Recent Developments of Machine Learning for Weather Forecasting

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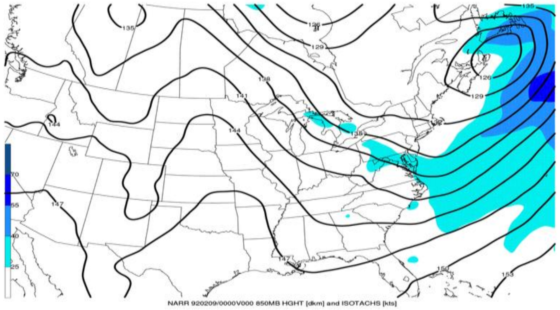
NCAR

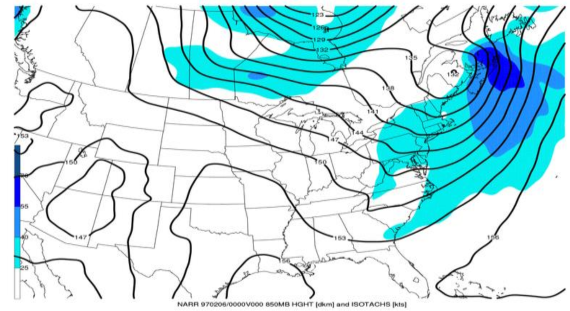
Common “analog” approach

Looking for similar past situations and following the past correspondent evolution

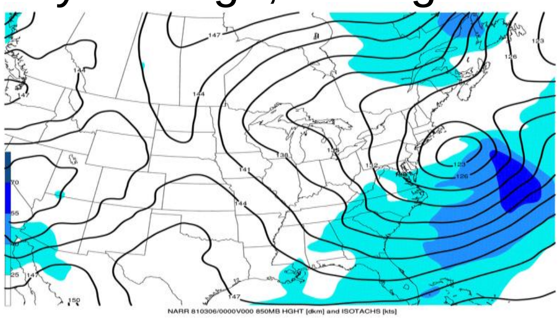
Today, 00 UTC analysis



+1 day, forecast field

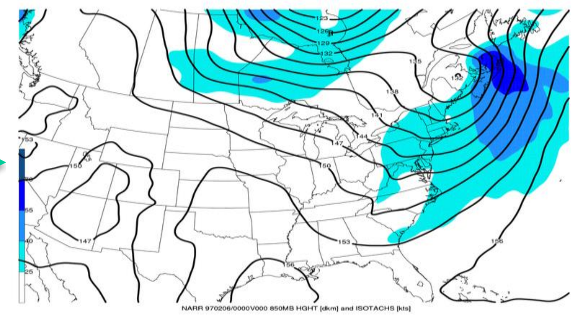


10 years ago, analogue analysis field



+1 day

+1 day, analysis field



But: The probability of finding good analogs is very small, unless one is satisfied with analogy over small areas or in just 2 or 3 degrees of freedom (Huug van den Dool, 1994)

Recent developments based on AI

• A machine-learning (ML)-based weather simulator called "GraphCast" developed to be used as an operational medium-range weather forecasting system.

• GraphCast is an autoregressive model that utilizes graph neural networks and a high-resolution multi-scale mesh representation.

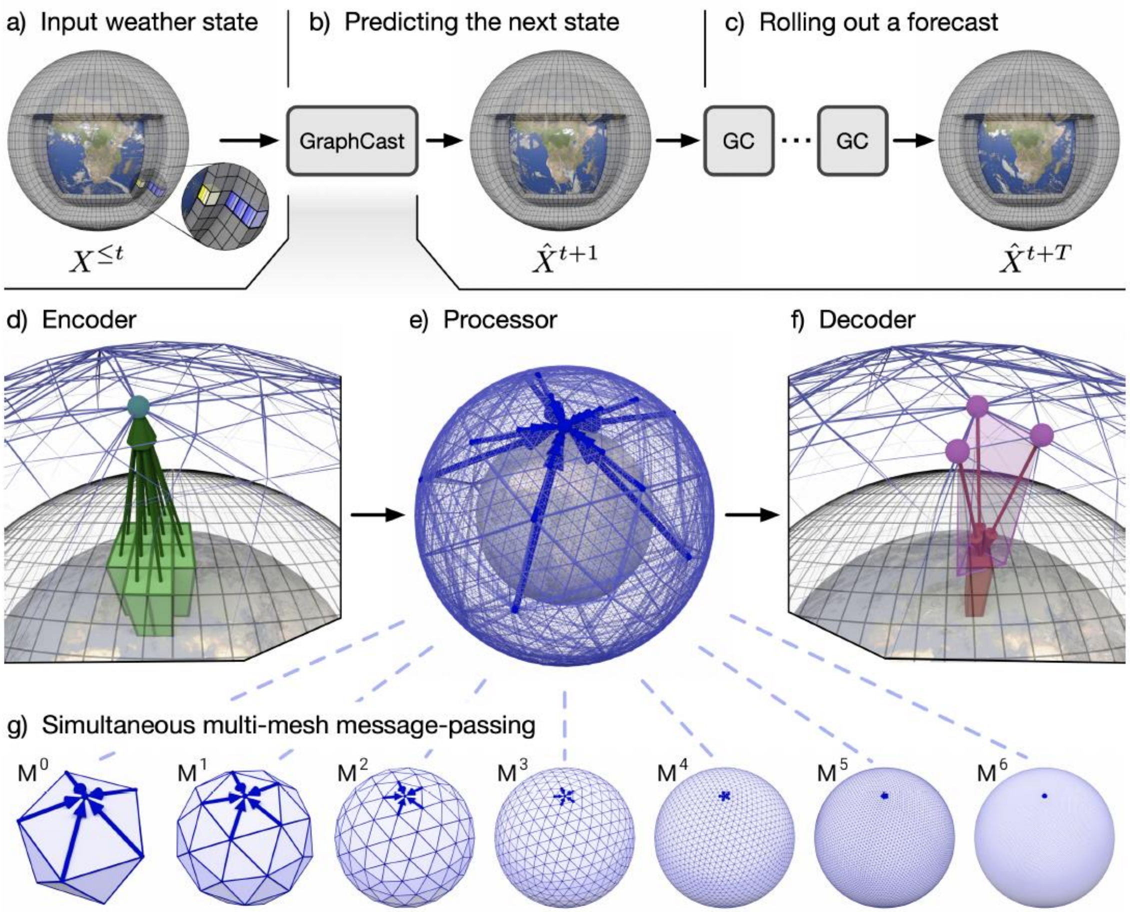
• It was trained on historical weather data from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 reanalysis archive.

• GraphCast can generate 10-day forecasts, with 6-hour intervals, for five surface variables and six atmospheric variables at 37 vertical pressure levels. The forecasts are produced on a 0.25° latitude-longitude grid, equivalent to approximately 25x25 kilometer resolution at the equator.

$$\hat{X}^{t+1} = \mathrm{GraphCast}(X^t, X^{t-1})$$

From: Lam et al., 2022. GraphCast: Learning skillful medium-range global weather forecasting. *arXiv preprint arXiv:2212.12794*.

Recent developments based on AI (GraphCast)



(a) The input weather state(s) are defined on a high-resolution latitude-longitude pressure-levels grid.

