Data assimilation with the Ensemble Kalman Filter in a high-resolution spectral wave model

- demonstrated on a case in the Southern North Sea

2nd International Workshop on Waves, Storm Surges and Coastal Hazards, Melbourne, Australia
November 2019

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Motivation

- Accurate prediction of wave conditions
  - Design of offshore and coastal structures (hindcast)
  - Operations at sea (forecast)

- MIKE21SW + EnKF = better wave predictions?

Research questions

- Can we reduce model complexity and calibration work...
  and rely on data and EnKF instead?

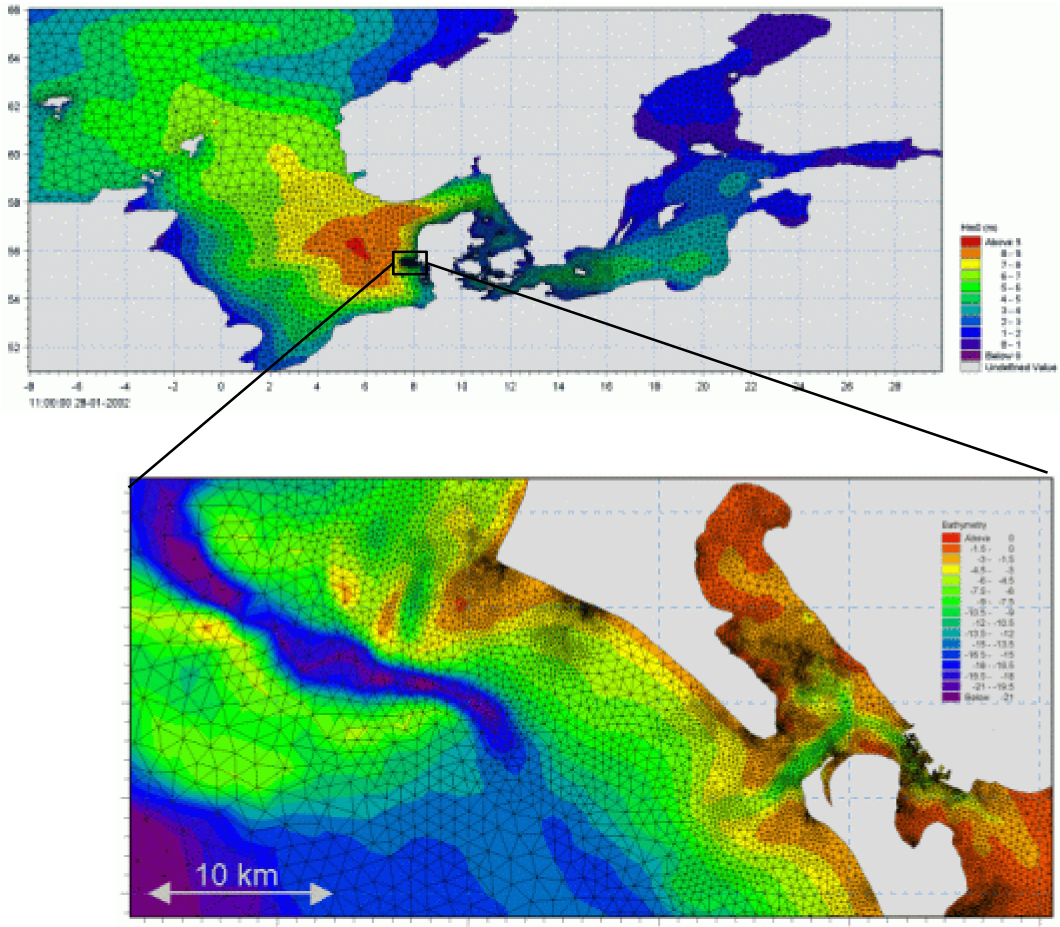
- Is EnKF necessary?
  or is a simpler data assimilation procedure sufficient?

Spectral wave modelling with MIKE 21 SW

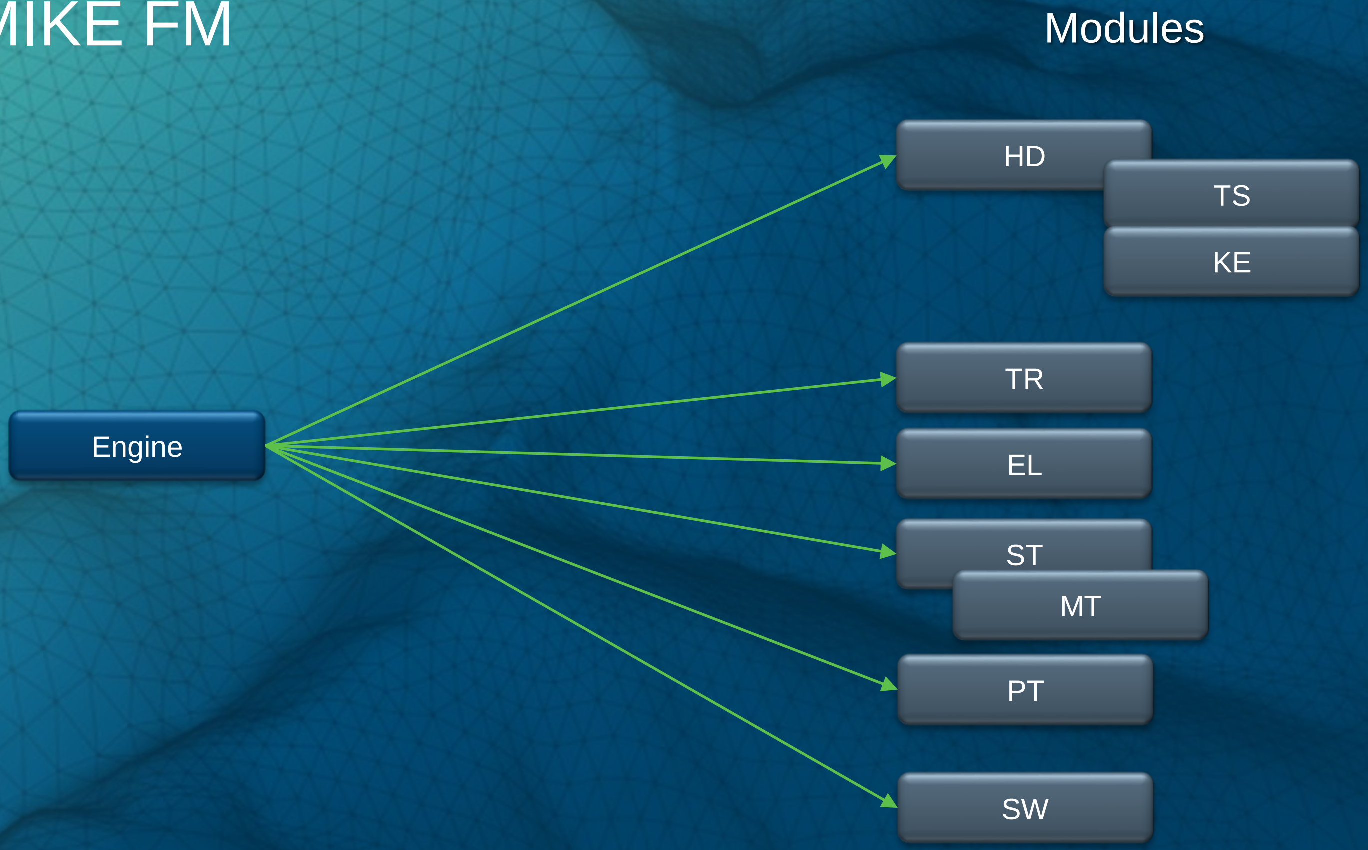
MIKE 21 SW

- 3rd generation spectral wind-wave model
- Unstructured mesh
- Finite volume
- Wave growth, decay and transformation

