Technical University of Denmark

DTU

Limited area forecasting for wind energy scheduling

Rosgaard, Martin Haubjerg; Hahmann, Andrea N.; Madsen, Henrik; Giebel, Gregor; Sørensen, Poul Ejnar; Nielsen, Henrik Aalborg; Nielsen, Torben Skov

DTU Library
Technical Information Center of Denmark

Limited area forecasting for wind energy scheduling

Martin H. Rosgaard (mhros@dtu.dk), **Andrea N. Hahmann** (ahah@dtu.dk),
Henrik Madsen (hmad@dtu.dk), **Gregor Giebel** (grgi@dtu.dk), **Poul E. Sørensen** (posq@dtu.dk)
Technical University of Denmark / DTU Wind Energy & DTU Compute
Henrik Aa. Nielsen (han@enfor.dk), **Torben S. Nielsen** (tsn@enfor.dk)
ENFOR A/S

ENFOR
Forecasting and Optimization for the Energy Sector

CITIES
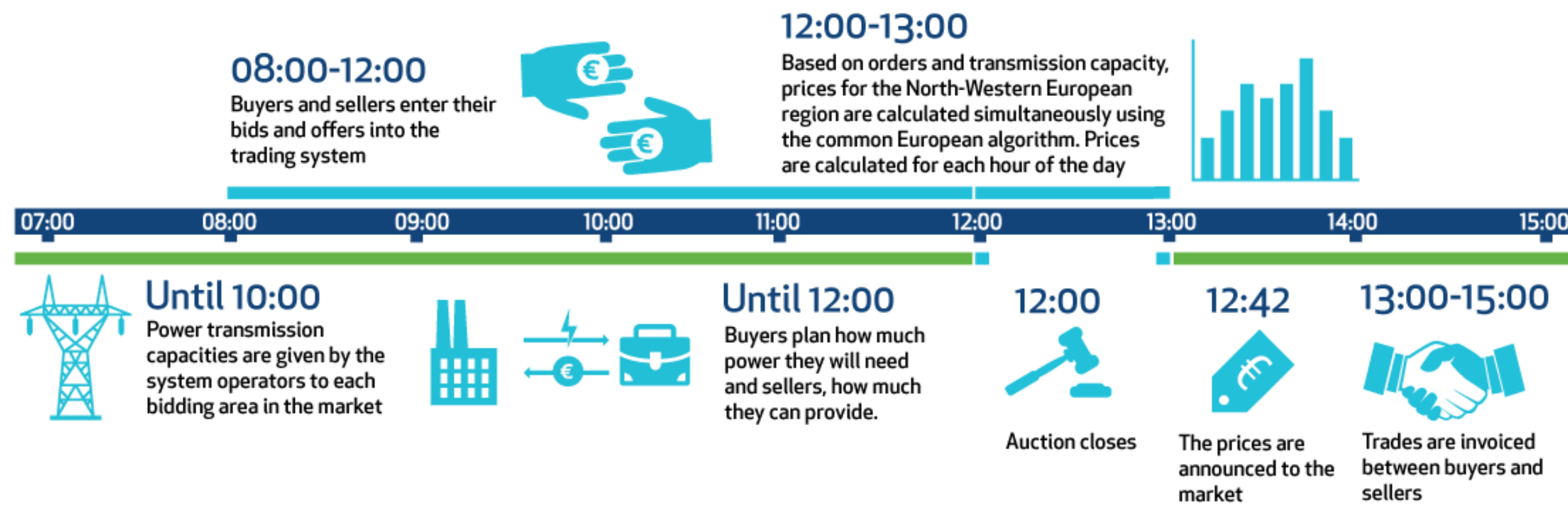Centre for IT Intelligent Energy Systems