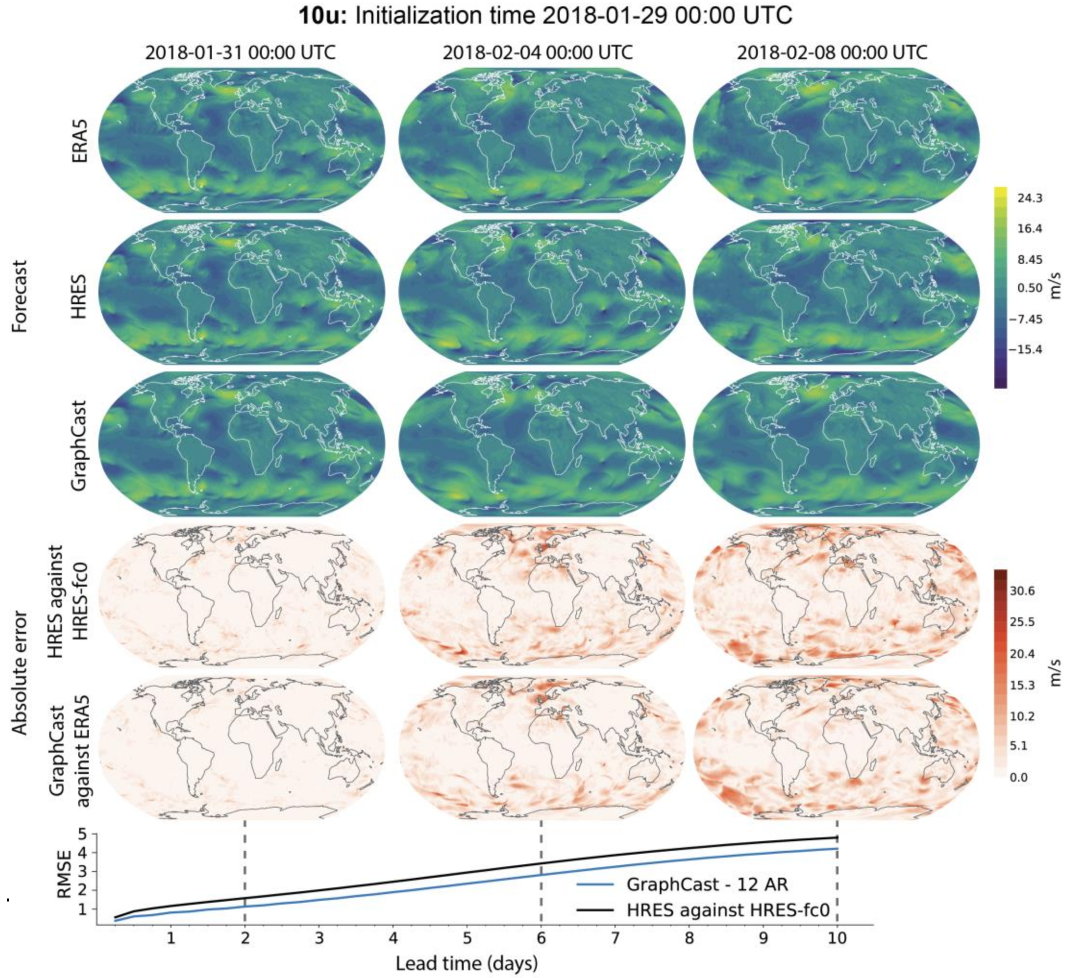
(b) GraphCast predicts the next state of the weather as the latitude-longitude-pressure-levels grid.

(c) A forecast is made by iteratively applying GraphCast to each previous predicted state, to produce a sequence of states which represent the weather as successive lead times.

From: Lam et al., 2022. GraphCast: Learning skillful medium-range global weather forecasting. *arXiv preprint arXiv:2212.12794*.

Recent developments based on AI

- The evaluation of GraphCast claims superior accuracy compared to ECMWF's deterministic operational forecasting system (HRES) on 90% of the 2760 variable and lead time combinations tested
- GraphCast can generate a 10-day forecast (35 gigabytes of data) in under 60 seconds using Cloud TPU v4 hardware.



From: Lam et al., 2022. GraphCast: Learning skillful medium-range global weather forecasting. *arXiv preprint arXiv:2212.12794*.

Some thoughts

- Is this the beginning of the end on numerical weather prediction (NWP) models?

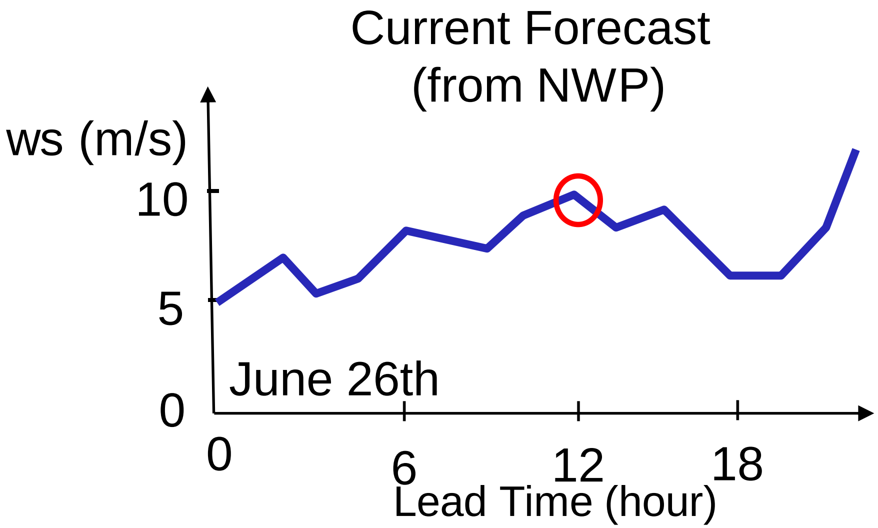
- GraphCast is still based on on reanalysis model (ERA5) which are based on NWP models to generate the background state

- What about increasing the spatial resolution?

