



Probabilistic Forecasting for Weather Prediction

Luca Delle Monache

National Security Applications Program

Research Applications Program

National Center for Atmospheric Research

Software Engineering Assembly

Boulder, CO – 2 April 2018

Acknowledgments



NCAR

• COLLABORATORS

- Stefano Alessandrini, Will Cheng, Sue Haupt, Tom Hopson, Jason Knievel, Chis Rozoff (NCAR, USA)
- Jan Keller (DWD, Germany)
- Roland Stull (University of British Columbia, Canada)
- Constantin Junk, Lueder von Bremen, Detlev Heinemann (ForWind, Carl von Ossietzky University, Germany)
- Iris Odak, Kristian Horvath (Meteorological and Hydrological Service of Croatia, Croatia)
- Badrinath Nagarajan (IBM, Australia)
- Federica Davo', Simone Sperati (RSE, Italy)
- Caroline Draxl, Bri-Mathias Hodge, Jie Zhang (NREL, USA)
- Tony Eckel (Climate Corporation, USA)
- Thomas Nipen (Norwegian Meteorological Institute, Norway)
- Irina Djalalova, Jim Wilczak (NOAA, USA)
- Emilie Vanvyve (UK Met Office, UK)
- Sam Hawkins, Jesper Nielsen Nissen (Vattenfall, UK, Denmark)
- Jessica Ma, Daran Rife (DNV GL, USA)
- Martina Calovi, Guido Cervone, Laura Harding, Mehdi Shahriari (Penn State, USA)
- Will Lewis (University of Wisconsin, Madison, USA)
- Marina Astitha, Jaemo Yang (University of Connecticut)
- Min Cheng, Zaiwen Wang (Institute of Urban Meteorology, Beijing, China)
- Sal Candido, Sam Ponda, Bradley Rhodes, Aakanksha Singh (Google X)

• SPONSORS

- U.S. Department of Defense (DOD) Army Test and Evaluation Command (ATEC)
- U.S. DOD Defense Threat Reduction Agency (DTRA)
- U.S. Department of Energy (DOE)
- U.S. National Aeronautics and Space Administration (NASA)
- U.S. National Renewable Energy Laboratory (NREL)
- U.S. National Oceanic and Atmospheric Administration (NOAA) Hurricane Forecast Improvement Program (HFIP)
- Vattenfall, Vestas Wind Systems, Xcel Energy
- Institute of Urban Meteorology (IUM)
- Google X

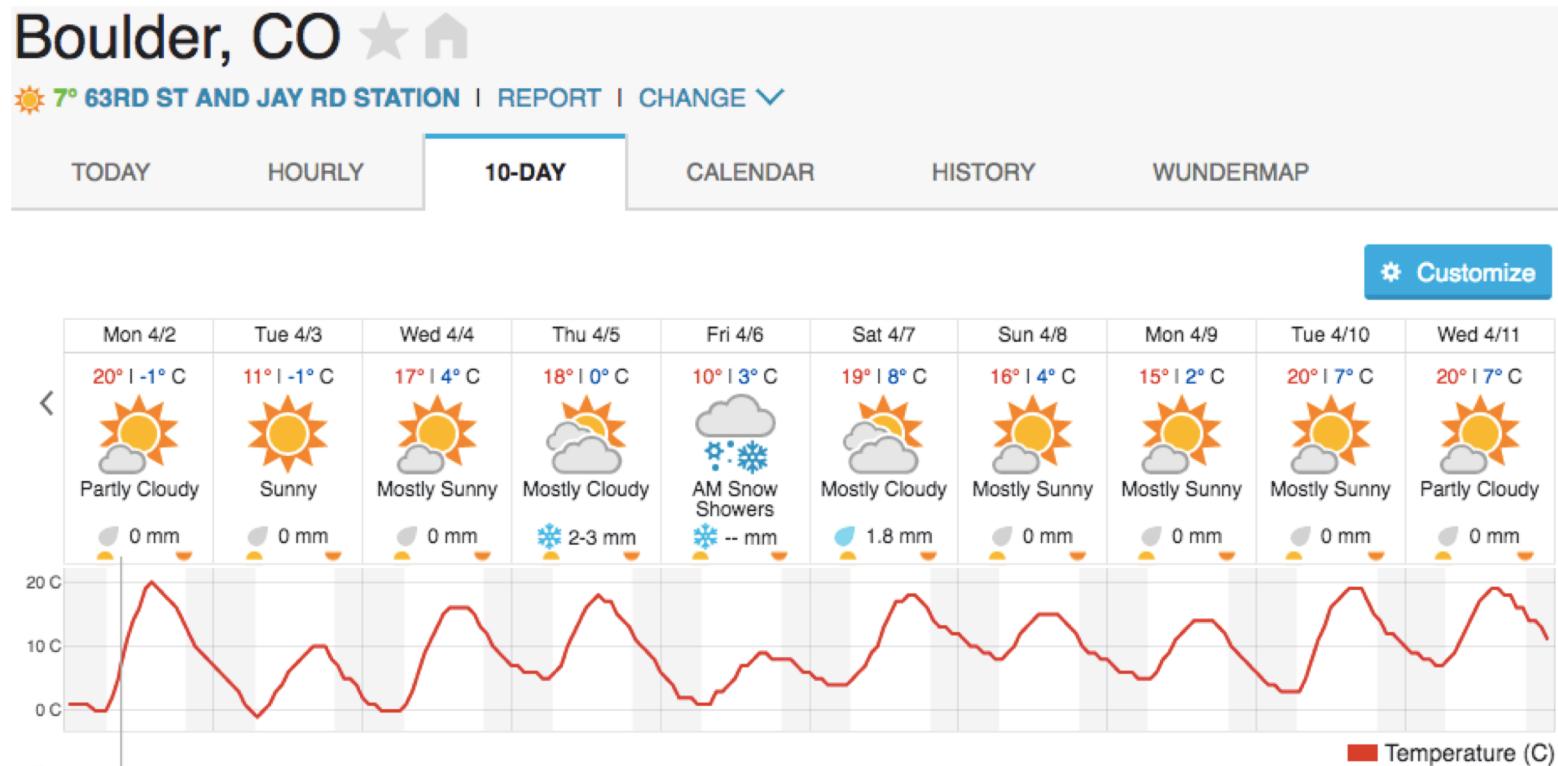
Outline



- Chaos, probabilistic predictions, ensembles
- Analog Ensemble (AnEn) basic idea and algorithm
- AnEn for point-based predictions and downscaling
 - Wind power
- AnEn for 2D/gridded probabilistic predictions
 - 10-m wind speed
- Summary



Traditional forecasting used to (and often still does) consist of one prediction from one model



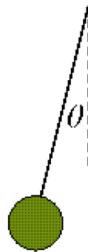
- Specific... but how likely? Unknown
- Likelihood <100% because the atmosphere is...

CHAOTIC!

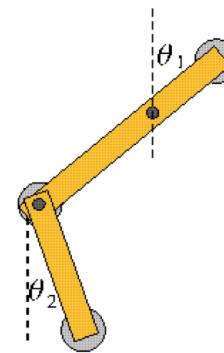
Chaos



NON-CHAOTIC
Simple pendulum



CHAOTIC
Double Pendulum



The Atmosphere is a Chaotic System



Edward Norton Lorenz
(May 23 1917 - April 16 2008)

**"Predictability: Does the Flap of a
Butterfly's Wings in Brazil Set Off
a Tornado in Texas?"**

The Atmosphere is a Chaotic System



NCAR

- Small differences in the initial conditions between two runs grow in time up to a point when the two simulations look as they were randomly chosen
- The Atmosphere predictability ***is limited***
- Lorenz estimated this limit at ~2 weeks
- Such limit varies with different scales of motion
- Predictability changes with different atmospheric flows, i.e., it is ***flow-dependent***

Prediction Goals



- Predict the observed distribution of events and atmospheric states
- Predict uncertainty in the day's prediction
- Predict the extreme events that are possible on a particular day
- Provide a range of possible scenarios for a particular forecast

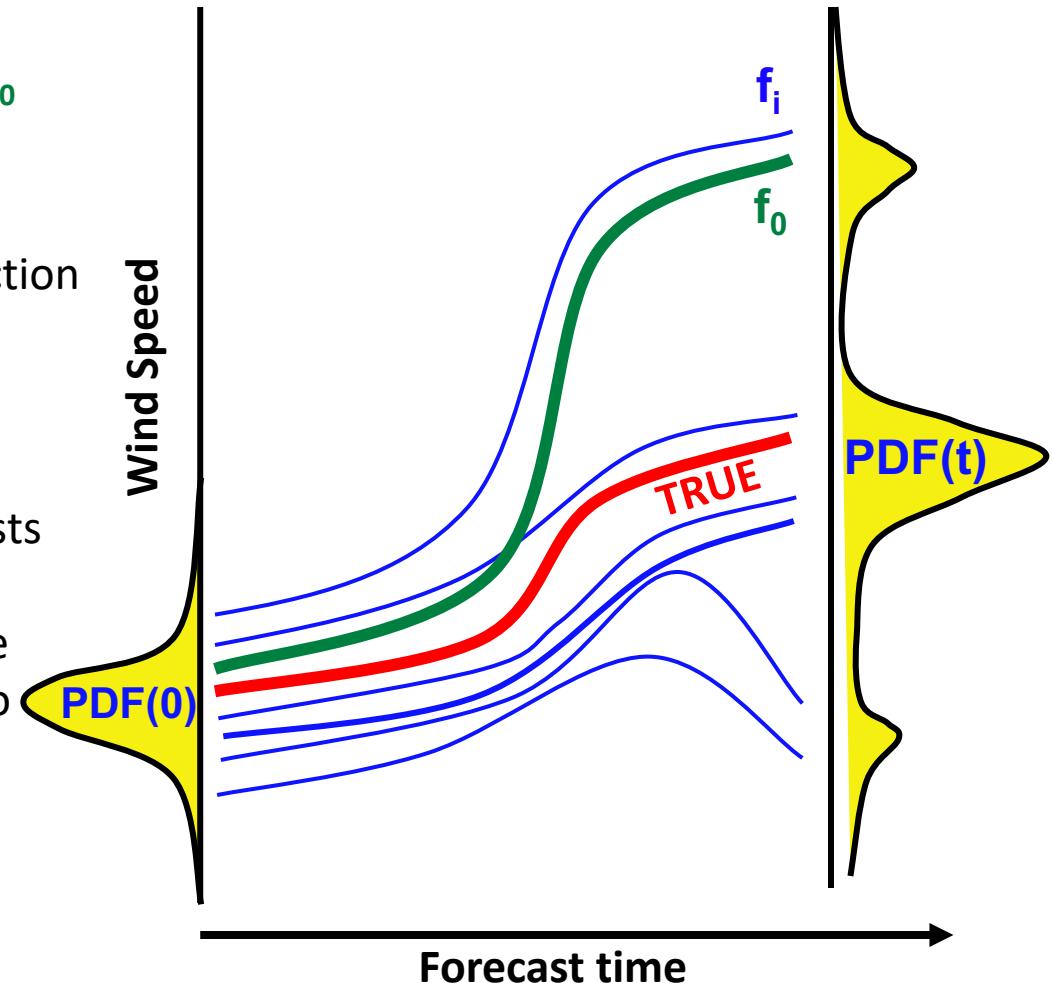
Ensemble Prediction



The single deterministic forecast f_0 fails to predict the **TRUE**

The initial probability density function **PDF(0)** represents the initial uncertainties

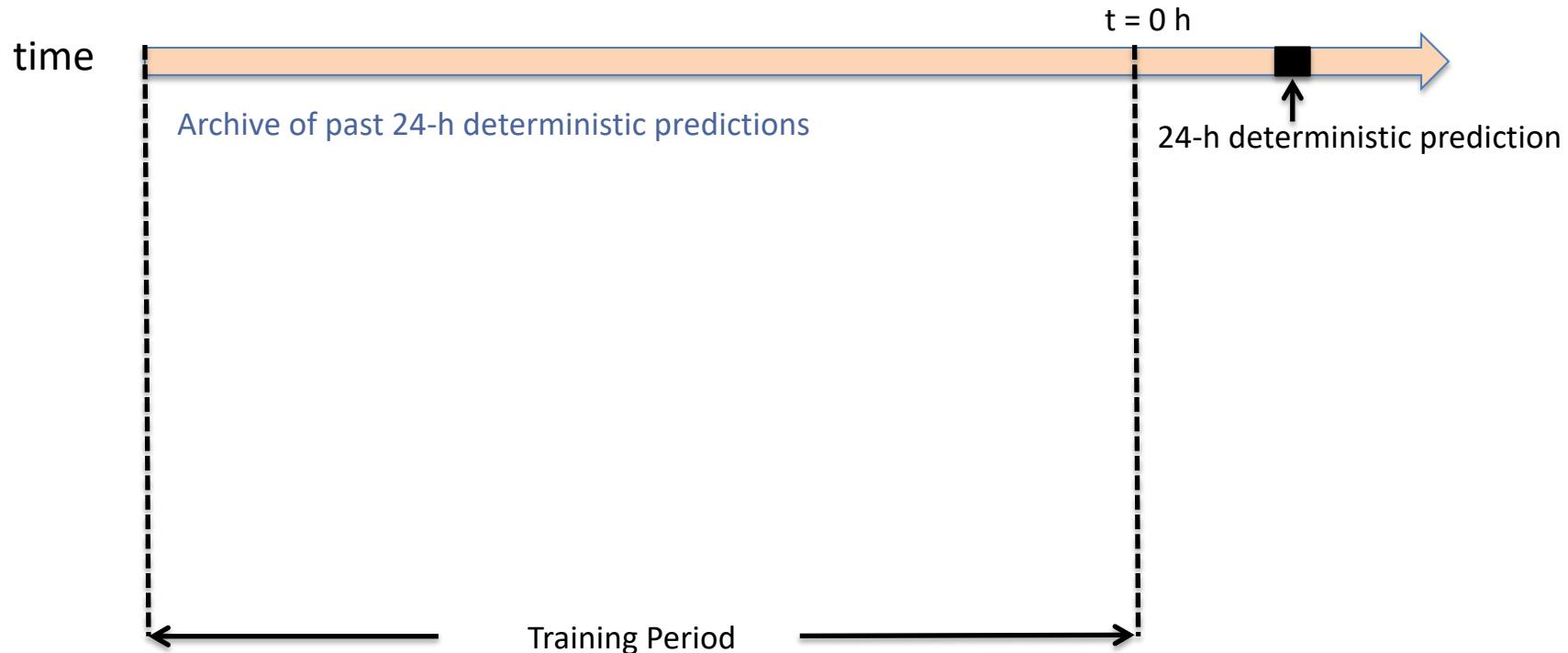
An ensemble of perturbed forecasts f_i , starting from perturbed initial conditions designed to sample the initial uncertainties can be used to estimate the probability of future states **PDF(t)**