DTU — Technical University of Denmark

INTRODUCTION

For any energy system relying on wind power detailed knowledge of near-future wind fluctuations is essential for efficient utilisation in the power grid. To this end, accurate weather forecasts constitute vital input and this study concerns assessment of the value added by increasing the resolution of global weather forecasts using a specific configuration of a limited area weather forecast model (LAM).
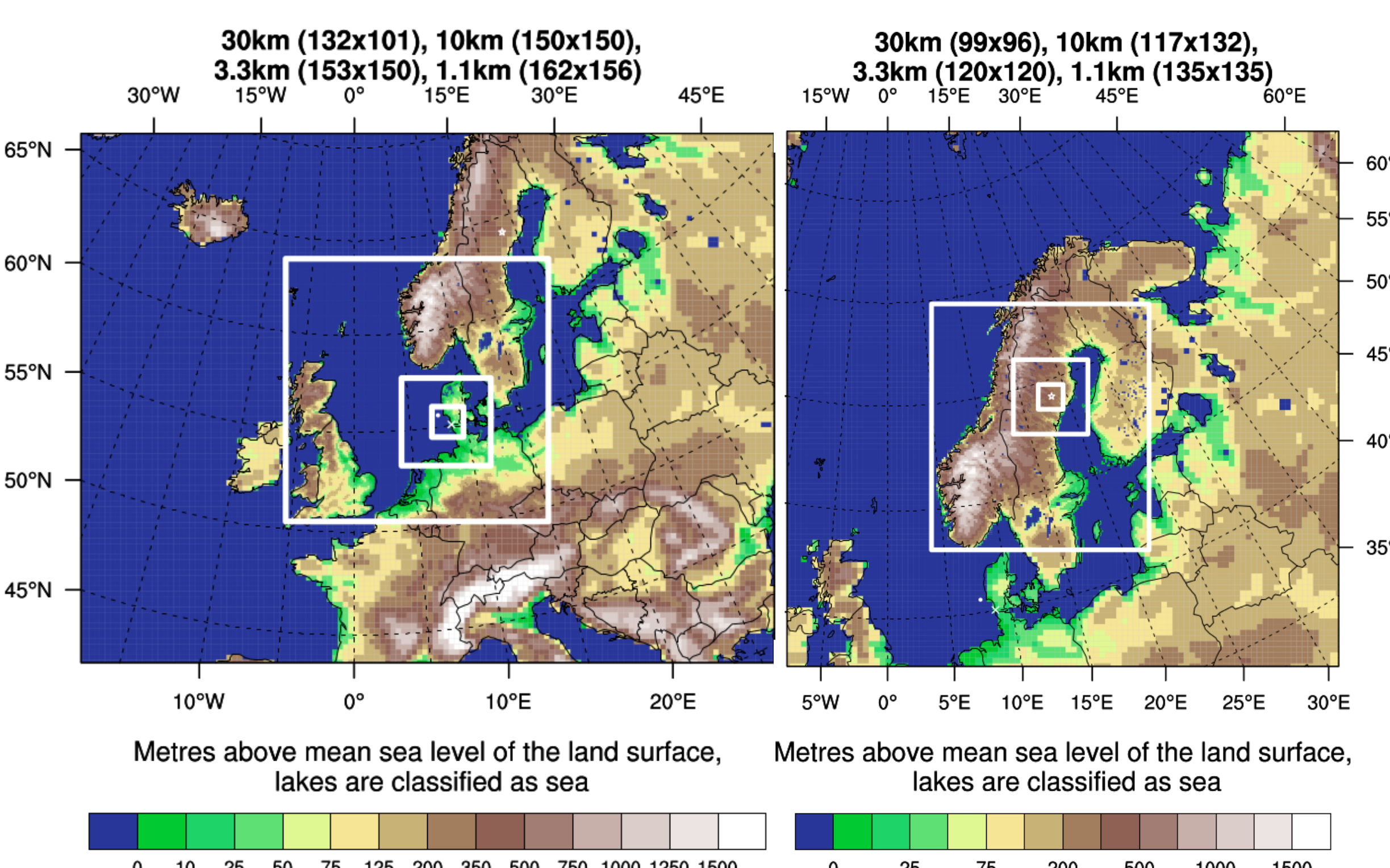
Objective:
Quantify the extent to which LAM predictions can add value to day ahead scheduling of wind power for efficient Elspot market trading.