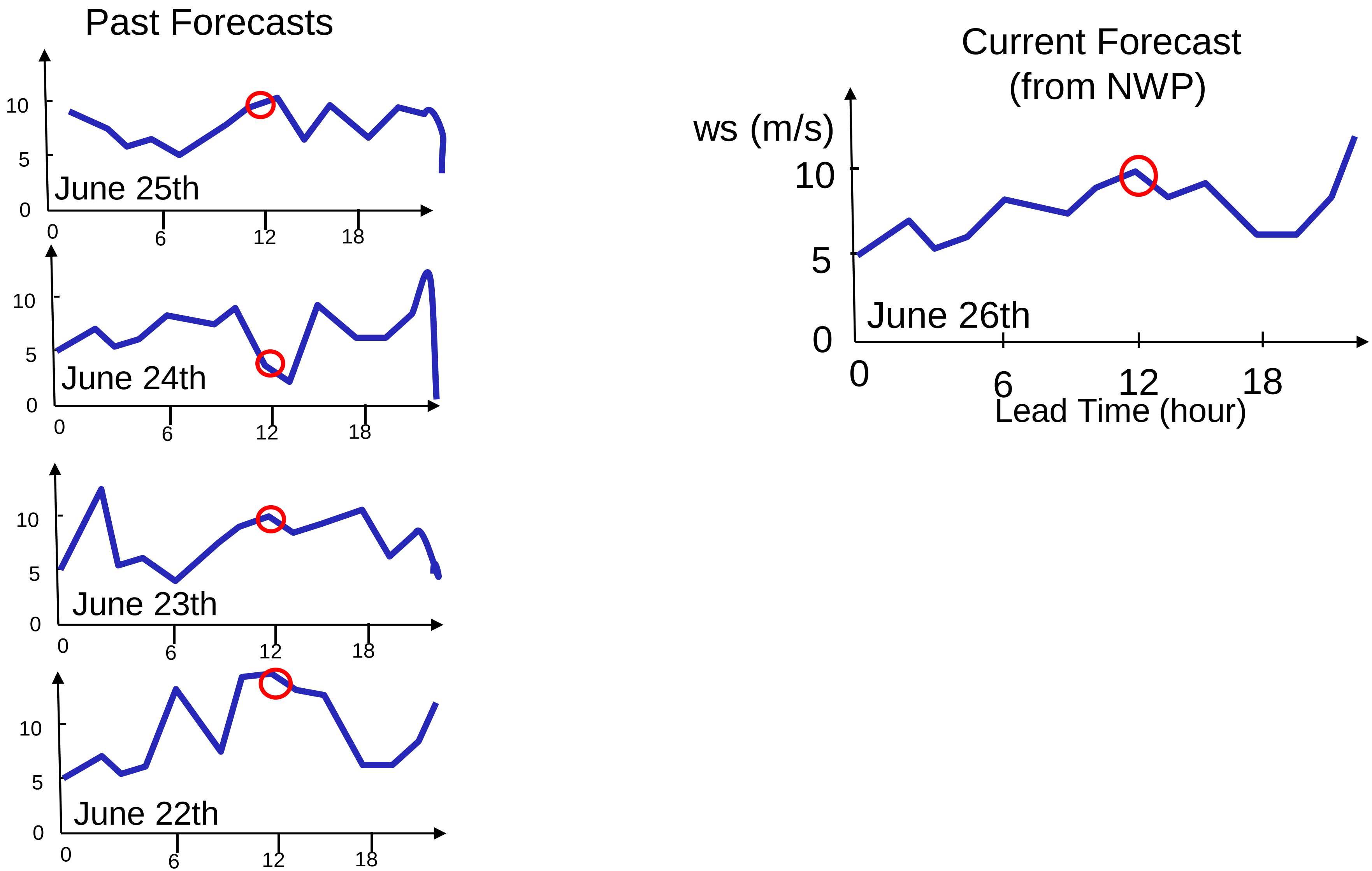
- GraphCast would need a reanalysis model with a higher spatial resolution to increase its own resolution

From: Lam et al., 2022. GraphCast: Learning skillful medium-range global weather forecasting. *arXiv preprint arXiv:2212.12794*.