$$\frac{\partial N}{\partial t} + \nabla \cdot (\vec{v}N) = \frac{S}{\sigma}$$



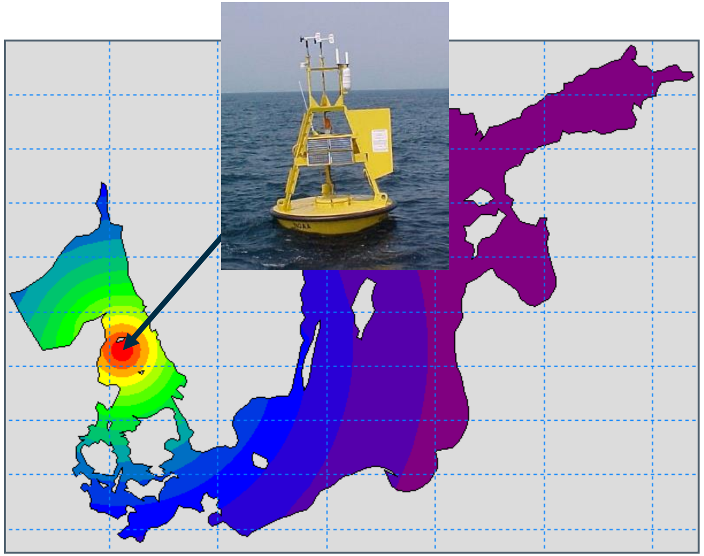
MIKE FM



DA in MIKE FM

Data assimilation and the EnKF

How to update the model?

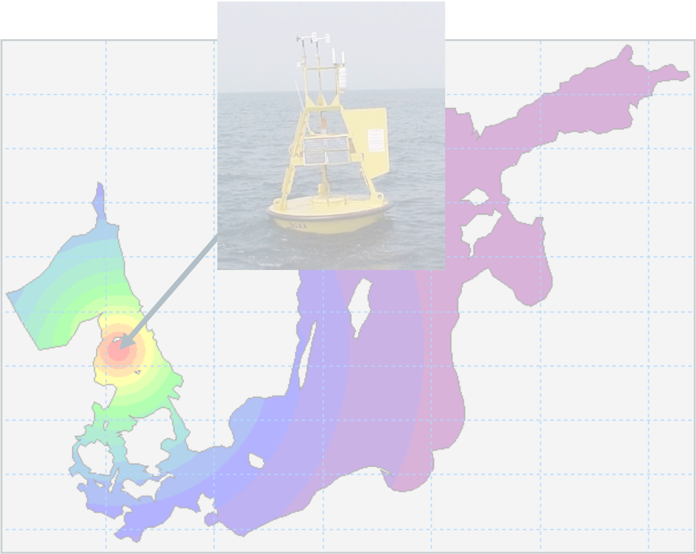


Distance-based

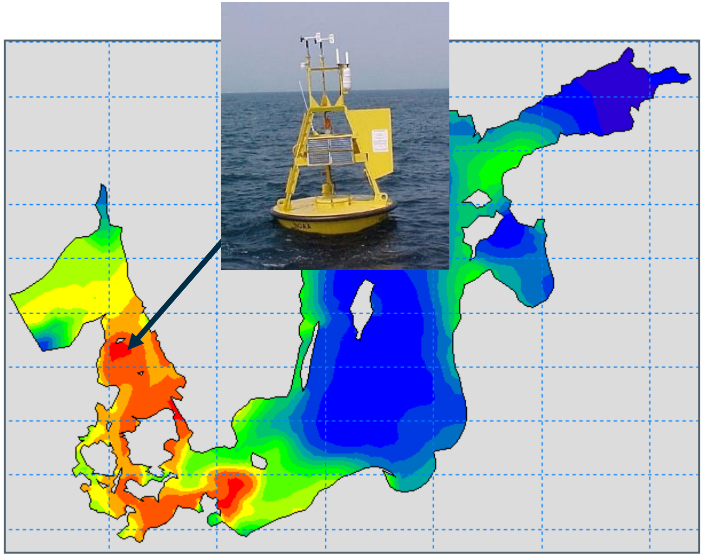
But how about…

- Other variables
- Physical consistency

How to update the model?

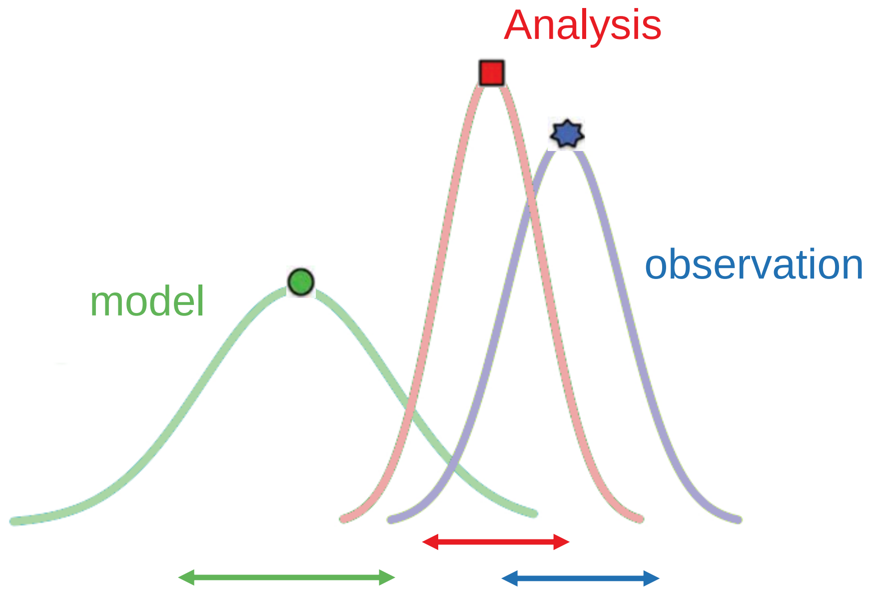


Distance-based

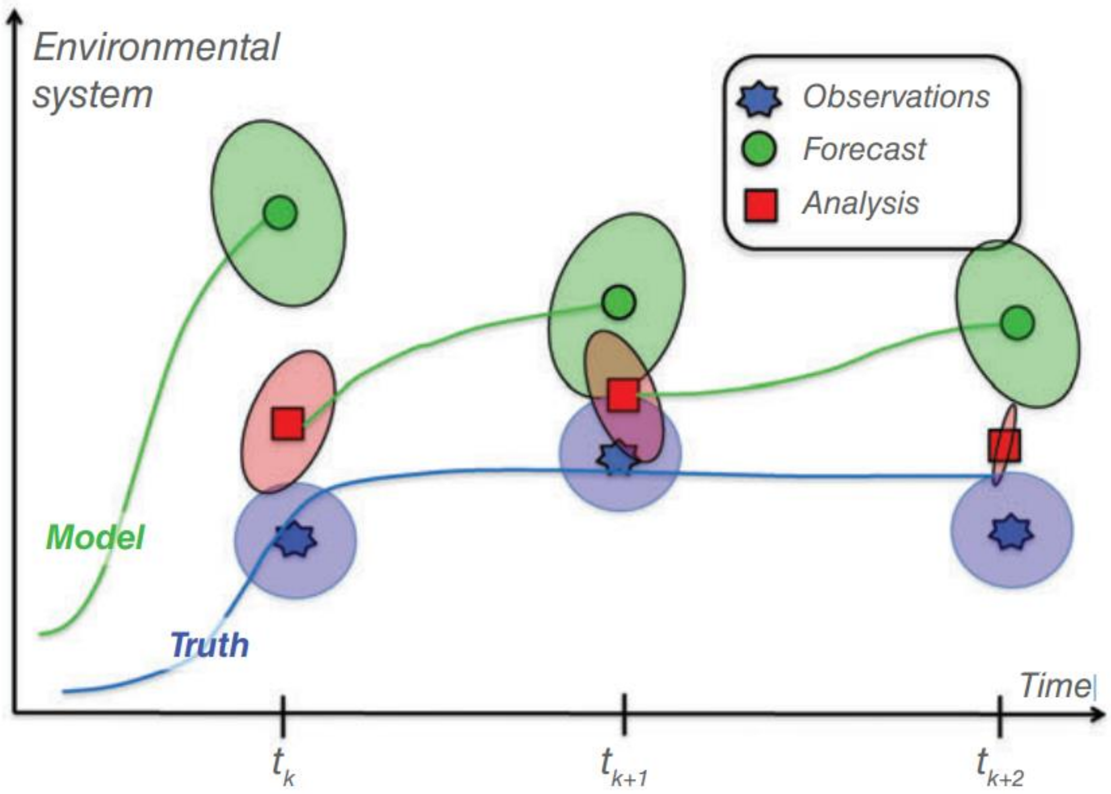


Correlation-based

Combining two uncertain pieces of information



Filtering



Kalman filter

Optimal combination of

- model (with errors) and
- observations (with errrors)