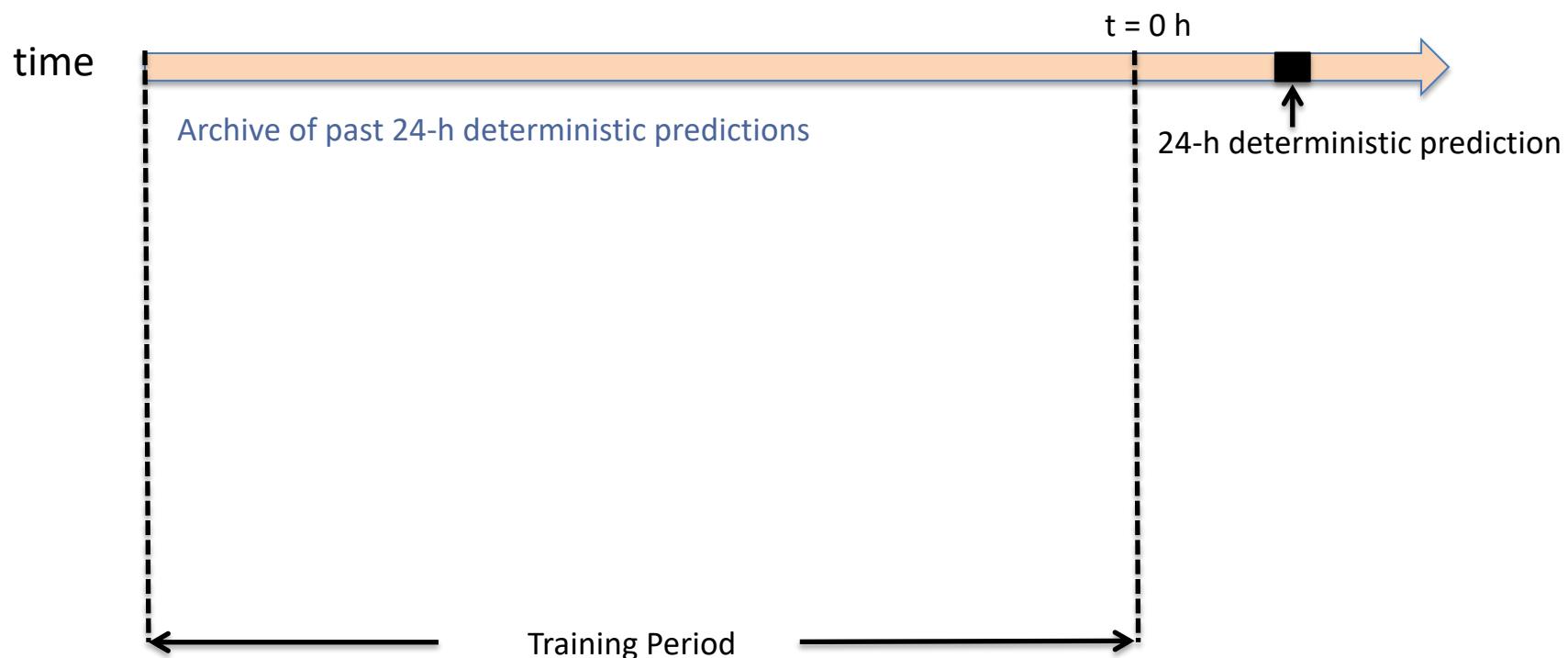


The Analog Ensemble (AnEn)

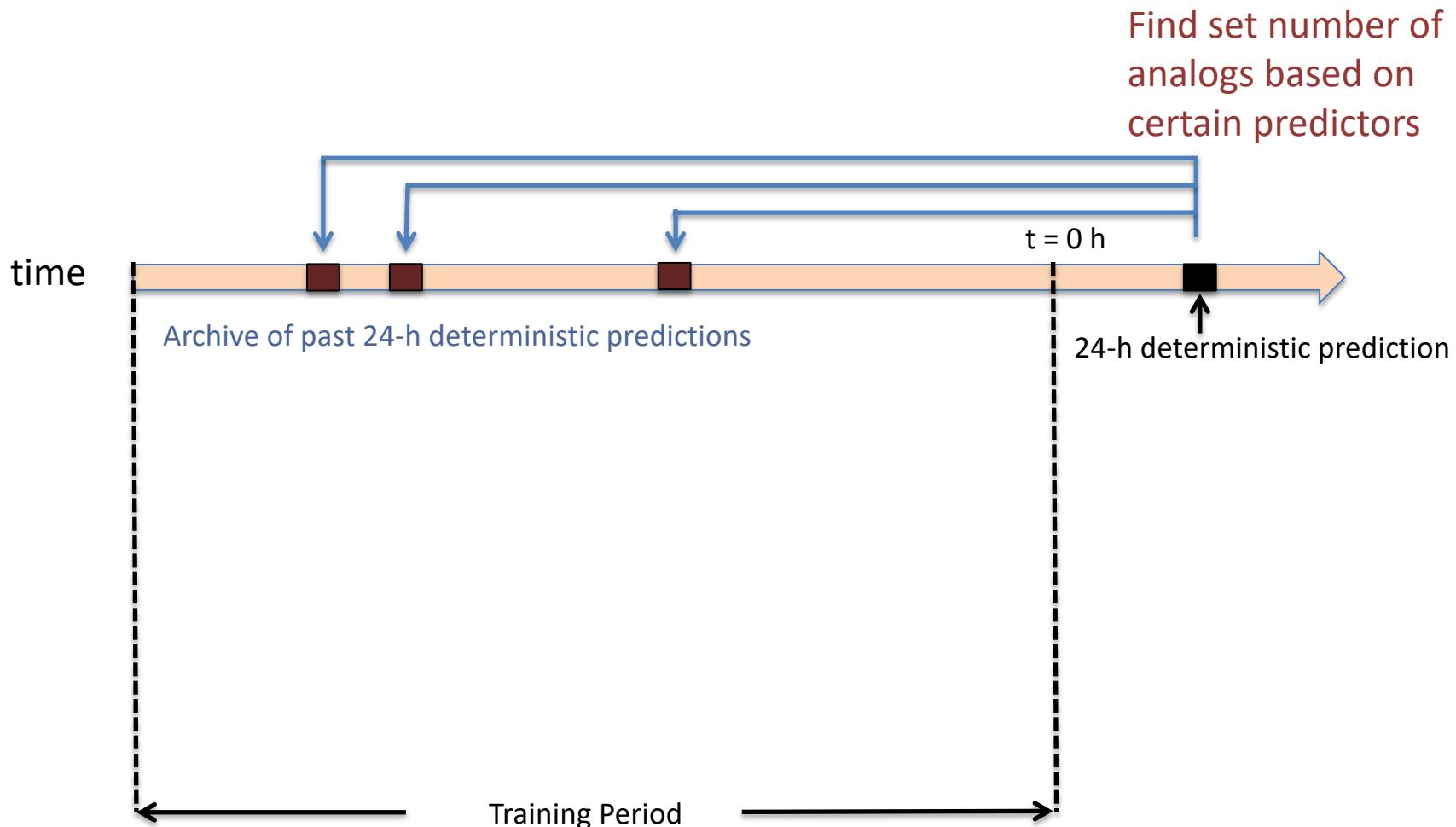
The Analog Ensemble



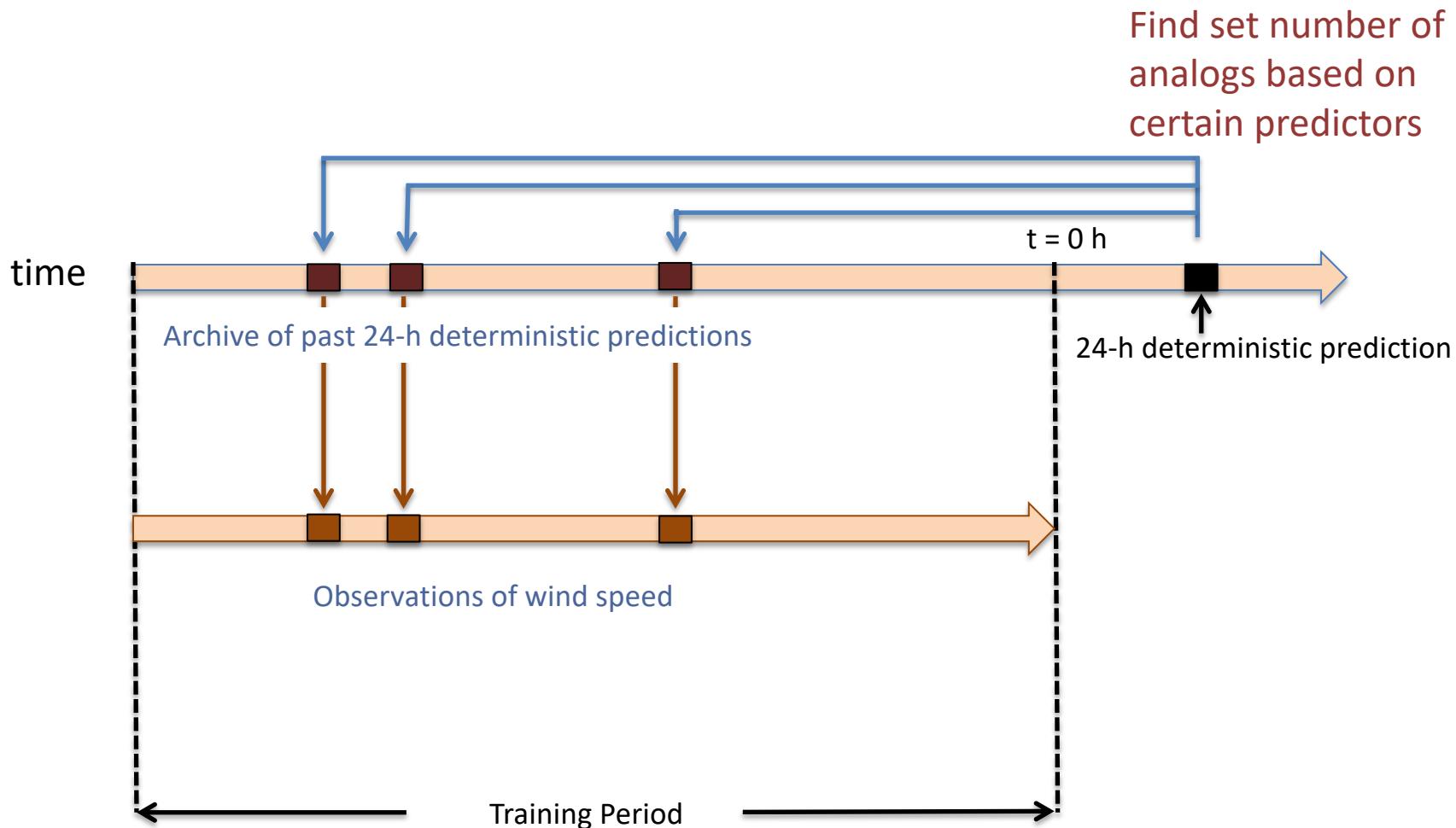
The Analog Ensemble



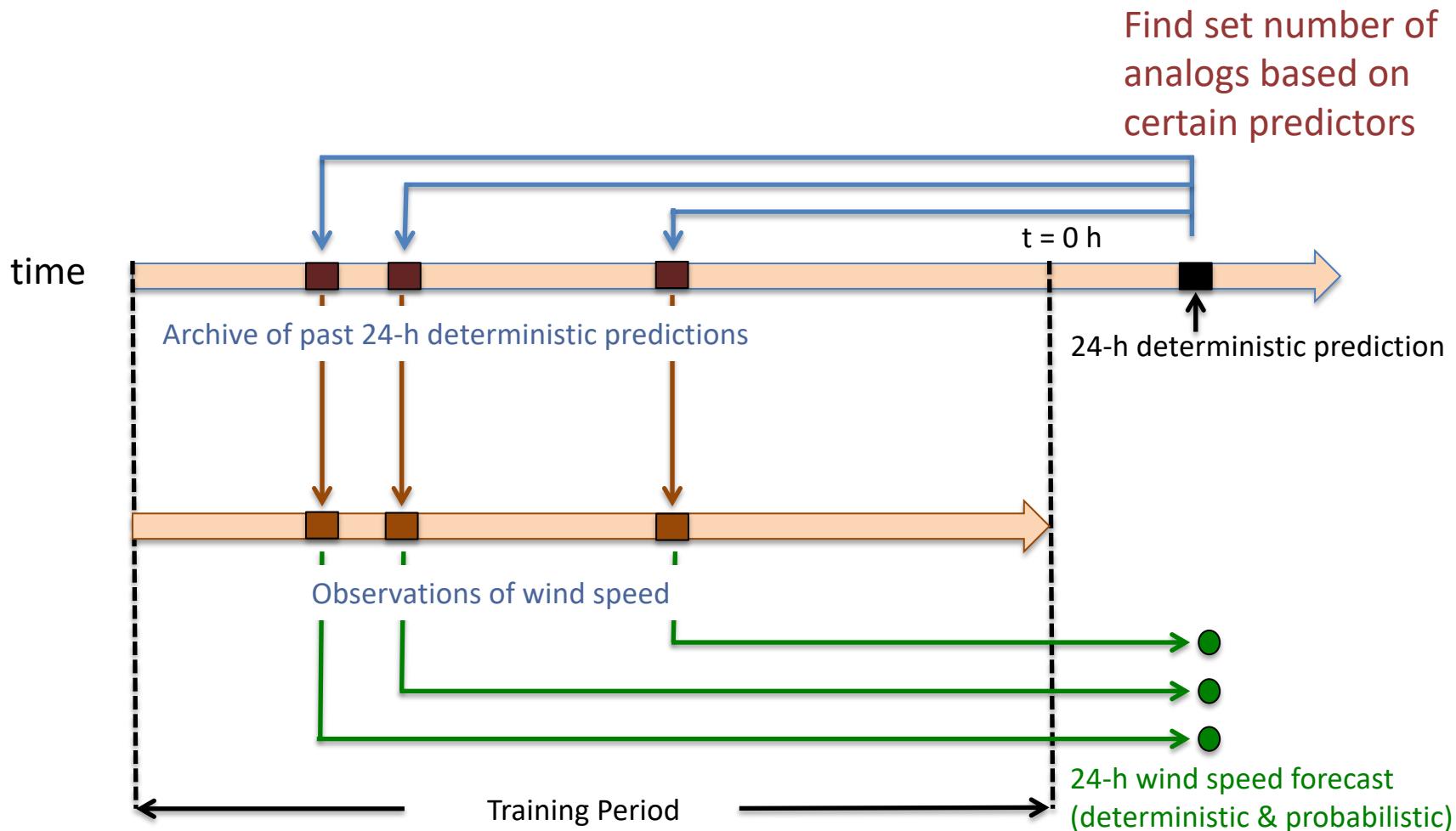
The Analog Ensemble



The Analog Ensemble



The Analog Ensemble





AnEn has been successfully applied for:

- Short-term predictions of:
 - 10- and 80-m wind speed, 2-m temperature, etc.
 - Wind and solar power
 - Energy load
 - Air quality predictions (ground level ozone, surface PM_{2.5})
 - Tropical cyclones intensity
 - Gridded/2D probabilistic predictions
- Downscaling, resource assessment:
 - Wind speed, precipitation
 - Computationally efficient dynamical downscaling



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 and solar power
Alessandrini et al. RE 2015, AE 2015, Davo et al. SE 2016
 - Energy 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. ACPD 2017
 - Tropical cyclones intensity
Alessandrini et al. MWR 2017
 - Gridded/2D probabilistic predictions
Sperati et al. QJRMS 2017
- Downscaling, resource assessment:
 - Wind speed, precipitation
 - Computationally efficient dynamical downscaling



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 and solar power
Alessandrini et al. RE 2015, AE 2015, Davo et al. SE 2016
 - Energy 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. ACPD 2017
 - Tropical cyclones intensity
Alessandrini et al. MWR 2017
 - 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



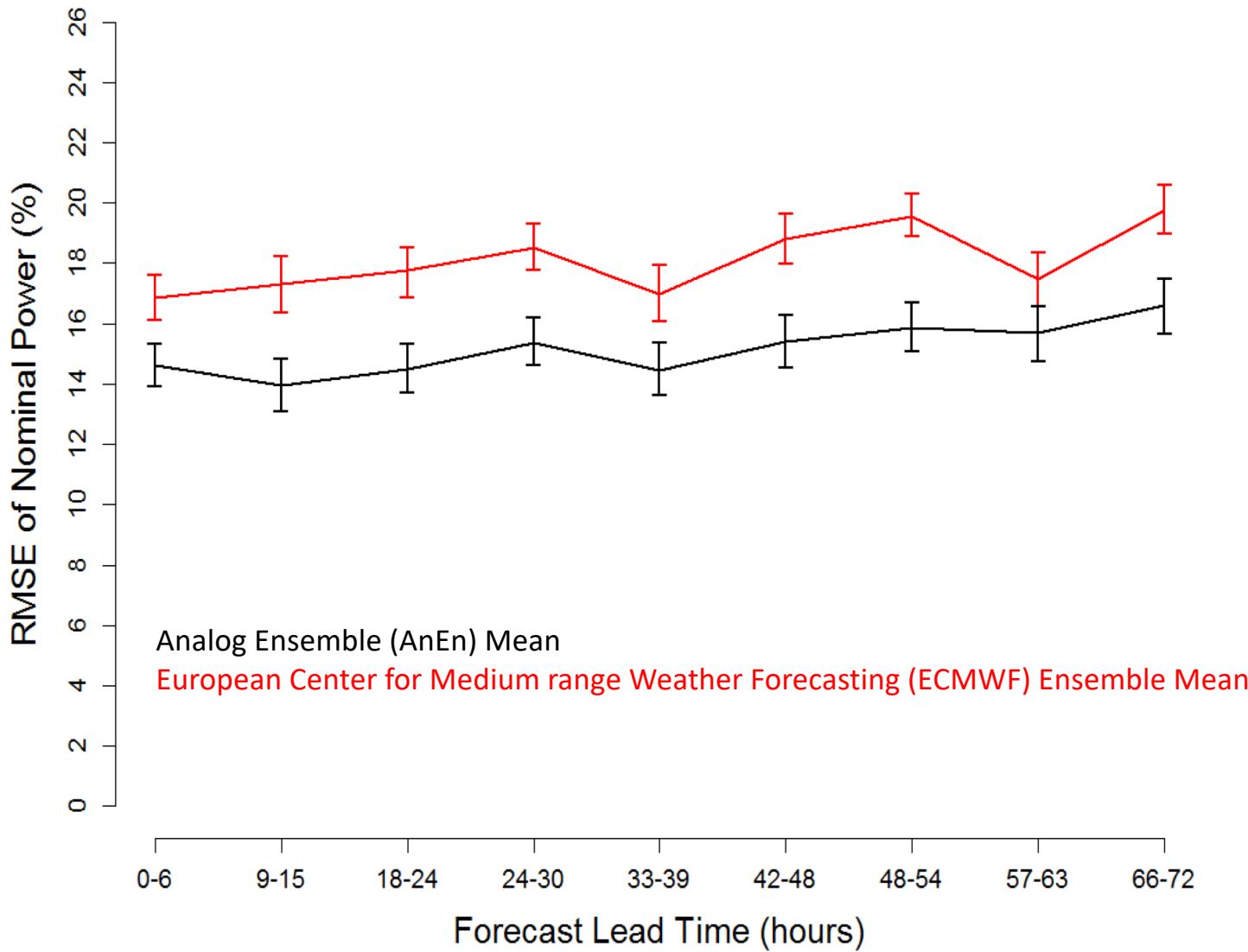
Point-based Probabilistic Predictions with AnEn

Power predictions: Experiment design

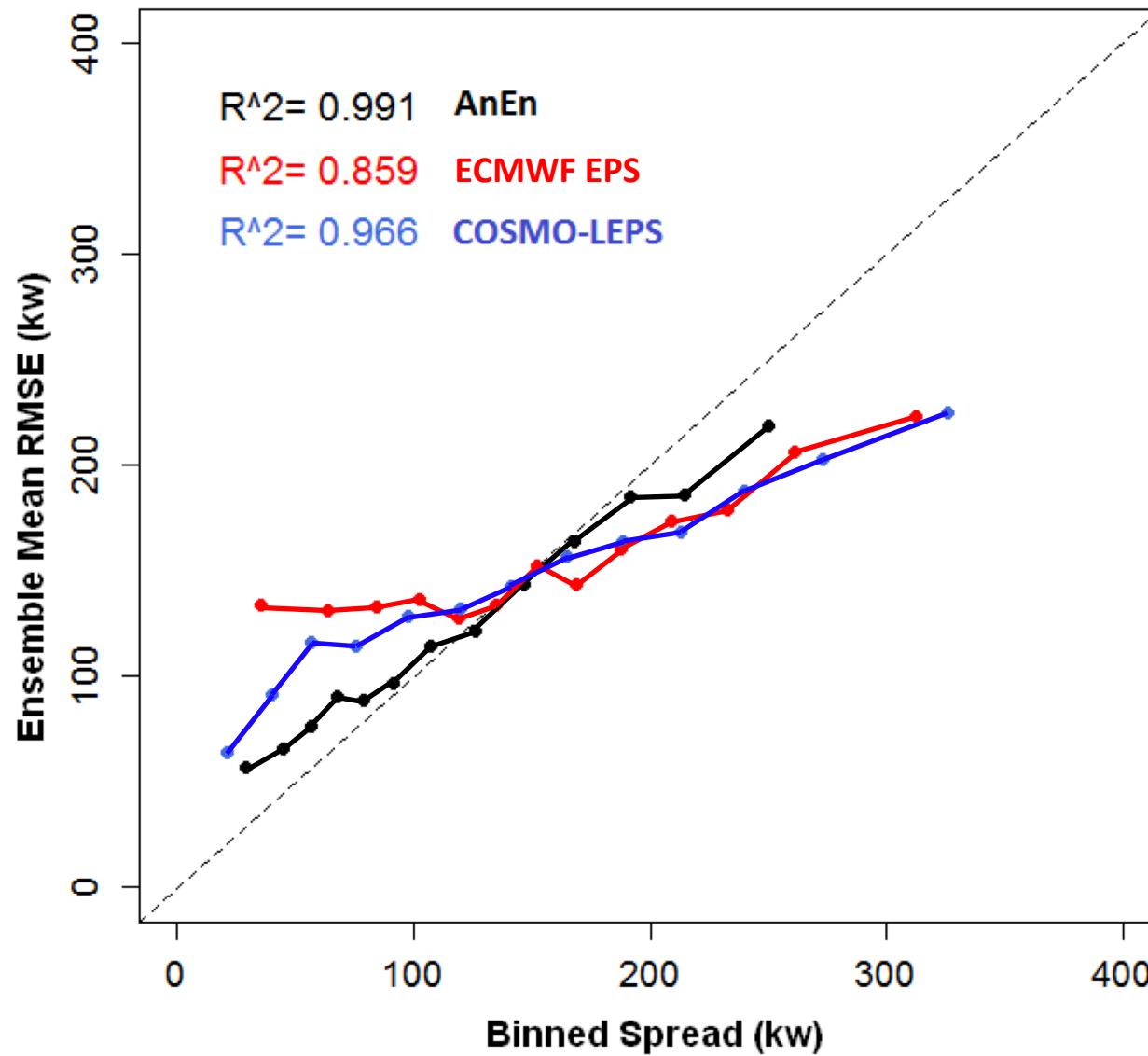


- Test site: Wind farm in northern Sicily – 9 turbines, 850 kW Nominal Power (NP)
- Training period: November 2010 - October 2012
- Verification period: November 2011 – October 2012
- Probabilistic prediction systems: ECMWF EPS, COSMO LEPS, AnEn

RMSE of ensemble means



Spread-skill relationship

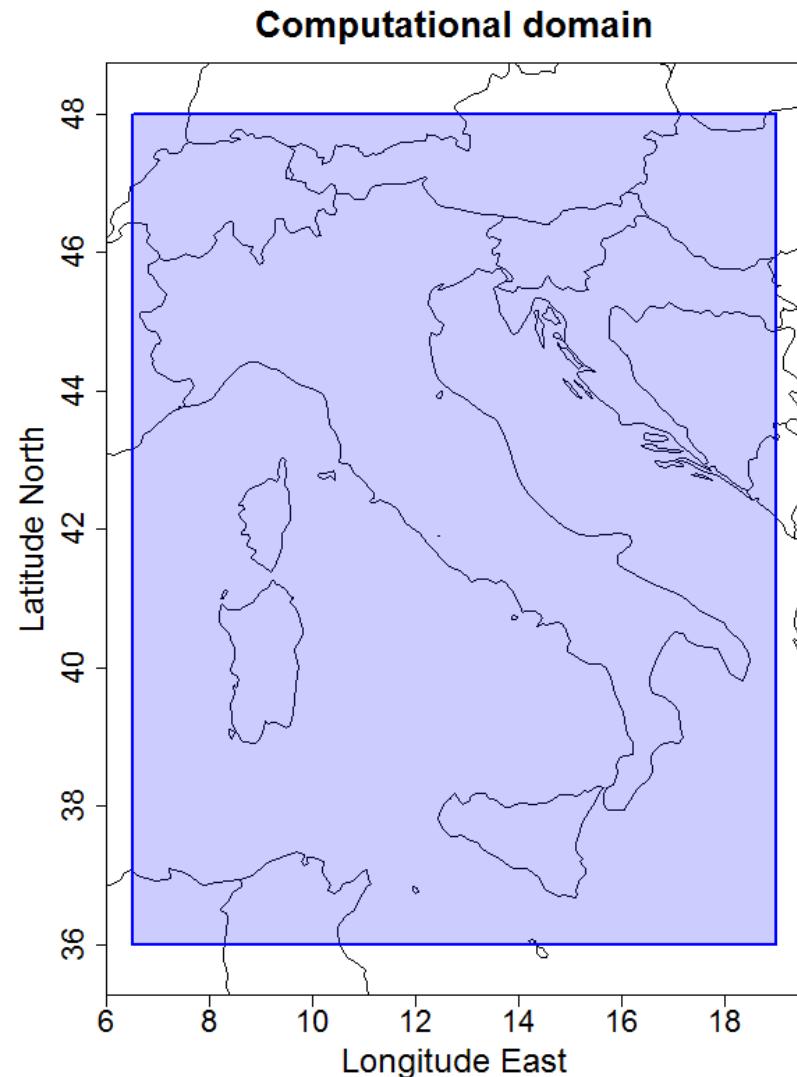




2D/Gridded Probabilistic Predictions with AnEn

Data sets

- Predictand variable: 10-m wind speed (WS)
- Predictors: WS, WD, T2M, MSLP, Z500
- Period: January 2013 – December 2015
- Domain (right): Italy, 1000 km x 1300 km
(0.25° horizontal resolution, 2499 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 (HRES)
(0.125° horizontal resolution; 0 UTC;
+144 h lead time; 3-hourly forecasts)
- ECMWF Ensemble Prediction System (EPS)
(0.25° horizontal resolution; 51 members;
0 UTC; +144 h lead time; 3-hourly forecasts)



Experiment set-up

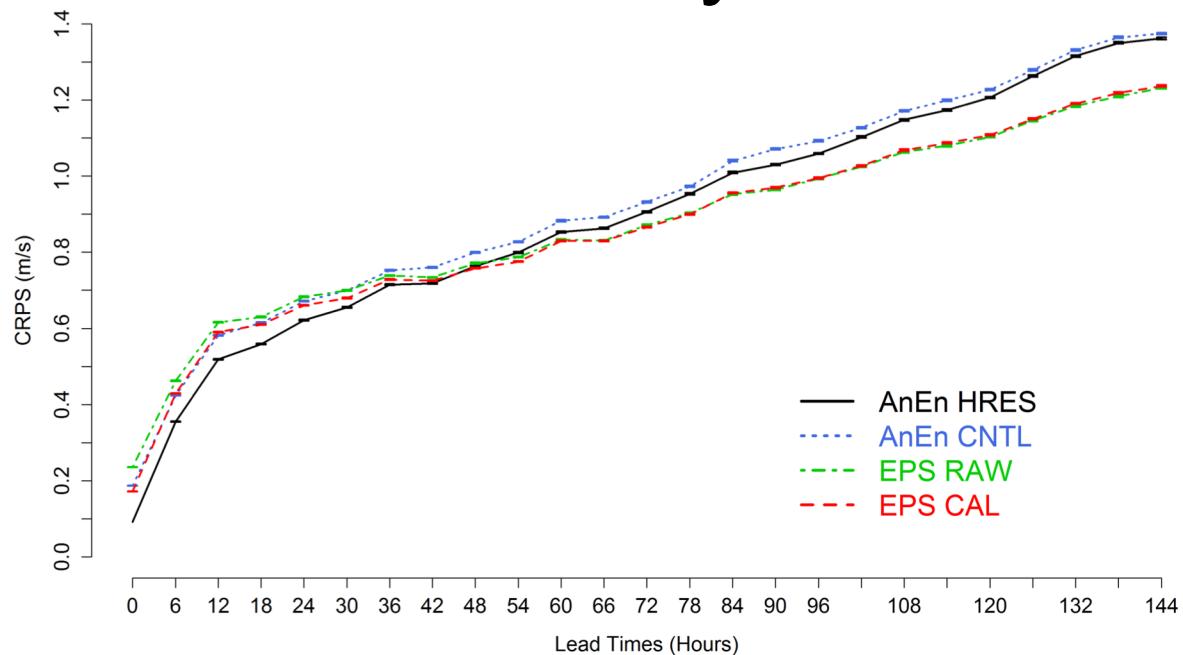


- Methods:
 - **EPS RAW**: ECMWF EP
 - **EPS CAL**: calibrated ECMWF EPS
 - **AnEn HRES**: AnEn generated from ECMWF deterministic run
NOTE: DA + forecast generation **~6-8 times** cheaper than EPS calibrated
 - **AnEn CNTL**: AnEn generated from ECMWF EPS control run
NOTE: forecast generation **51 times** 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