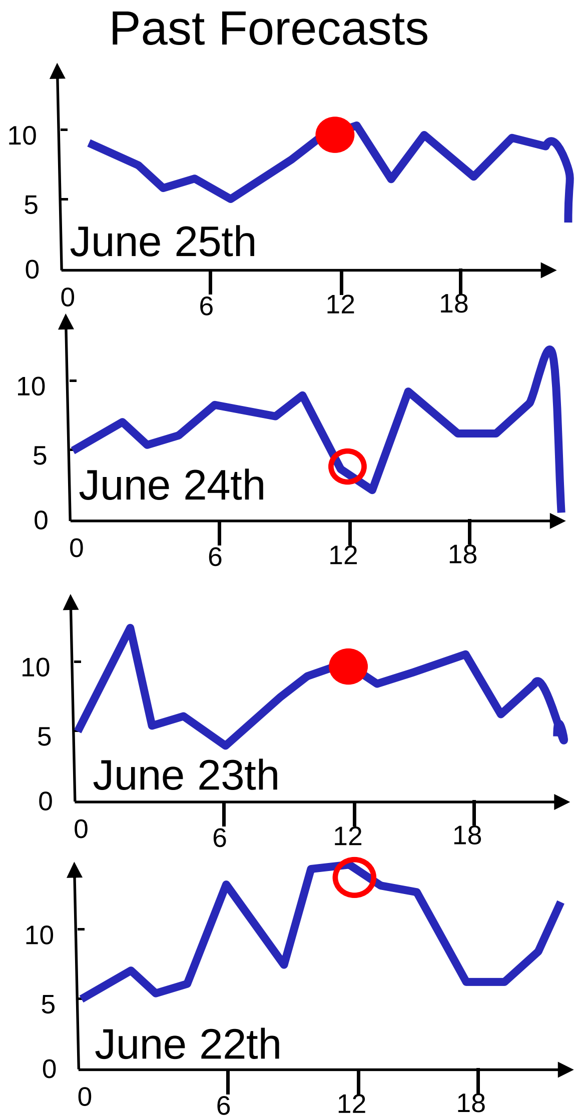
The AnEn algorithm

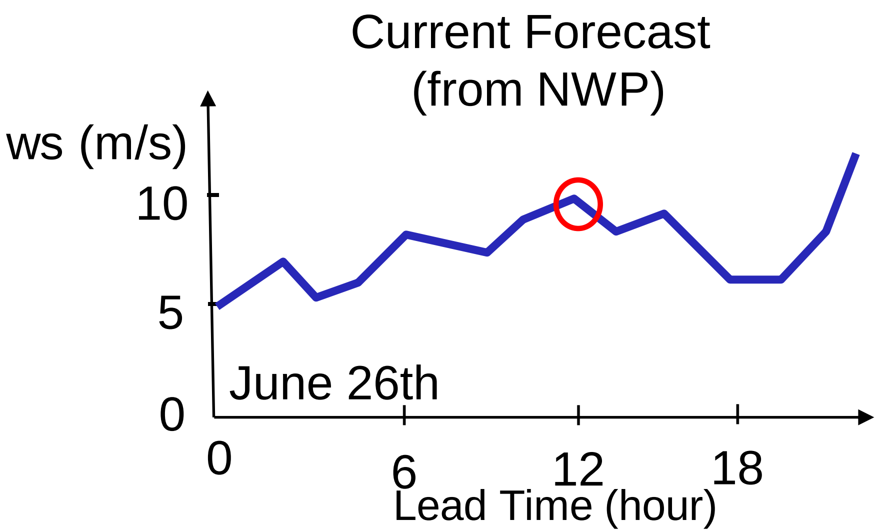


The AnEn algorithm

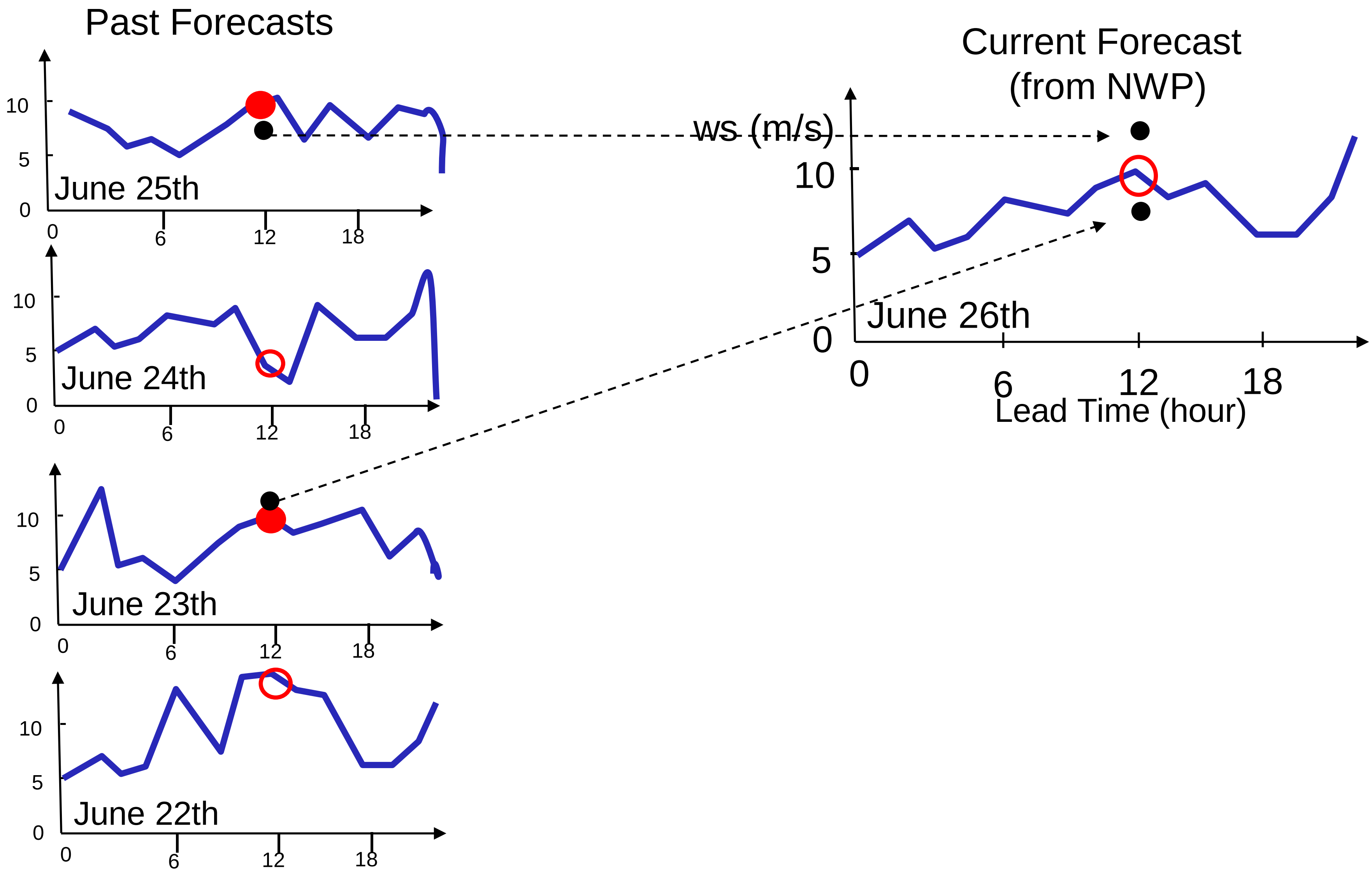


The AnEn algorithm

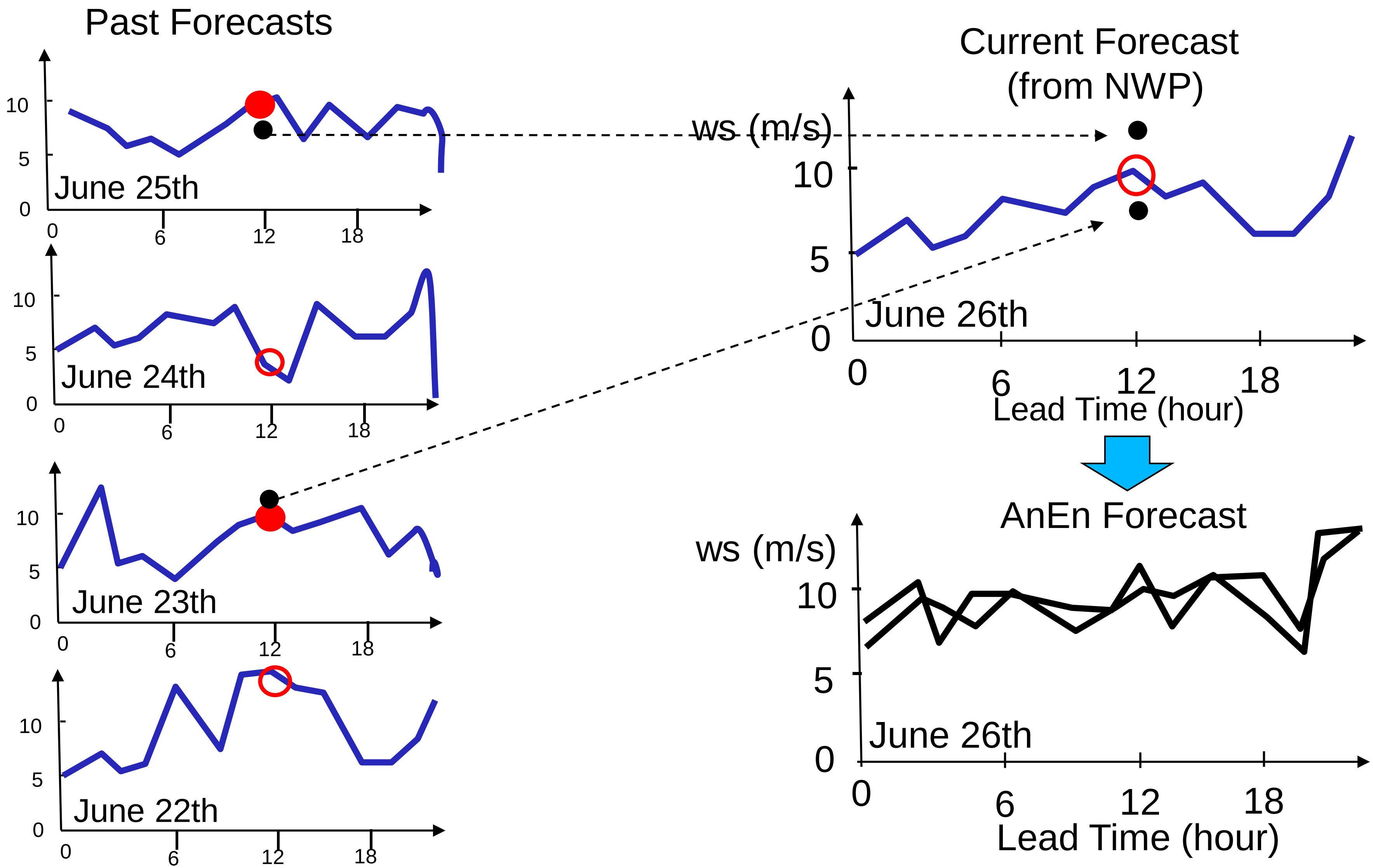




The AnEn algorithm



The AnEn algorithm

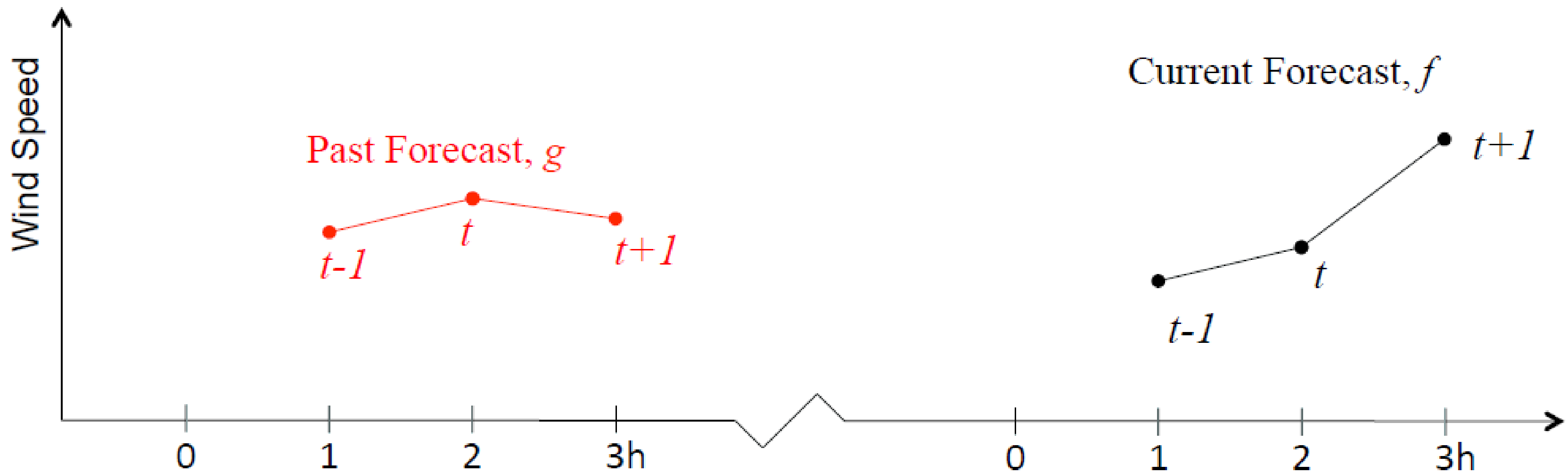


Analog Ensemble (AnEn)

Similarity criterion to search and sort the past analog forecast

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

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



Delle Monache et al. *MWR* (2013)

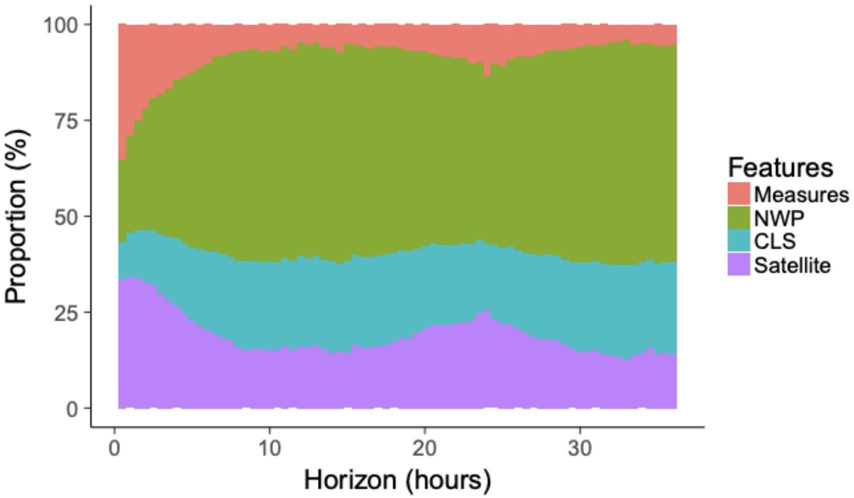