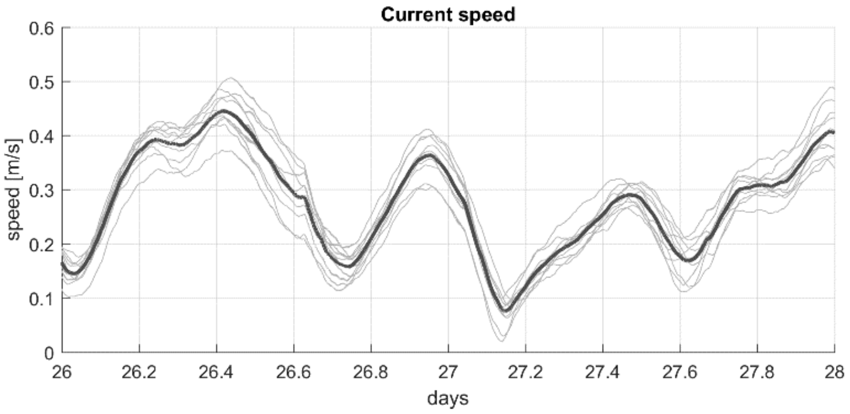
But…

It only works for **small**, **linear** problems

The Ensemble Kalman filter

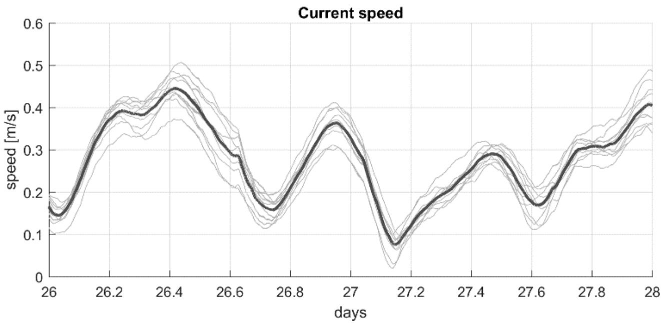
Ensemble models

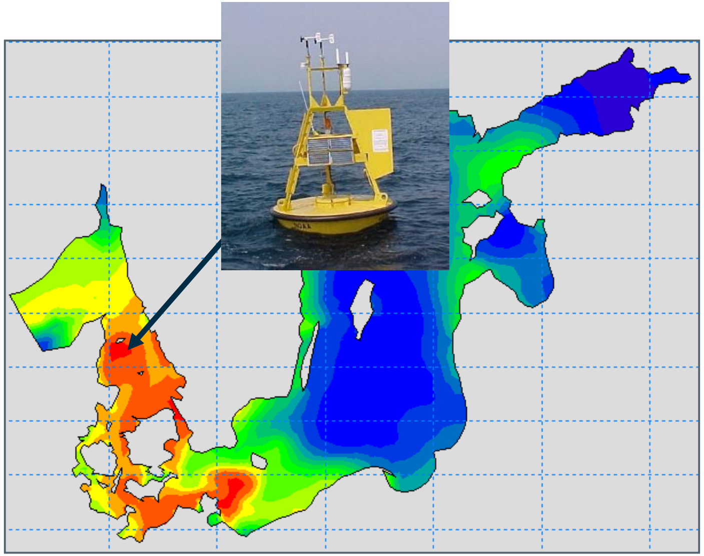
- Ensemble consisting of m *members*
- Representing model uncertainty



How to update the model?

- Use ensemble
- Model error ≈ difference from mean

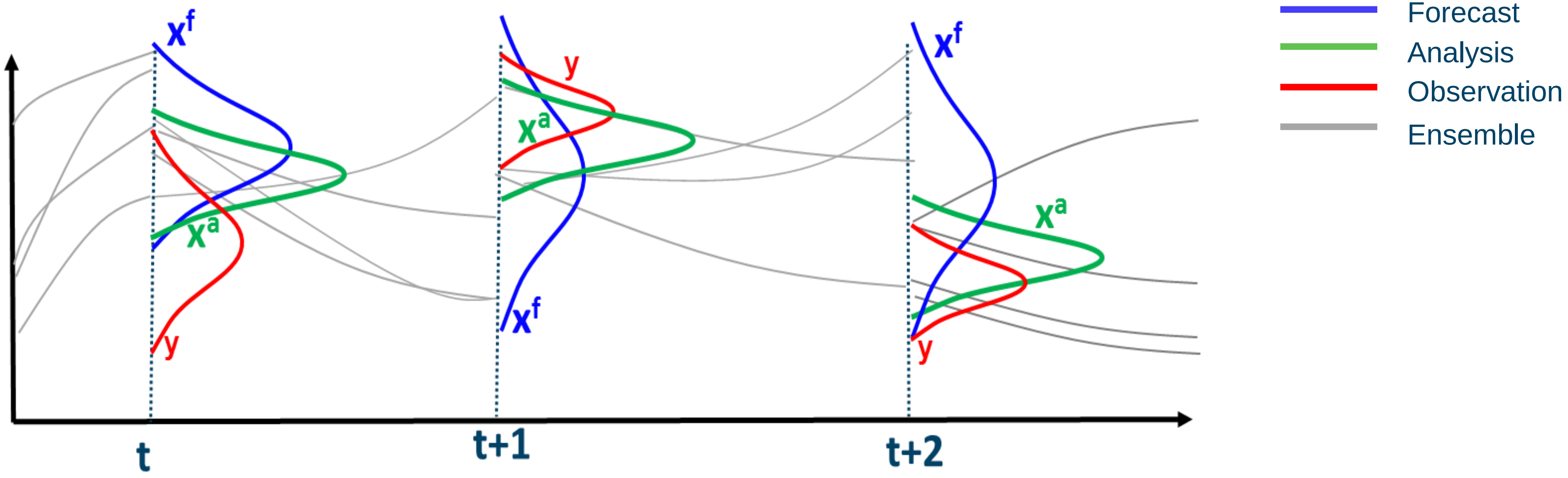




Correlation-based update

Ensemble Kalman filter

- Idea: Monte Carlo approximation to Kalman filter
- Approximate model uncertainty by samples (ensemble members)



Ensemble modelling in MIKE FM

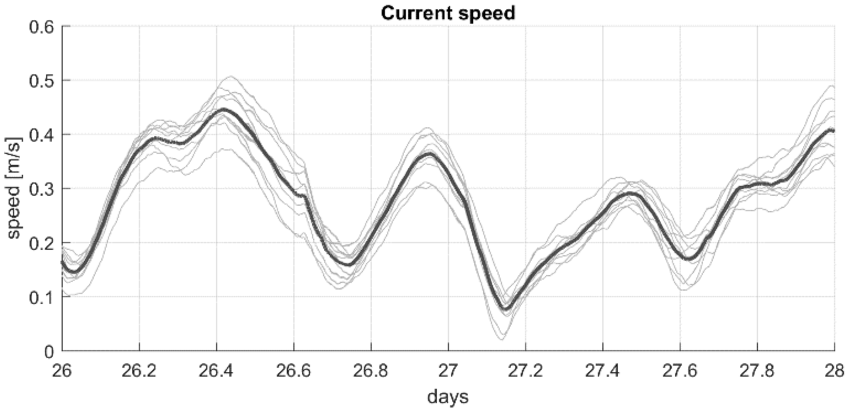
DA in MIKE FM

Ensemble models

- Ensemble consisting of m *members*

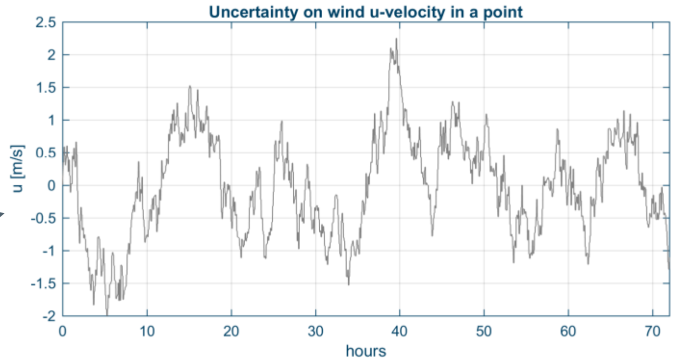
How to introduce variability in model?

