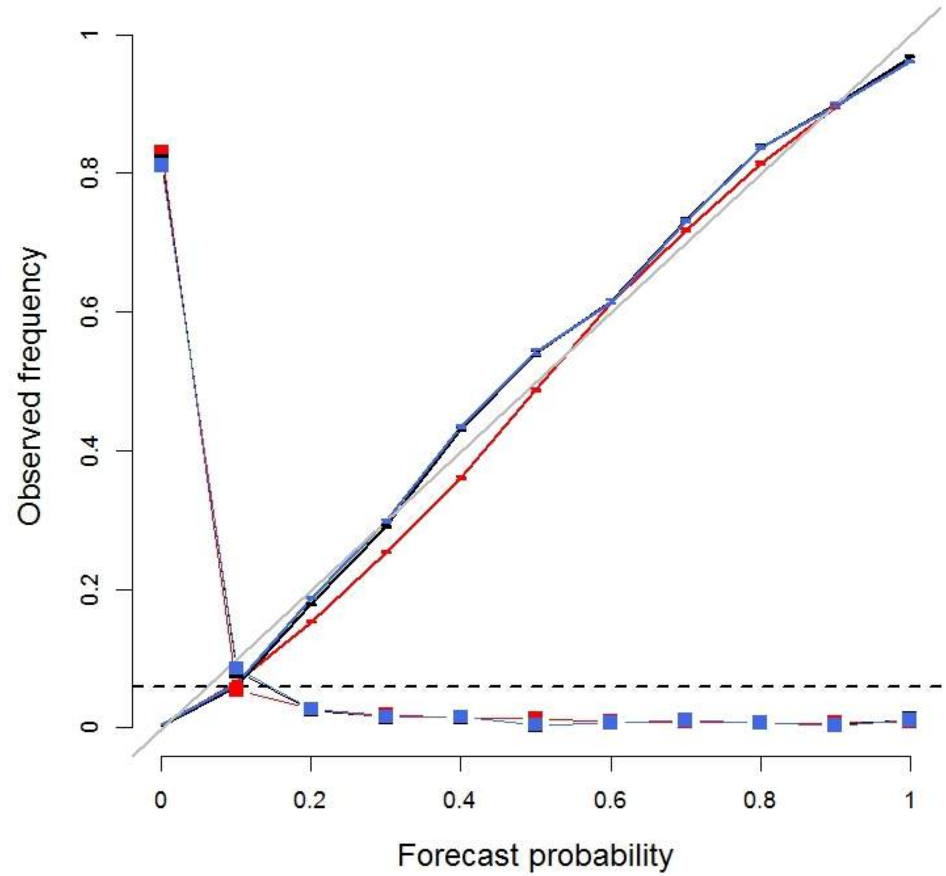


# Reliability and Sharpness

**Threshold: WS > 2.5 m s$^{-1}$**




**Threshold: WS > 5.0 m s$^{-1}$**

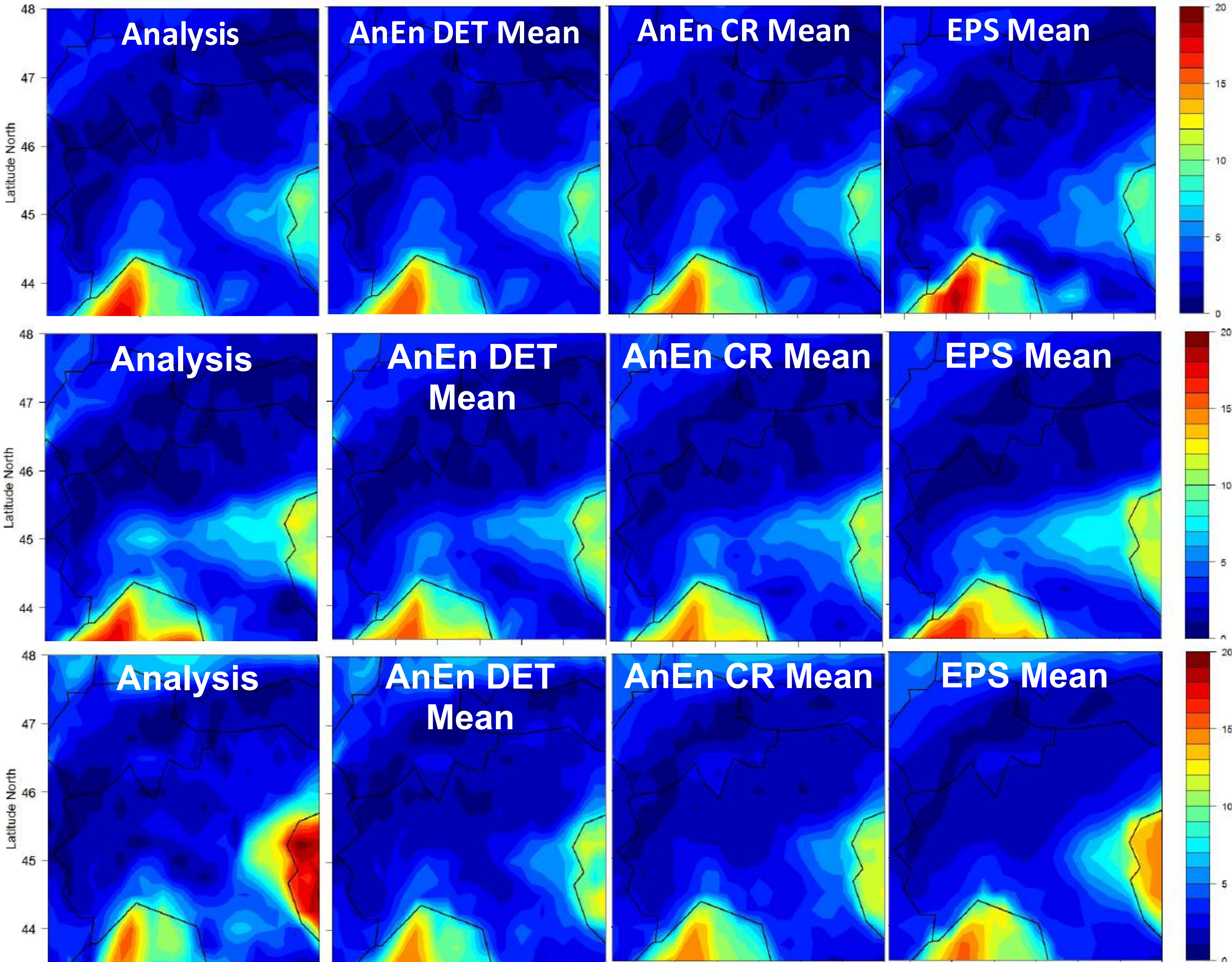


# WS (m s$^{-1}$)

4 Feb 15 00 UTC 0-h Lead Time

5 Feb 15 00 UTC 24-h Lead Time

6 Feb 15 00 UTC 48-h Lead Time



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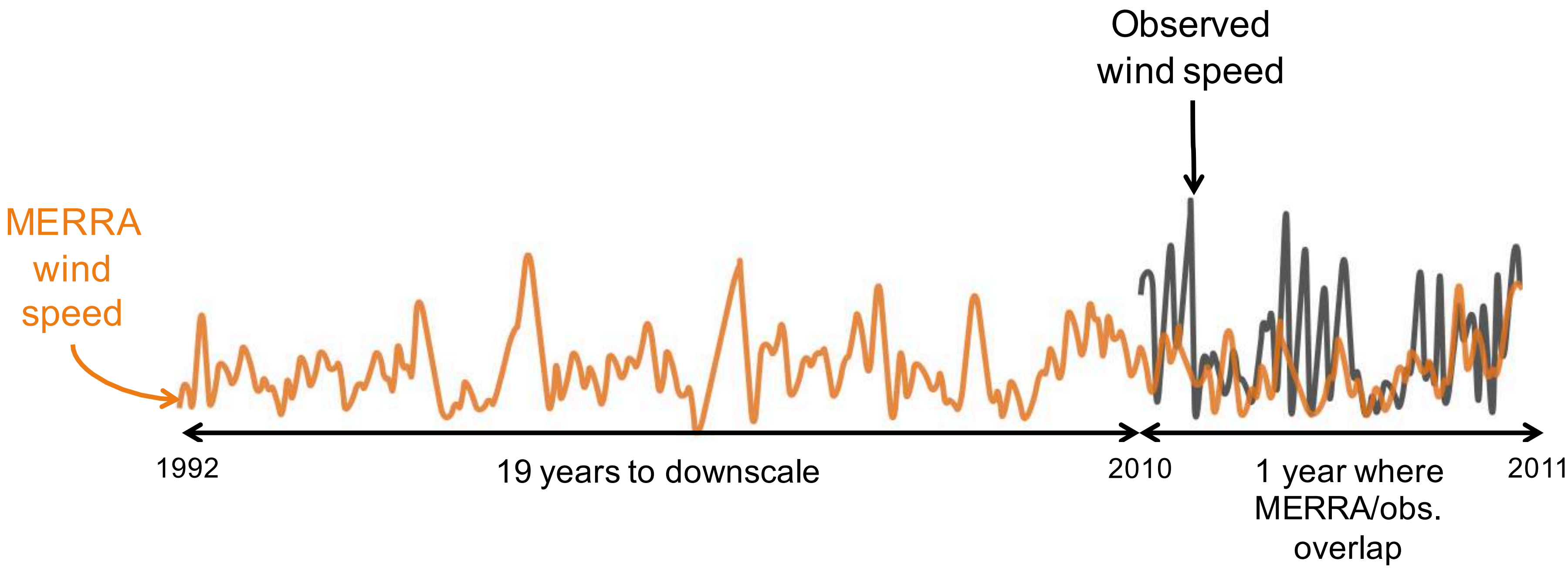
# AnEn for wind resource assessment

NCAR

- Recreate a long-term observation-based wind climatology at site
- Downscale a long-term NASA Modern-Era Retrospective Analysis for Research and Applications (MERRA) time series using a short-term record of observations



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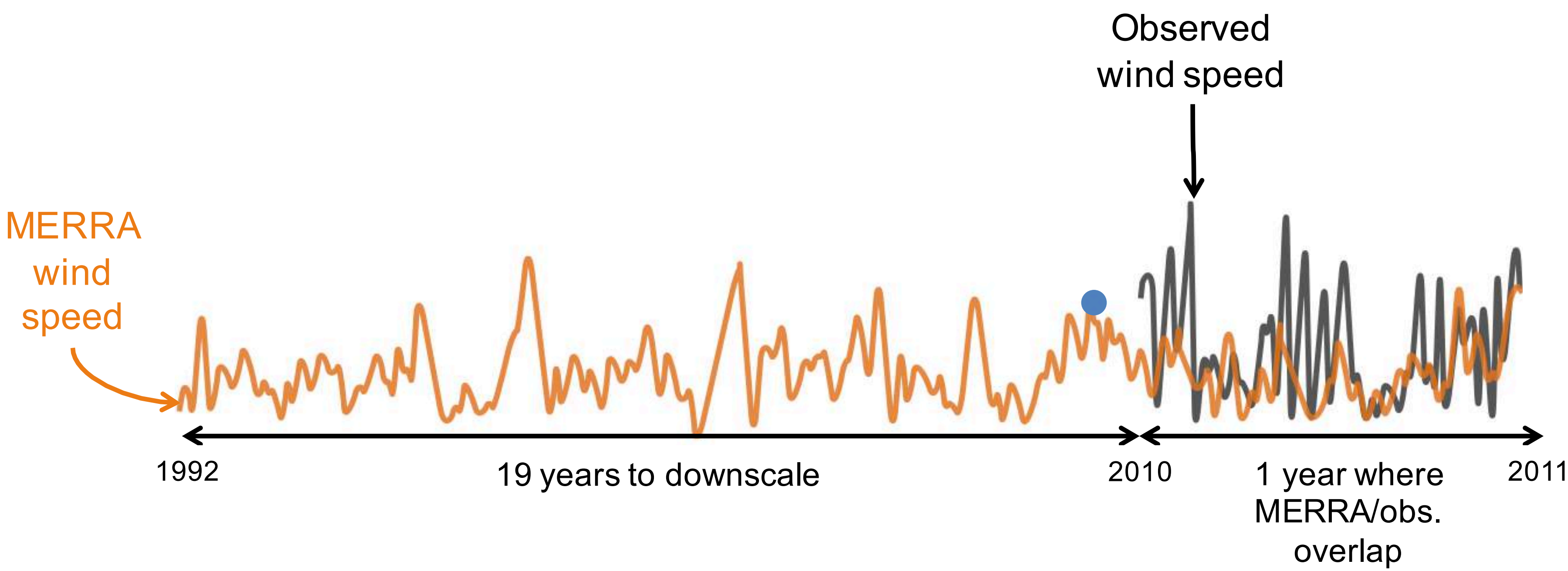

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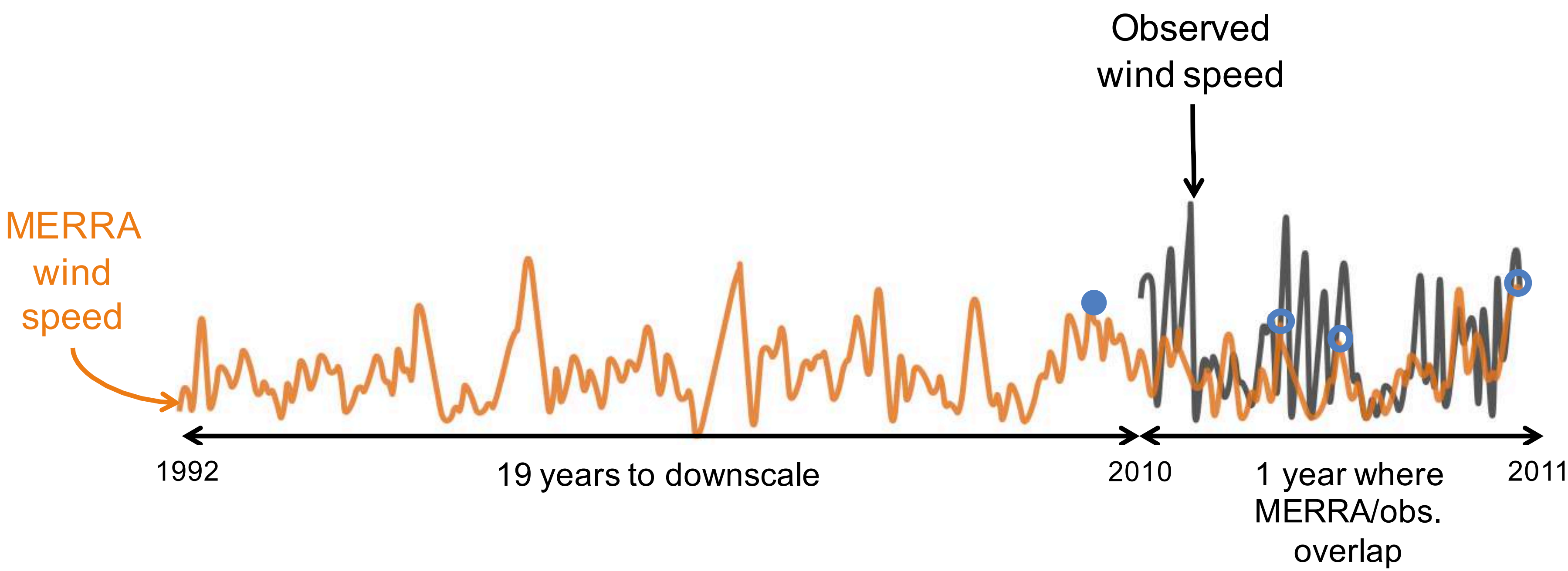