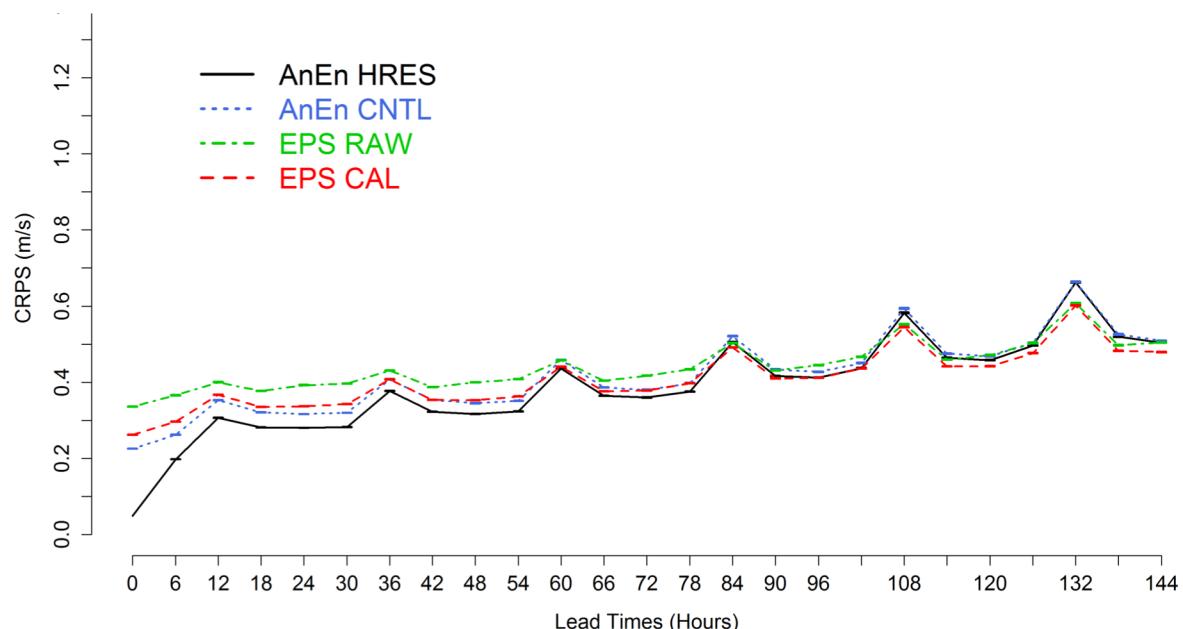
Continuous Ranked Probability Score



Grid points
below 100 m asl



Grid points
above 100 m asl

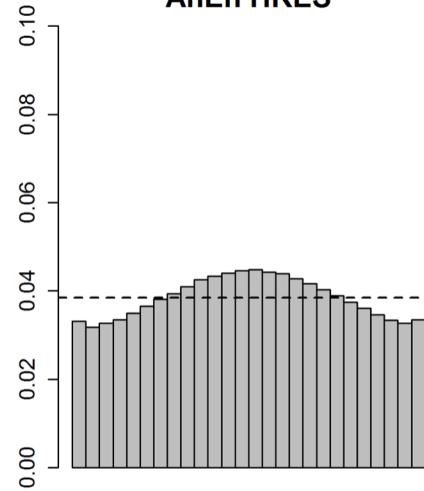




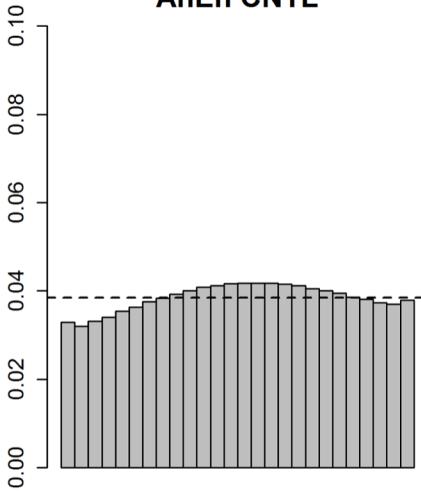
Rank histograms

6-24 h ahead

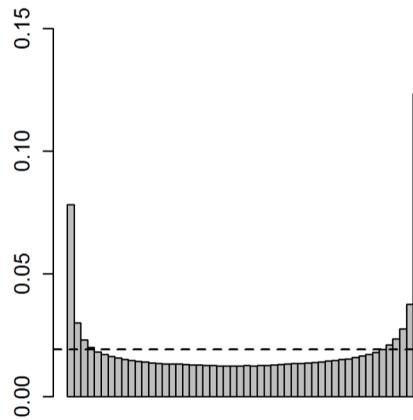
AnEn HRES



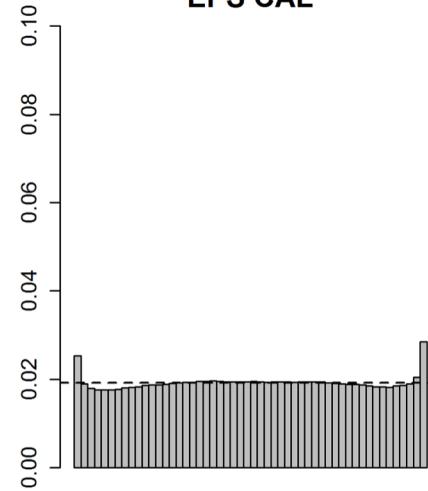
AnEn CNTL



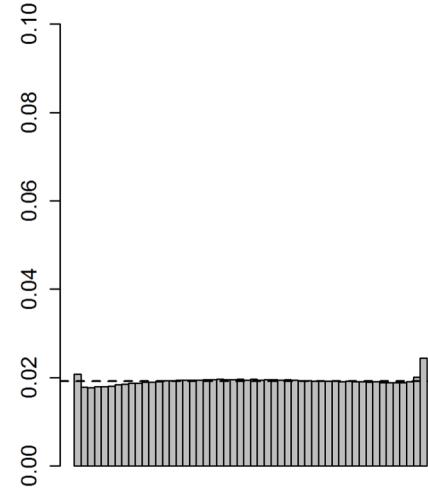
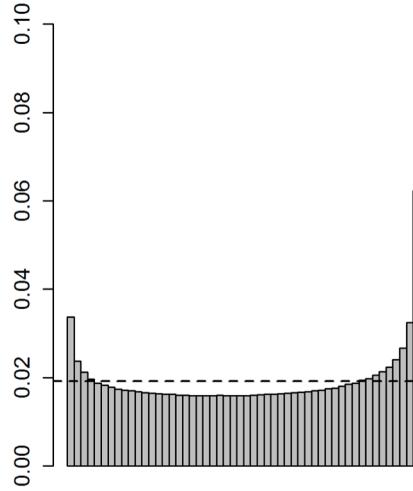
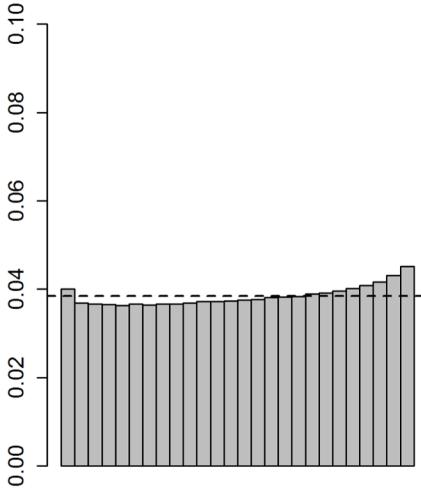
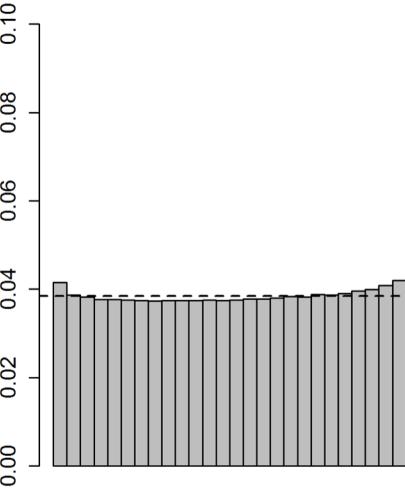
EPS RAW



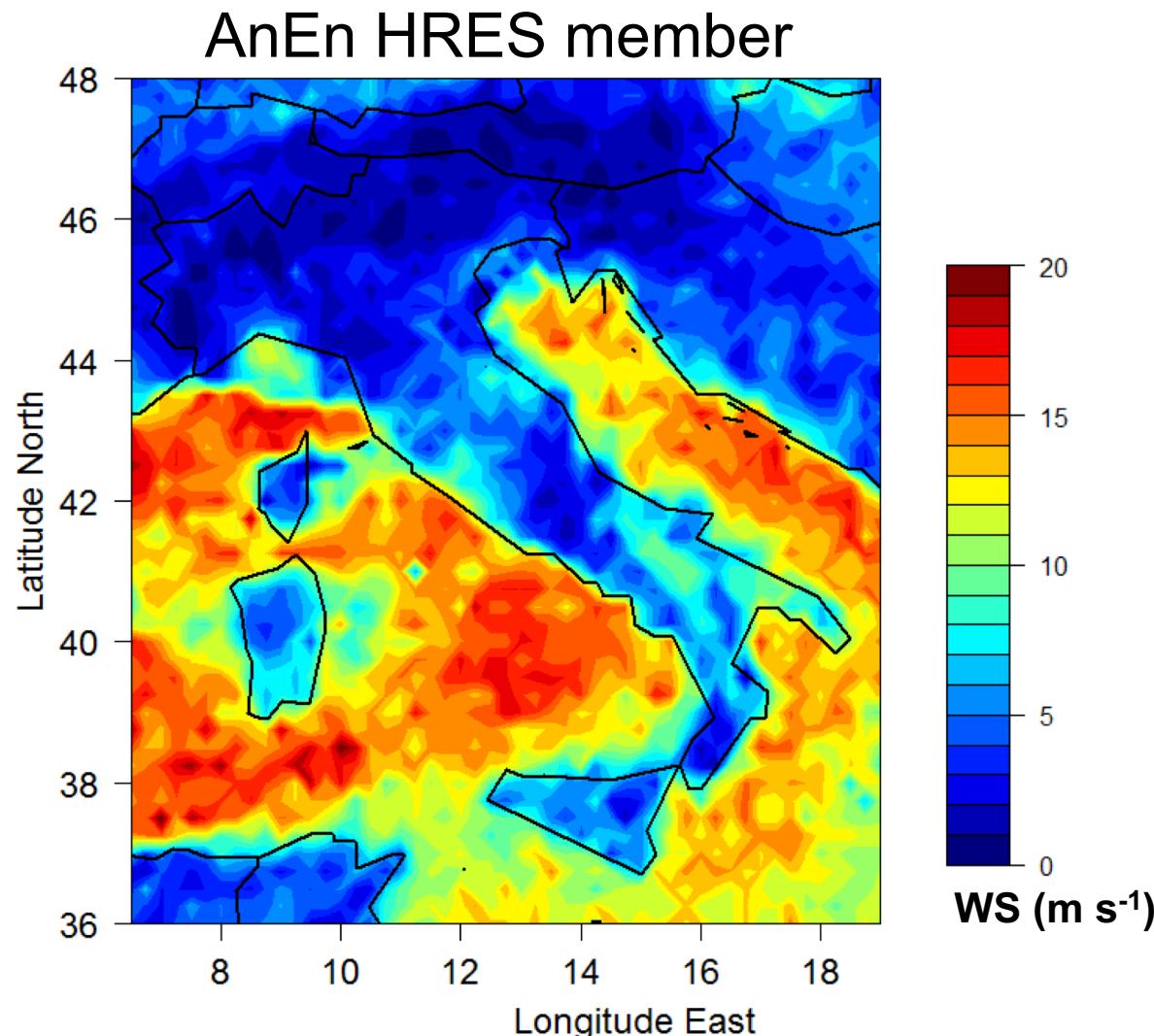
EPS CAL



72-96 h ahead



Is spatial/temporal consistency preserved?

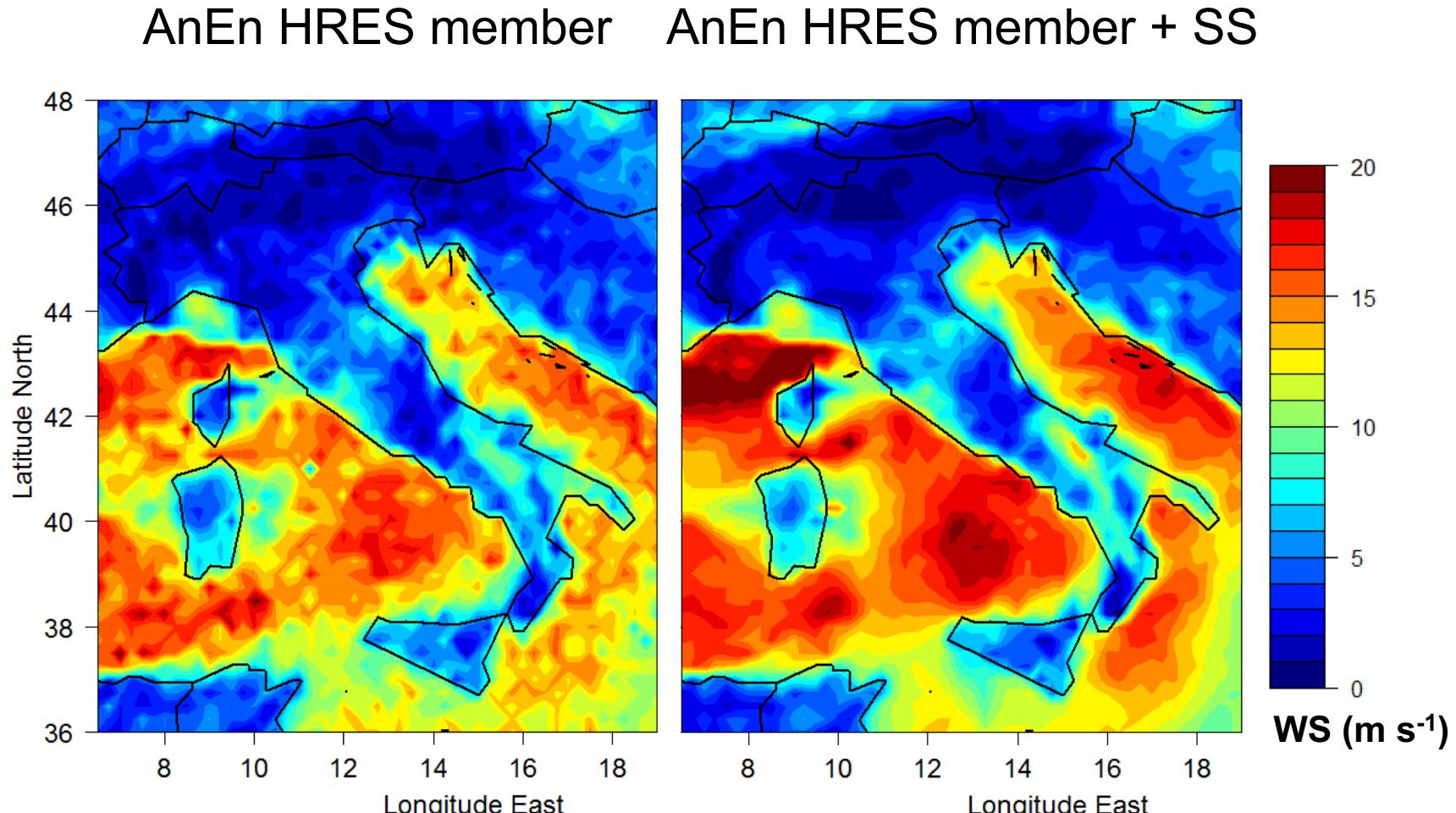


30 Jan 15, 06 UTC, +6 h



Is spatial/temporal consistency preserved?