Seamless AnEn approach for Solar

- A seamless probabilistic forecasting approach based on the Analog Ensemble (AnEn) model, adapted to select the most appropriate input for each horizon from a pool of available data has been proposed by Carriere et al. 2019 *IEEE Transactions on Smart Grid*

- The model enhances short-term predictability by incorporating satellite images

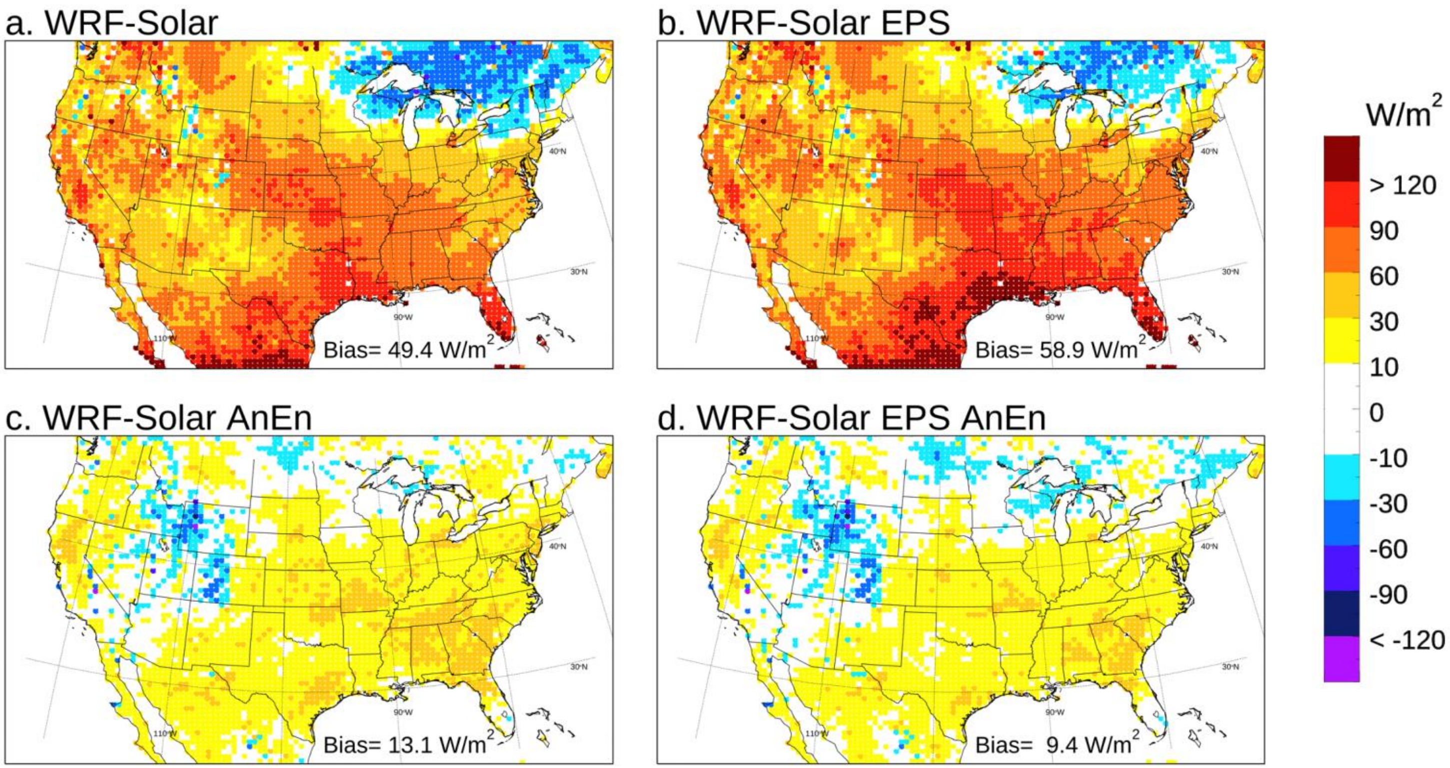
- It achieves performance comparable to state-of-the-art models developed specifically for short-term (up to 6 hours) and day-ahead forecasting.

