WEPROG

Weather & wind Energy PROGnosis

A new algorithm for Upscaling and Short-term forecasting of wind power using Ensemble forecasts

8th International Workshop on Large-Scale Integration of Wind Power into Power Systems as well as on Transmission Networks for Offshore Wind Farms
14-15 Oct. 2009 in Bremen, Germany

Including physical Uncertainty from Ensembles

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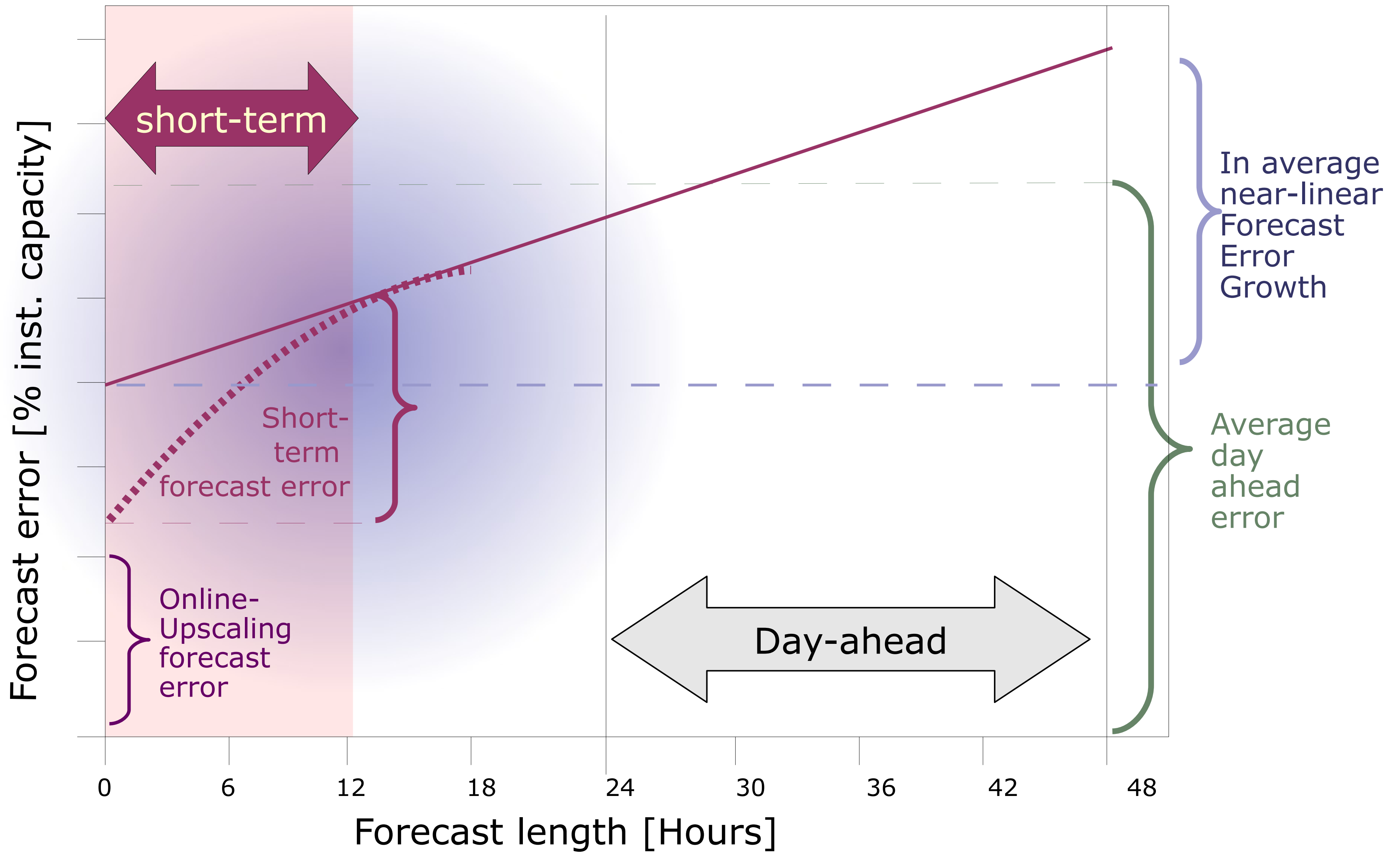
Which forecast horizon are we looking at ?



Data assimilation problem

Data assimilation: The combining of diverse data, possibly sampled at different times and intervals and different locations, into a unified and consistent description of a physical system, such as the state of the atmosphere.

In meteorology, there exist two main streams of techniques:

Variational techniques
(e.g. 3DVAR and 4DVAR)
"Cost functions" that measure the difference between model output and observations are optimised over a pre-defined time interval.