08:00-12:00
Buyers and sellers enter their bids and offers into the trading system

12:00-13:00
Based on orders and transmission capacity, prices for the North-Western European region are calculated simultaneously using the common European algorithm. Prices are calculated for each hour of the day

07:00 — 08:00 — 09:00 — 10:00 — 11:00 — 12:00 — 13:00 — 14:00 — 15:00

Until 10:00
Power transmission capacities are given by the system operators to each bidding area in the market

Until 12:00
Buyers plan how much power they will need and sellers, how much they can provide.

12:00
Auction closes

12:42
The prices are announced to the market

13:00-15:00
Trades are invoiced between buyers and sellers

METHODOLOGY

The LAM employed is the open source Weather Research and Forecasting (WRF) model developed and maintained by the National Center for Atmospheric Research (NCAR), Boulder CO, USA. Initialisation and lateral boundary conditions are derived from the National Centers for Environmental Prediction (NCEP) developed and maintained Global Forecast System (GFS); four daily global weather forecasts are freely available for download.

The forecast dataset consists of twice-daily (0000 and 1200 UTC) 48-hour WRF model forecasts, generated for the time period May 2012 to May 2013, for three wind farms offshore, on the coast and inland, respectively. The forecast reference is farm-averaged wind turbine nacelle anemometer measurements.

30km (132x101), 10km (150x150), 3.3km (153x150), 1.1km (162x156)

30km (99x96), 10km (117x132), 3.3km (120x120), 1.1km (135x135)

Metres above mean sea level of the land surface, lakes are classified as sea

0 10 25 50 75 125 200 350 750 1000 1250 1500

Metres above mean sea level of the land surface, lakes are classified as sea

0 25 75 200 500 1000 1500

WRF grid values are tricube-weighted according to wind farm radius and GFS grid values are bilinearly interpolated to wind farm centre coordinates. Wind speed prediction accuracy is assessed in terms of standard scalar accuracy metrics, namely root mean square error (RMSE), mean absolute error (MAE), and Pearson correlation coefficient (PCC), respectively, as well as in terms of ramp objects;

$$\text{Critical Success Index} \atop (a.k.a. \text{ Threat Score}) = \frac{\text{Hits}}{\text{Hits} + \text{False alarms} + \text{Misses}}$$

though the ramp object evaluation results are not shown, only the results are mentioned. Likewise, the effect on performance of temporal smoothing is mentioned, yet not explicitly shown. Last, the WRF model source code is modified such that wind speed variability (standard deviation) is output; the potential of this quantity to assess the level of wind power point prediction uncertainty is explored.
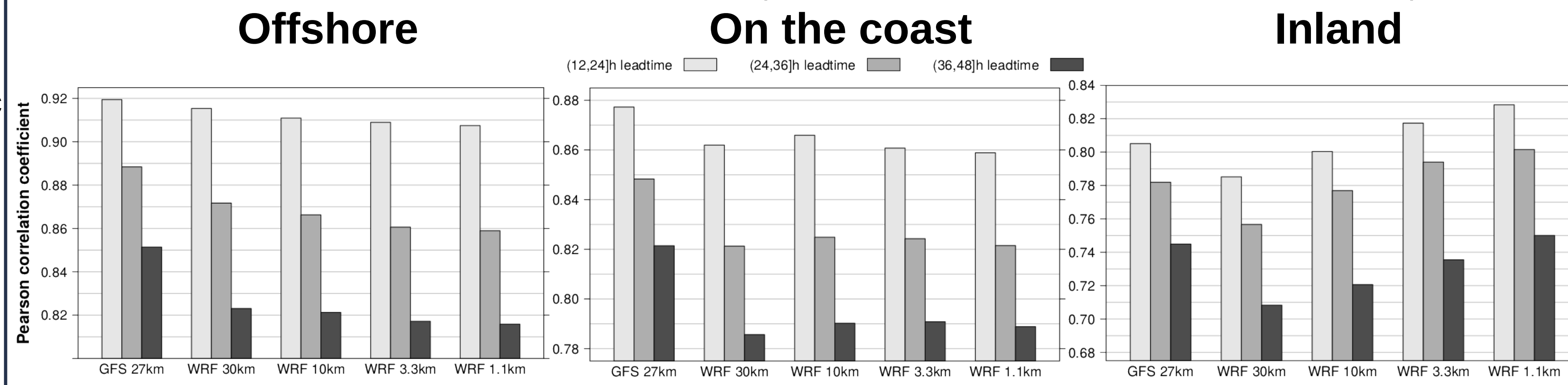
CONCLUSIONS