- Add small “errors” (=pertubations) to…
  - Initial conditions
  - Forcings
  - Parameters

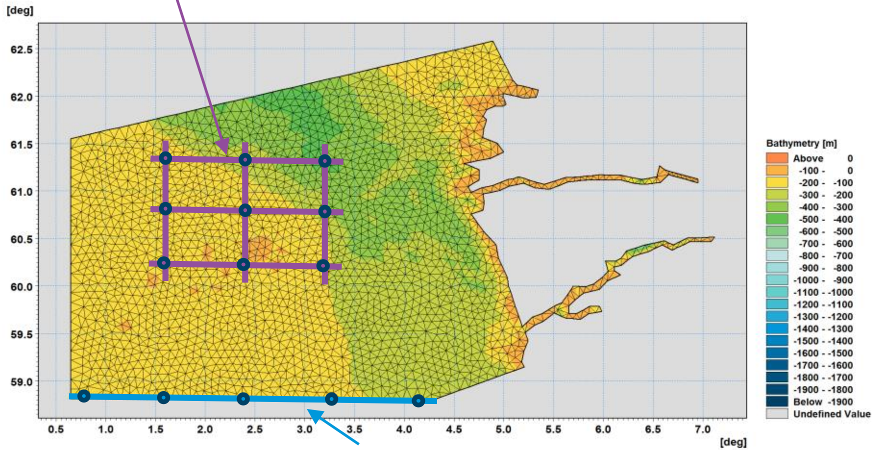


Uncertainty modelling in MIKE FM

- Amplitude (e.g. wind st.dev 1m/s)
- Time scales, AR(1)
- Spatial scales
  - Discretization (coarse)
  - Covariance Q (e.g. 300 km)
- Vector ϵ



Discretized wind uncertainty (part)



Discretized boundary uncertainty

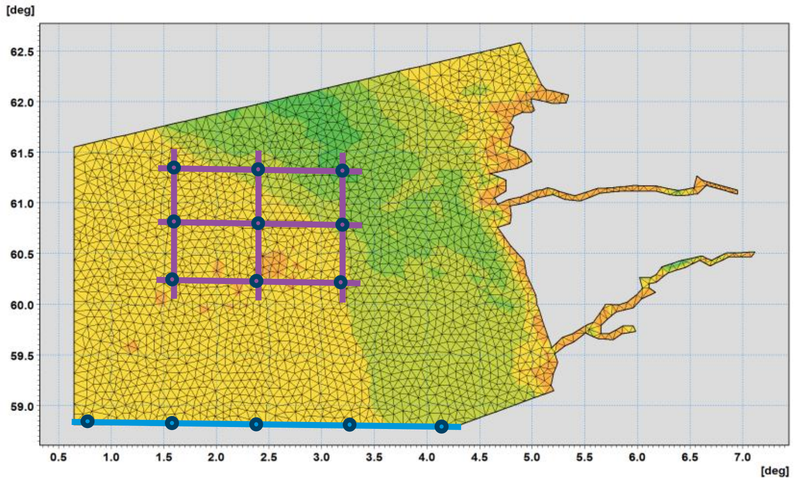
State representation in MIKE FM

- Model variables according to selected modules
  - State variables x_{model} =(wl, u, v, …)

- Model errors
  - Types: open bc, wind-u, wind-v, …
  - Discretized on a grid: ϵ

- Augmented state

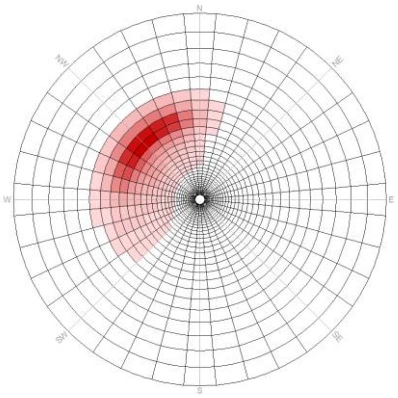
$$x_{state} = \begin{bmatrix} x_{model} \\ \epsilon \end{bmatrix}$$



Data assimilation for MIKE 21 SW

State representation

- Action density!
- And… variables that we would like to assimilate
  - Hm0, Tp
- Model errors



Creating the MIKE 21 SW ensemble

- Forcings
  - Wind velocity components
  - Windspeed

- Parameters
  - Whitecapping
  - Bottom friction

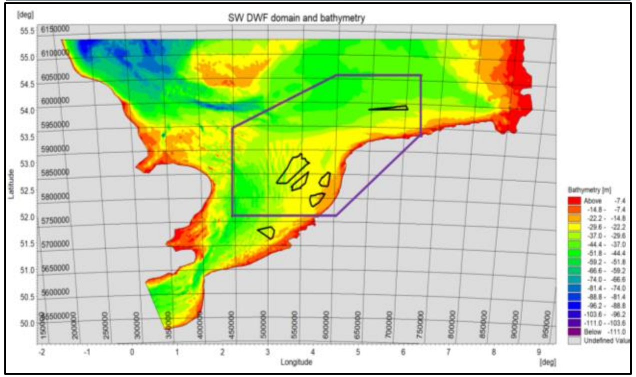
- Boundary conditions (later)

Case study

Case Study: Dutch Coast Metocean Desk Study

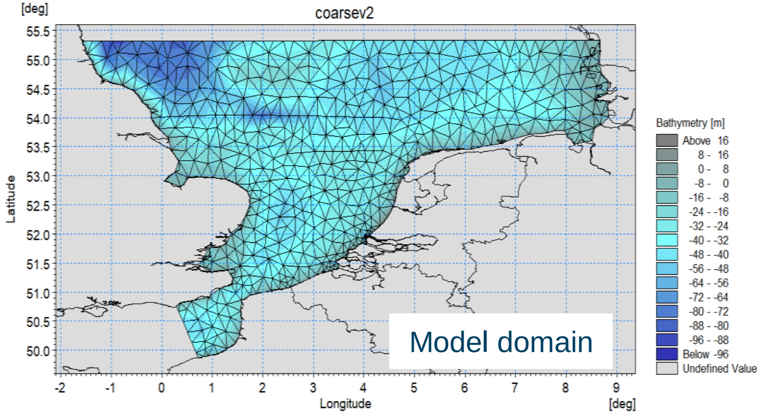
- DHI Project to provide meteorological and oceanographic (metocean) design conditions for the Dutch Coast wind Farm zone

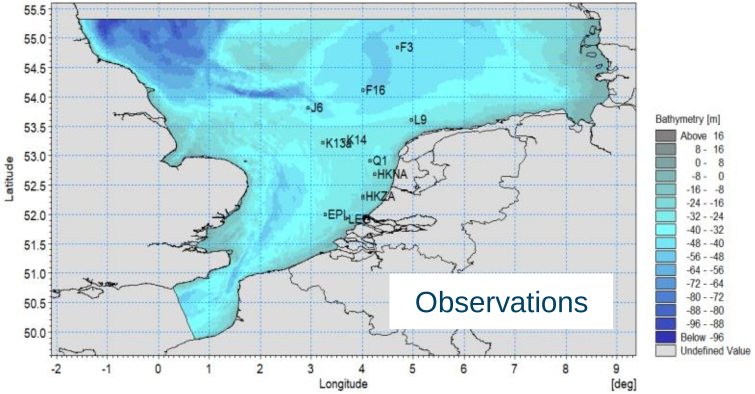
- Based on numerical modelling over 39 years