AnEn + Schaake Shuffle = spatial consistency



30 Jan 15, 06 UTC, +6 h

Clark et al. (2004, JH)

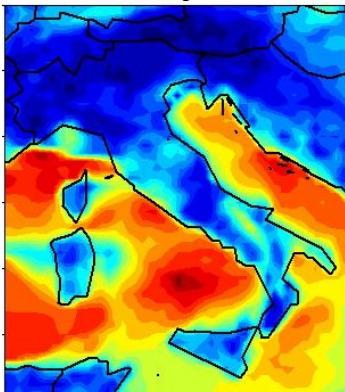
Ensemble mean maps



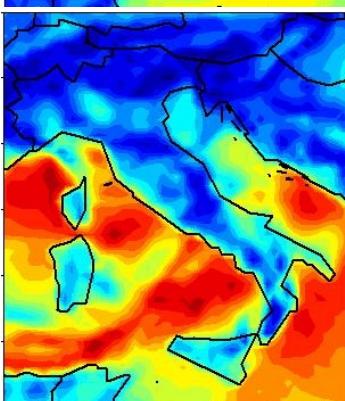
NCAR

Analysis

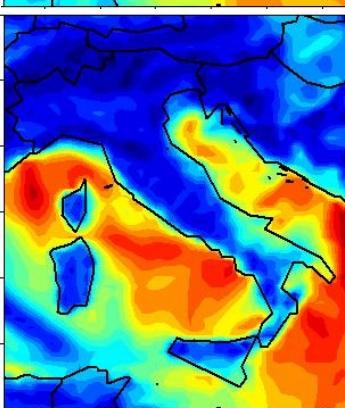
30 Jan 15
06 UTC
+6 h



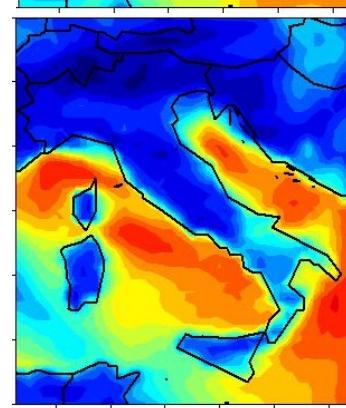
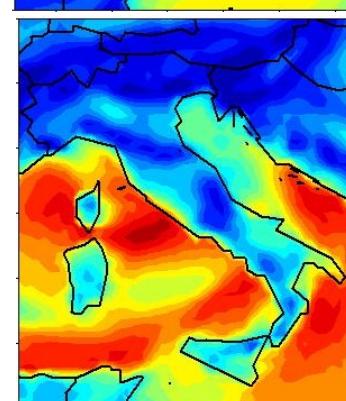
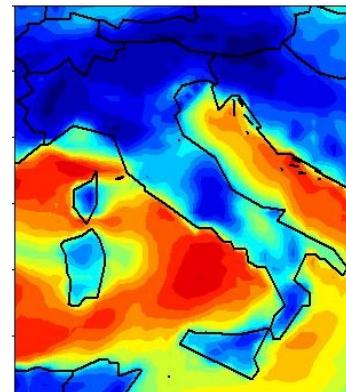
30 Jan 15
12 UTC
+12 h



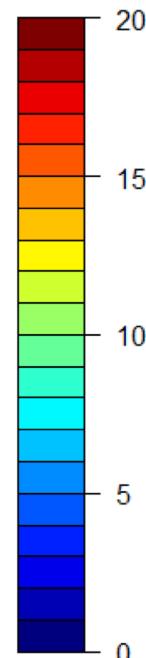
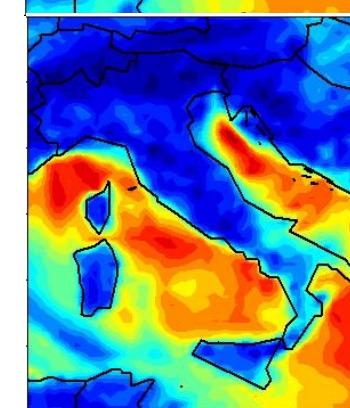
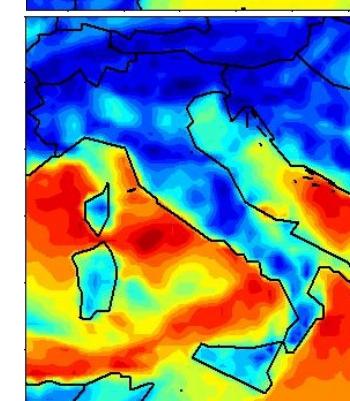
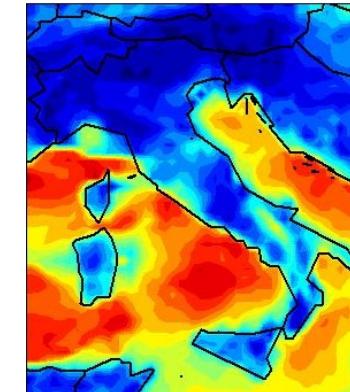
30 Jan 15
18 UTC
+18 h



EPS (BC+VD) mean



AnEn HRES mean



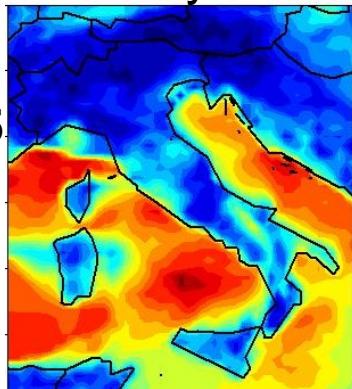
AnEn + SS spatial/temporal consistency



NCAR

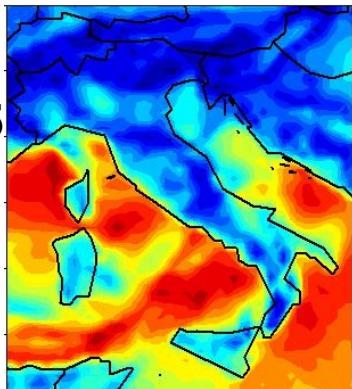
Analysis

30 Jan 15
06 UTC
+6 h

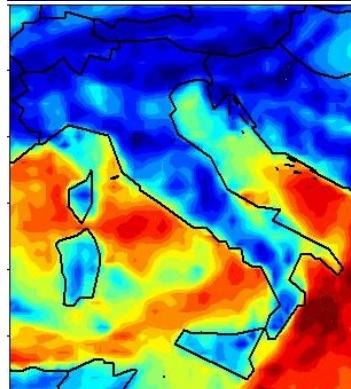
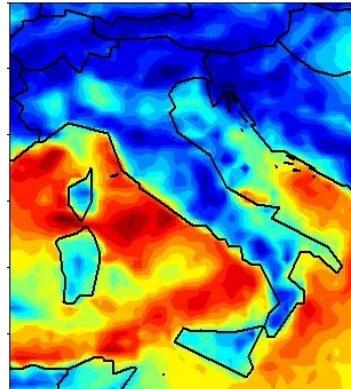
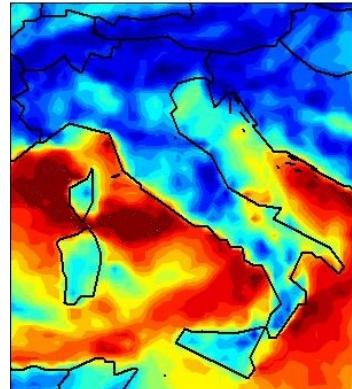
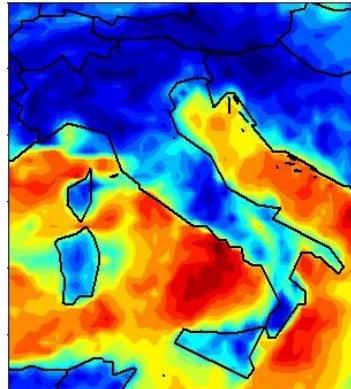
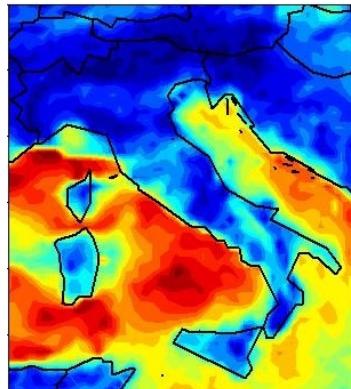
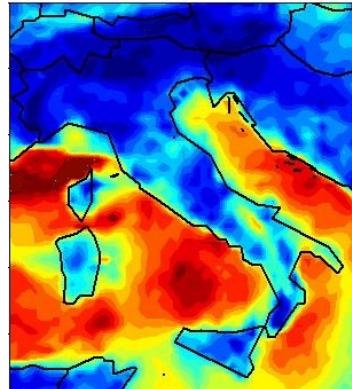
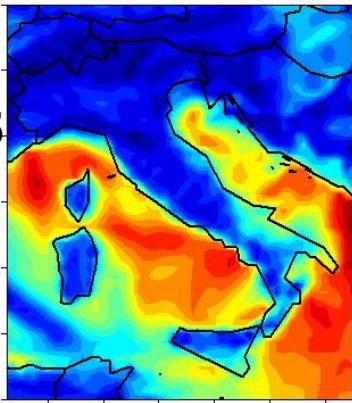


AnEn HRES + SS members

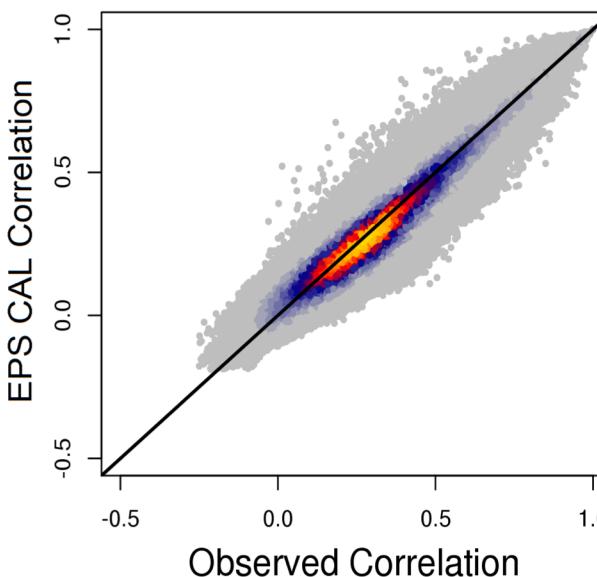
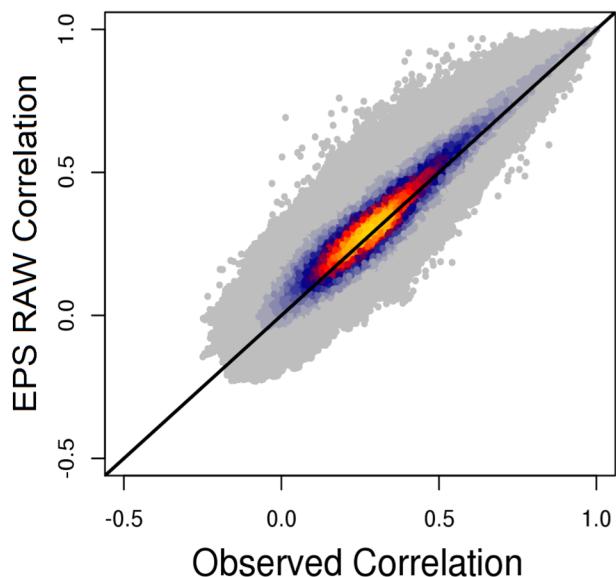
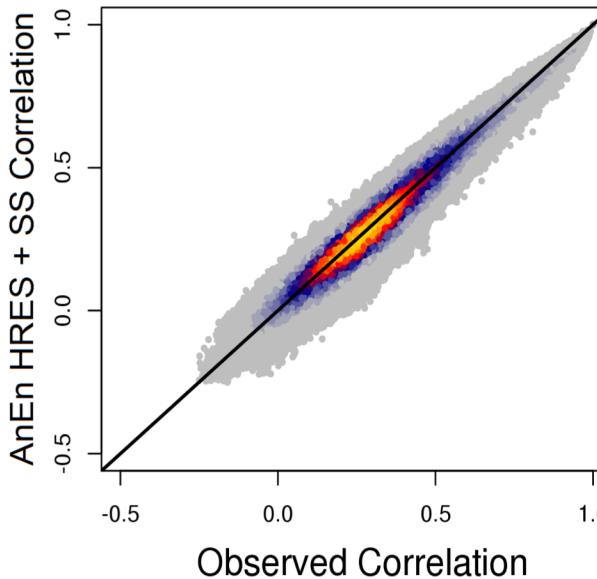
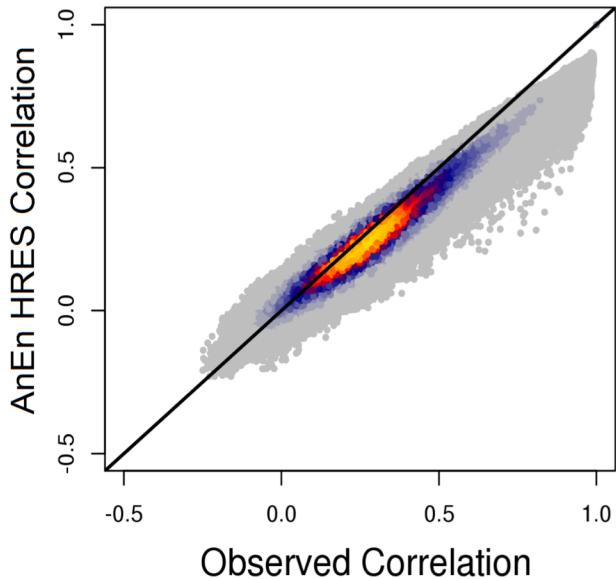
30 Jan 15
12 UTC
+12 h