WRF model performance in terms of scalar accuracy metrics is deteriorating with model resolution offshore and on the coast, while improvement relative to the GFS forecasts is achieved inland. The forecast examples illustrate how close-to-correct wind speed simulations subject to slight phase errors and/or temporal dilation are severely penalised in terms of PCC.
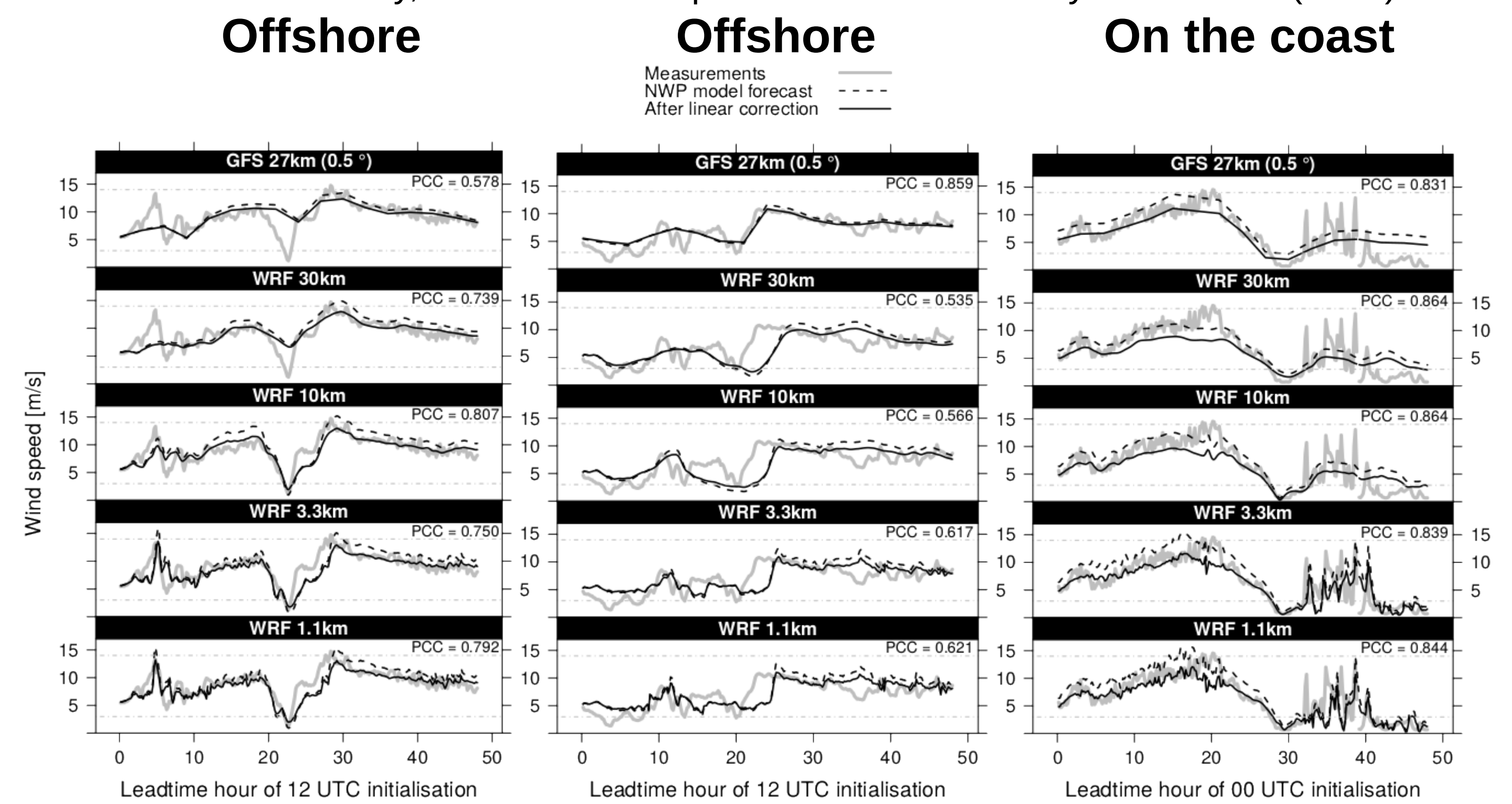
However, in terms of wind speed ramp objects a nearly consistent improvement in the Critical Success Index is observed across a range of different ramp widths (*not shown*). Finally, forecasted wind speed variability may serve as predictor for wind speed prediction uncertainty — and hence also wind *power* prediction uncertainty.