Case Study: MIKE 21 SW settings

- Coarse-resolution edition of existing SW model setup
- CFSR wind
- **Study period** 2017

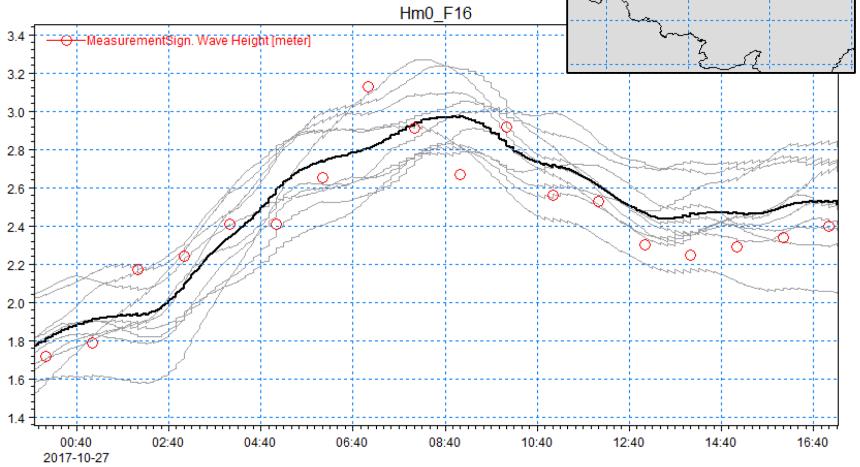


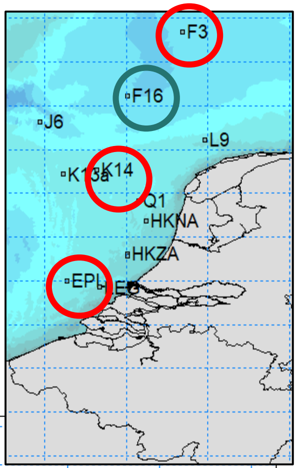


Case Study: DA model

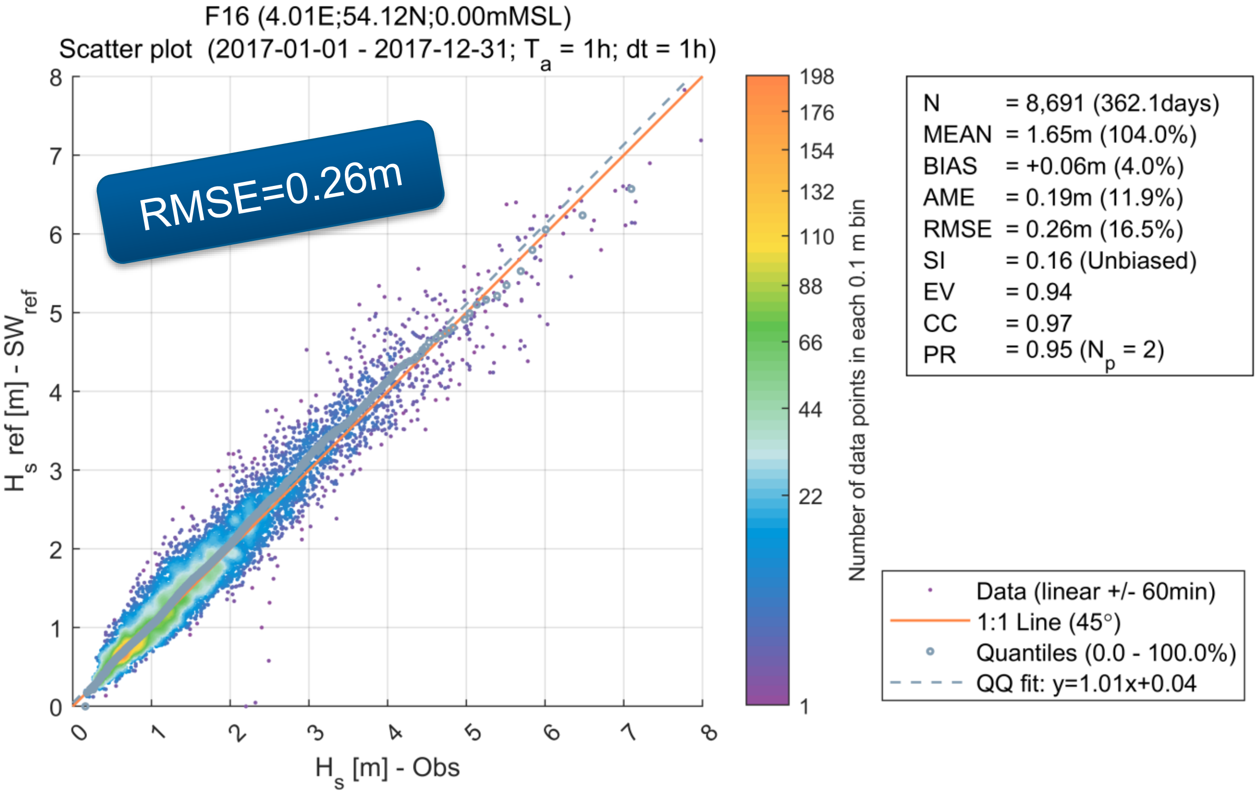
- Ensemble size: 10
- Perturbation of wind forcing:
  - 1.5m/s additive error on 80km grid

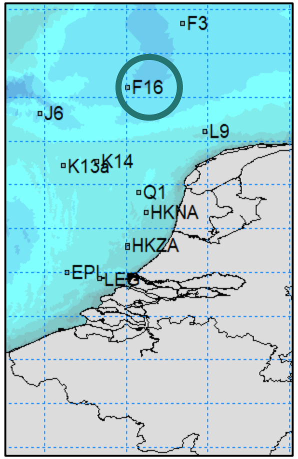
- Assimilate significant wave height
- Assimilate every 10 minutes