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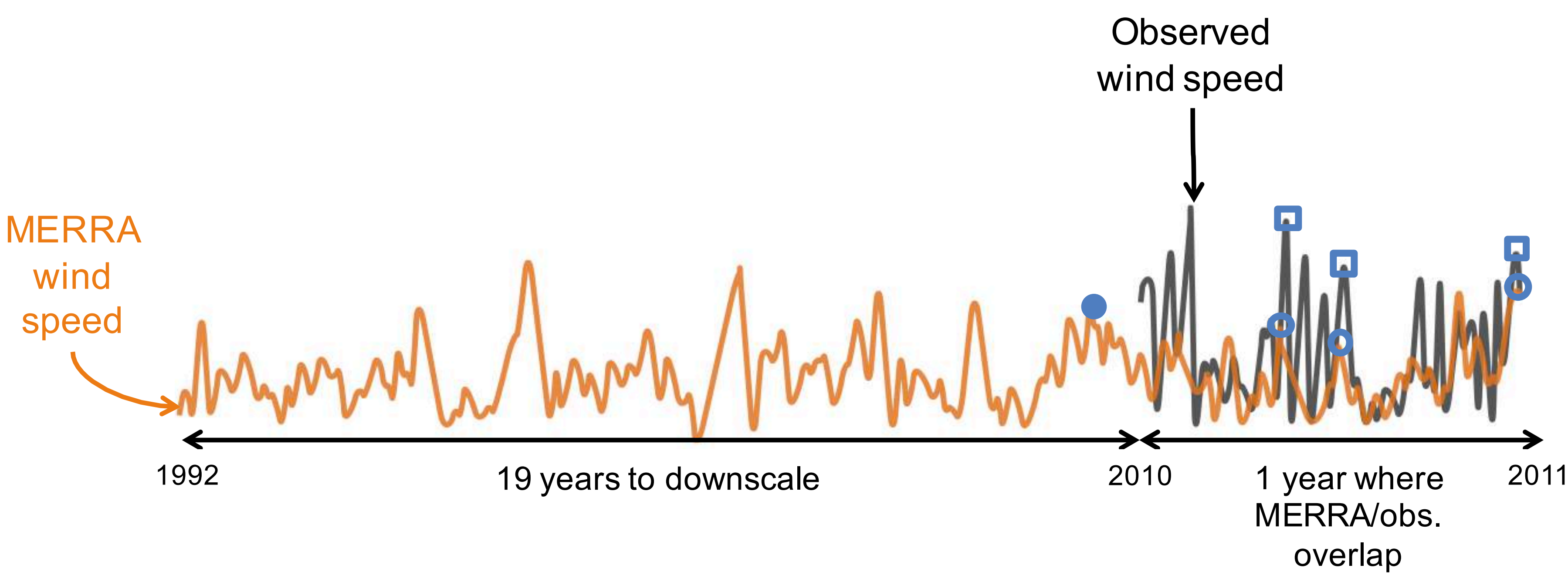

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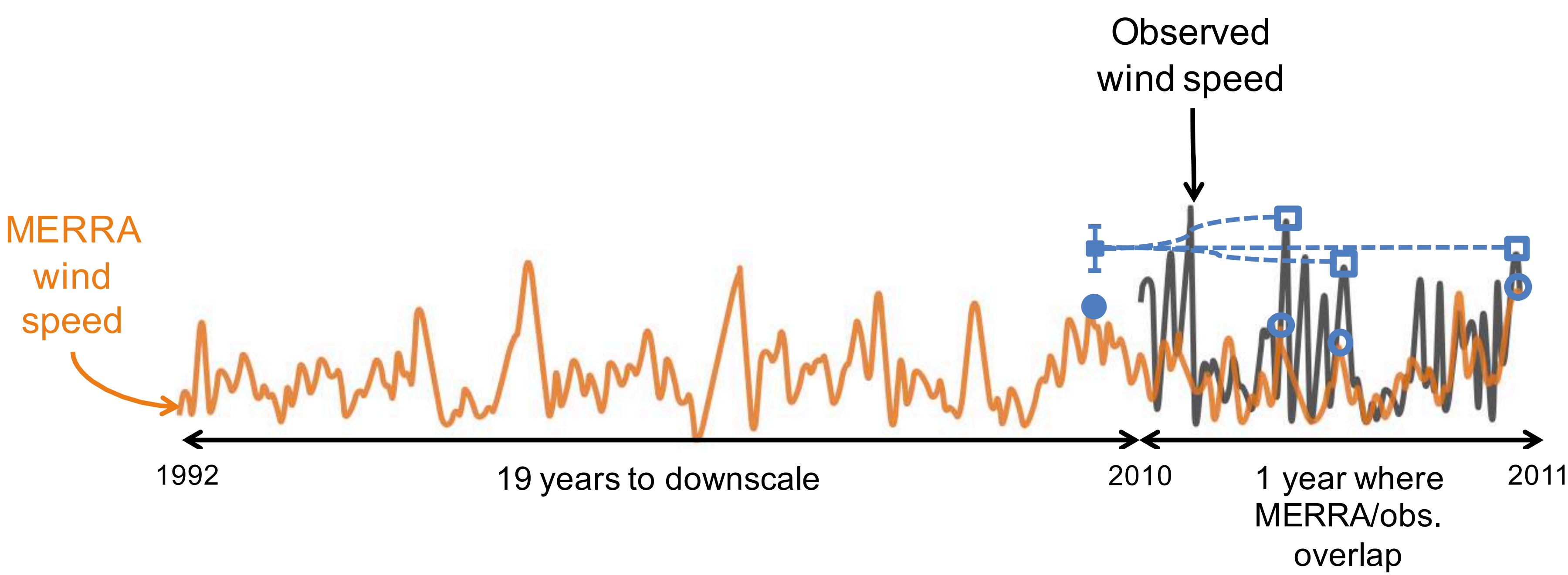
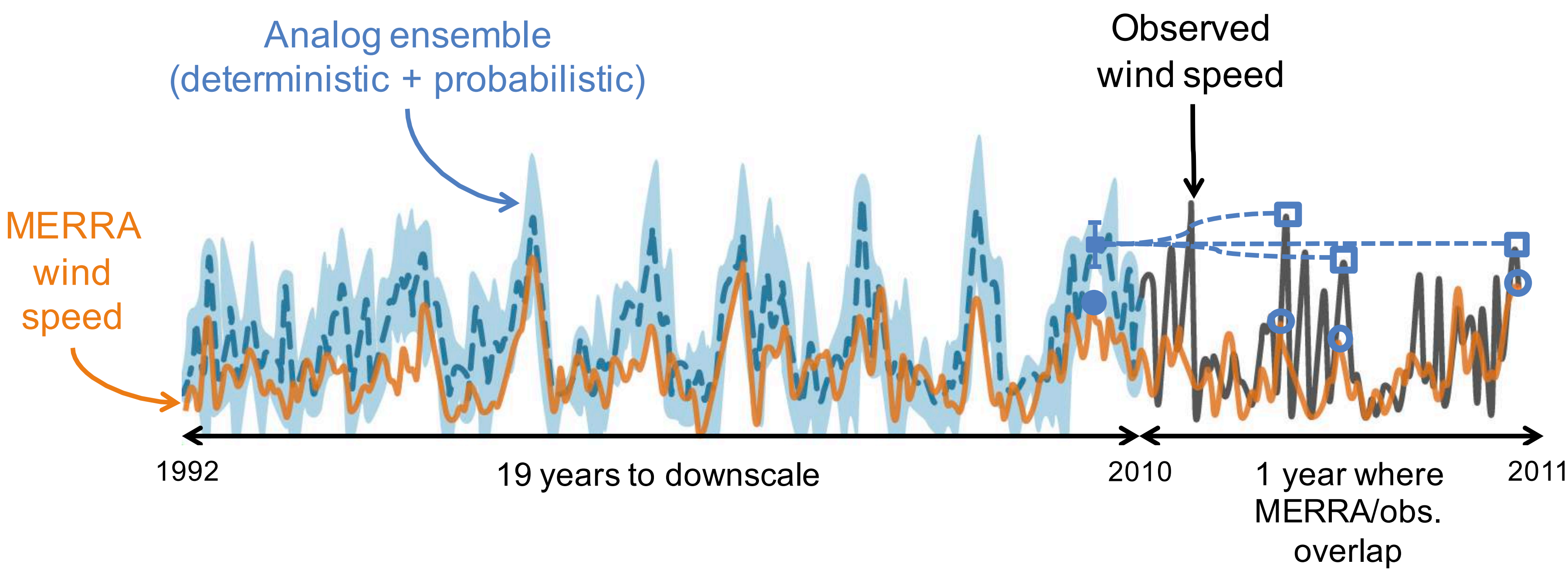


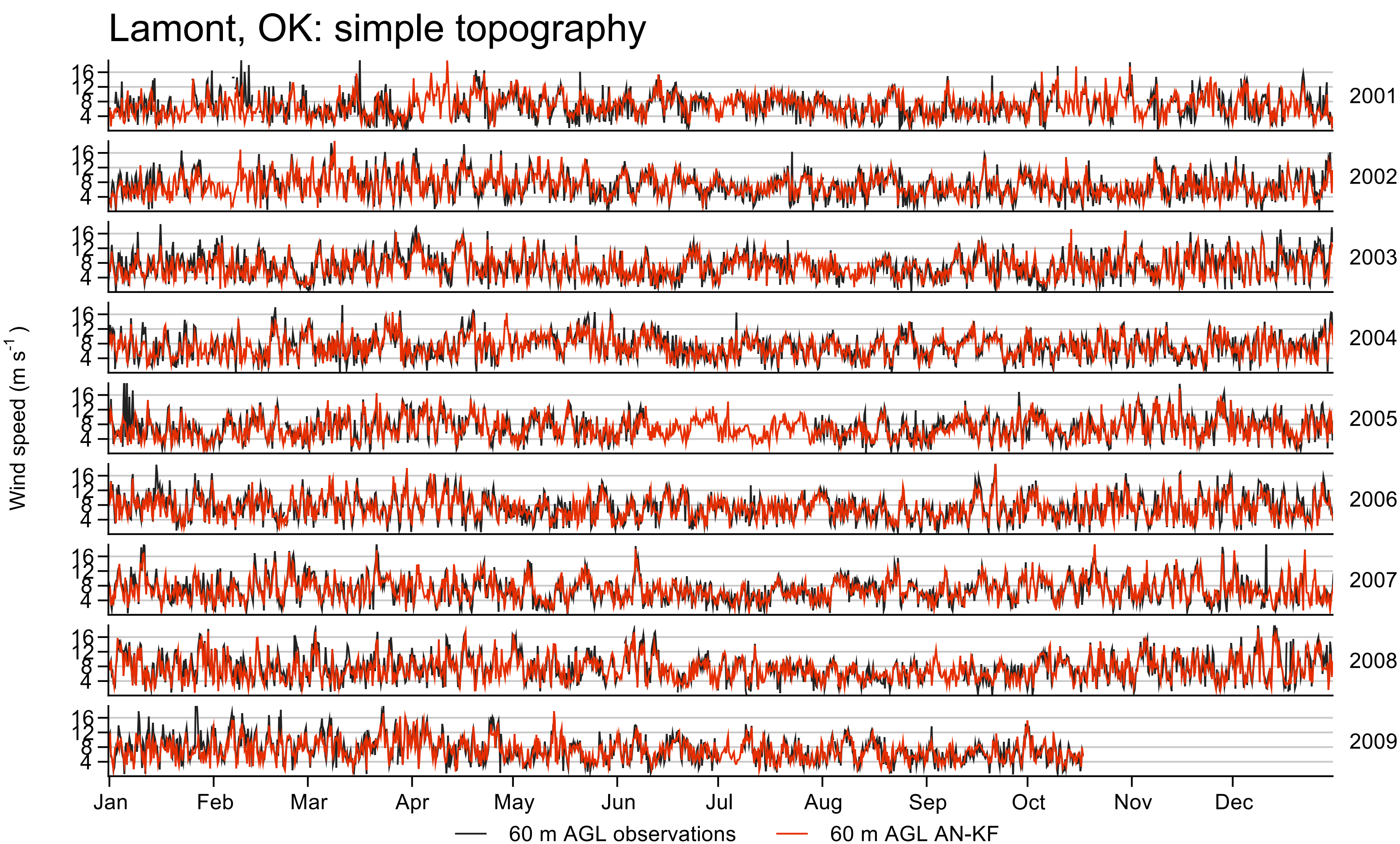
# AnEn for wind resource assessment

- Recreate a long-term observation-based wind climatology at site
- Downscale a long-term NASA Modern-Era Retrospective Analysis for Research and Applications (MERRA) time series using a short-term record of observations



# Results: example of time series (Lamont, OK)

NCAR

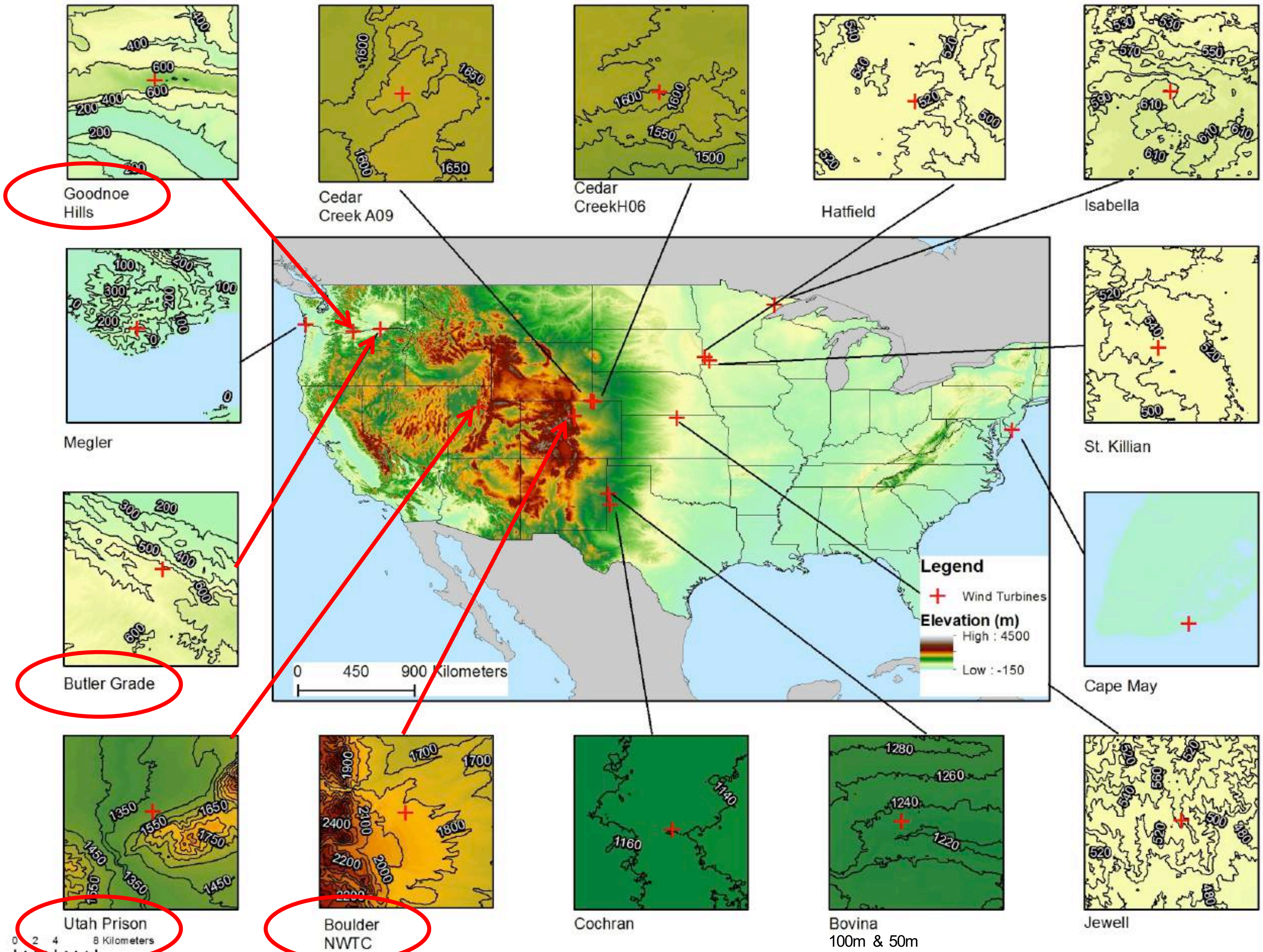



Training period: 2009-10-18 to 2010-10-17, downscale period: 2001-01-01 to 2009-10-17