Sequential technique
(e.g. Optimal Interpolation (3DDA), Kalman Filters (4DDA))
The model solution is recursively updated in a forward integration step with weights on observation and model output according to their uncertainties

***The question is**: How and to which extent can the limit of predictability of weather forecast models be overcome with the help of data assimilation?*

A note on Ensemble Kalman Technique

Traditional Kalman filter technique:

- account dynamically for the model errors
- account for the uncertainty in the weather development

but are:

- computationally very expensive
- mostly only solvable for low-order problems

Ensemble Kalman filter techniques:

- have the same characteristics of the Kalman filters
- computationally much cheaper, because uncertainties are estimated from ensemble forecasts (error covariance matrix is given by the ensemble data) !

but

- *inbreeding problem* if ensembles are built from perturbations of observations (observation error covariance matrix is no longer independent of background error covariance)

Solution: Generation of Ensemble weather data with independent ensembles, e.g. a Multi-Scheme Ensemble technique

Principle of the MSEPS Ensemble Kalman Filter technique for Wind Power

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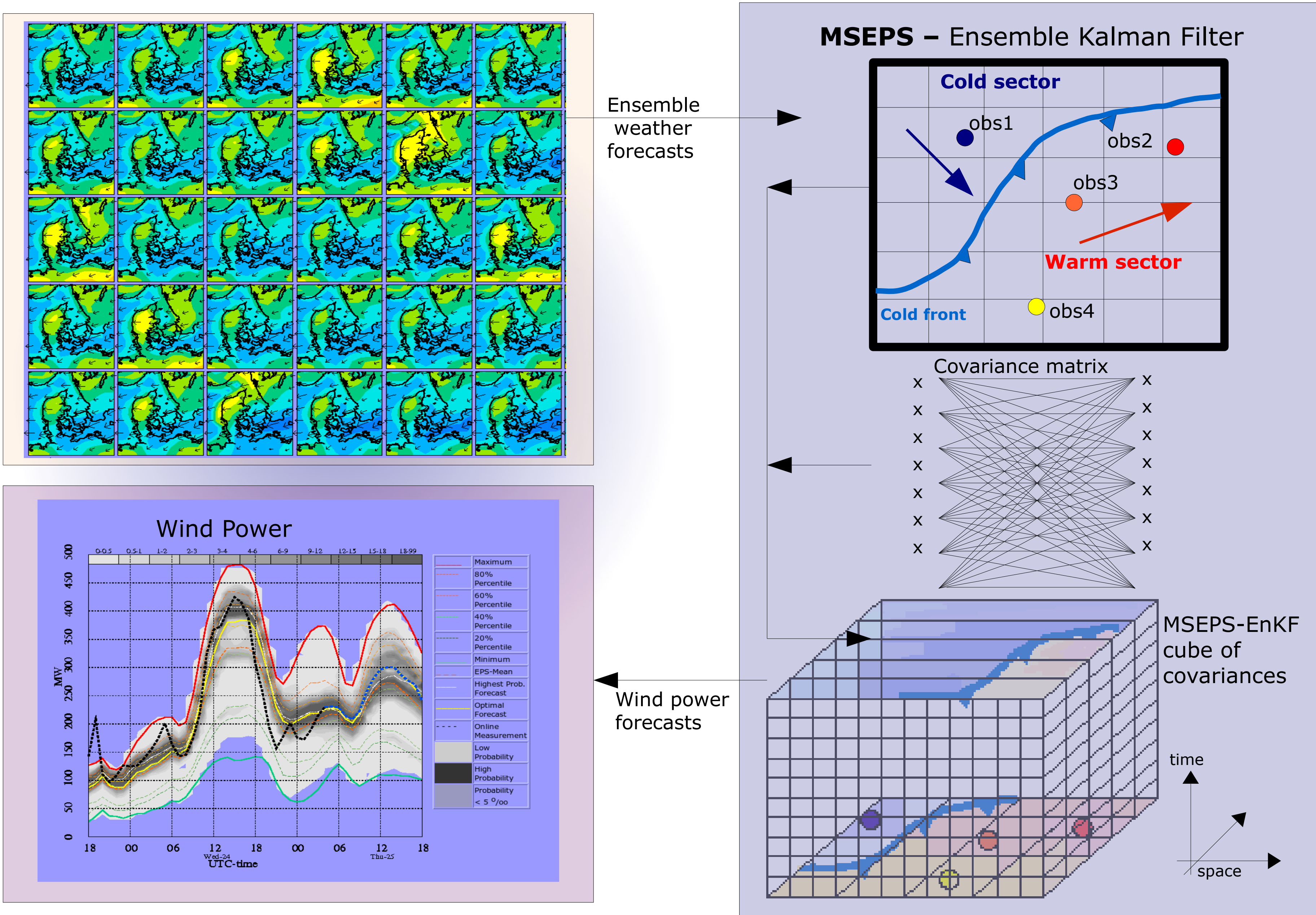
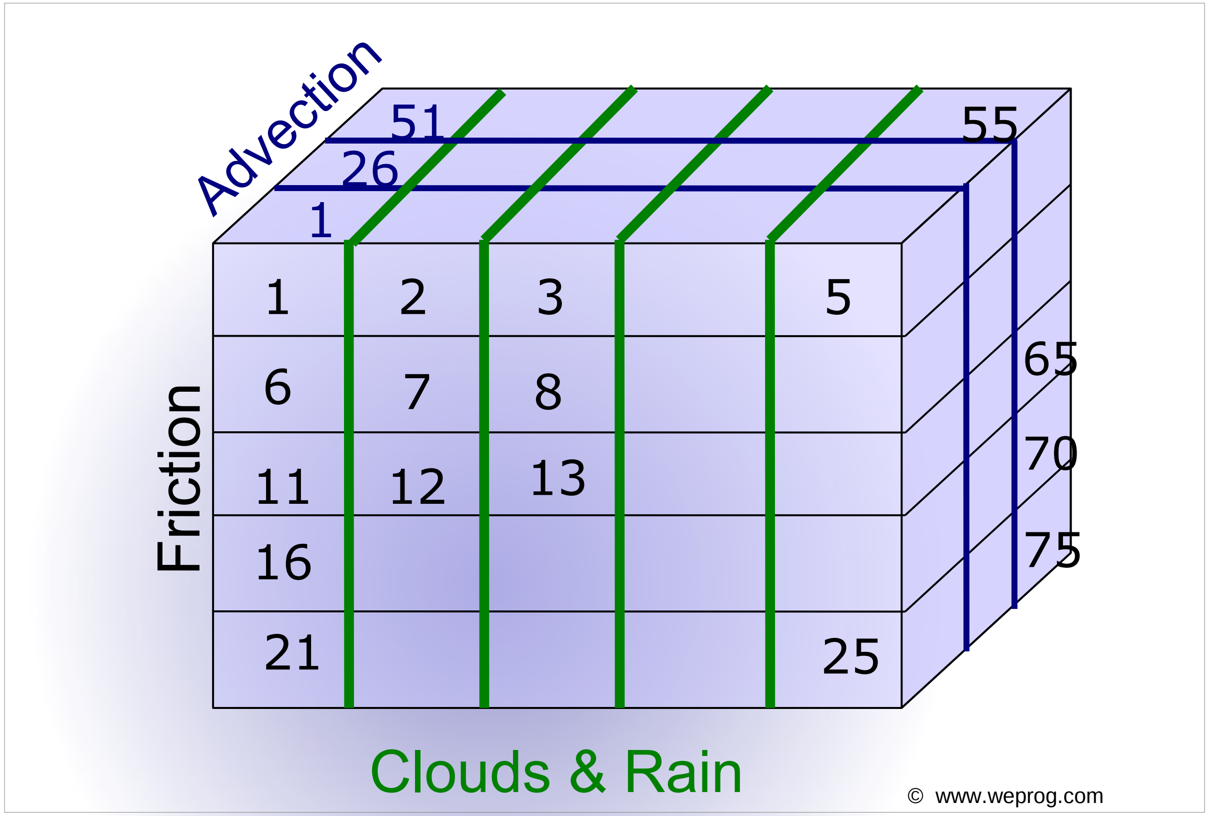