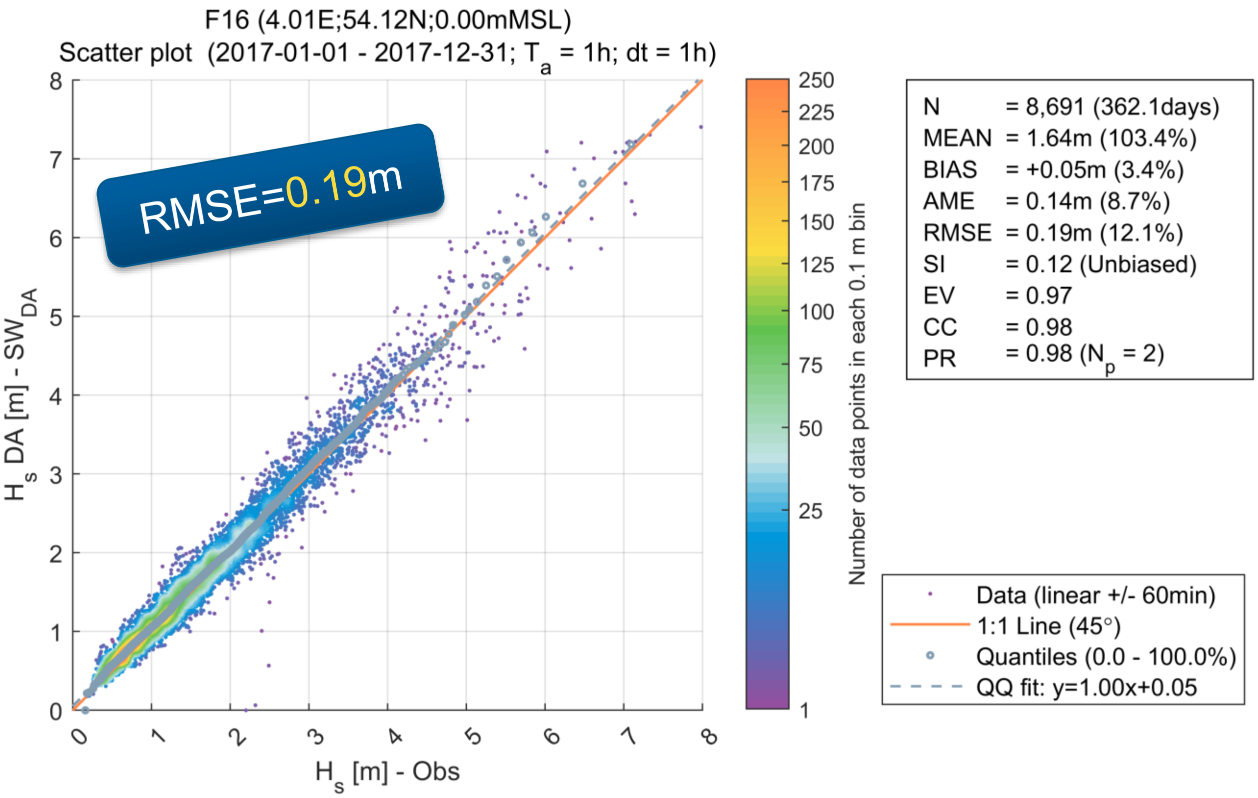


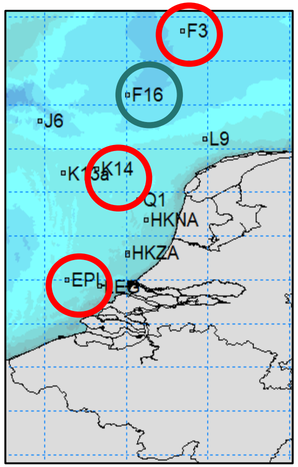
Station F16 – no DA



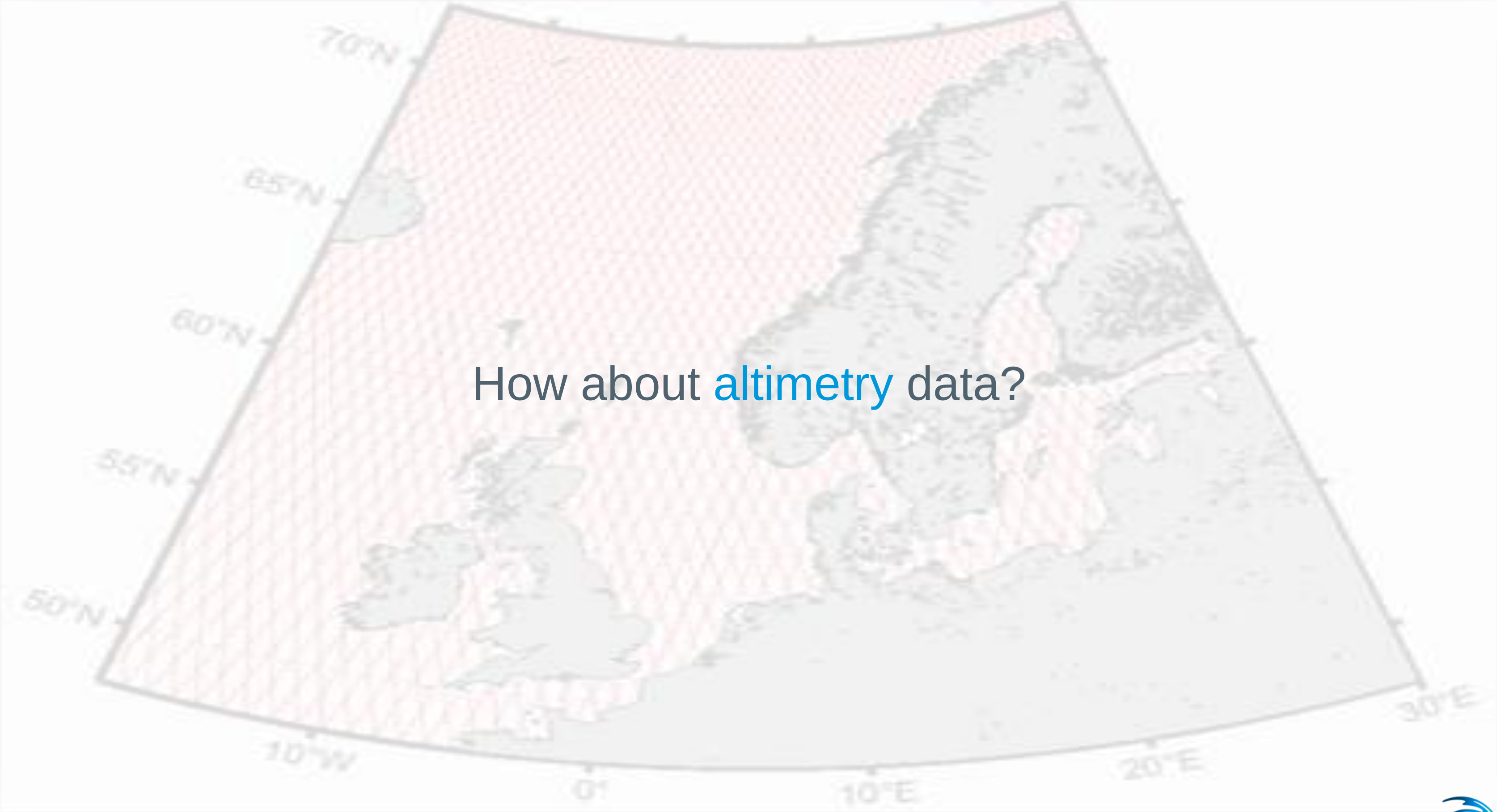


Station F16 – DA with 3 stations





How about altimetry data?

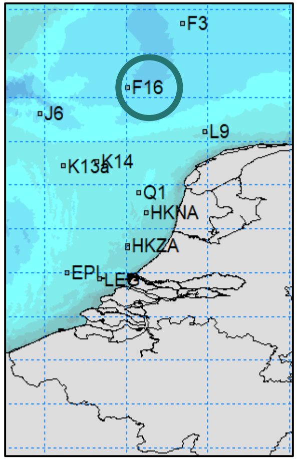


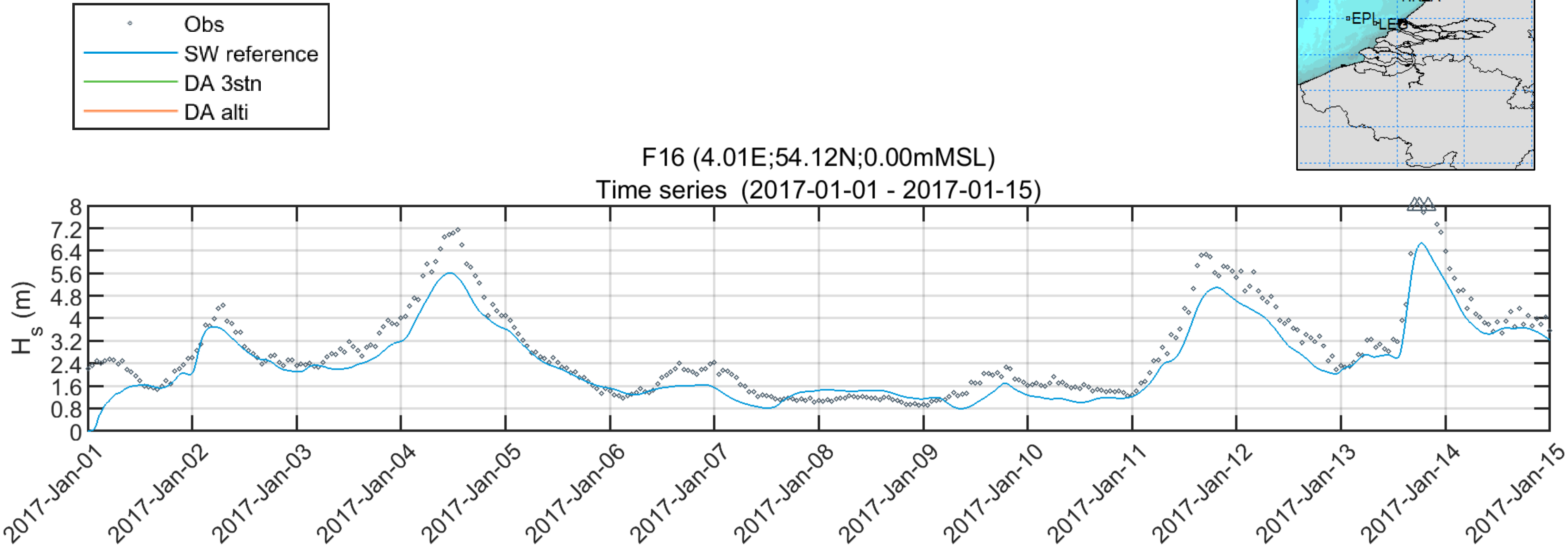
Forcings and model too good!?