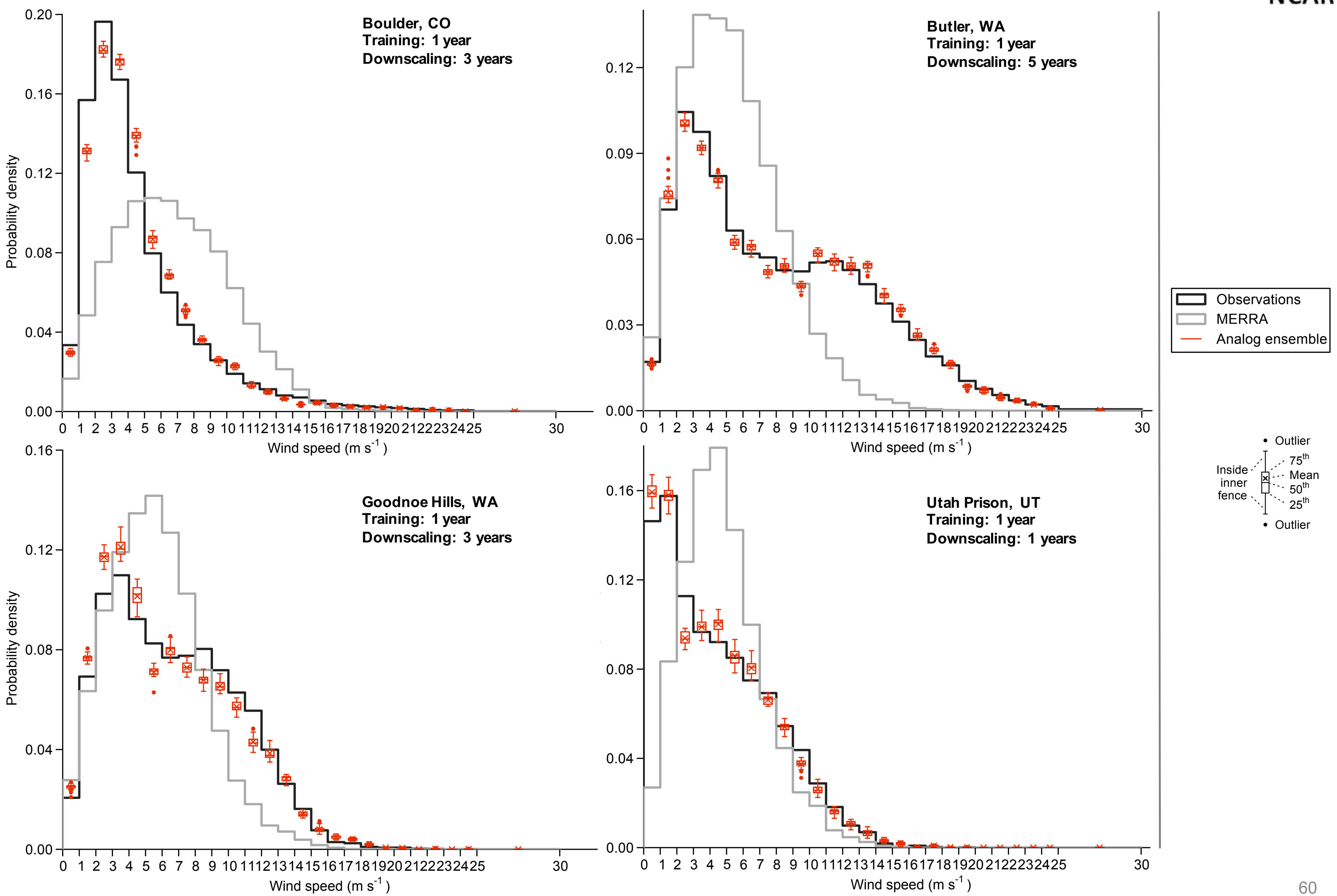
Pearson $r^2$ = 0.80, Spearman r = 0.89 (across period shown; daily)

Vanvyve et al. (RE 2014), Zhang et al. (AE 2015)

# Downscaled wind tower locations



# Wind distributions comparison



# Outline

- Analog Ensemble (AnEn) basic idea
- AnEn for short-term (i.e., 0-48 h) weather predictions
- AnEn for short-term (i.e., 0-72 h) power predictions
- AnEn for 2D/gridded probabilistic predictions
- AnEn for long-term (i.e., multi-year) wind resource assessment
- Summary and future work

# Summary and future work

NCAR

- The analog ensemble provides accurate predictions/estimates and reliable uncertainty quantification (at a lower computational cost) for
  - Short-term (0-48 h) weather predictions
  - Short-term (0-72 h) power predictions
  - 2D/gridded probabilistic predictions
  - Long-term wind resource assessment
- The analog ensemble could also be used to drastically reduce the computational cost of dynamical downscaling (with the added value of uncertainty quantification)
- Recent applications:
  - Solar power and energy load forecasting
  - Hurricane intensity prediction
  - Air quality forecasting

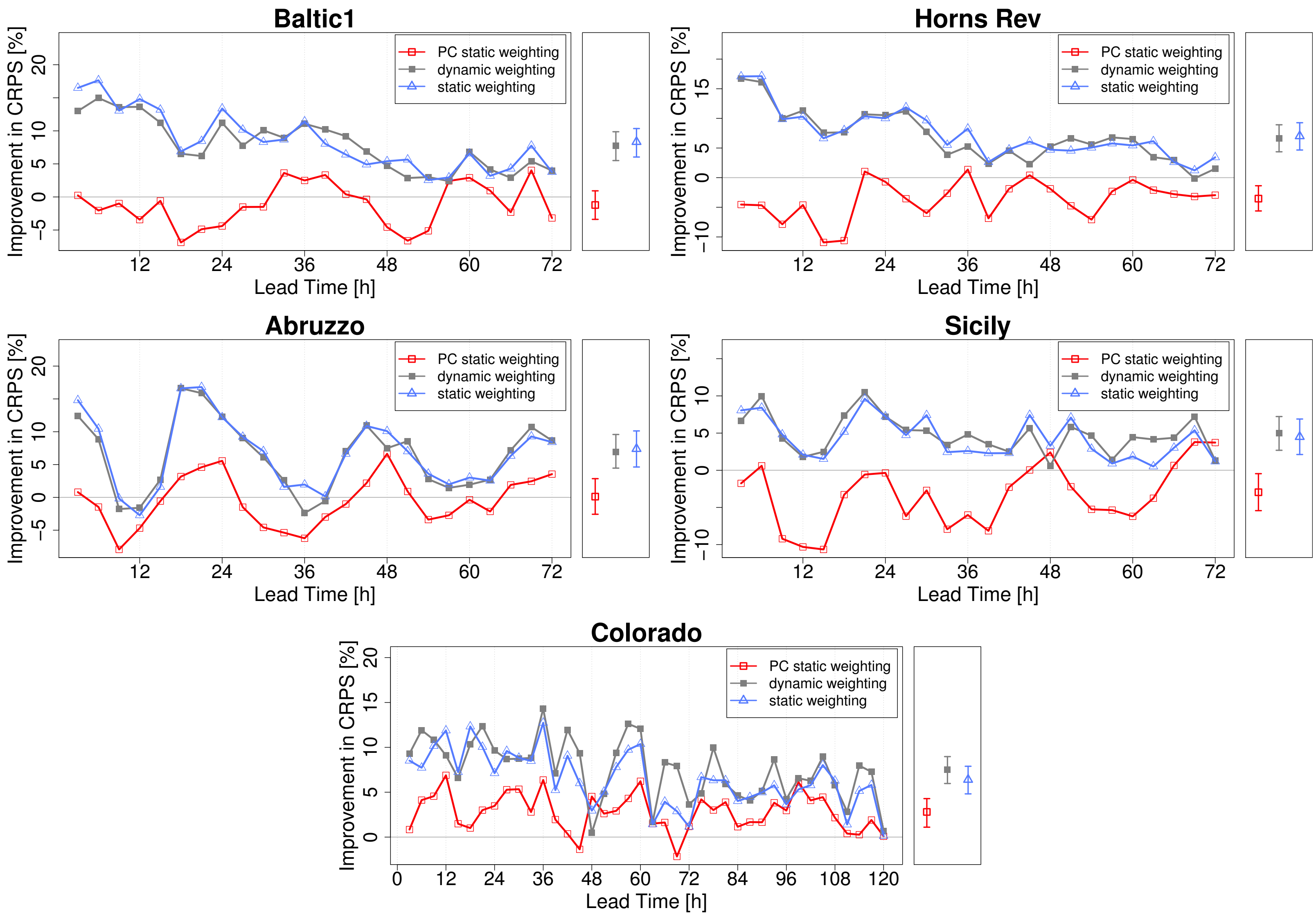
# Thanks!

NCAR

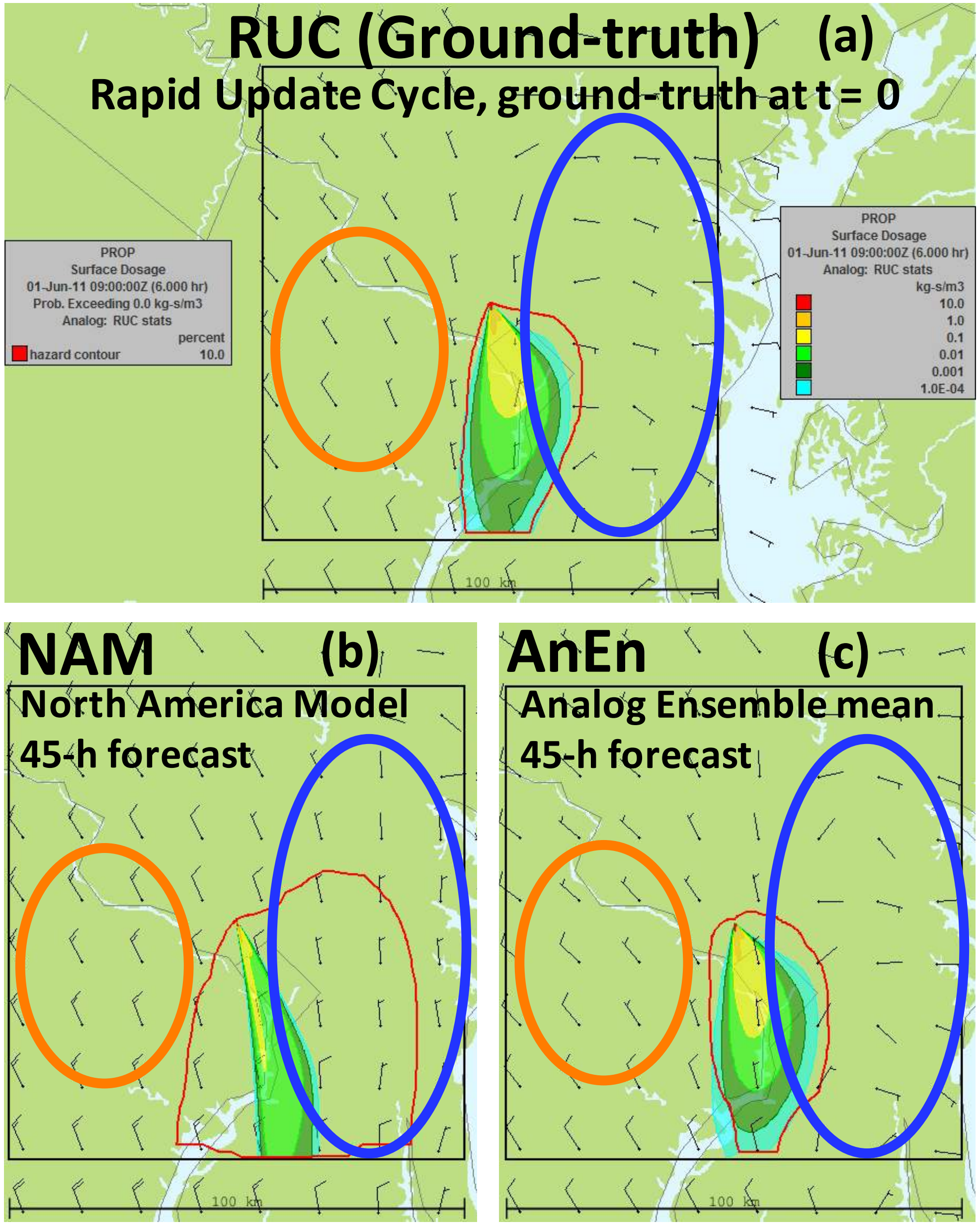
## References


1. Delle Monache, L., T. Nipen, Y. Liu, G. Roux, and R. Stull, 2011: Kalman filter and analog schemes to postprocess numerical weather predictions. Mon. Wea. Rev., 139, 3554–3570
2. Delle Monache, L., T. Eckel, D. Rife, and B. Nagarajan, 2013: Probabilistic weather prediction with an analog ensemble. Mon. Wea. Rev., 141, 3498–3516
3. Mahoney, W.P., K. Parks, G. Wiener, Y. Liu, W.L. Myers, J. Sun, L. Delle Monache, T. Hopson, D. Johnson, S.E. Haupt, 2012: A wind power forecasting system to optimize grid integration. IEEE Trans. Sustainable Energy, 3, 670–682
4. Alessandrini, S., Delle Monache, L., Sperati, S., and Nissen, J, 2015. A novel application of an analog ensemble for short-term wind power forecasting. *Renewable Energy*, 76, 768-781
5. Vanvyve, E., Delle Monache, L., Rife, D., Monaghan, A., Pinto, J., 2015. Wind resource estimates with an analog ensemble approach. *Renewable Energy*, 74, 761-773
6. Nagarajan, B., Delle Monache, L., Hacker, J., Rife, D., Searight, K., Knievel, J., and Nipen, T., 2015. An evaluation of analog-based post-processing methods across several variables and forecast models. *Weather and Forecasting*, 30, 1623–1643
7. Djalalova, I., Delle Monache, L., and Wilczak, J., 2015. PM2.5 analog forecast and Kalman filtering post-processing for the Community Multiscale Air Quality (CMAQ) model. *Atmospheric* Environment, 119, 431–442
8. Junk, C., Delle Monache, L., Alessandrini, S., von Bremen, L., and Cervone, G., 2015. Predictor-weighting strategies for probabilistic wind power forecasting with an analog ensemble. *Meteorologische Zeitschrift*, 24, 361-379
9. Junk, C., Delle Monache, L., and Alessandrini, S., 2015. Analog-based ensemble model output statistics. *Monthly Weather Review*, 143, 2909–2917
10. Alessandrini, S., Delle Monache, L., Sperati, S., and Cervone, G., 2015. An analog ensemble for short-term probabilistic solar power forecast. Applied *Energy*, 157, 95–110
11. Eckel, T., and Delle Monache, L., 2015. A hybrid, analog-NWP ensemble. Accepted to appear on *Monthly Weather Review*
12. Zhang, J., Draxl, C., Hopson, T., Delle Monache, L., and Hodge, B.-M., 2015. Comparison of deterministic and probabilistic wind resource assessment methods on numerical weather prediction. *Applied Energy*, 156, 528–541

# Analog predictors weighting strategies: Impact on probabilistic prediction



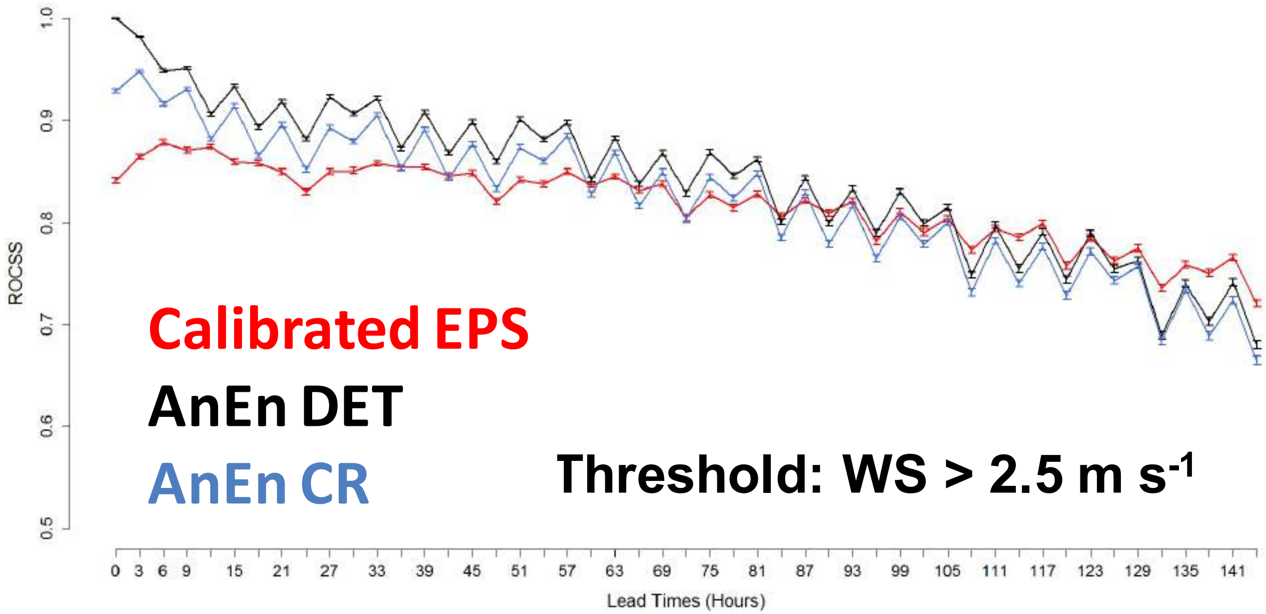
# AnEn in 2/3-D

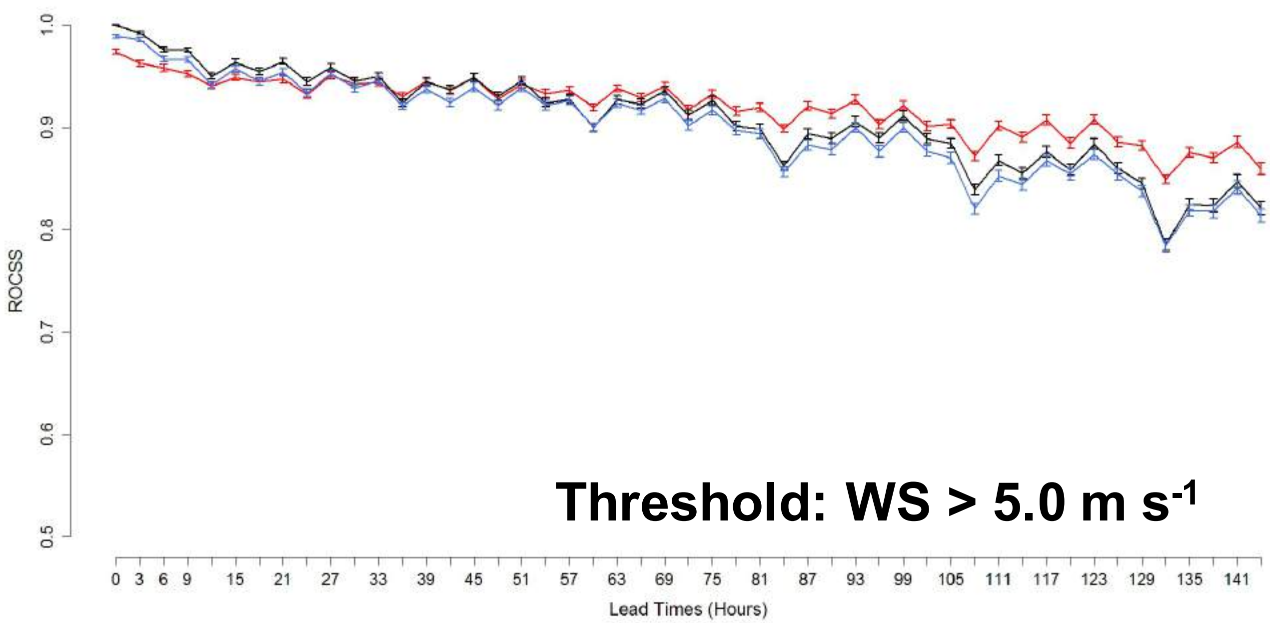



Hypothetical atmospheric release in Washington, D.C., at 9:00 UTC, 1 June 2011

Surface wind vectors (arrows with barbs)
6-h dosage (shading)
Hazard contour (red line)