- Evaluation of the model was conducted on three PV plants in France over a one-year period.



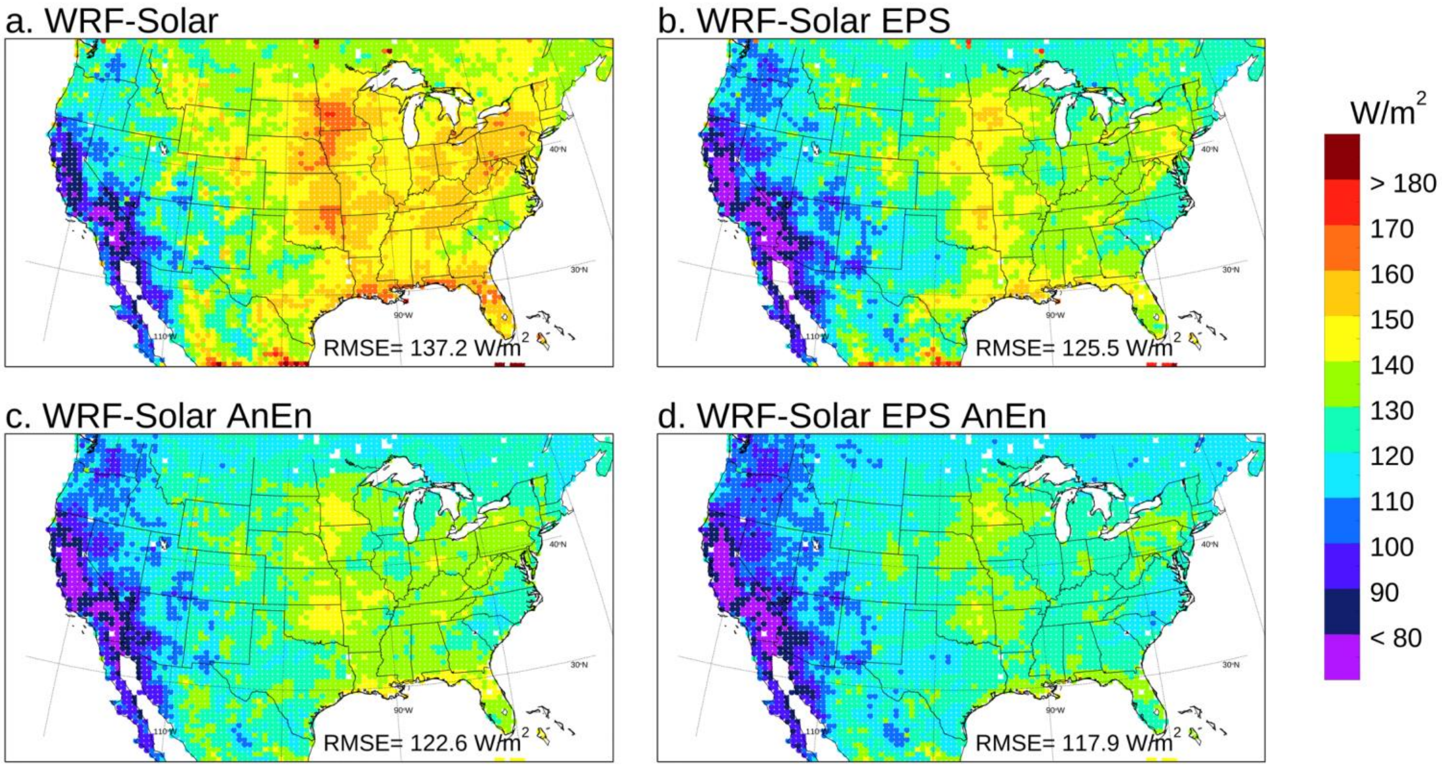
Recent developments of AnEn Solar Power (gridded predictions)

- AnEn Applied over CONUS using GHI National Solar Radiation Database (NSRDB) measurements
- Used to correct or calibrate WRF-Solar and WRF-Solar Ensemble Prediction System
- Resolution:9 km^2
- 365 runs for 2018 used for verification

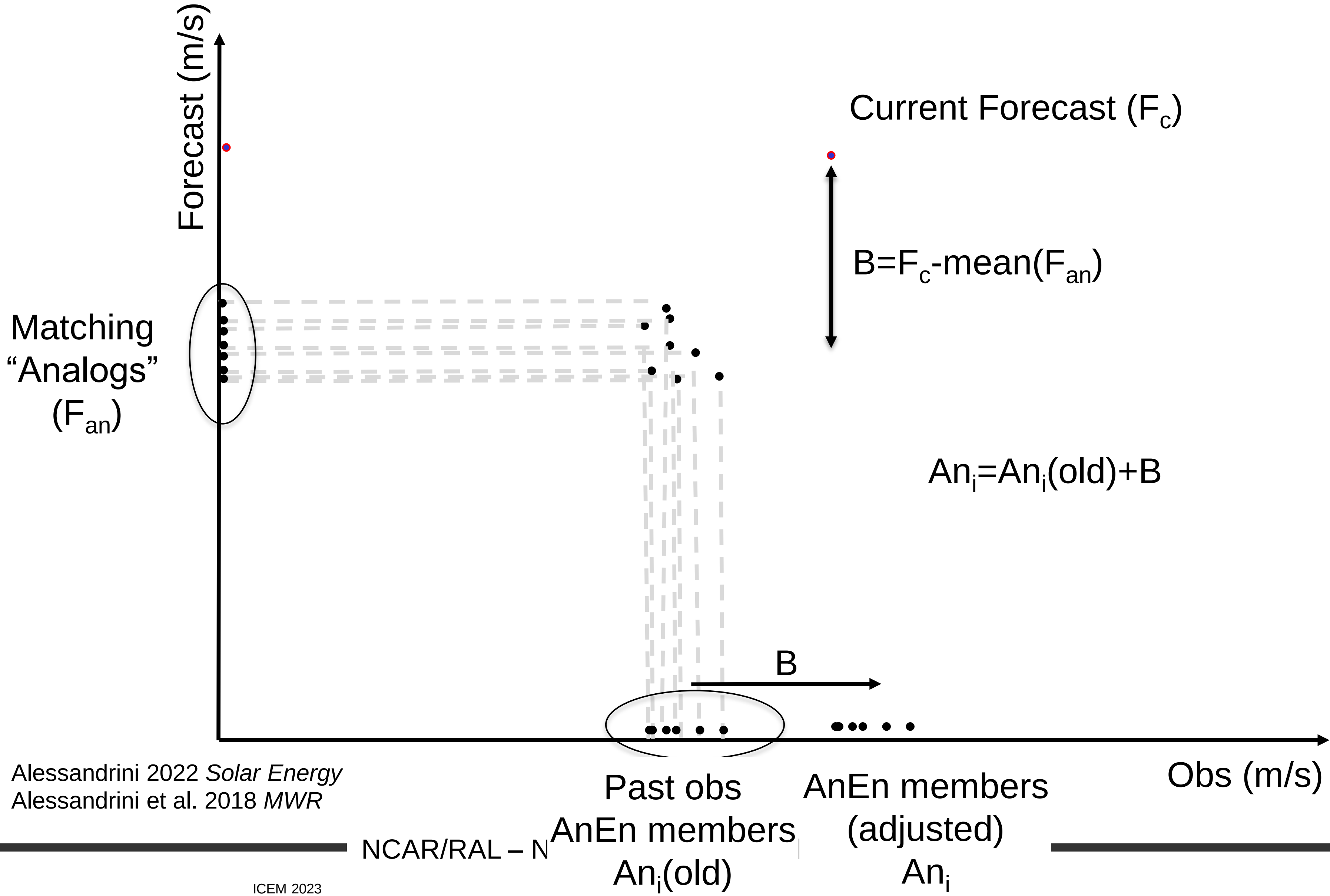


Alessandrini, S., Kim, J.H., Jimenez, P.A., Dudhia, J., Yang, J. and Sengupta, M., 2023. A Gridded Solar Irradiance Ensemble Prediction System Based on WRF-Solar EPS and the Analog Ensemble. *Atmosphere*, *14*(3), p.567.