30 Jan 15
18 UTC
+18 h



AnEn + SS spatial consistency



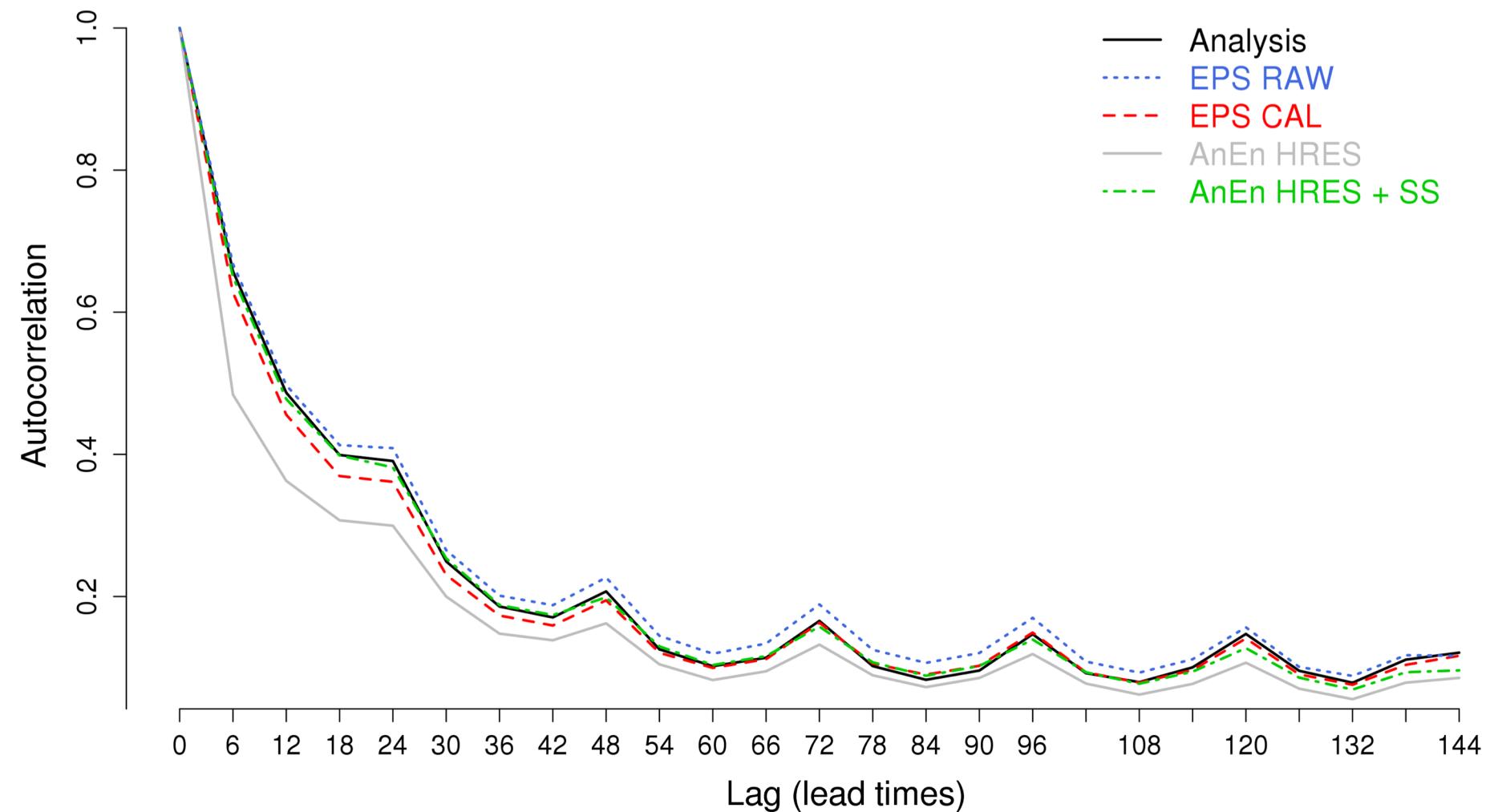
Lead time
36 h

X = correlation($A_i(t), A_j(t)$) where i and j are any two points in the map, k are the members
Y = correlation($F_{i,k}(t), F_{j,k}(t)$)

AnEn + SS temporal consistency



NCAR



Mean autocorrelation across all grid points and ensemble members

Summary



NCAR

- Need for probabilistic predictions -- we are dealing with a chaotic system!
- AnEn successfully tested point-based probabilistic predictions and downscaling (e.g., wind power)
- AnEn can be used also to generate sharp, reliable, spatially and temporally consistent, and computationally efficient probabilistic predictions over a 2D grid
- AnEn key aspects:
 - 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
 - Intrinsically parallel algorithm

Thanks!



Luca Delle Monache: lucadellemona@gmail.com

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. Clark, M., Gangopadhyay, S., Hay, L., Rajagopalan, B., Wilby, R., 2004: The Schaake Shuffle: A method for reconstructing space–time variability in forecasted precipitation and temperature fields. *J. Hydrometeor.*, 5, 243–262
6. 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
7. 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
8. 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
9. 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
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. *Monthly Weather Review*, 144, 897–911
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
13. Gneiting T, Stanberry LI, Grimit EP, Held L, Johnson NA. 2008. Assessing probabilistic forecasts of multivariate quantities, with an application to ensemble predictions of surface winds. *TEST* 17: 211-235.
14. Sperati, S., Alessandrini, S., Delle Monache, L., 2017. Conditionally Accepted, *Quarterly Journal of the Royal Meteorological Society*



The metric (1)

NCAR

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

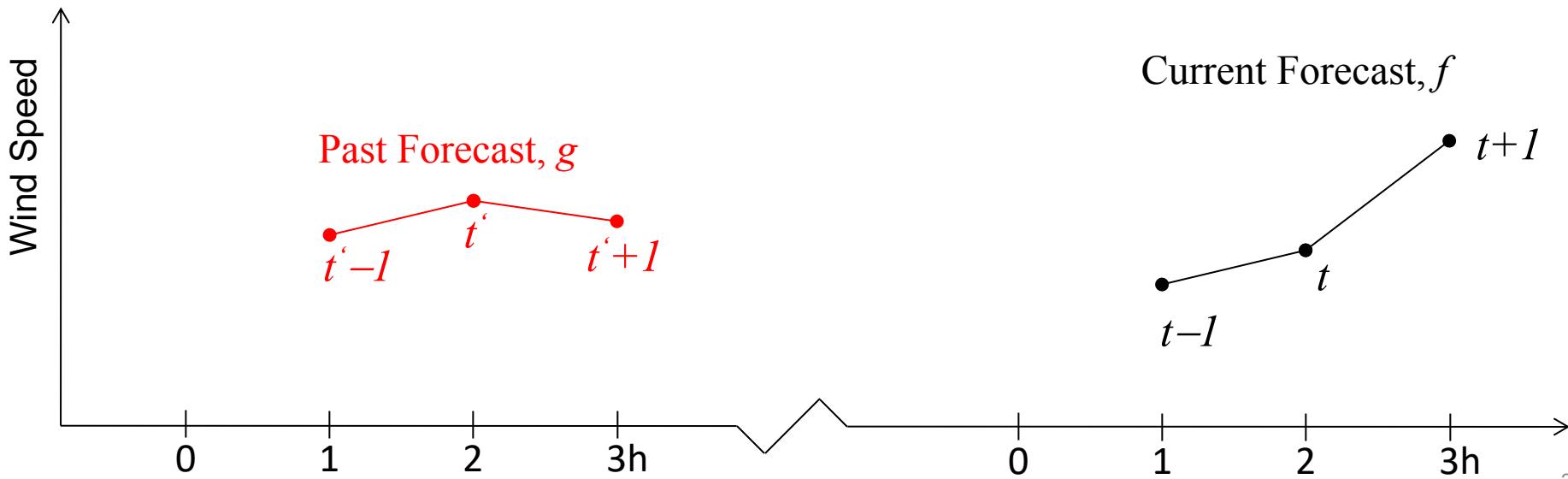
$$\|f_t - g_{t'}\| = \frac{1}{\sigma_f} \sqrt{\sum_{k=-\tilde{t}}^{+\tilde{t}} (f_{t+k} - g_{t'+k})^2}$$

σ_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)

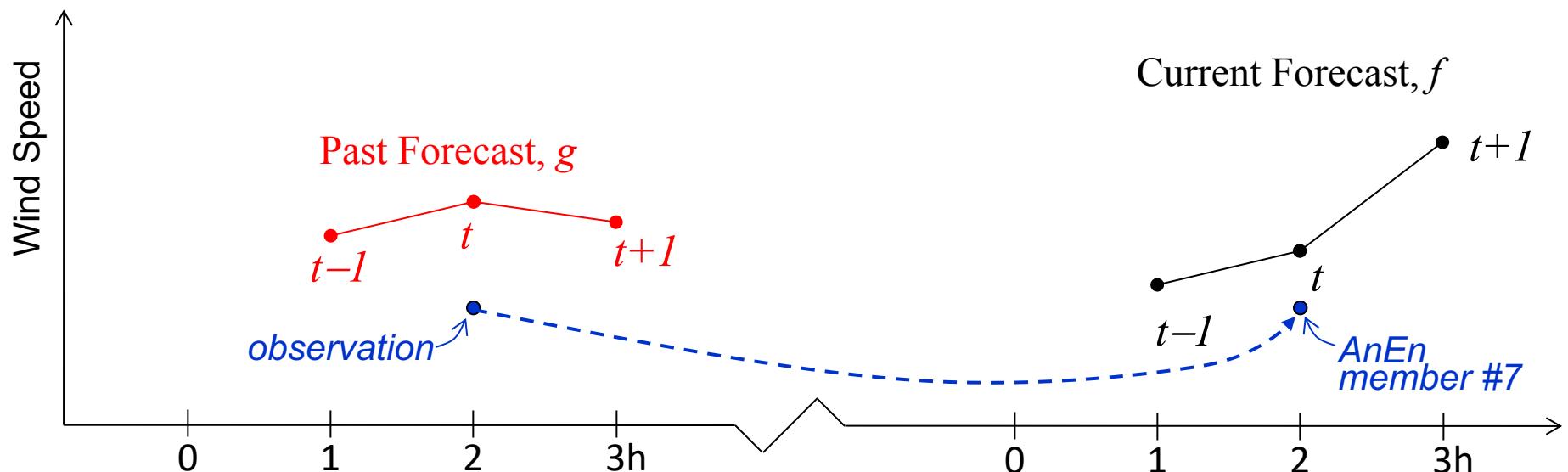
$$\|f_t - g_{t'}\| = \sum_{v=1}^{N_v} \frac{w_v}{\sigma_{f^v}} \sqrt{\sum_{k=-\tilde{t}}^{+\tilde{t}} (f_{t+k}^v - g_{t'+k}^v)^2}$$

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

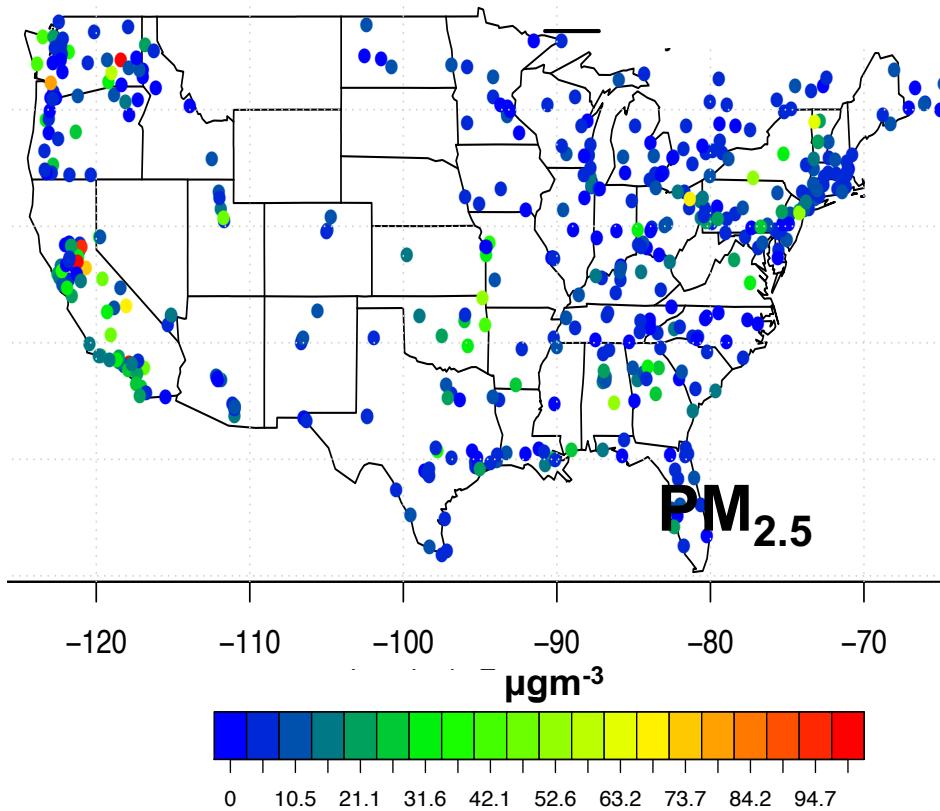
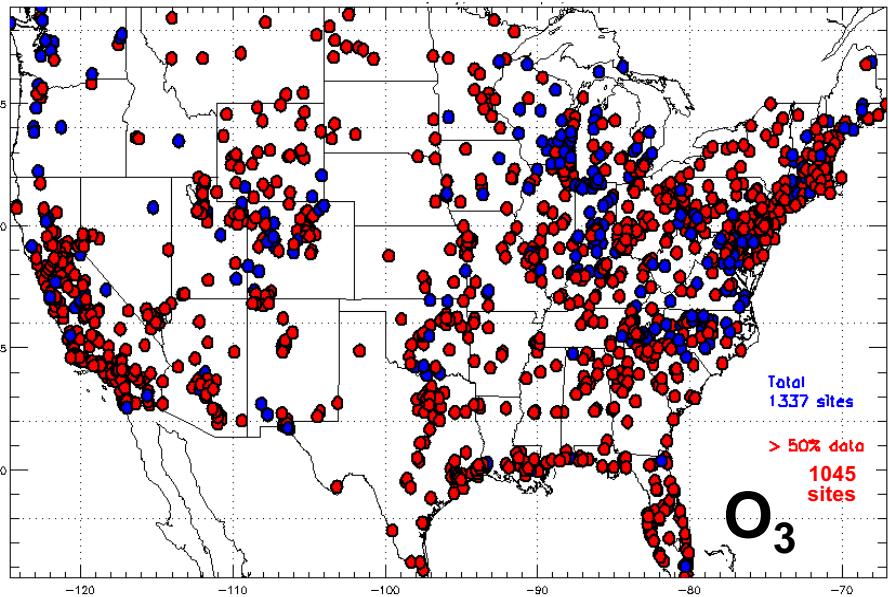