# Relative Operating Characteristics Skill Score



# Precipitation downscaling over Germany with AnEn

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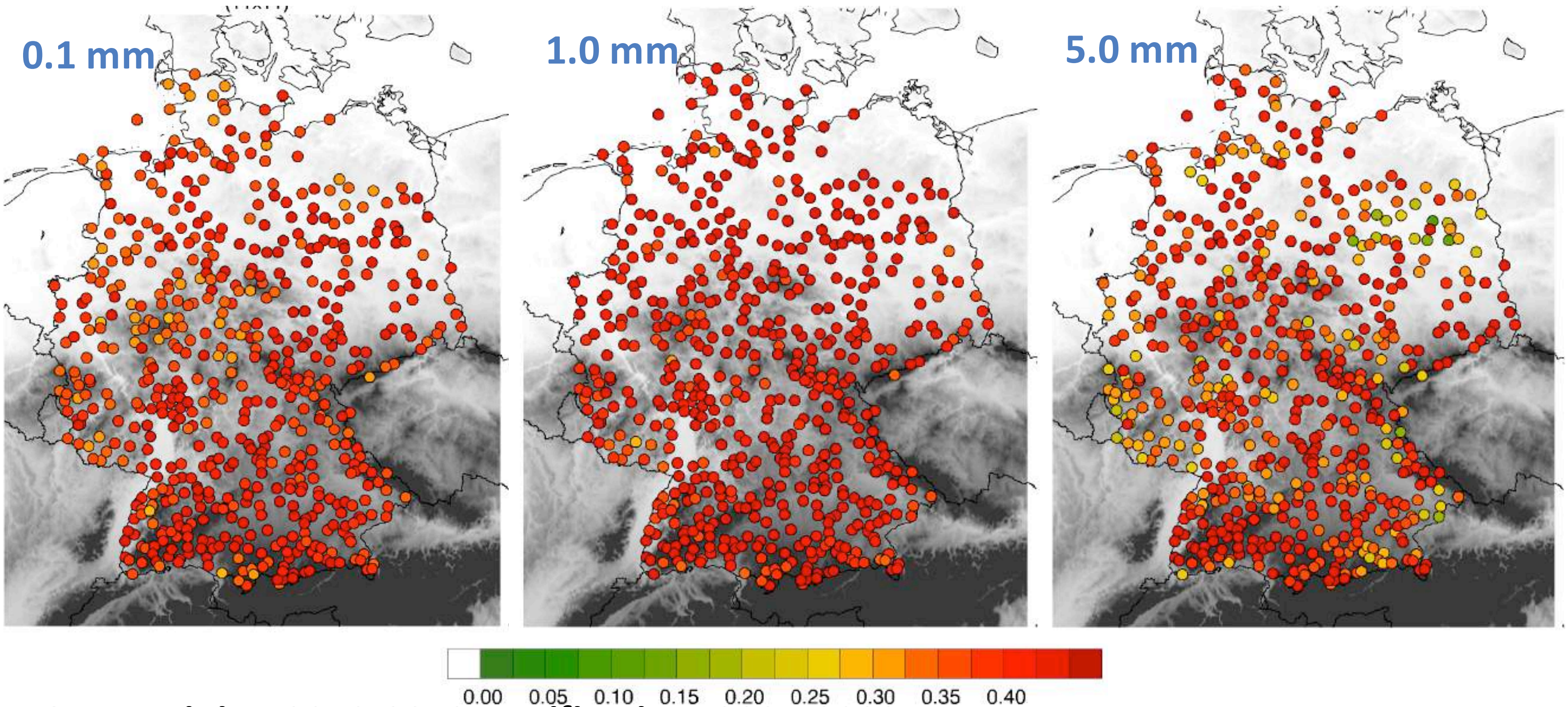
**Brier Skill Score Against DWD 6-km Reanalysis**
**(AnEn = Rean.→ BSS = 0, AnEn perfect →BSS = 1)**

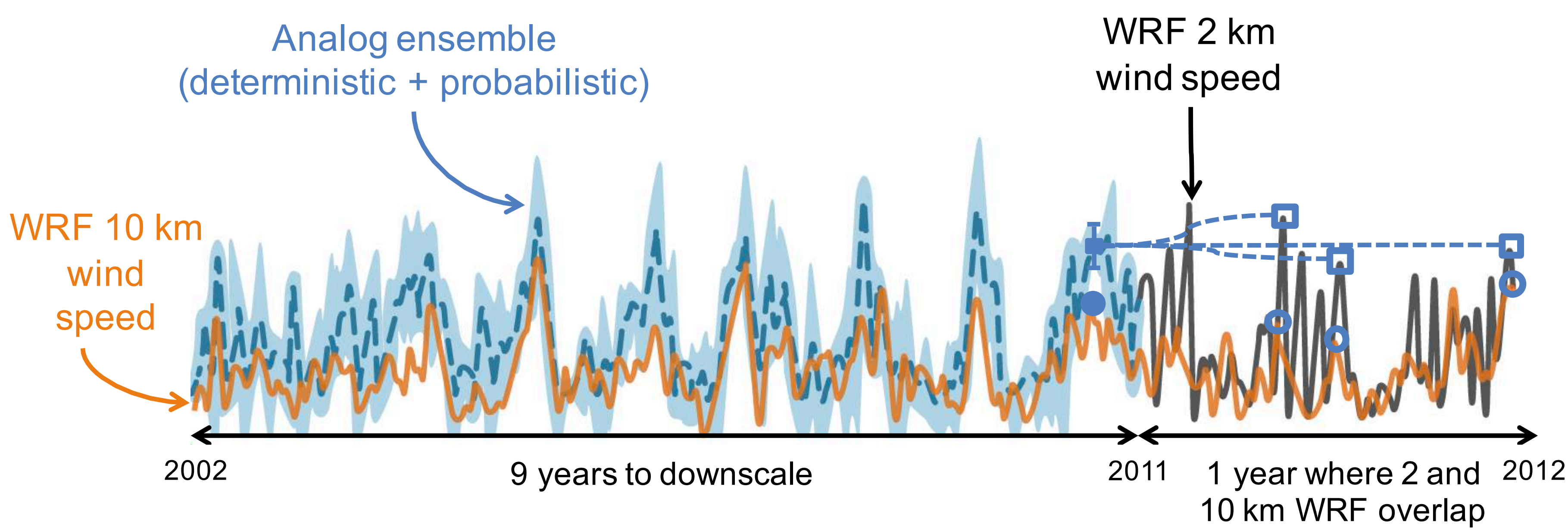



**NOTE: Training:2010-2012, Verification: 2007-2009**

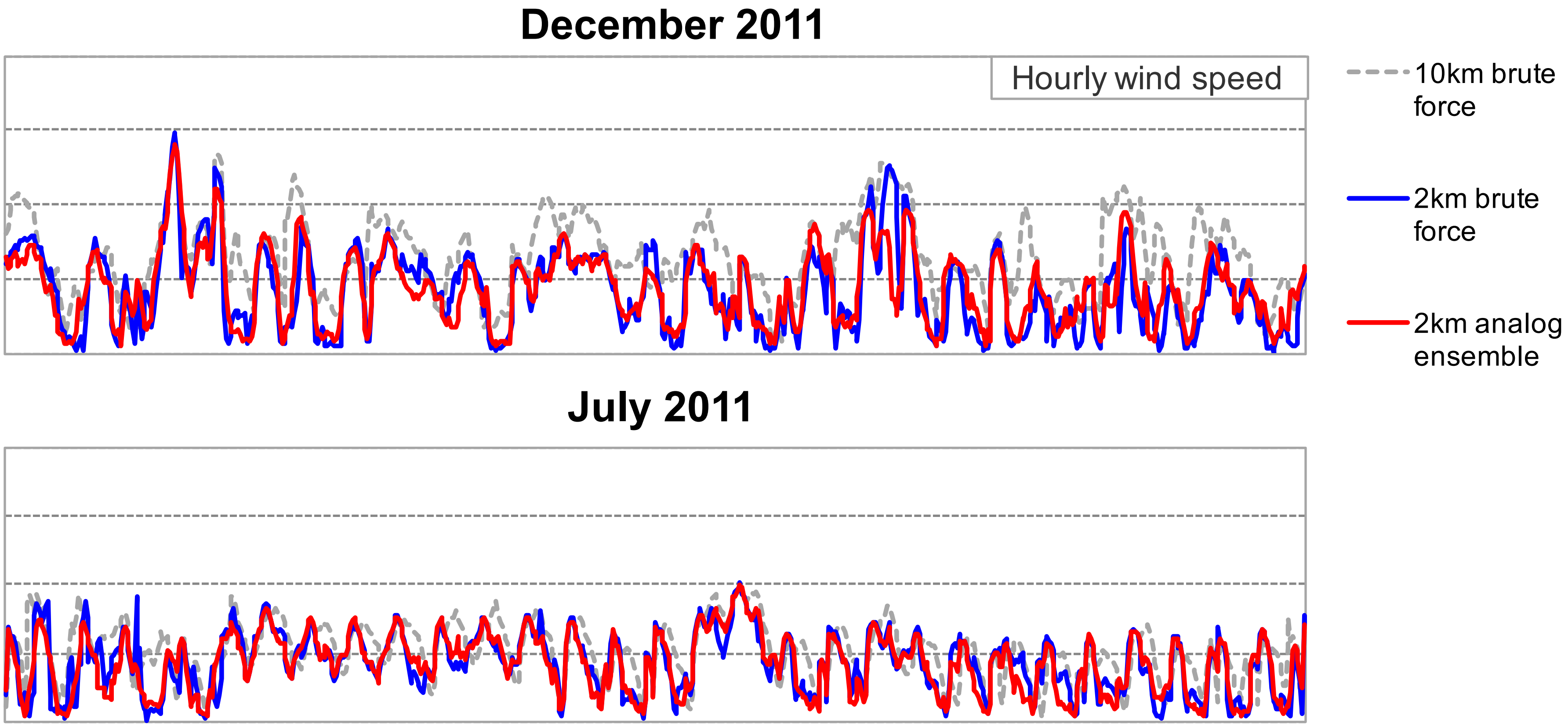
Lead: Jan Keller (DWD, University of Bonn)

# AnEn for wind resource assessment in areas with no observations

- Brute force WRF simulations at 17 mast sites for 2002-2012
- Nested 10 km – 2 km grid configuration (one way nesting)
- Analog ensemble used to downscale 10 km WRF



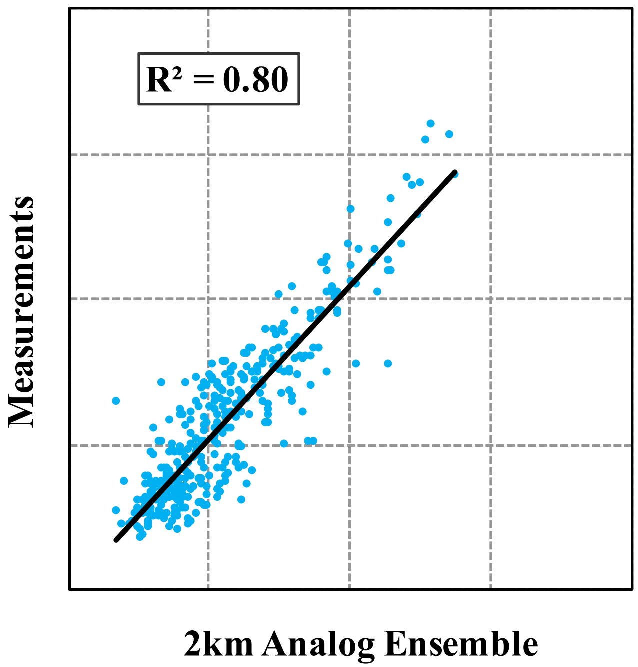
# U.S. West Coast Site 1: Time series for 2 representative months

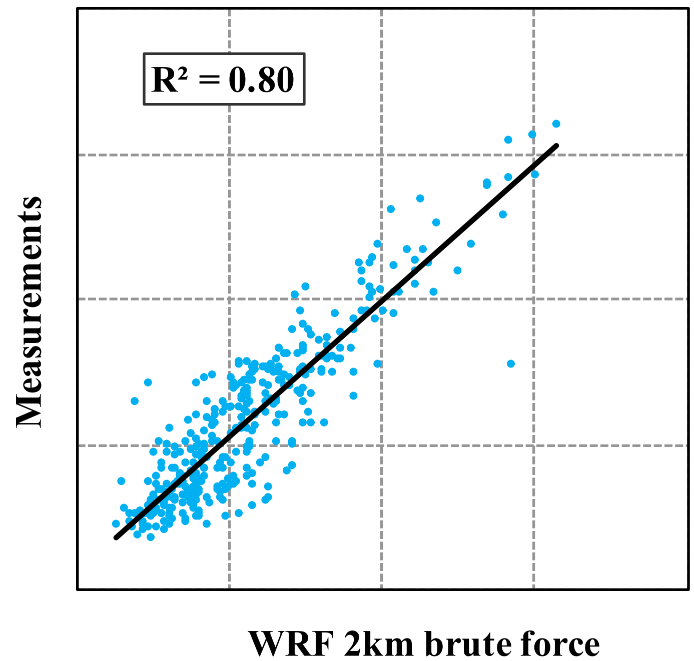



Rife et al. (JAMC 2015)