Principle of the building of the Multi-Scheme EPS



Every „Scheme" is an assumption of a series of equations in the 3D numerical weather prediction model to describe and solve a physical process – a "parameterisation".

- Every element in the cube represents a complete 3D numerical weather prediction model with the same kernel and different well-defined physical parameterisation schemes
- The differences of the NWP models (members) are different assumptions when solving dynamical and mathematical equations to compute physical processes.

=> **Difference of the Ensemble Members are of physical nature** !

Ensemble flow pattern responsible for the influence distribution in the short-term module

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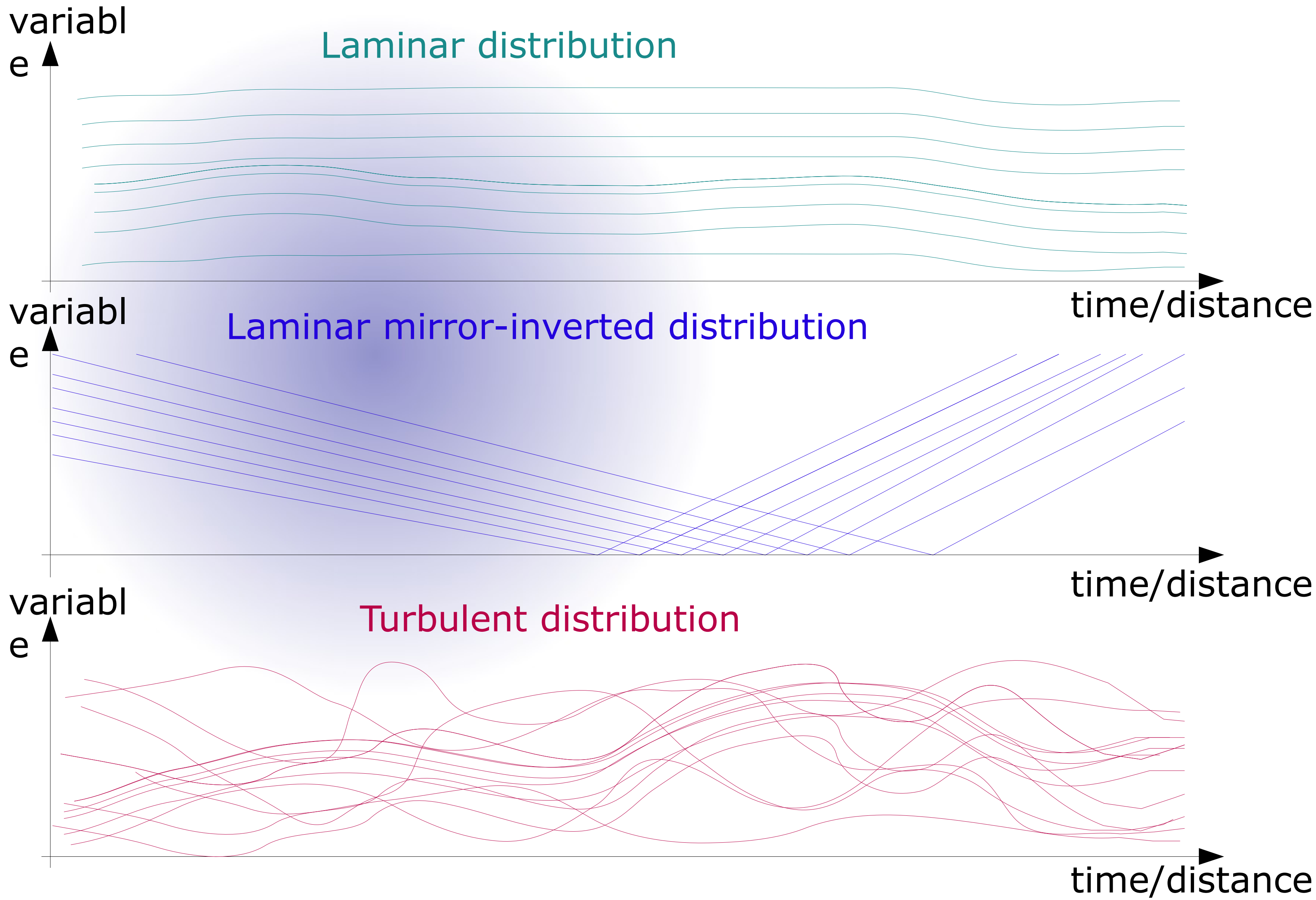
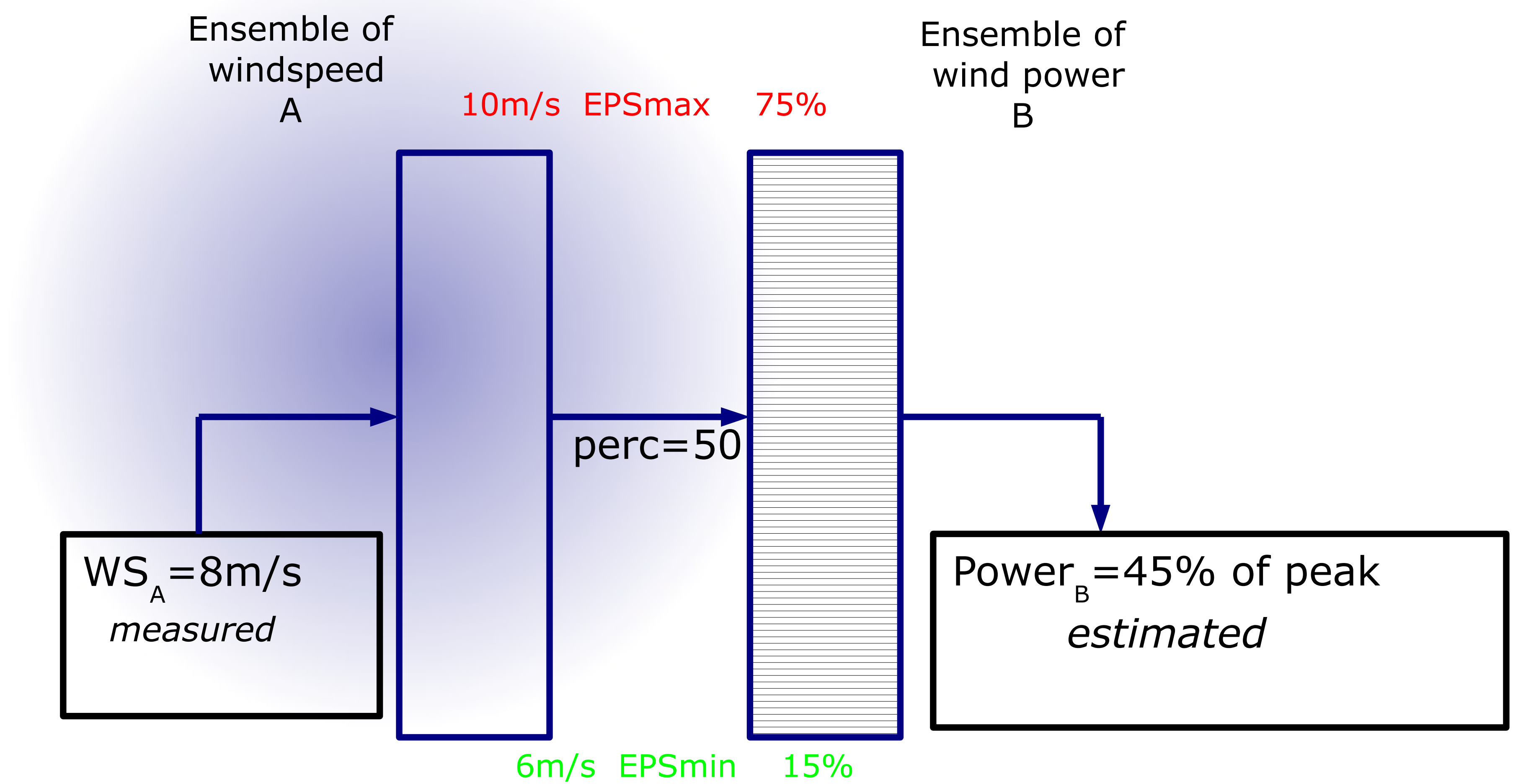
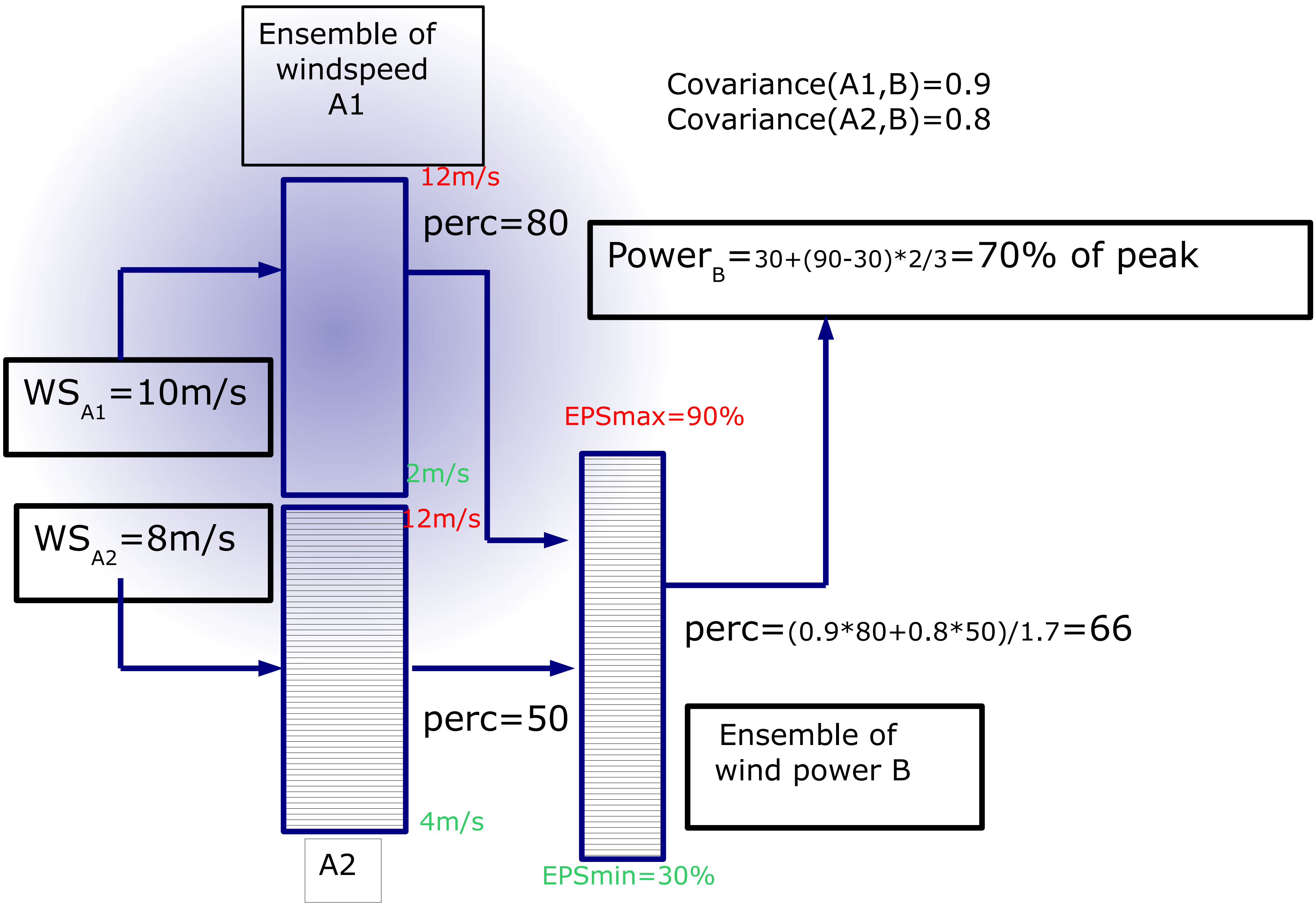