RESULTS

- Weather forecasts and wind farm measurements are postprocessed to hour-resolution
- Performance in terms of PCC is shown below (MAE and RMSE are sensitive to model bias[†])

Offshore **On the coast** **Inland**

Pearson correlation coefficient

(12,24]h leadtime (24,36]h leadtime (36,48]h leadtime

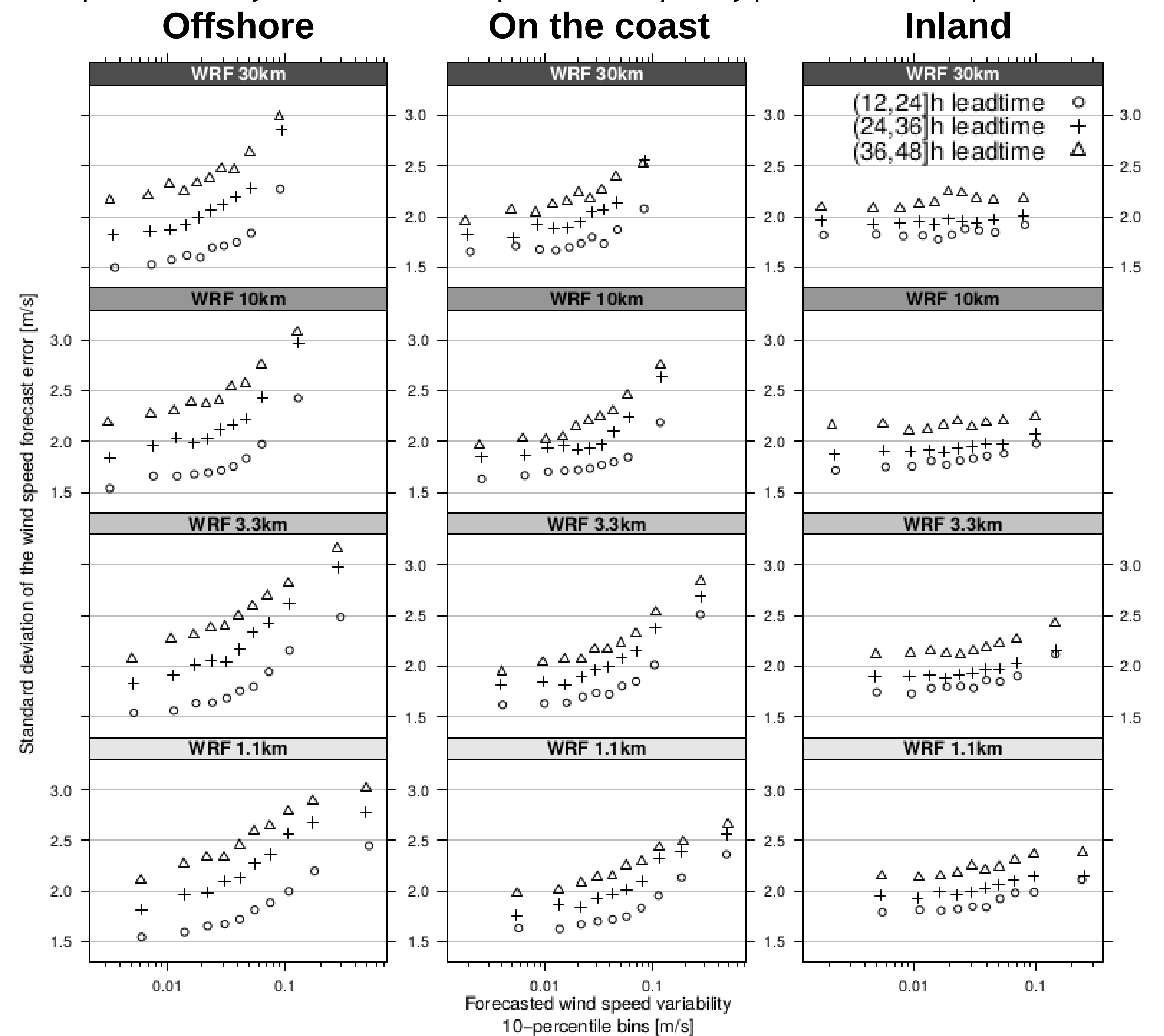GFS 27km WRF 30km WRF 10km WRF 3.3km WRF 1.1km