# U.S. West Coast Site 1: Fit to measurements

Daily wind speed

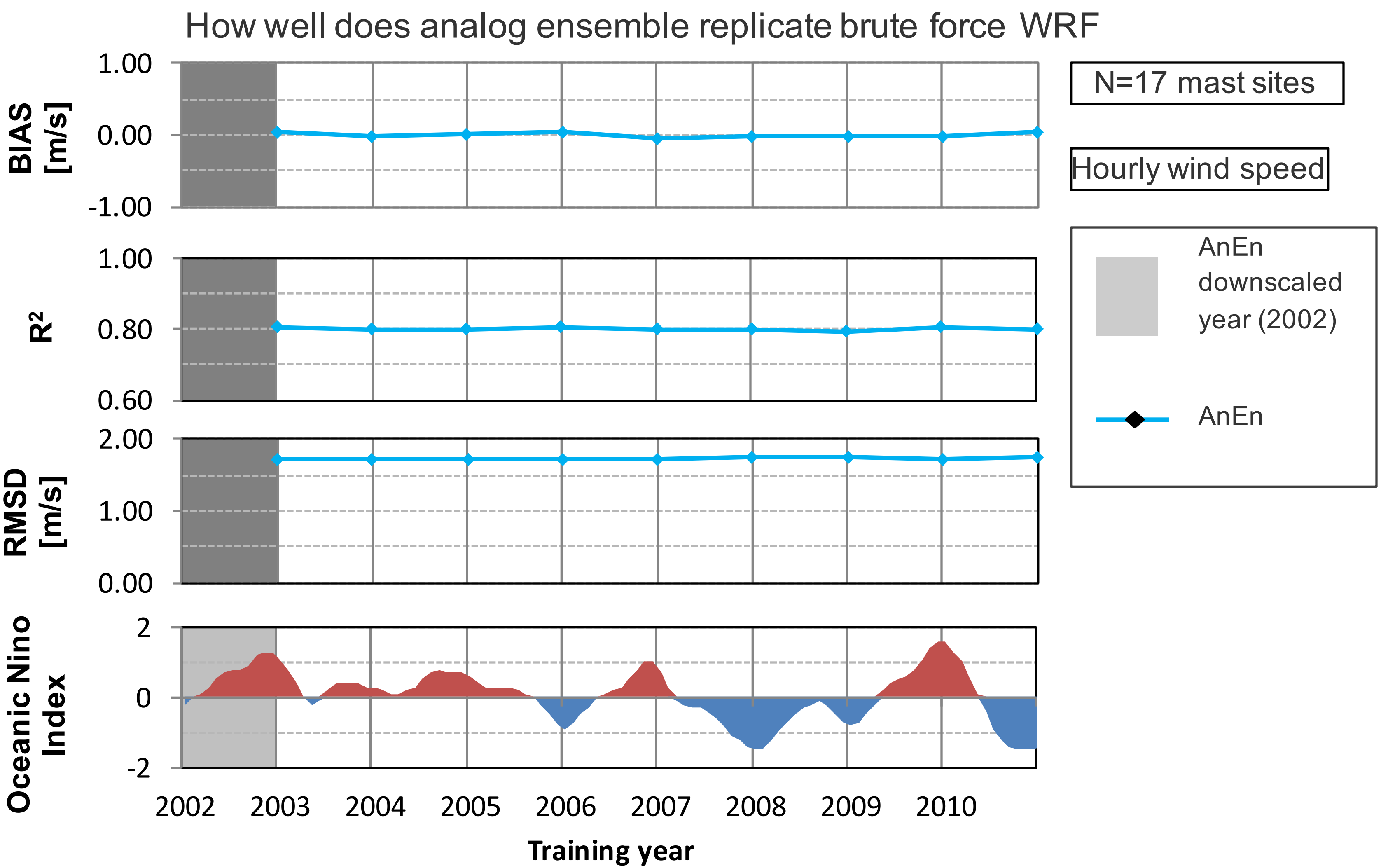



| | |
|---|---|
| RMSD [m/s] | 1.28 |
| BIAS [m/s] | 0.23 |

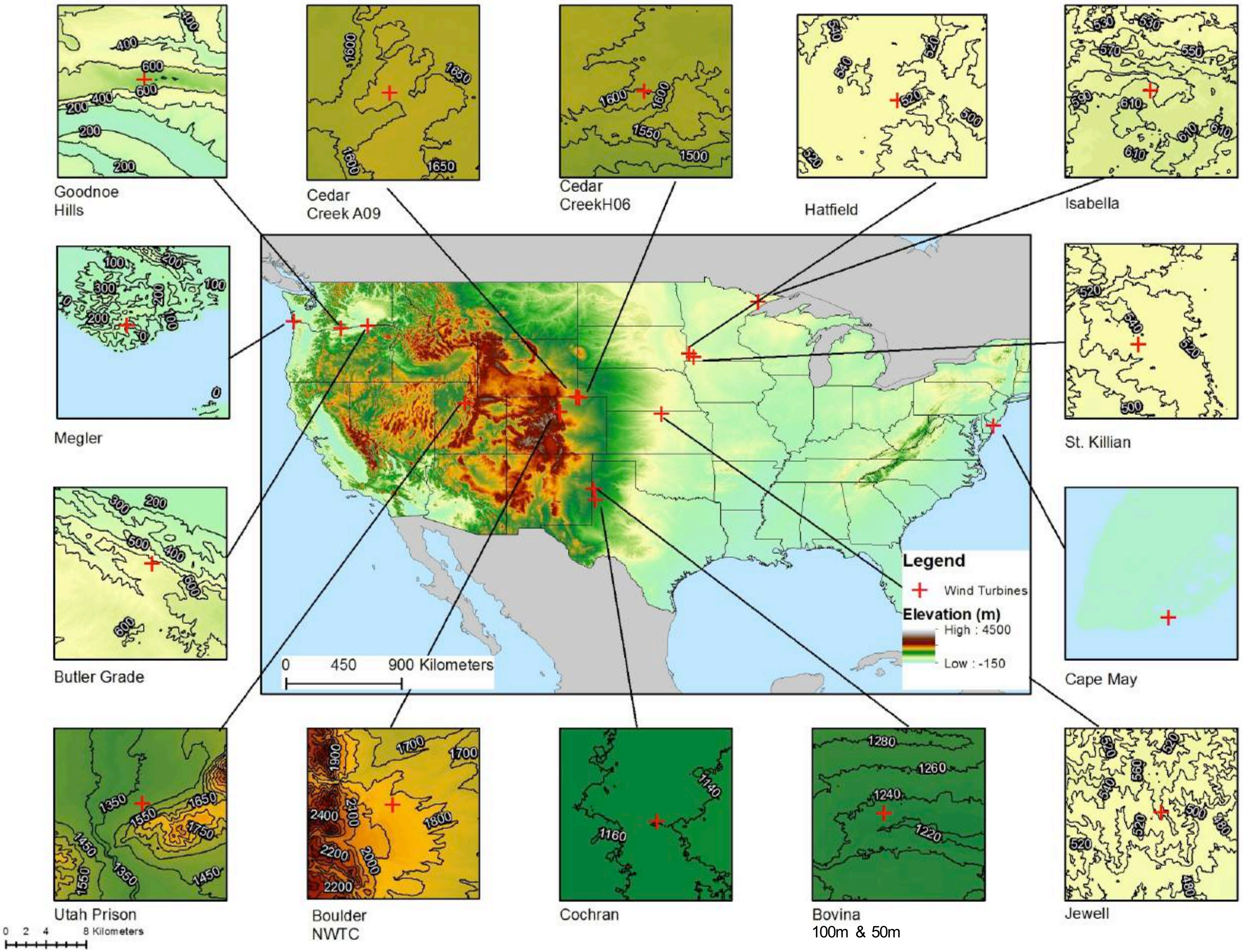
| | |
|---|---|
| RMSD [m/s] | 1.29 |
| BIAS [m/s] | 0.24 |

# Sensitivity tests:
# Specific year(s) used for training

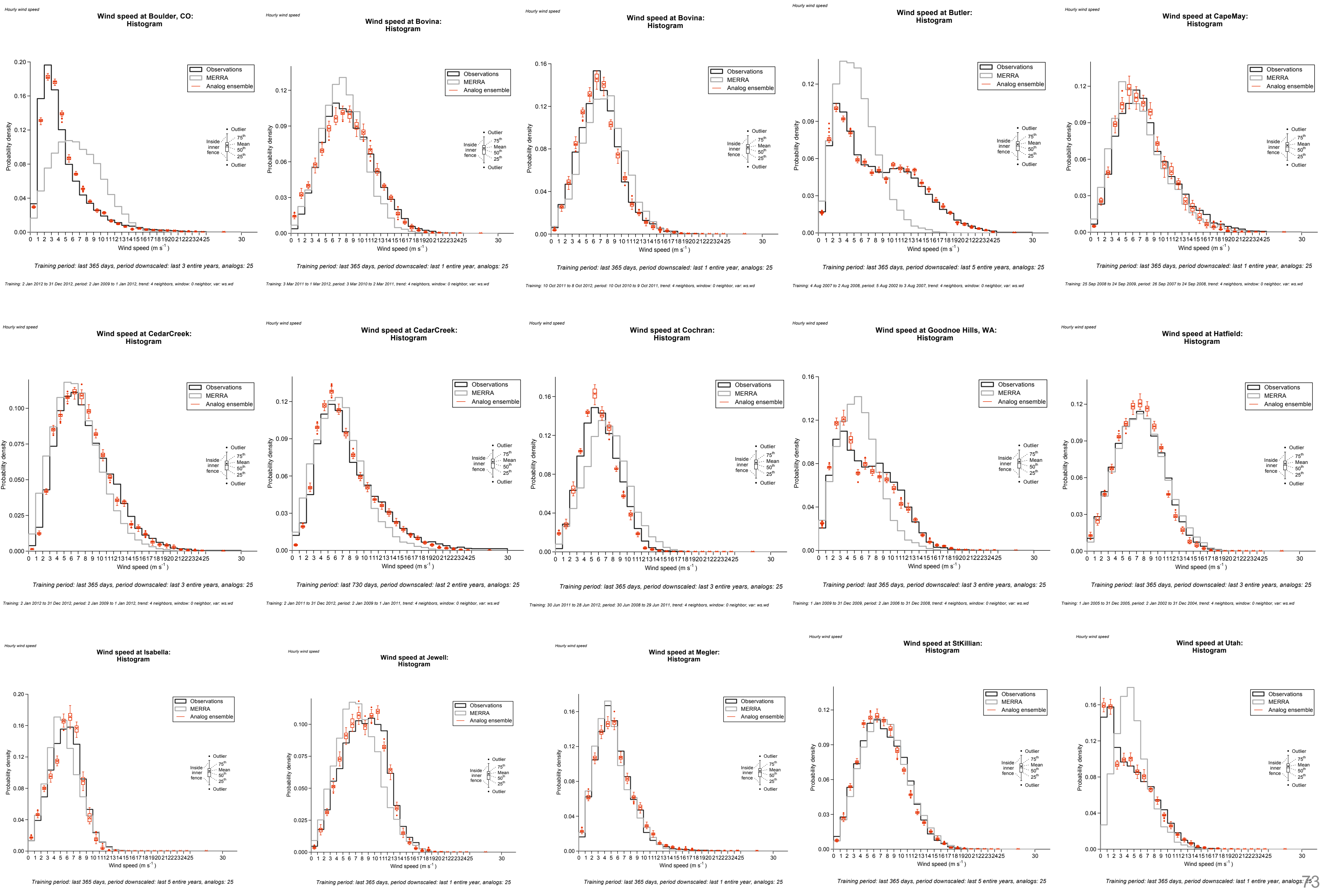



10 km WRF downscaled to 2 km with AnEn. Training data: 2 km WRF for a single year.

# Downscaled wind turbine locations



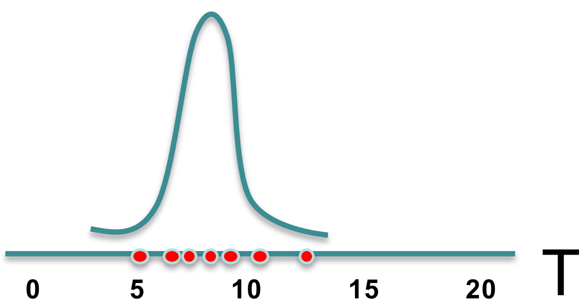
# PDF comparisons



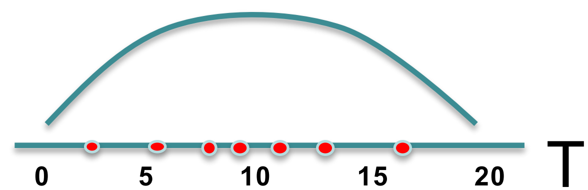
# Probabilistic forecast attributes: Sharpness

Sharpness refers to the degree of concentration of a forecast PDF's probability density, and is a property of the forecasts only.

Ideally, we want the forecast system, while mainly reliable, with as many forecasts as possible close to 0% and 100%, corresponding to a perfect deterministic forecast system. However, an improvement in sharpness does not necessarily mean that the forecast system has improved.