The metric (2)

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



AnEn for air quality: available obs

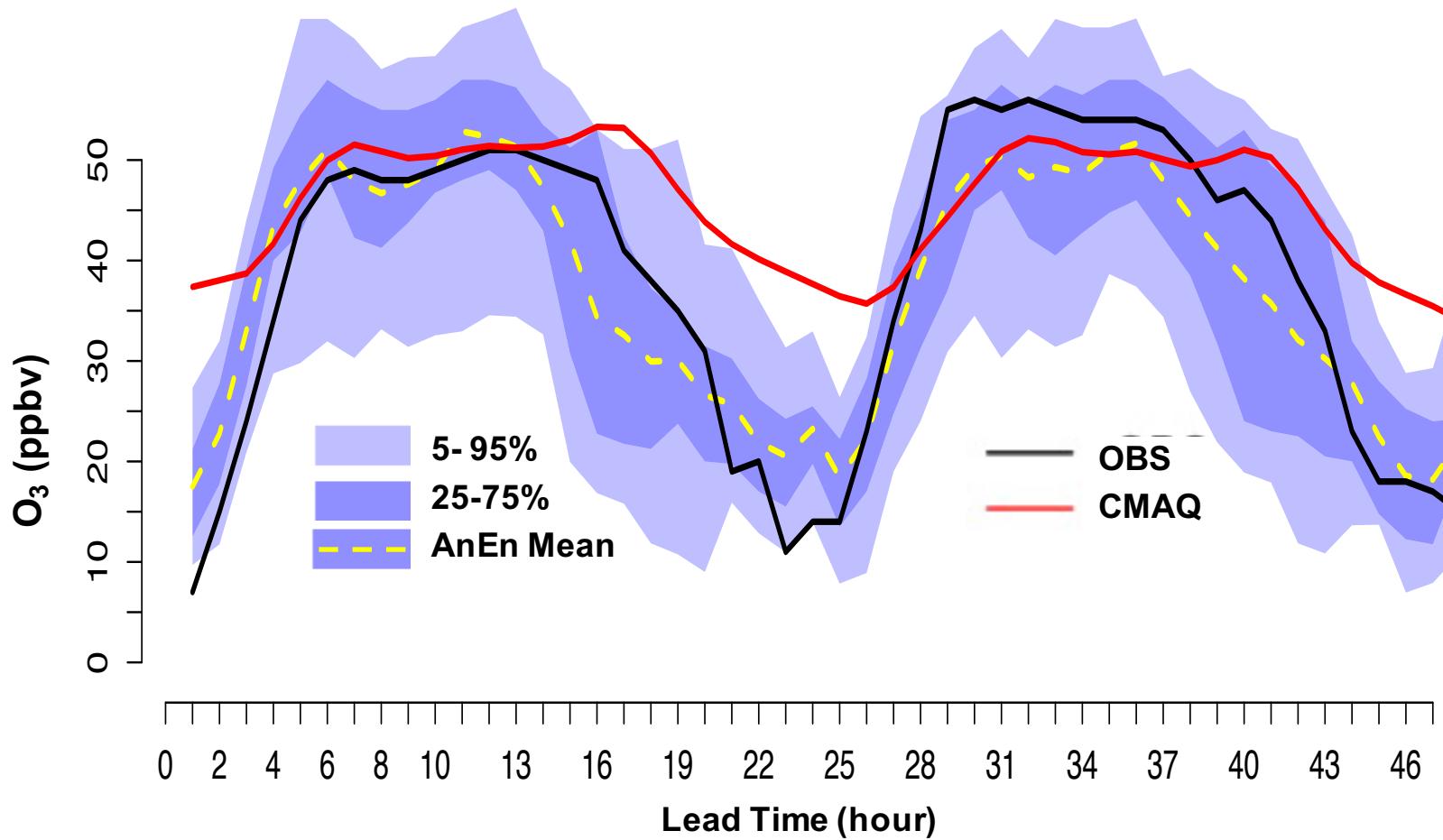


- 1337 AirNow stations
- Training: 15 months, Jul 2014 – Sept 2015
- Verification: May – Sept 2015
- Data availability: 1045 stations with more than 50% of valid data

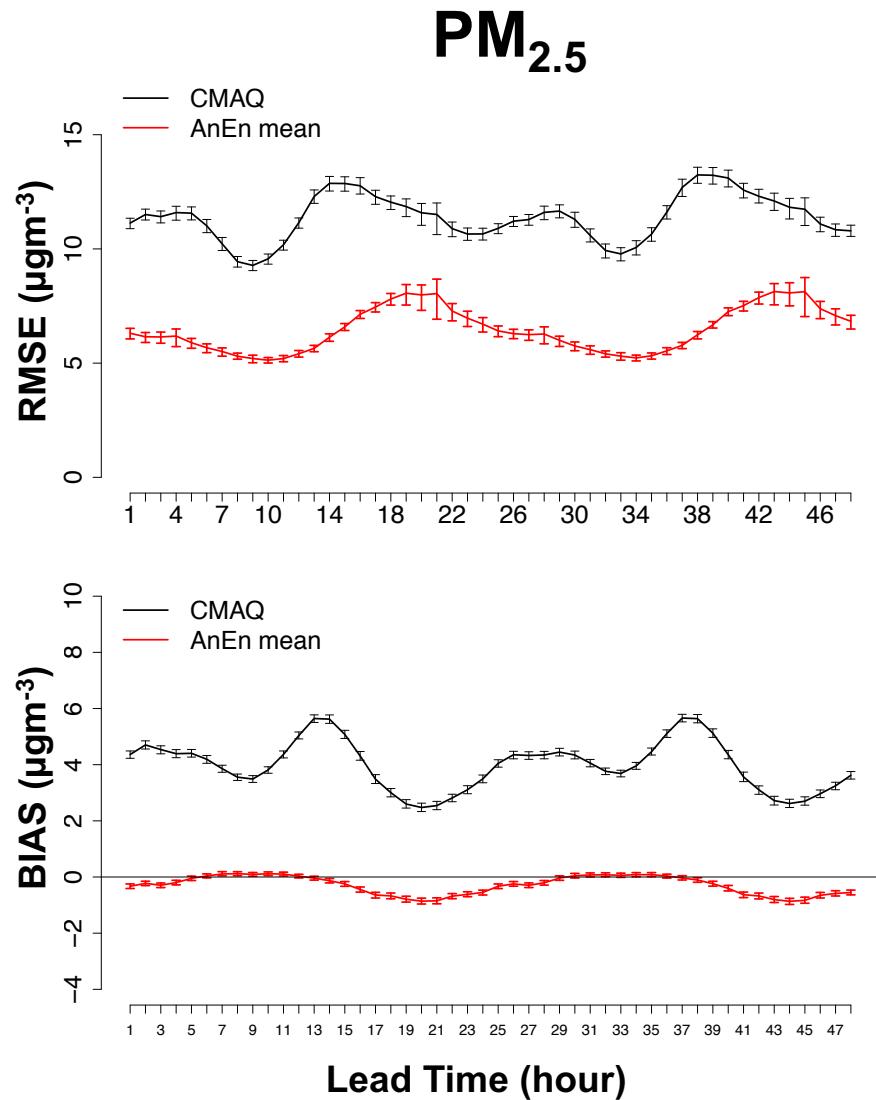
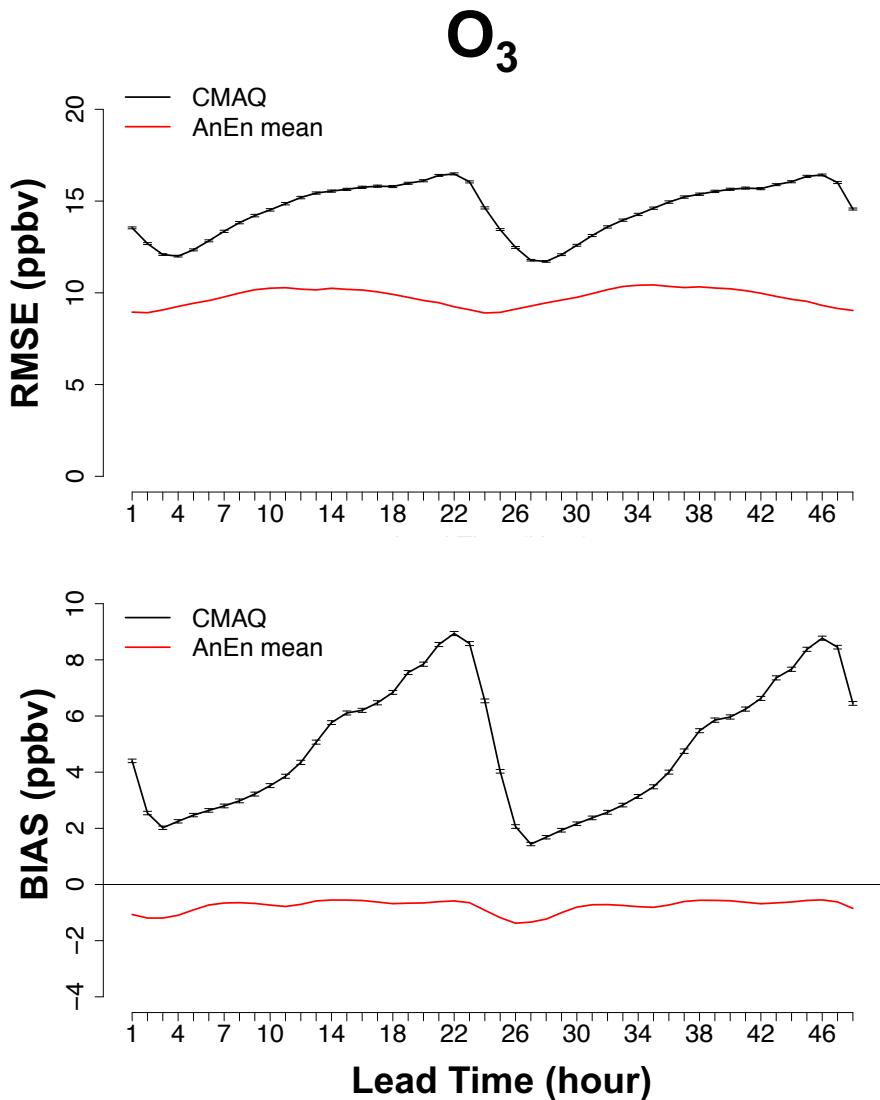
- 564 AirNow stations
- Training: 13 months, July 2014 – July 2015
- Verification: Dec 2014, Jan 2015
- Data availability: 465 stations with more than 50% of valid data

Deterministic prediction to build AnEn: Community Multi-scale Air Quality Model (CMAQ)

AnEn for air quality: example



Drastic reduction of CMAQ errors



AnEn error reductions with respect to CMAQ (O₃ and PM_{2.5}):
~35-50% RMSE, ~85-95% BIAS

Schaake Shuffle (SS) (1)



Choose N Past Dates, where N = n. of AnEn members
same dates for every grid point (00 UTC)

Dates = (18 Dec, 10 Dec, 8 Nov, 5 Nov, 25 Nov)



Corresponding Observations =(13., 7., 18., 5., 11.)



Sorted Observations = (5., 7. ,11. ,13. ,18.)



Establishing function (B) linking positions of observations before and after sorting

$$B(1, 2, 3, 4, 5) = (4, 2, 5, 1, 3)$$

Schaake Shuffle (SS) (2)



Raw ensemble forecast (AnEn) at any given grid point
e.g., first available lead time 00 UTC, 15 Dec 2015



AnEn = (15., 3., 17., 12., 9.)



Sorted AnEn members



AnEn Sorted = (3., 9., 12., 15., 17.)



B(AnEn sorted) = (15, 9, 17, 3, 12)

IMPORTANT

- (1) past selected dates must remain the same for consecutive lead times
- (2) B function is location and lead time dependent
- (3) For spatial consistency, past selected dates must be the same across multiple locations



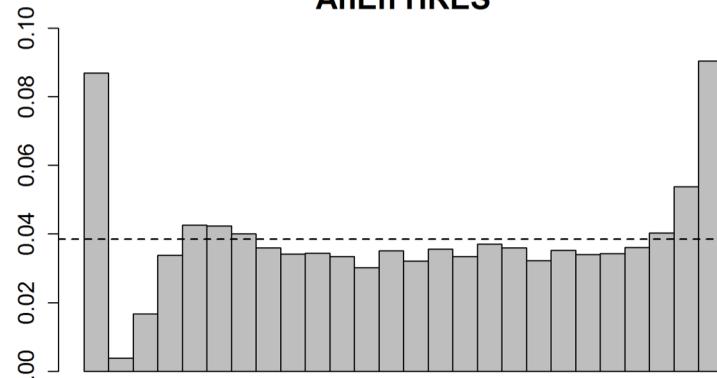
Multivariate forecast performance

Multivariate rank histograms (Gneiting *et al.*, 2008)

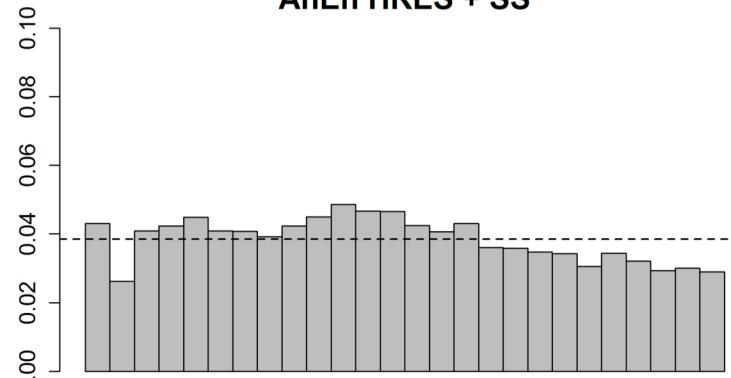
Assign pre-ranks to the ensemble forecast: $\rho_j = \sum_{k=0}^m I(x_k \leq x_j)$