- ...or altimetry data (Sentinel 3A) too sparse

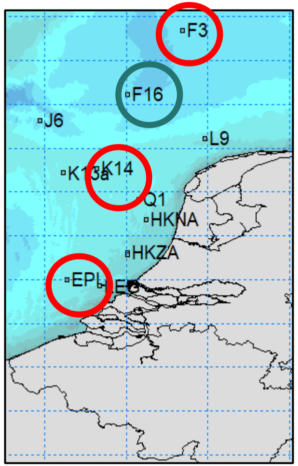
- Reduce accuracy in forcings
  - Let wind be biased 20% low
  - Simplify boundary conditions

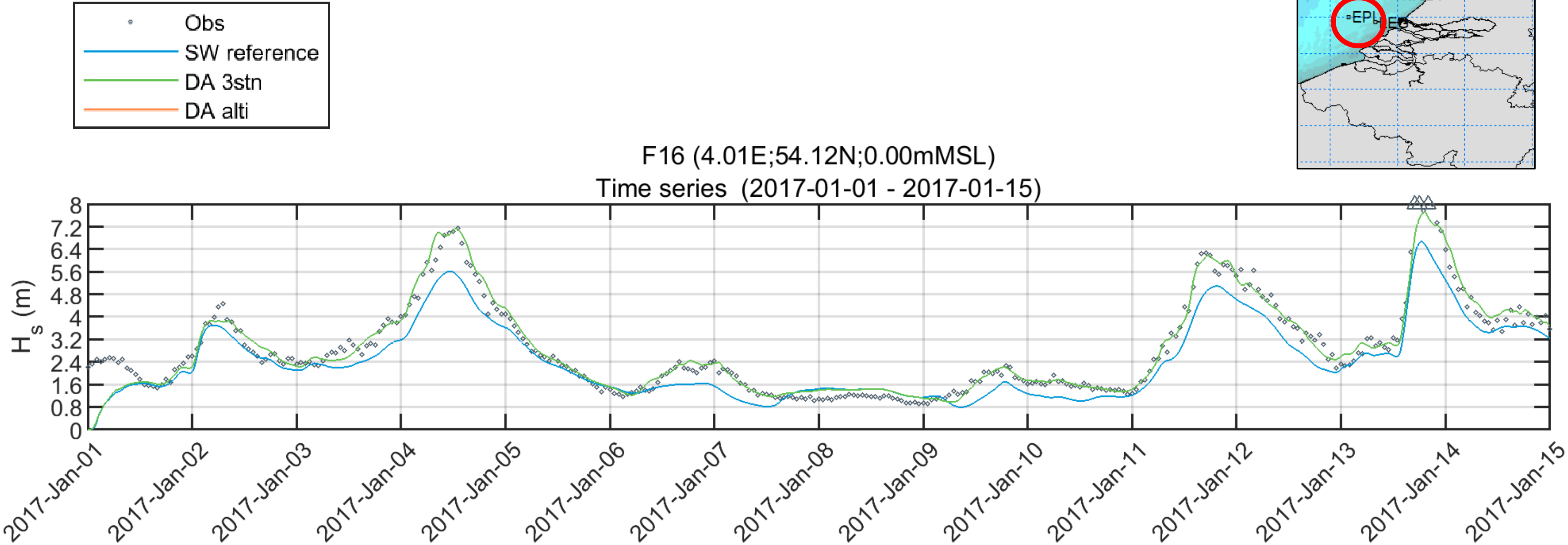
Time series of Hs at F16



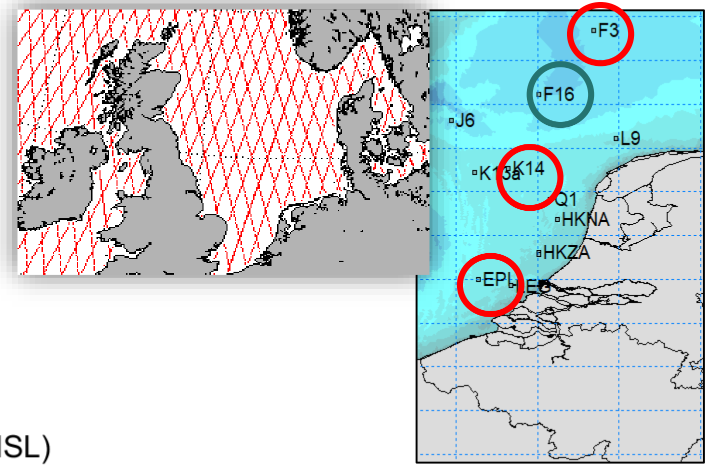


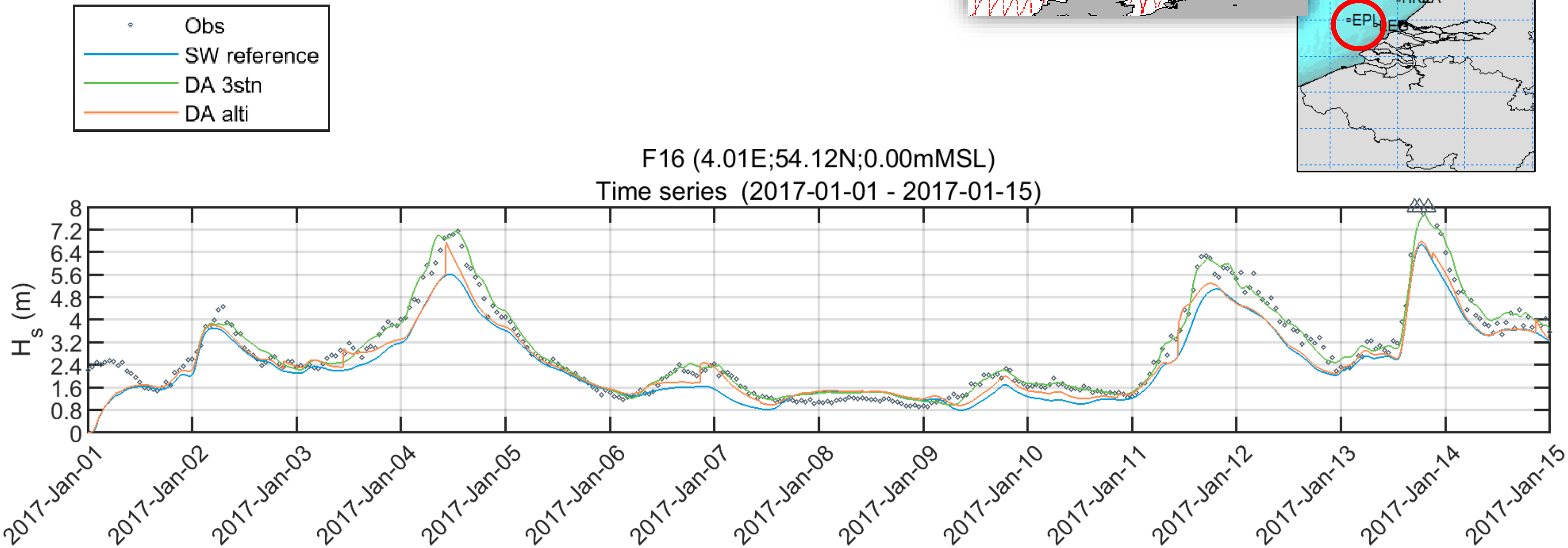