Solar Power (CONUS)

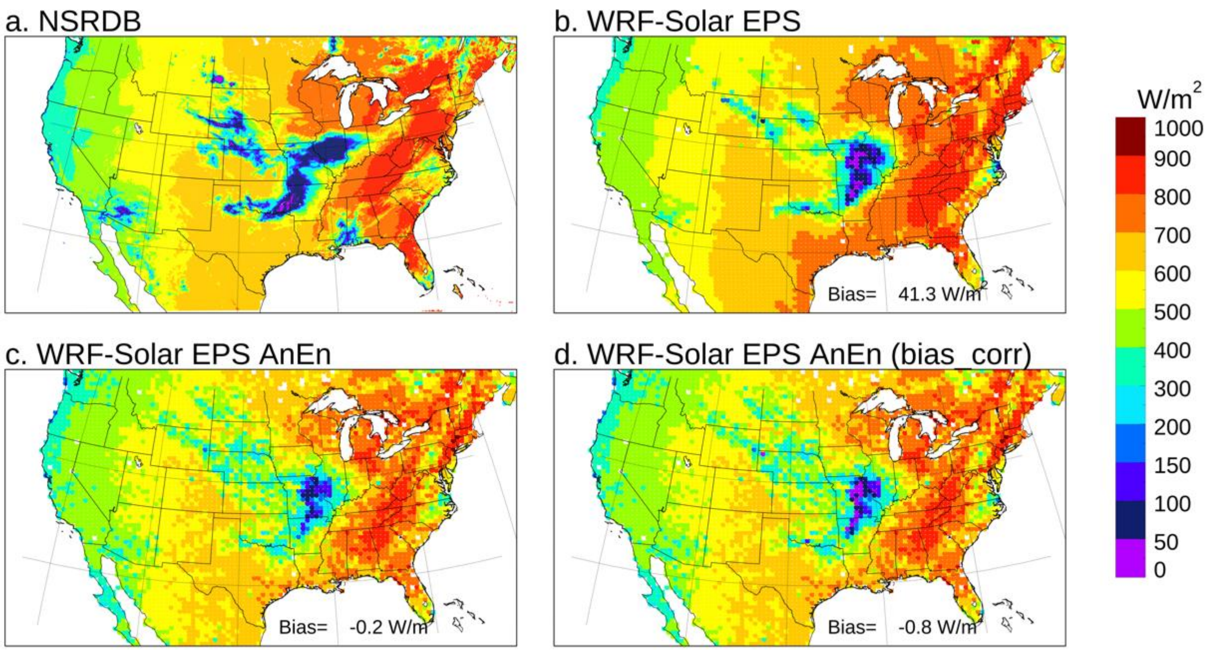


Bias Correction (BC) for rare events



Alessandrini 2022 *Solar Energy*
Alessandrini et al. 2018 *MWR*

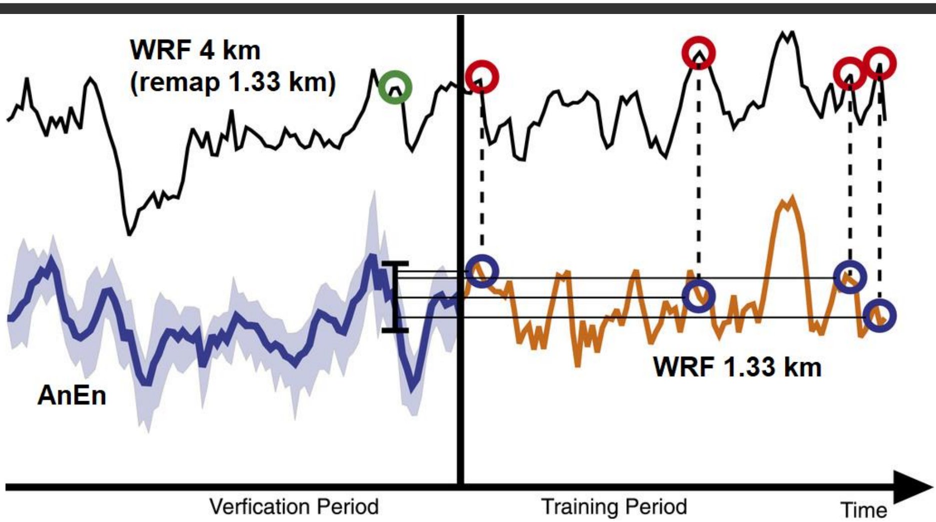
Bias Correction (BC) for rare events



NSRDB GHI map **(a)** at 1530 UTC on July 29, 2018. Model predictions from the ensemble mean of WRF-Solar EPS **(b)**, WRF-Solar EPS AnEn **(c)**, and WRF-Solar EPS AnEn with bias correction **(d)**.

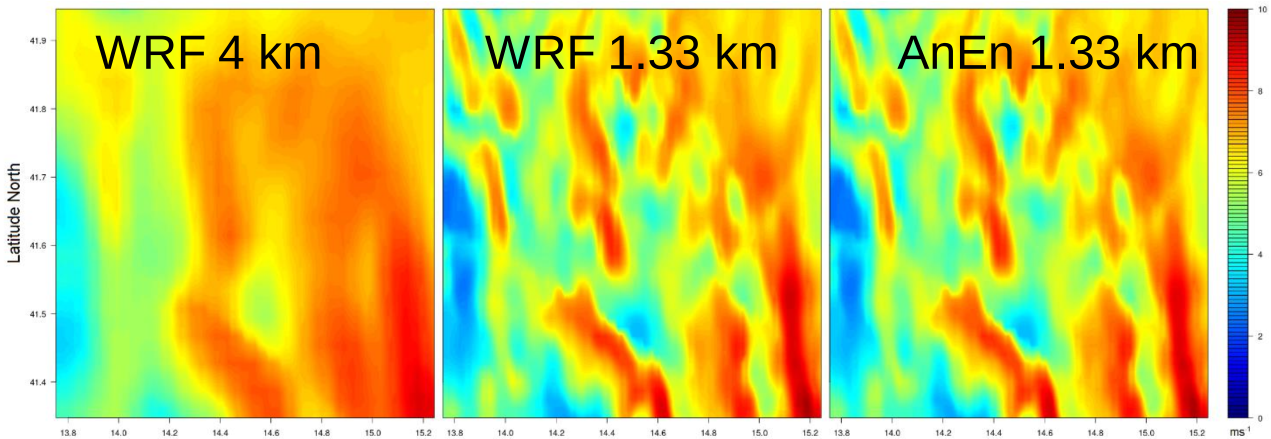
1. Algorithm for addressing AnEn negative bias for rare events is applied as in Alessandrini 2022 *Solar Energy*
2. When comparing with the NSRDB map (a), a positive bias is introduced by the AnEn calibration (c) over the area with a GHI lower than 100 W/m^2 (GHI values under 50 W/m^2 are missing).
3. 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).