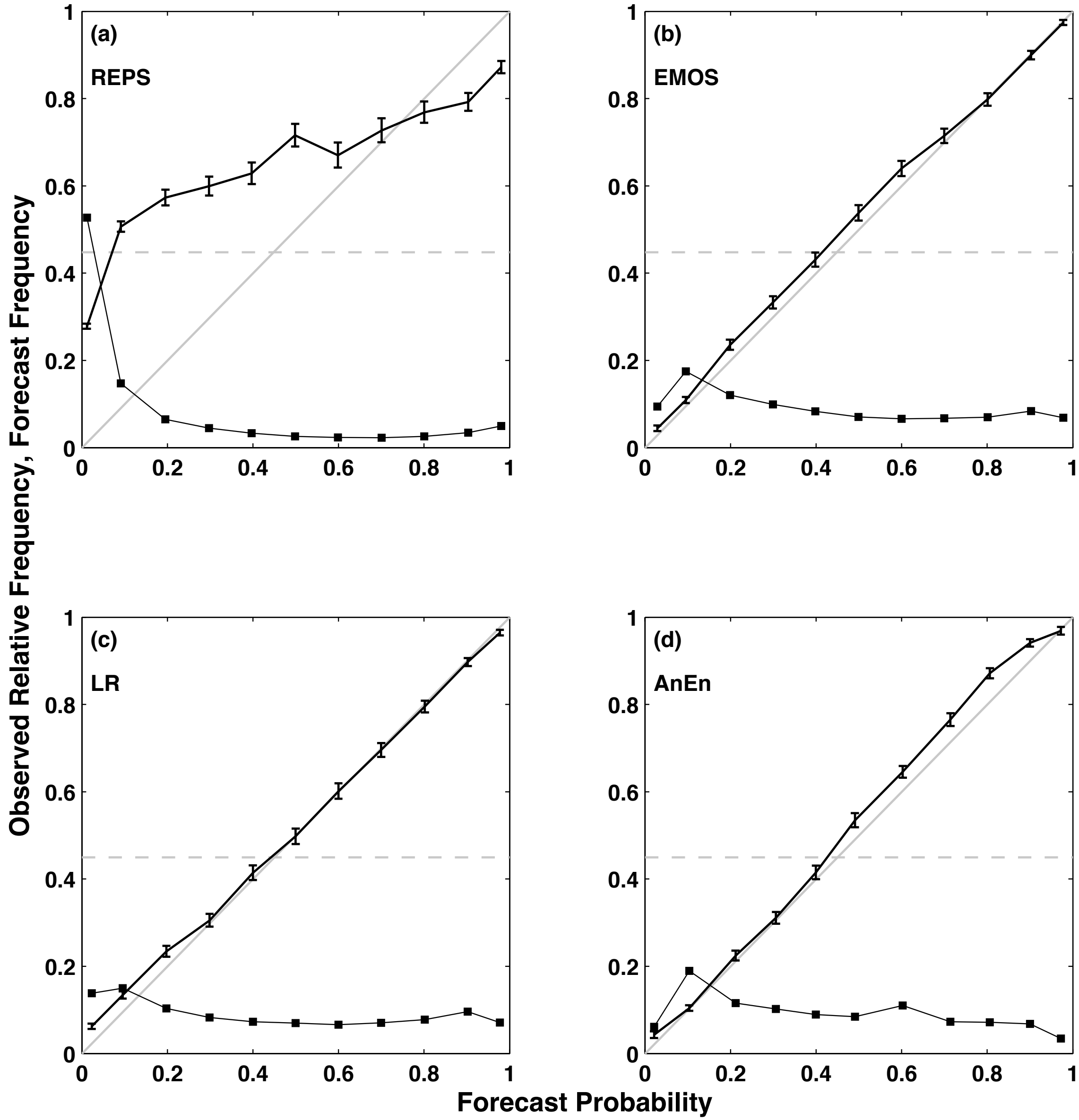

**Sharper Forecast**




**Less Sharp Forecast**

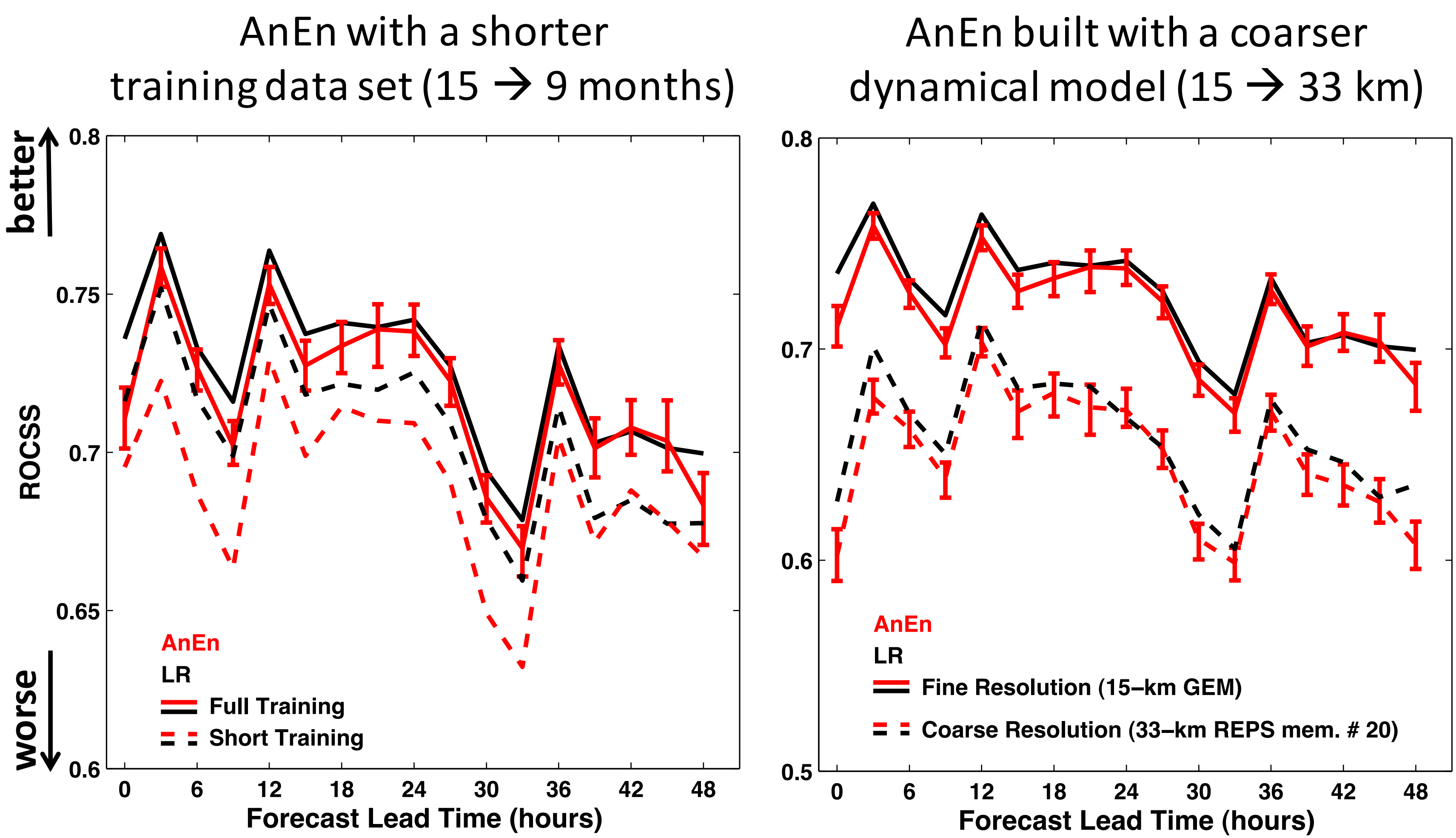
# Analysis of reliability & sharpness

Reliability and sharpness diagram: 10-m wind speed > 5 m $s^{-1}$, 9-h fcst



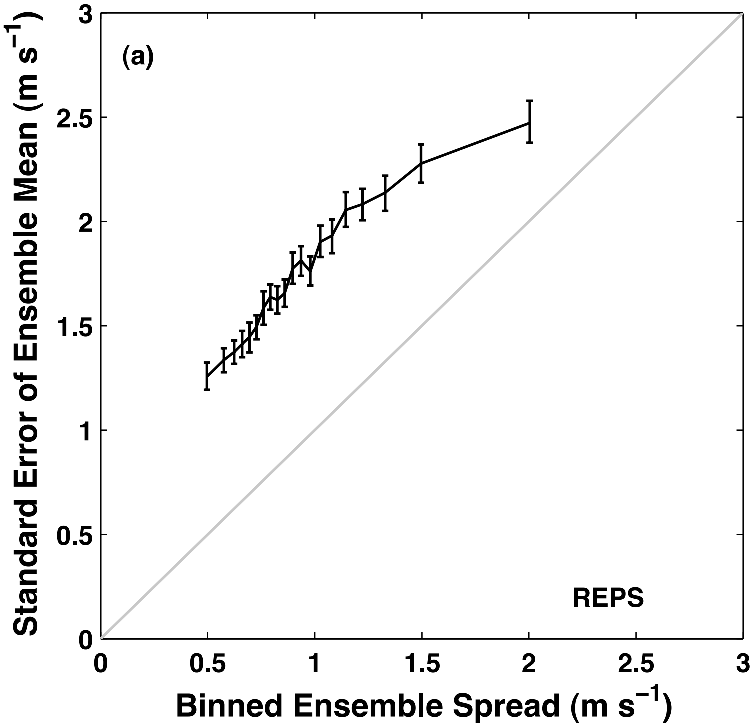
# AnEn sensitivity

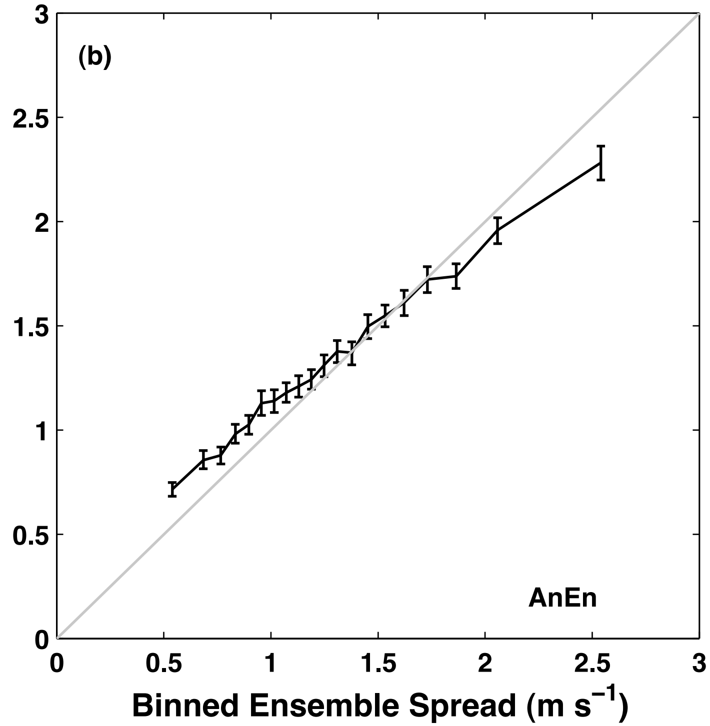
Relative Operating Characteristics skill score, 10-m wind speed ≥ 5 m $s^{-1}$



# Analysis of spread-error consistency (2)

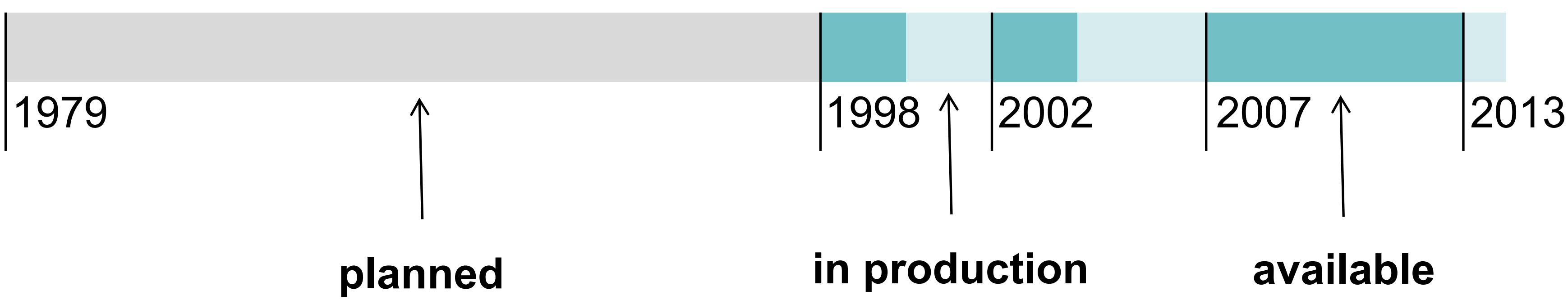
## Binned spread-skill diagram, 10-m wind speed, 42-h fcst



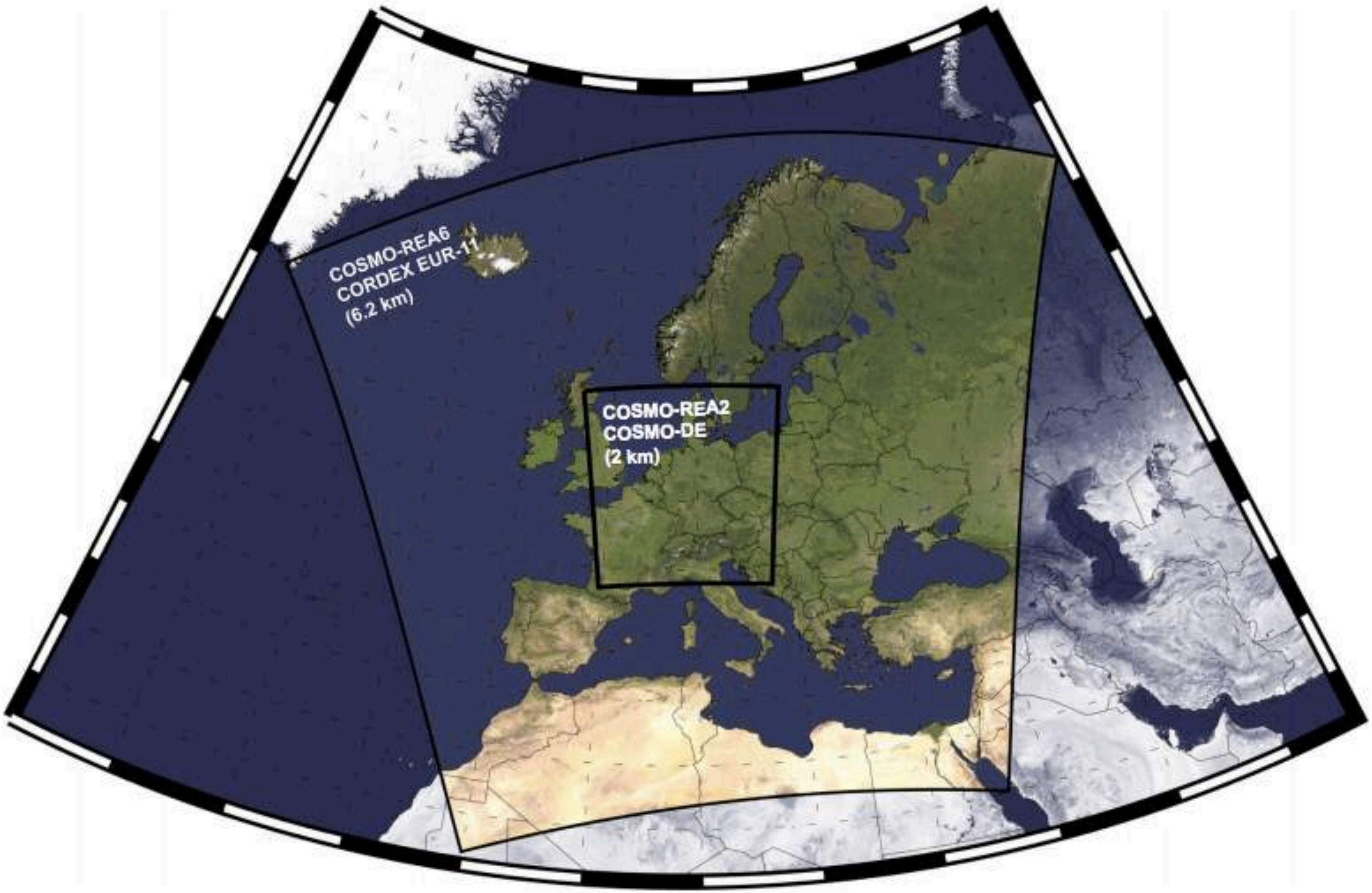



# COSMO 6 km Reanalysis

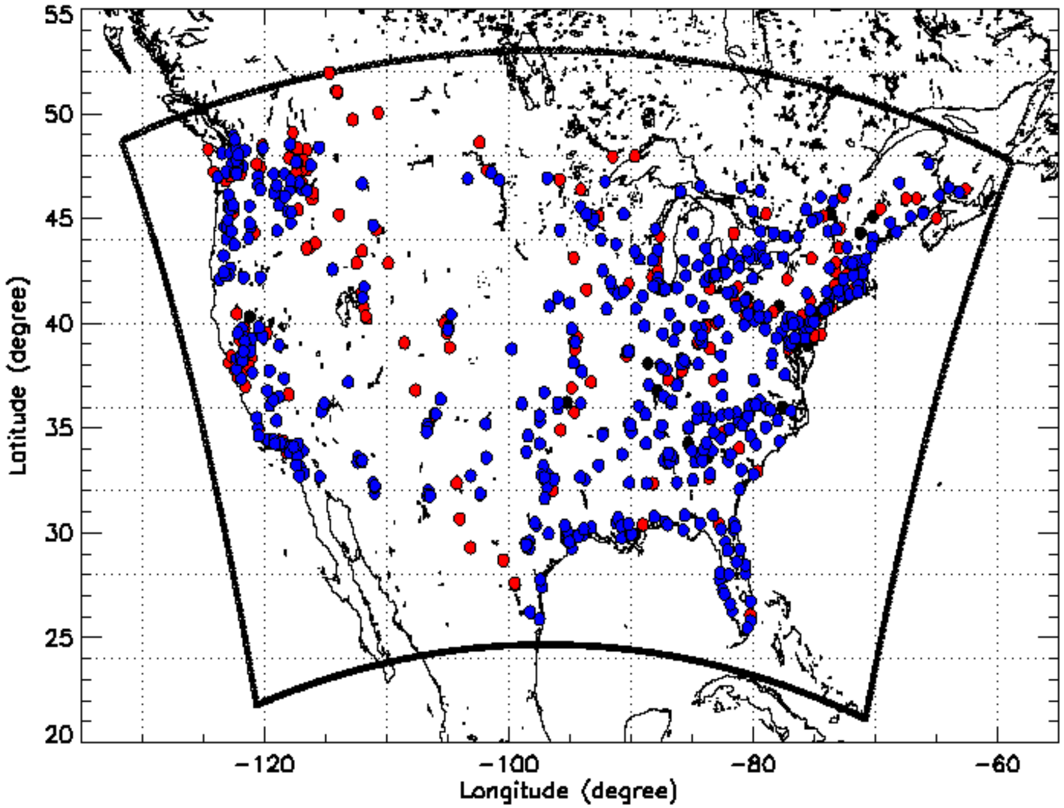
- Regional reanalysis generated in the framework of the Hans-Ertel-Centre for Weather Research
- COSMO model
  - 6 km horizontal resolution for domain covering whole Europe
  - 40 vertical levels
- Output
  - 3D atmospheric state - 60 minutes interval
  - 2D parameters - 15 minutes interval
- Production
  - 16 years finished by end of the year, final 35 year period intended



# COSMO 6 km Reanalysis



# AnEn for $PM_{2.5}$ predictions

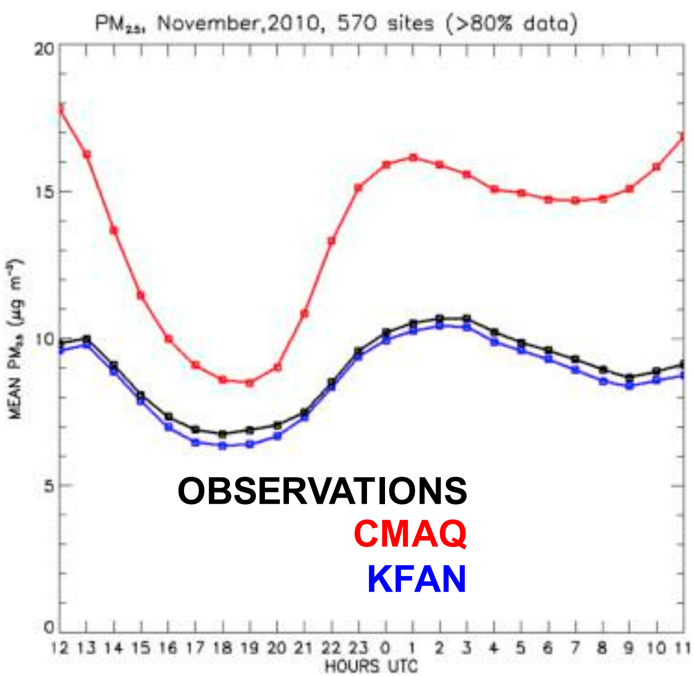



NOTE:

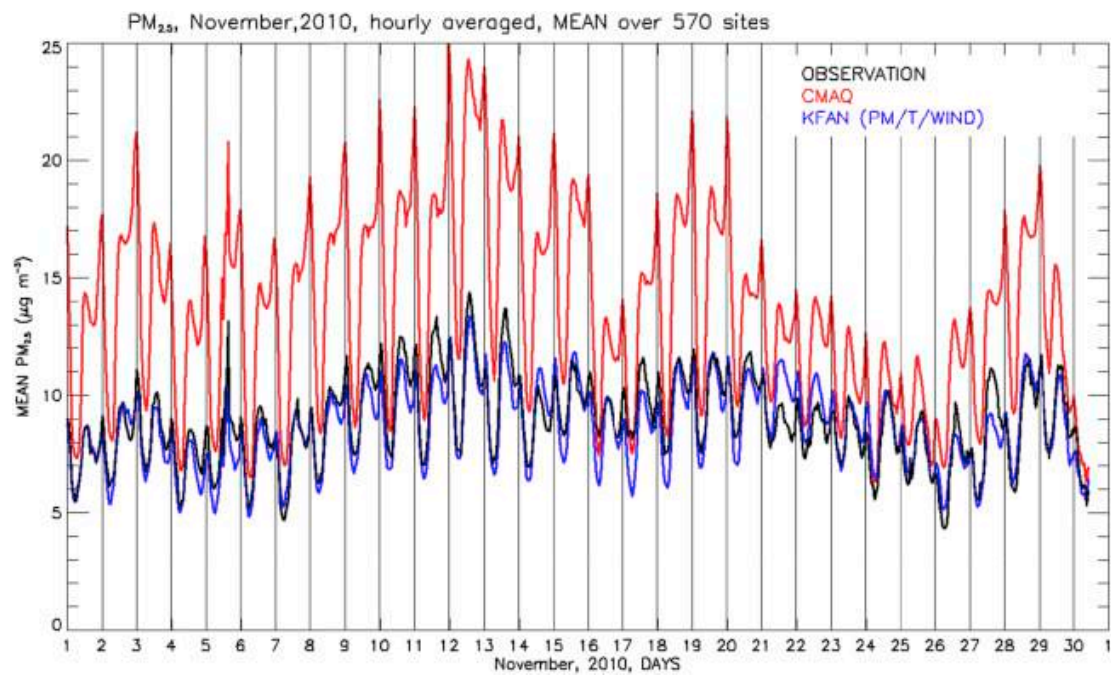
- Used 518 (blue) stations out of 716 (blue + red) (80% data availability cut-off)
- Data availability:1 Dec 09 – 30 Nov 10 (11-12 months training, Nov verification)