Transformation of measurements with the help of Percentiles in the short-term forecasting module



Covariance(A,B)=1.0

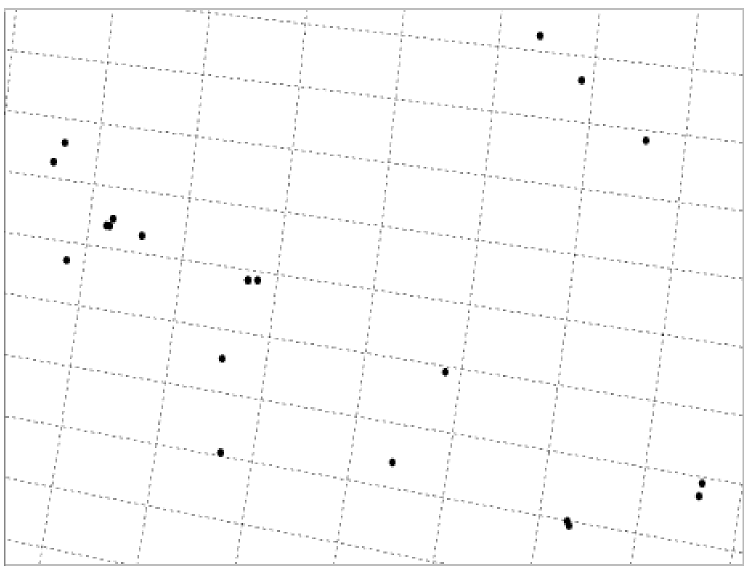
Transformation of measurements with the help of Percentiles in the short-term forecasting module