Given $s^< = \sum_{j=0}^m I(\rho_j - \rho_0)$ and $s^= = \sum_{j=0}^m I(\rho_j - \rho_0)$ the multivariate rank r is chosen from a discrete uniform distribution on the set on $\{s^< + 1, \dots, s^< + s^=\}$

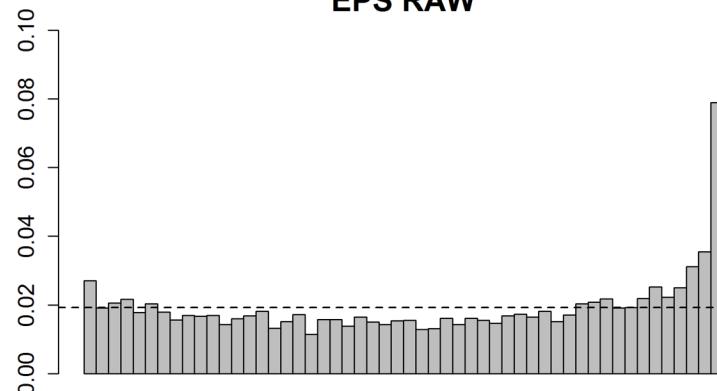
AnEn HRES



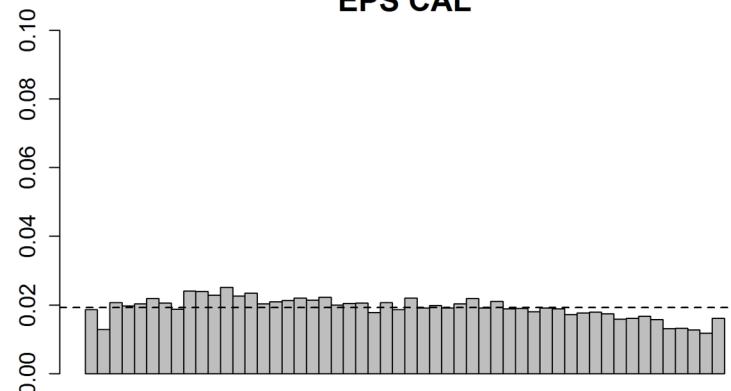
AnEn HRES + SS



EPS RAW



EPS CAL

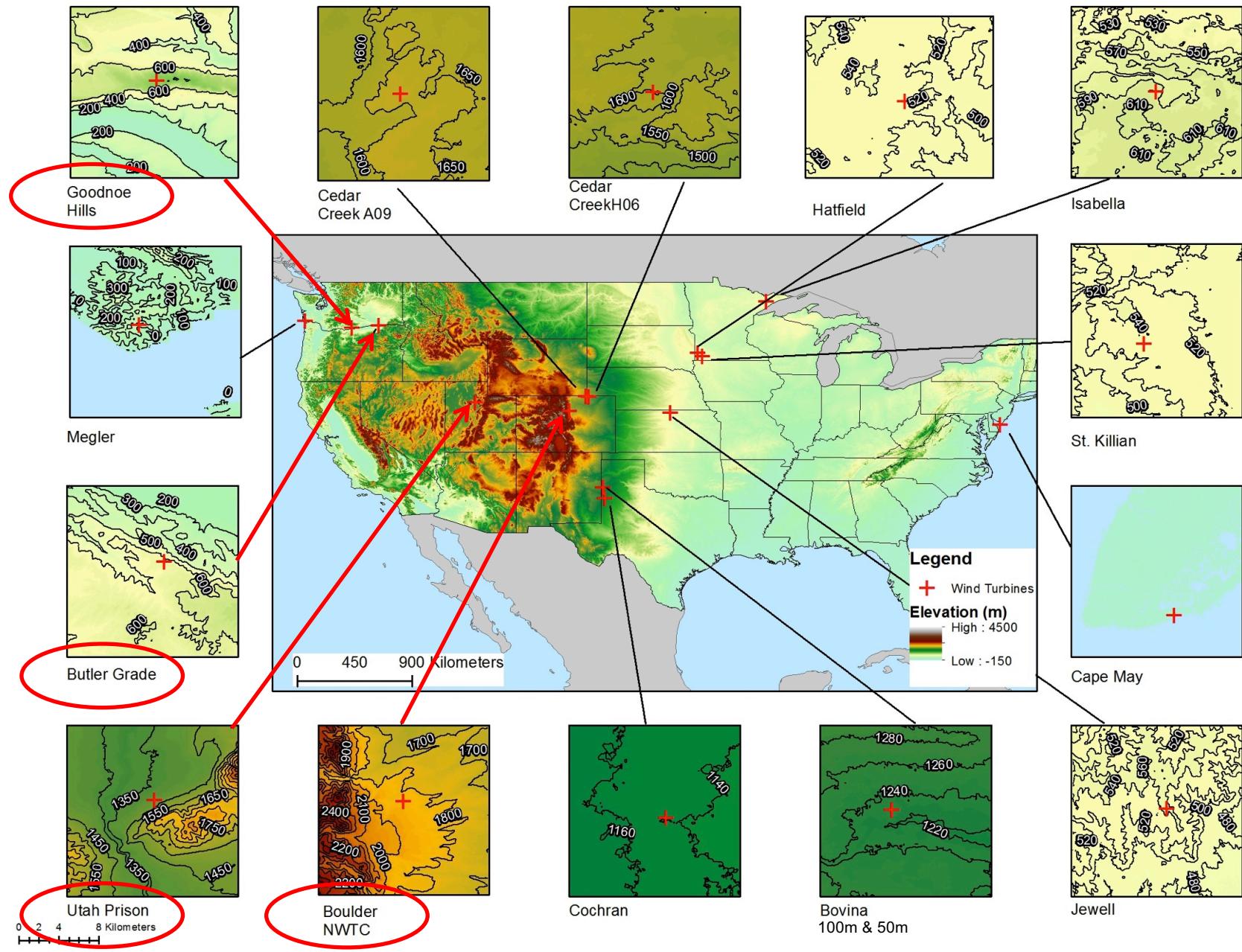


2 adjacent
grid points

Downscaled wind tower locations



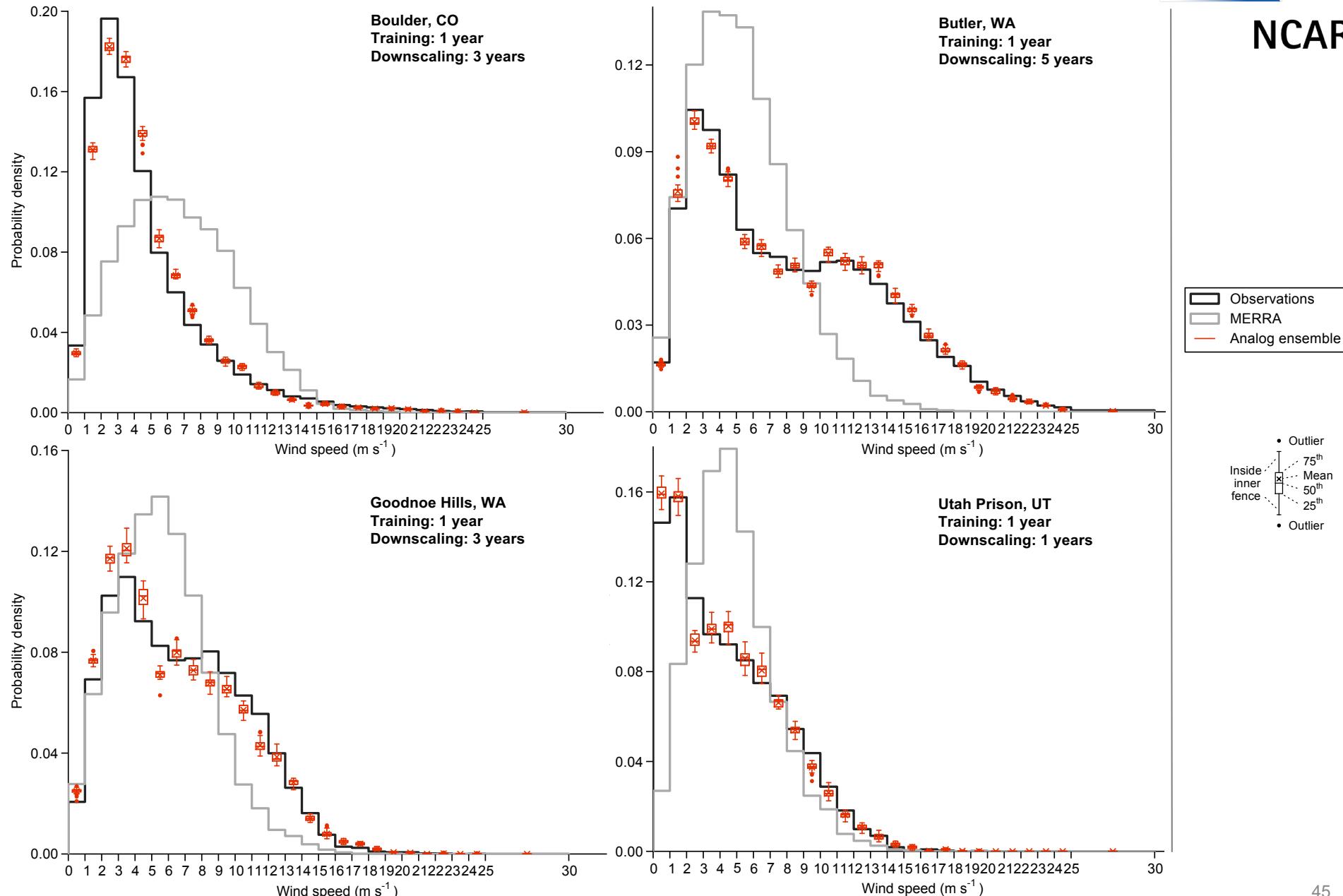
NCAR



Wind distributions comparison



NCAR



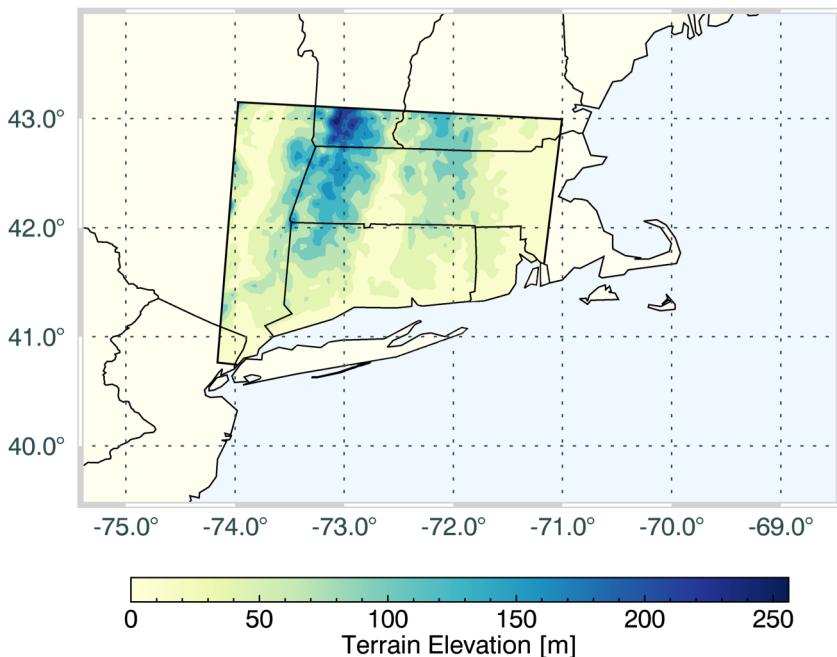
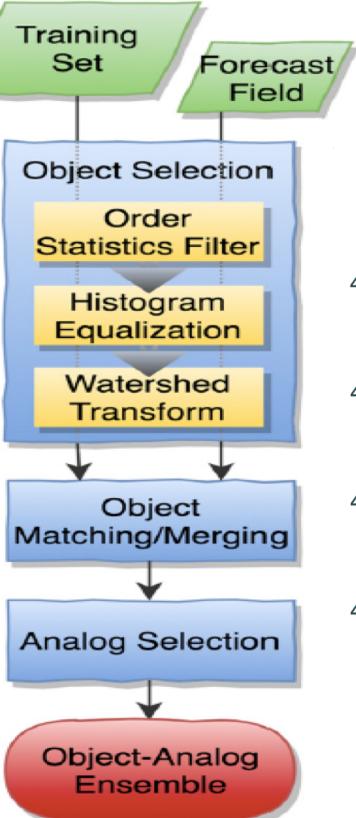


Object-based Probabilistic Predictions with AnEn

Object-based Analog Ensemble

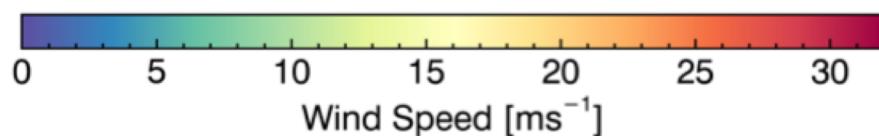
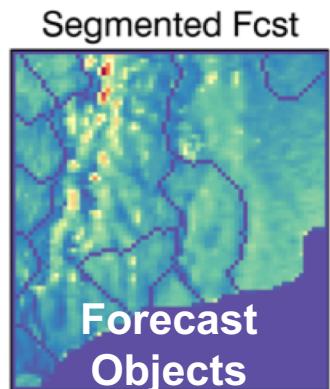
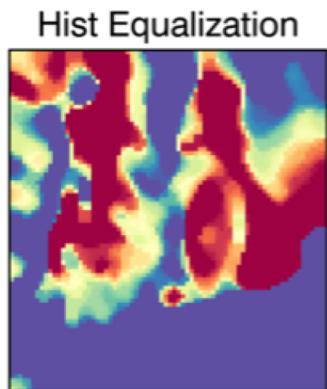
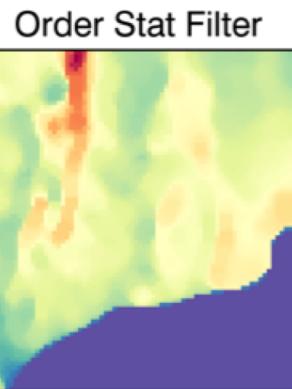
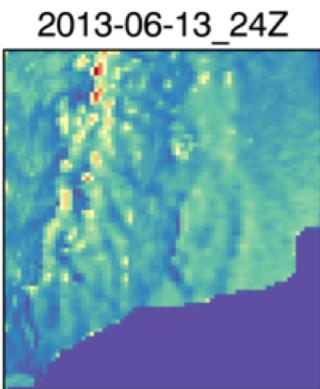


NCAR



Frediani et al. (2017)

- Forecasts: WRF
- Ground-truth: CFSR
- 89 storms
- ~6000 fcst hours



Object-based Analog Ensemble: Results



NCAR