- LAM improvement for inland site where the global model cannot resolve topography in sufficient detail
- Near-ocean LAM results are inferior to global model (GFS) results in terms of scalar accuracy metrics
- In order to understand why, individual wind speed forecasts are analysed for LAM (WRF) and the GFS

Offshore **Offshore** **On the coast**

Measurements
NWP model forecast
After linear correction

GFS 27km (0.5 °) PCC = 0.578 / PCC = 0.859 / PCC = 0.831
WRF 30km PCC = 0.739 / PCC = 0.535 / PCC = 0.864
WRF 10km PCC = 0.807 / PCC = 0.566 / PCC = 0.864
WRF 3.3km PCC = 0.750 / PCC = 0.617 / PCC = 0.839
WRF 1.1km PCC = 0.792 / PCC = 0.621 / PCC = 0.844

Wind speed [m/s]

Leadtime hour of 12 UTC initialisation Leadtime hour of 12 UTC initialisation Leadtime hour of 00 UTC initialisation

- Small fluctuation phase offset severely penalises performance **in terms of scalar accuracy metrics**
- Temporal smoothing improves WRF performance in terms of scalar accuracy metrics (*not shown*)
- Prediction of wind speed ramp objects is more accurate at high WRF model resolution (*not shown*)

- GFS forecasts are @ three-hour resolution, WRF resolution may be as fine as integration time step
- Wind speed variability added to WRF output; *can this quantity predict wind farm production uncertainty?*

Offshore **On the coast** **Inland**

WRF 30km
(12,24]h leadtime ○
(24,36]h leadtime +
(36,48]h leadtime △
WRF 10km
WRF 3.3km
WRF 1.1km

Standard deviation of the wind speed forecast error [m/s]

Forecasted wind speed variability
10-percentile bins [m/s]

- Forecasted wind speed variability is a feasible predictor for wind power uncertainty **near the ocean**
- Over land the explanatory effect severely diminishes

ACKNOWLEDGEMENT

† Allan H. Murphy. *Skill Scores Based on the Mean Square Error and Their Relationships to the Correlation Coefficient*. Mon. Wea. Rev. **116**: 2417-2424 (1988)