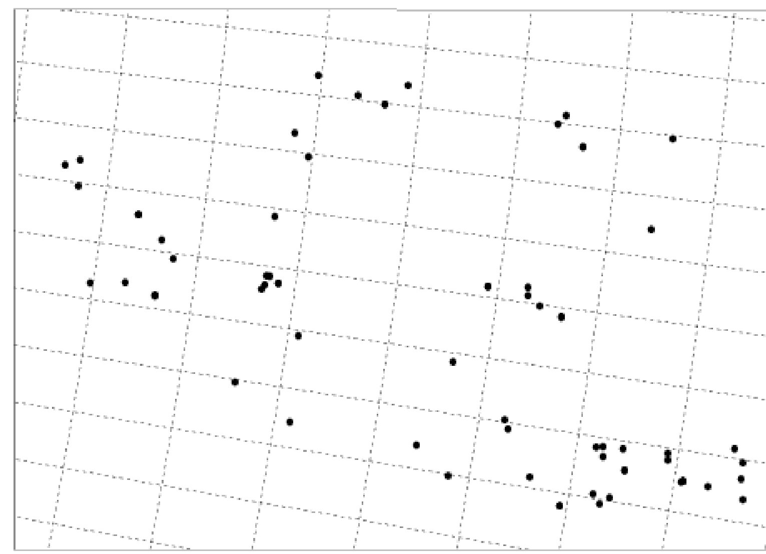
Experiment: Upscaling and short-term forecasting of 80 measurement sites from 20 reference sites

Data:
- Wind power measurement data from 80 sites in 15min resolution
- Wind power forecasts from 75 Ensemble members

Time period: 6 months (January - June)



Area showing distribution of 20 reference sites



Area showing distribution of all 80 measurement sites

Statistical Results of Experiment

fcl	mean	ShFC bias	FCraw bias	P bias	ShFC mae	FCraw mae	P mae	ShFC rmse	FCraw rmse	P rmse
-3	29.9	1.3	1.3	0.0	2.2	5.1	0.0	2.9	6.8	0.0
-2	29.9	1.3	1.2	0.0	2.2	5.1	0.0	2.9	6.9	0.0
-1	29.9	1.2	1.1	0.0	2.2	5.2	0.0	2.9	7.0	0.0
0	29.8	1.2	1.1	0.0	2.2	5.2	0.0	3.0	7.1	0.0
1	29.8	1.0	1.1	-0.9	2.6	5.3	2.0	3.6	7.2	6.8
2	29.8	1.2	1.1	-1.9	3.6	5.4	4.8	5.0	7.3	10.3
3	29.8	1.3	1.2	-2.4	4.3	5.5	6.6	5.8	7.4	12.0
4	29.8	1.3	1.2	-2.8	4.7	5.6	8.2	6.4	7.5	13.5
5	29.8	1.3	1.3	-3.1	5.0	5.7	9.4	6.8	7.6	14.7
6	29.9	1.2	1.3	-3.4	5.2	5.7	10.5	7.1	7.7	15.9
7	29.9	1.2	1.2	-3.7	5.4	5.8	11.5	7.3	7.9	17.1
8	29.9	1.1	1.2	-3.9	5.5	5.8	12.4	7.6	8.0	18.2
9	29.9	1.0	1.1	-4.1	5.6	5.9	13.2	7.8	8.1	19.0
10	29.8	1.0	1.1	-4.3	5.6	5.9	13.9	7.9	8.2	19.9
11	29.8	0.9	1.0	-4.4	5.7	6.0	14.5	8.1	8.3	20.5
12	29.8	0.8	1.0	-4.5	5.8	6.0	15.0	8.2	8.4	21.2
13	29.8	0.8	0.9	-4.5	5.8	6.1	15.2	8.3	8.5	21.4

Root Mean square error:

Already in the first hour the short-term MSEPS-EnKF forecast is better than persistence

After 2 hours, the raw forecast is better than persistence

the MSEPS-EnKF forecast is better for all 12 forecast hours than the raw forecast