Italian Wind Atlas



A schematic of the current application of the AnEn as applied for each 4-km grid point remapped onto the 1.33-km grid.

Adapted from Sperati et al. 2023
Wind Energy Under review



Qualitative comparison between the WRF wind field at 4 km bilinearly interpolated to 1.33 km (left), the WRF wind field at 1.33 km (center) and the AnEn wind field (right). Averaged over the MAM season in 2015.

Italian Wind Atlas

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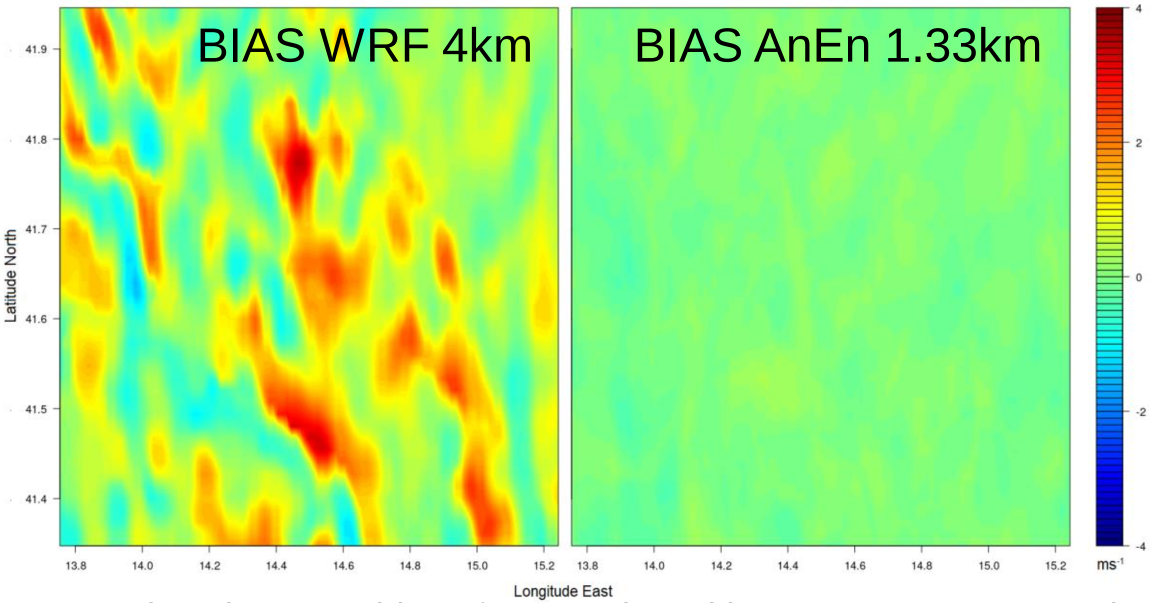
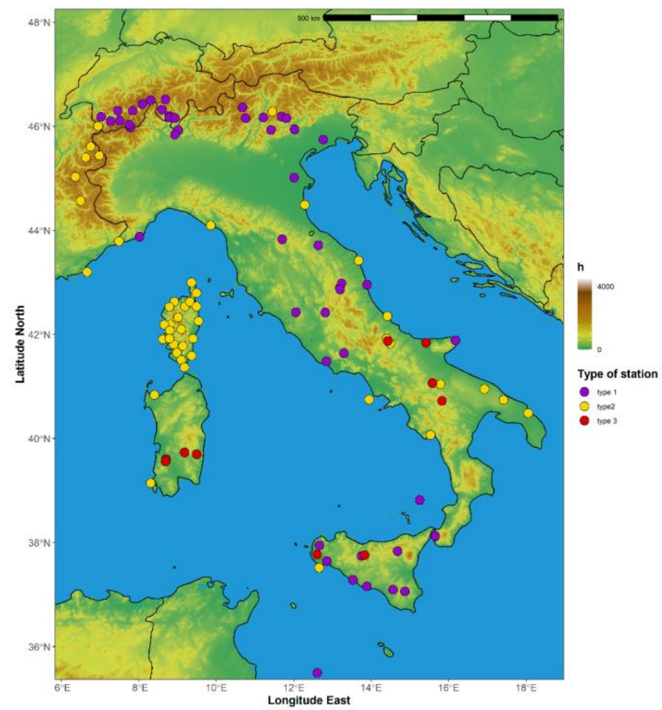
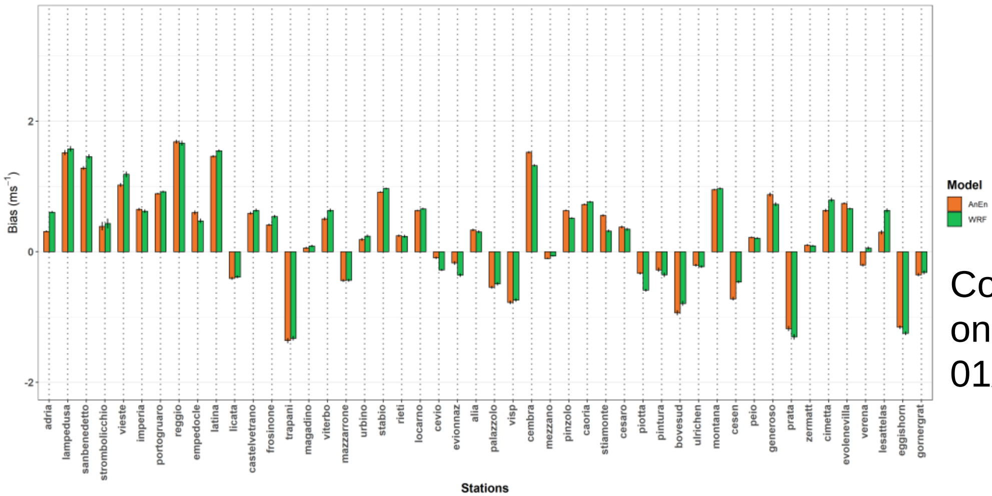


Comparison between bias of WRF 4 km with respect to WRF 1.33 km (left) and bias of AnEn with respect to WRF 1.33 km (right).





Comparison between WRF (green) and AnEn (orange) on periods of availability of equal length around 01/01/2015.

Applications Program

Features of the AnEn

- No need for initial conditions and model perturbation strategies to generate an ensemble.
- AnEn can use a higher resolution model for an ensemble prediction (since only one real-time forecast is needed for AnEn)
- Flow-dependent error characteristics are captured
- Very cheap real-time method compared to a standard meteorological ensemble
- AnEn has proved to generate bias-free reliable predictions on a wide range of applications
- AnEn needs a training dataset of “frozen” model data (computationally expensive but can be done off-line)
- Easy to be interpreted by looking at the selected “analog” dates

Acknowledgments

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Thanks! (AnEn is on github/ncar)

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