Reference: Djalalova et al., *Atmospheric Environment*, 2015

# $PM_{2.5}$: comparison with observations




**Diurnal variation of $PM_{2.5}$**
**Nov 2010, averaged over 518 stations**

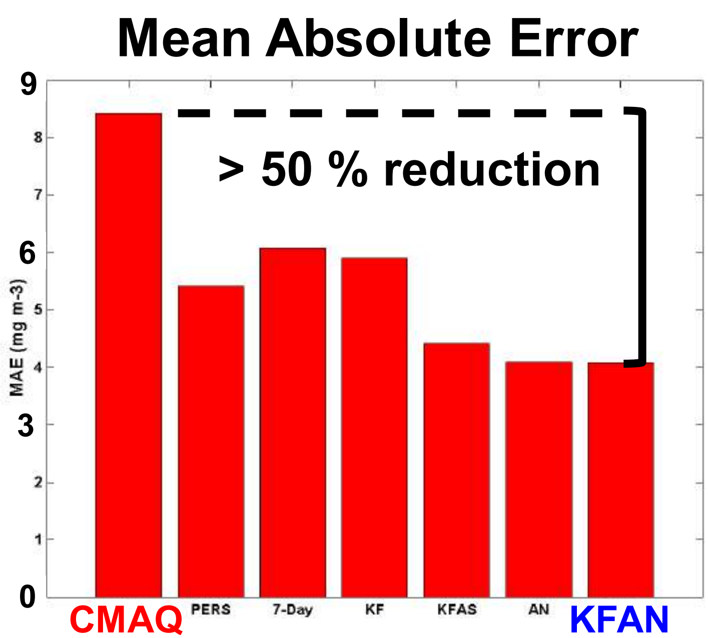


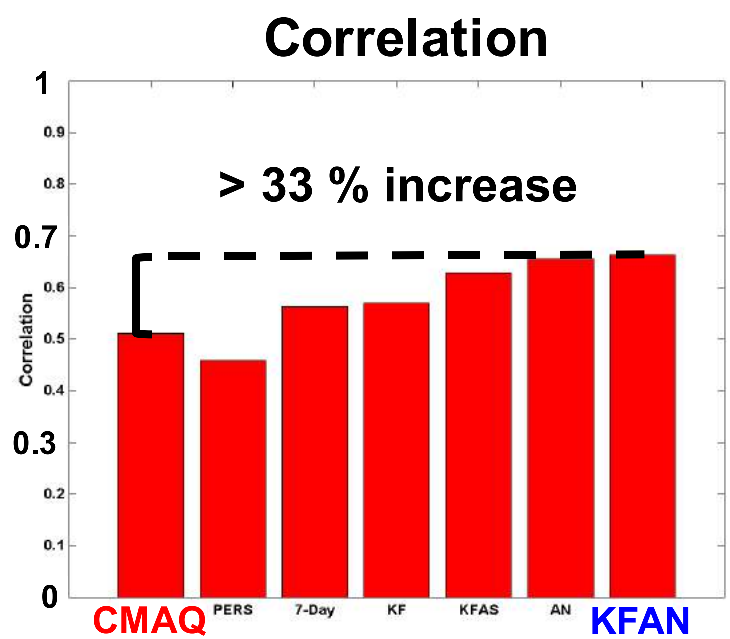

**1-24 h forecasts hourly time series of $PM_{2.5}$**
**Nov 2010, averaged over 518 stations**

**CMAQ**: NOAA/NCEP's WRF-NMM/CMAQ (12-km, CB4, SMOKE), 1-24 h forecast
**KFAN**: Kalman filter bias correction applied to the analog ensemble mean

Reference: Djalalova et al., *Atmospheric Environment*, 2015

# $PM_{2.5}$: verification metrics

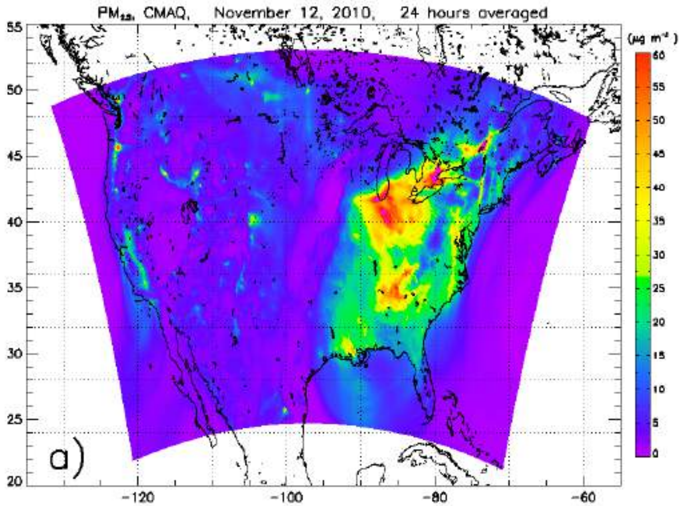


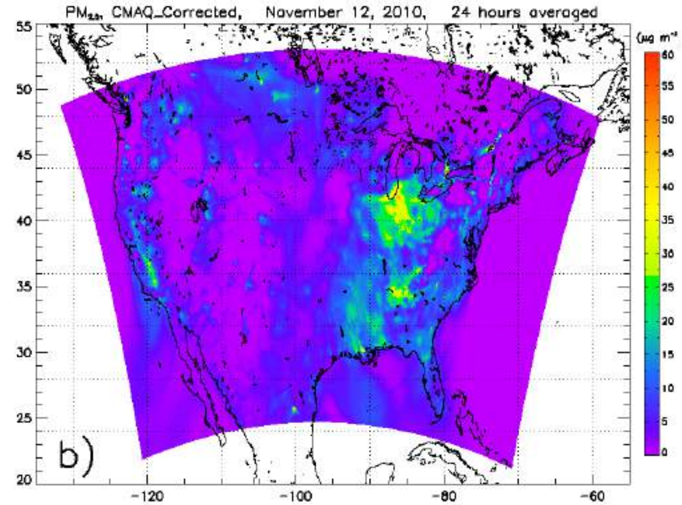

- Training: 1 Dec 09 – 31 October 10
- Verification: November 2010
- 518 AirNow sites

Reference: Djalalova et al., *Atmospheric Environment*, 2015

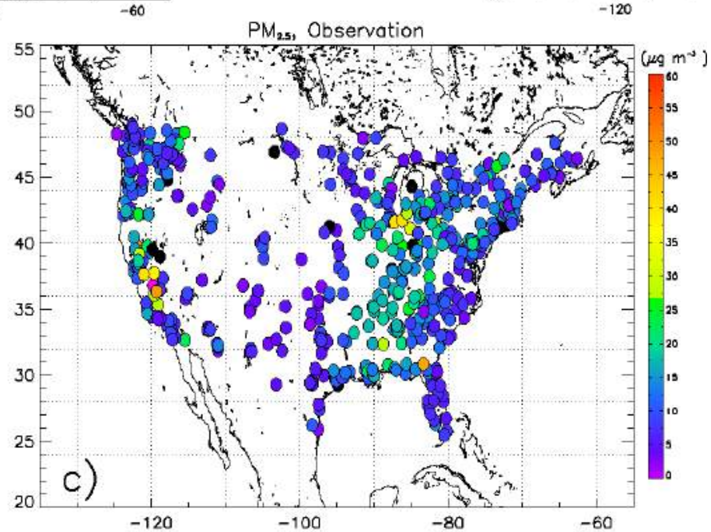
# Spreading over a 2-D grid (*Glahn et al., 2012*)




**CMAQ**




**KFAN**



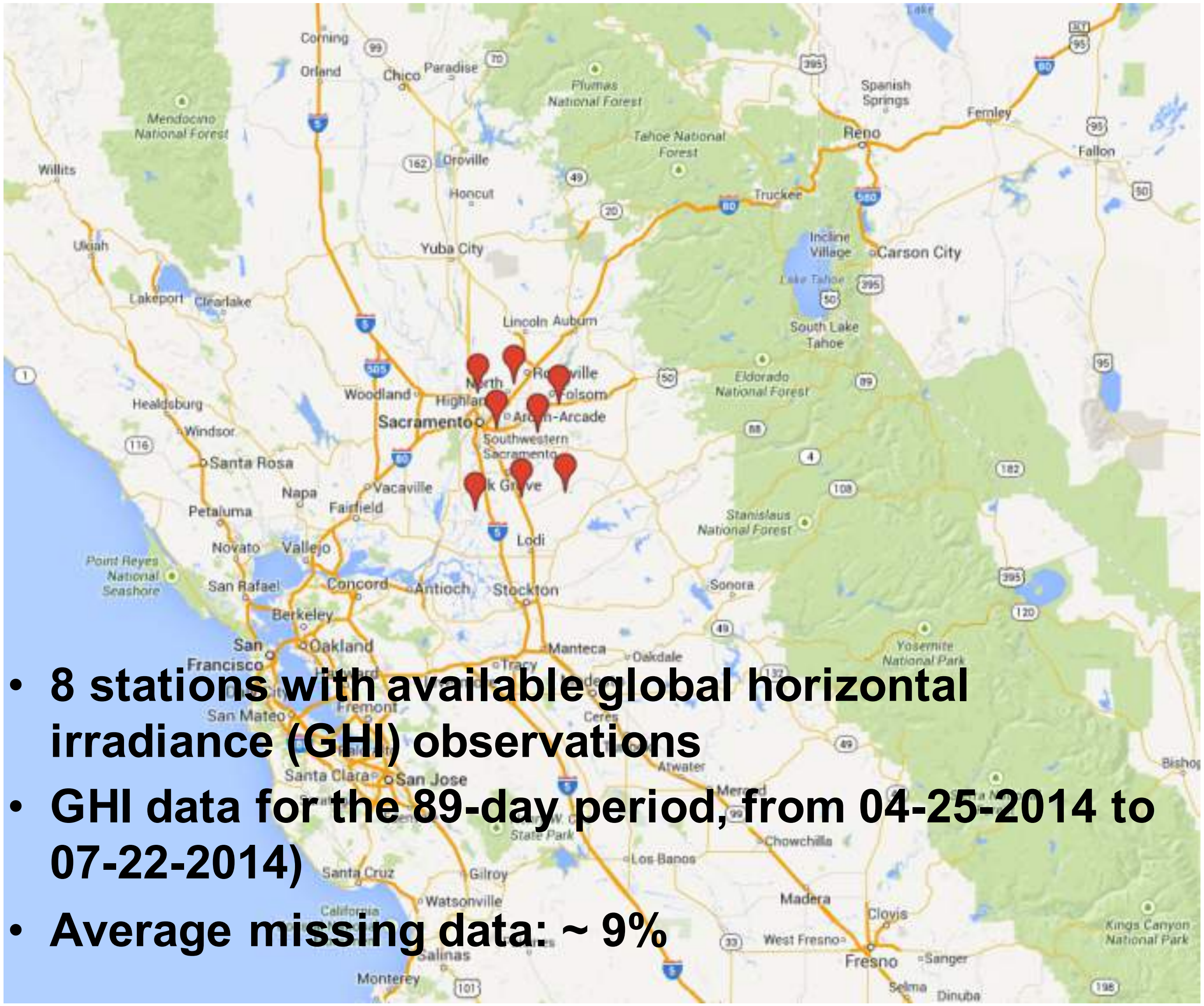

**OBSERVATION**

Reference: Djalalova et al., *Atmospheric Environment*, 2015

# AnEn for solar power predictions

NCAR

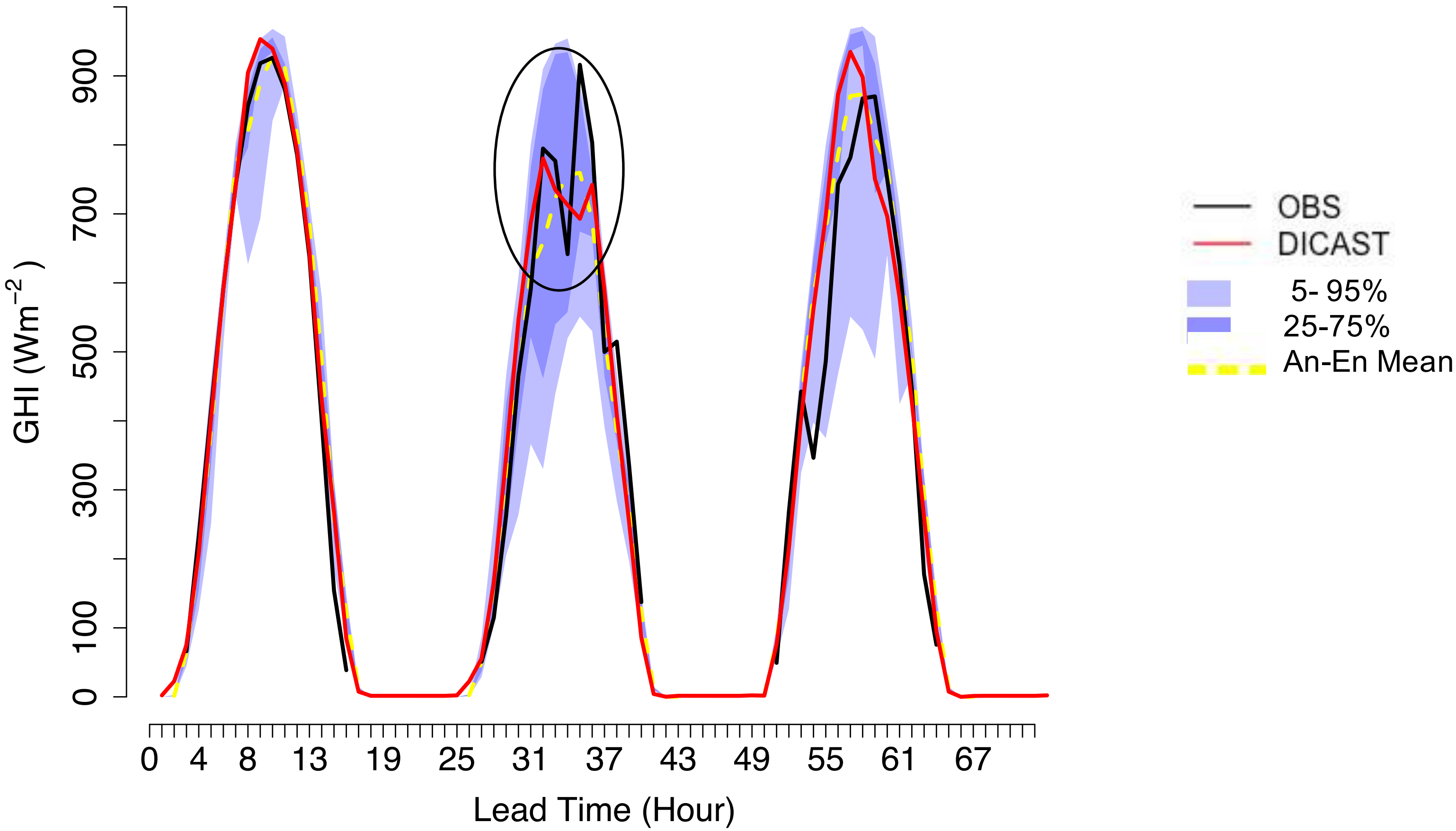
## Training data: SMUD observations




- **8 stations with available global horizontal irradiance (GHI) observations**
- **GHI data for the 89-day period, from 04-25-2014 to 07-22-2014)**
- **Average missing data: ~ 9%**