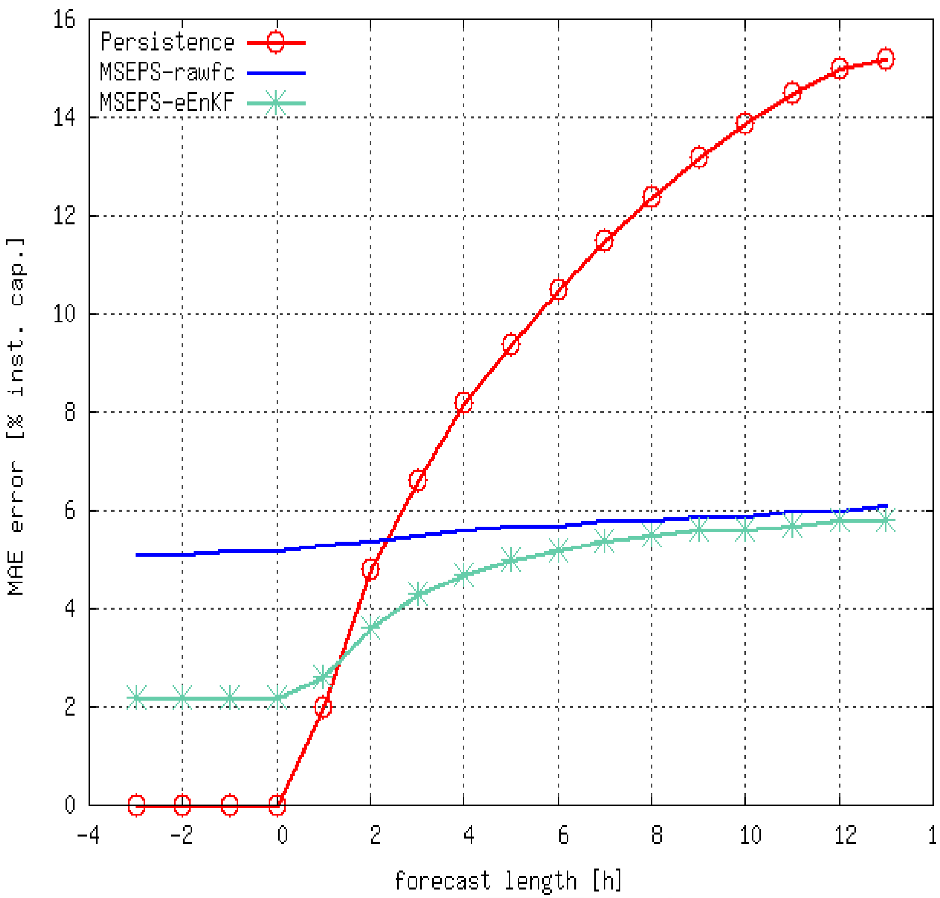
Mean absolute error:

After 2 hours the short-term forecasts is better than persistence

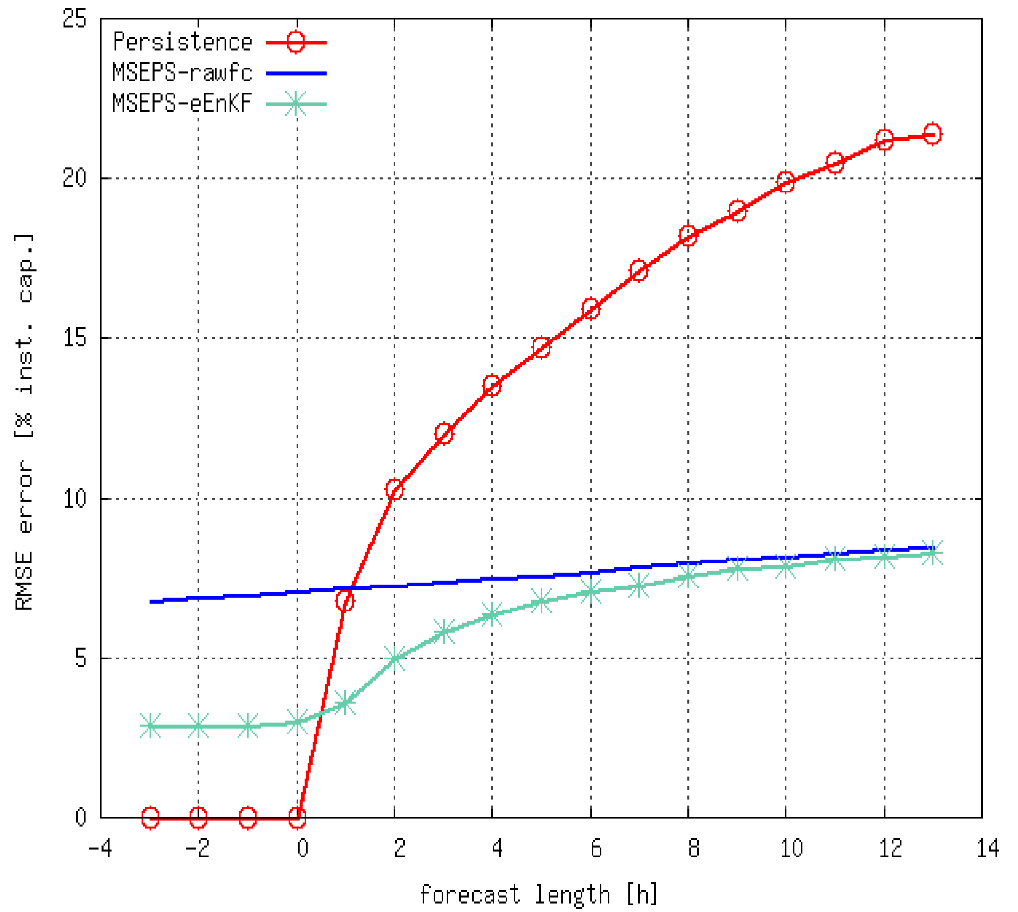
After 3 hours, the raw forecast is better than persistence

the MSEPS-EnKF short-term forecast is better for all 12 forecast hours than the raw forecast

Statistical Results of Experiment



Mean absolute error



Root mean square error

Summary & Conclusion

Distributing measurements in space and time is weather dependent

weather dependency in time (**phase errors**) can be solved mathematically with the help of covariance matrices in the Ensemble Kalman Filter technique

Use of anti-correlation in the formation of the covariance matrices helps **identifying** the borders (in meteorological context **fronts**) of certain changes in the weather are **in space and time**

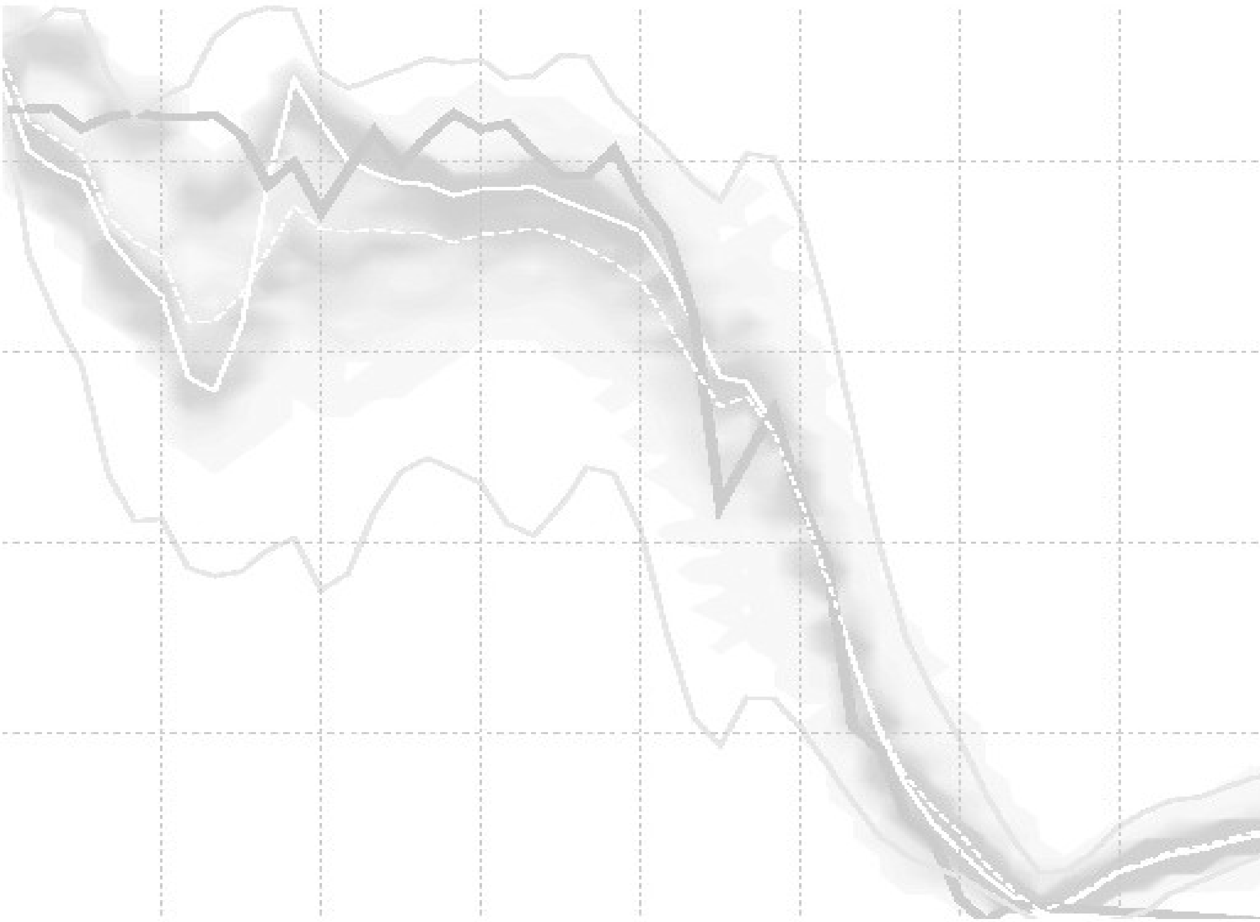
The MSEPS-iEnKF is future compatible, as **any type of measurements can be used** in the data assimilation step for wind power forecasts

it is the first physically consistent methodology, where meteorological ensemble forecasts provide the framework for the distribution of observational influence and where it is possible to back-scale aggregated total production measures of an area physically consistent for the statistical training of wind power forecasts

>> the MSEPS-iEnKF is the first algorithm that provides a feedback mechanism to the NWP model for the generation of power curves

>> This is a milestone in wind energy forecasting and will be of great value for the large-scale integration and requirements of reliable handling of wind power

Questions ?



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