# Results: Time series example: AnEn, DICAST

Station SMUD 67, forecast initialized at 12 UTC, 14 July 2014

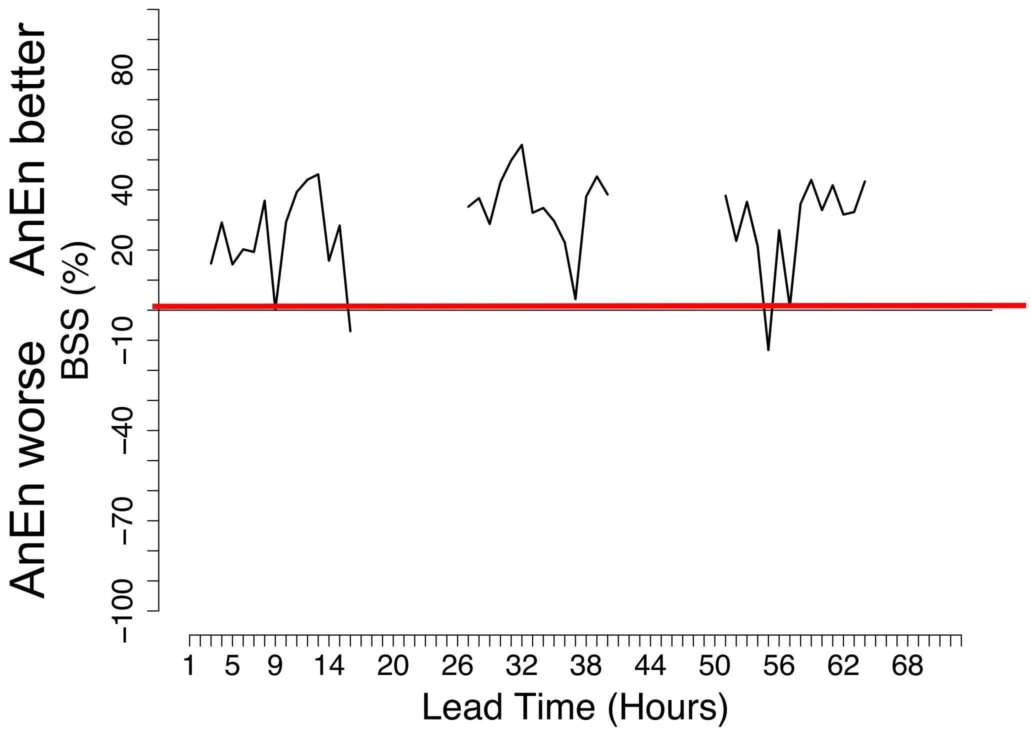


# An-En vs. DICAST (Brier Skill Score)

- The Brier Skill Score (BSS) compares two skill of probabilistic predictions for a given event
- Values > 0 indicate that AnEn has more skill than DICAST
- Shown is the BSS index as a function of forecast lead time, with the event considered being GHI > mean(obs. GHI at the given lead time)

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

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




**Conclusion:** AnEn is nearly always better than the already optimized DICast forecast, even for this short training and validation period

# Analysis of spread-error consistency

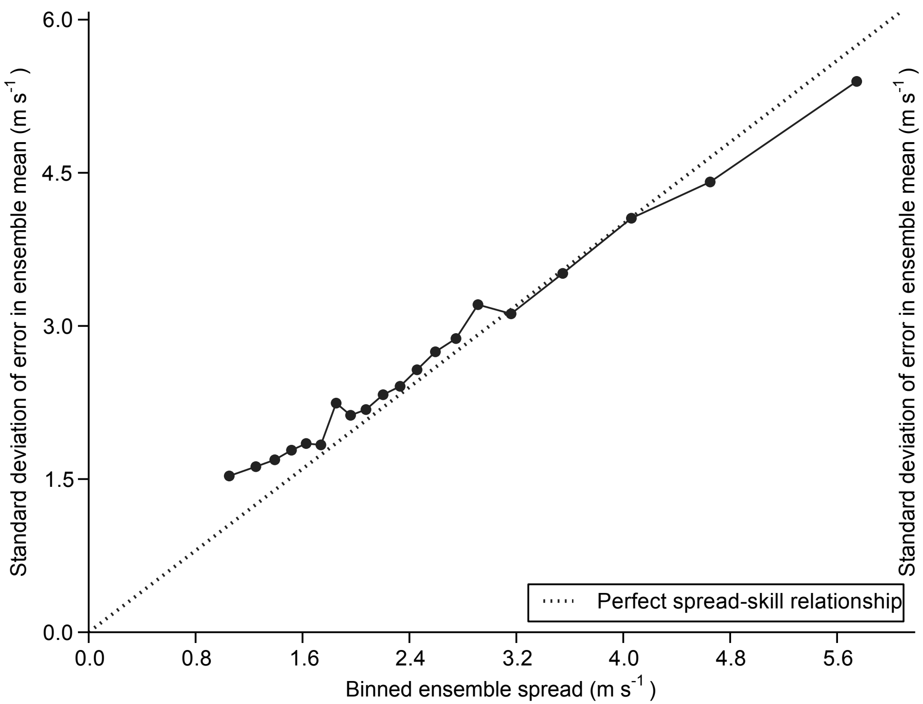
## Binned spread-skill diagram

## Boulder, CO and Bovina at 50m

*Hourly wind speed*

*N = 8644*

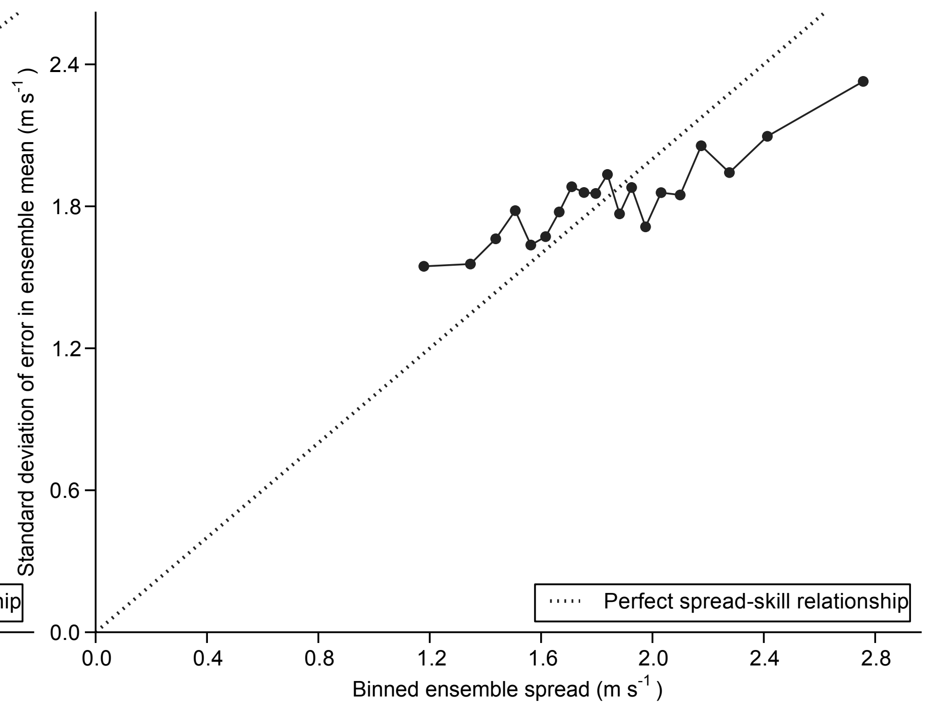
**Wind speed at Boulder, CO: Binned spread-skill diagram**




*Training period: last 365 days, period downscaled: last 3 entire years, analogs: 25*

*Training: 2 Jan 2012 to 31 Dec 2012, period: 2 Jan 2009 to 1 Jan 2012, trend: 4 neighbors, window: 0 neighbor, var: ws.wd*

**Wind speed at Bovina: Binned spread-skill diagram**




*Training period: last 365 days, period downscaled: last 1 entire year, analogs: 25*

*Training: 10 Oct 2011 to 8 Oct 2012, period: 10 Oct 2010 to 9 Oct 2011, trend: 4 neighbors, window: 0 neighbor, var: ws.wd*

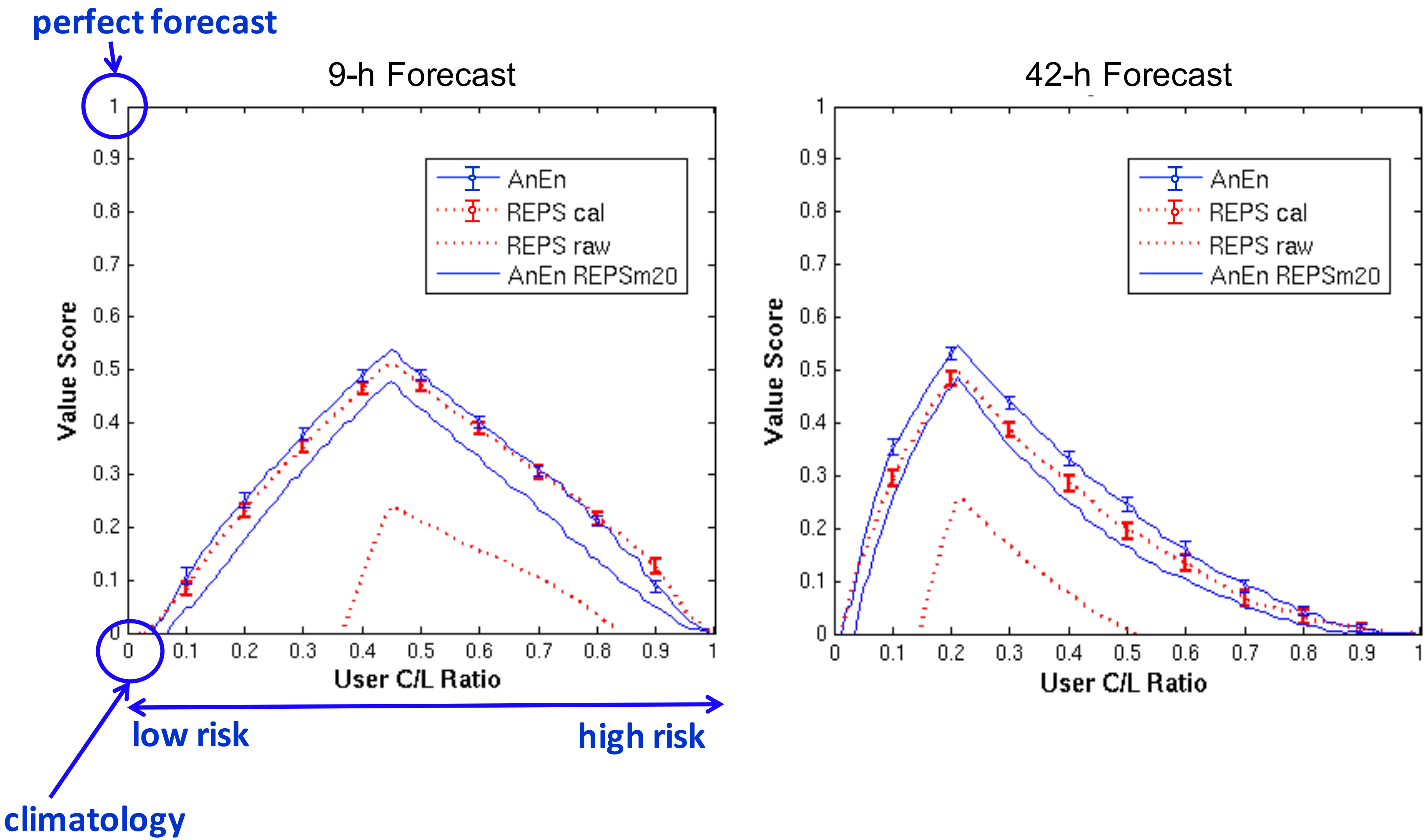
# Probabilistic forecast attributes: Economic value (value score)

Potential value of a forecast in a decision making framework; it can be estimated using a static cost-loss decision model for a dichotomous event (Wilks, 2006).

A decision maker can chose to pay a cost C (e.g., cost of evacuation efforts) to protect against a possible loss L (with L > C): if protective action is not taken, than the decision maker incurs a loss L if the adverse event incurs (e.g., lost lives).

# Analysis of Value

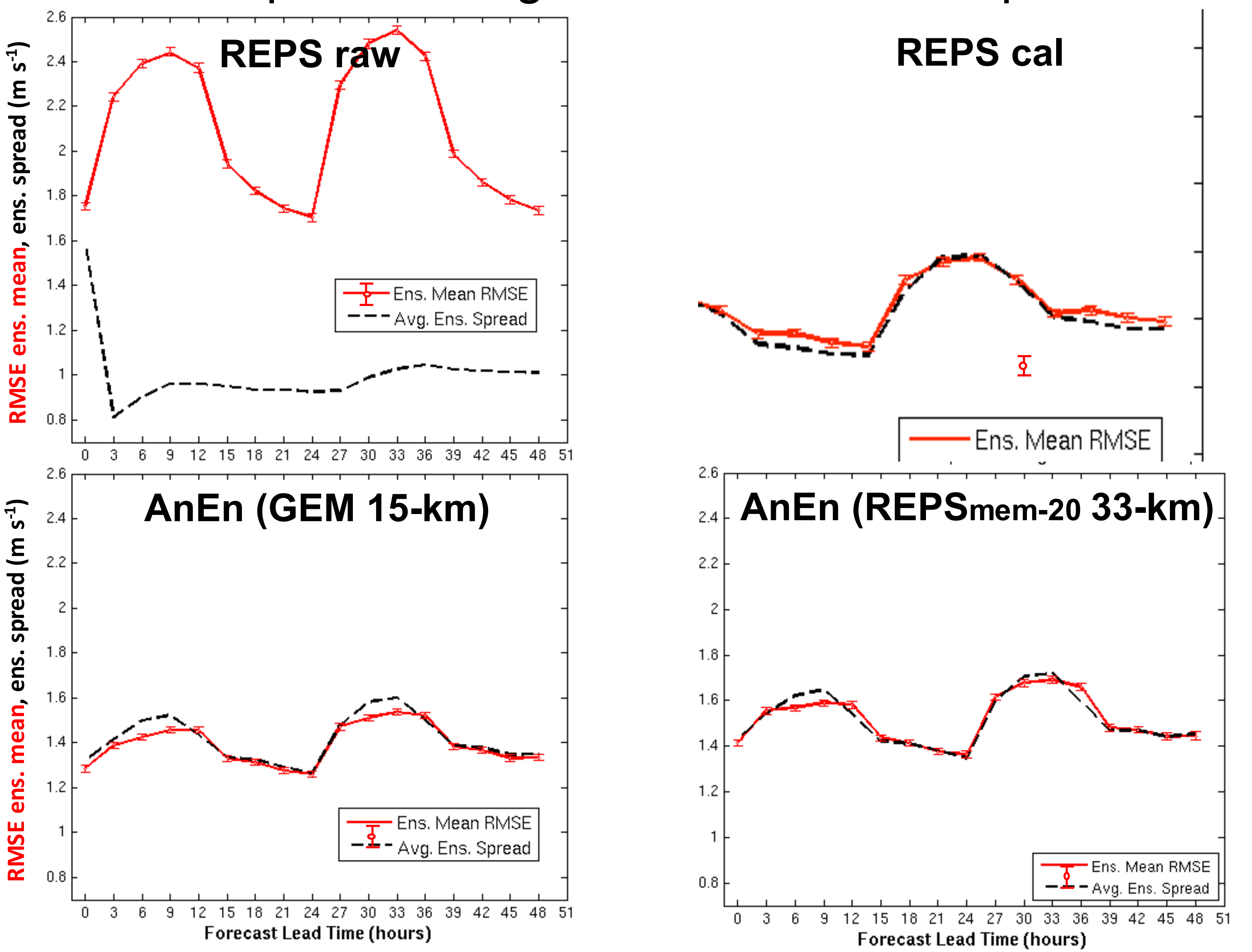
## Economic value diagram, 10-m wind speed ≥ 5 m/s



# Analysis of spread-error consistency (1)

NCAR

## Dispersion diagram for 10-m wind speed



# Measuring Value

NCAR

**Value Score** *(or expense skill score)*

$$\boxed{VS = \frac{E_{fcst} - E_{clim}}{E_{perf} - E_{clim}}}$$

$E_{fcst} =$ Expense from follow *the* forecast

$E_{clim} =$ Expense from follow a climatological forecast

$E_{perf} =$ Expense from follow a perfect forecast

$$\boxed{VS = \frac{\frac{1}{M}(a\alpha + b\alpha + c) - \min(\alpha, \bar{o})}{\bar{o}\,\alpha - \min(\alpha, \bar{o})}}$$

$a =$ # of hits

$b =$ # of false alarms

$c =$ # of misses

$d =$ # of correct rejections

$\alpha =$ *C/L* ratio

$\bar{o} =$ *(a+c) / (a+b+c+d)*

| Forecast and/or Prepare | | Event Observed: Yes | Event Observed: No |
|---|---|---|---|
| | Yes | *a* | *b* |
| | No | *c* | *d* |

# NASA's MERRA

- Introducti
  on

- NASA Modern-Era Retrospective Analysis
  for Research and Applications (MERRA)
  - Based on NASA's Global Atmospheric Model
    and Data Assimilation System
  - 3-D worldwide record of weather from 1979
  - 1/2 degrees latitude × 2/3 degrees longitude
  - Hourly surface 2D and 6 hourly 3D fields
  - Assimilation of all NASA historical satellite data
  - Conventional data