Time series of Hs at F16



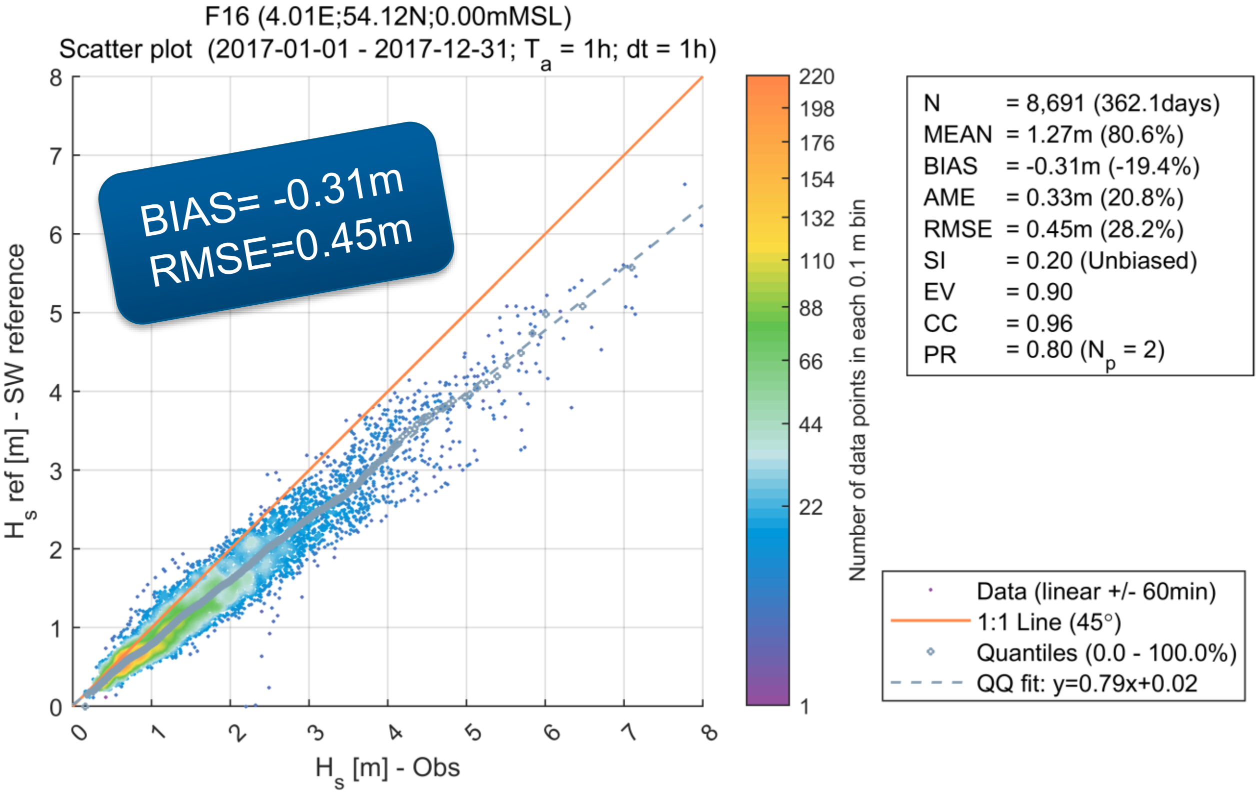


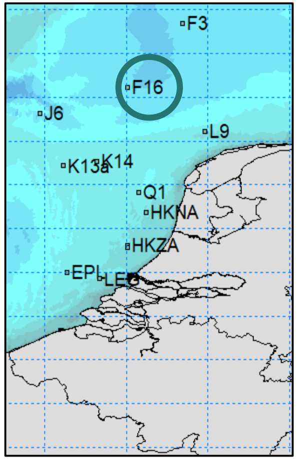
Time series of Hs at F16



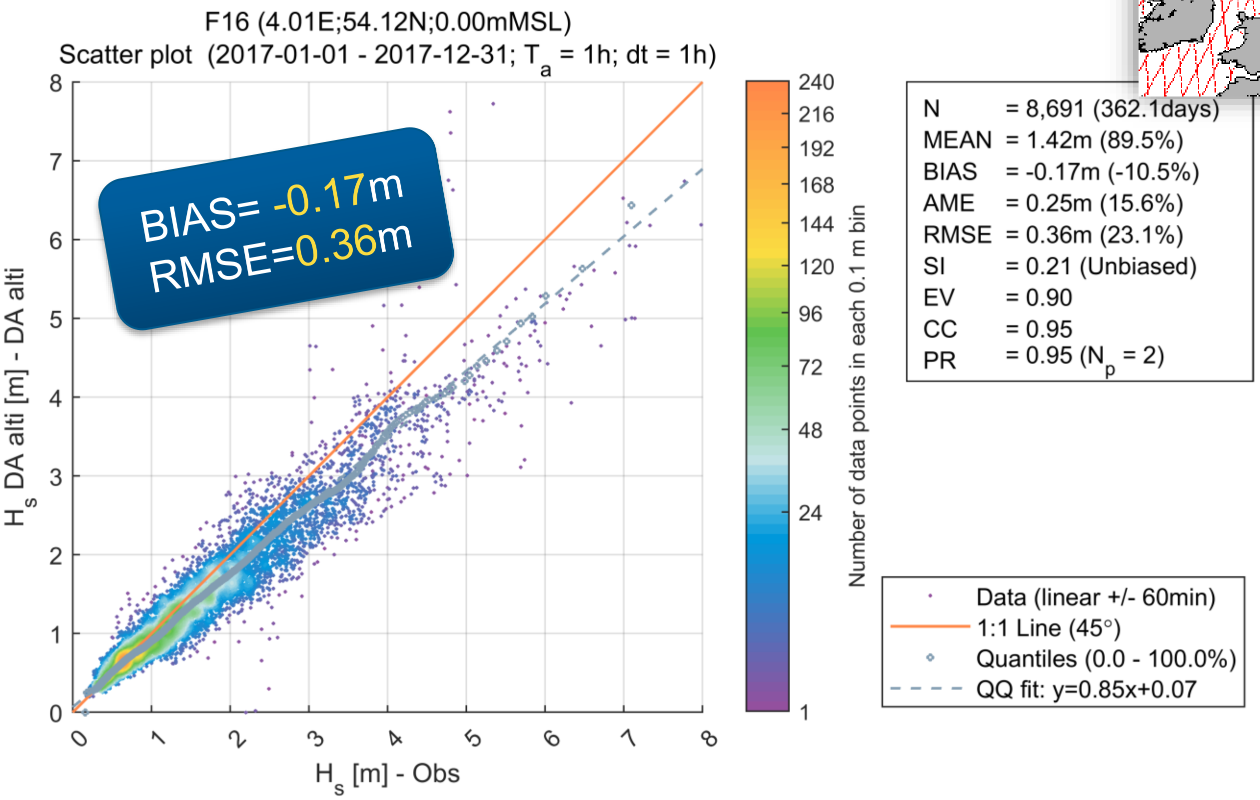


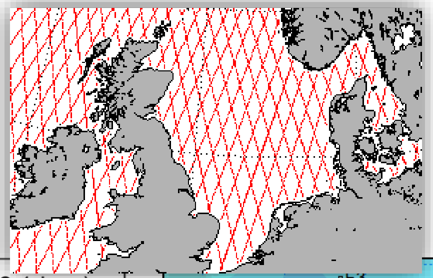
Station F16 – no DA, bad input

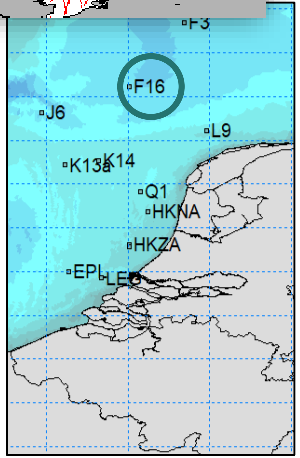




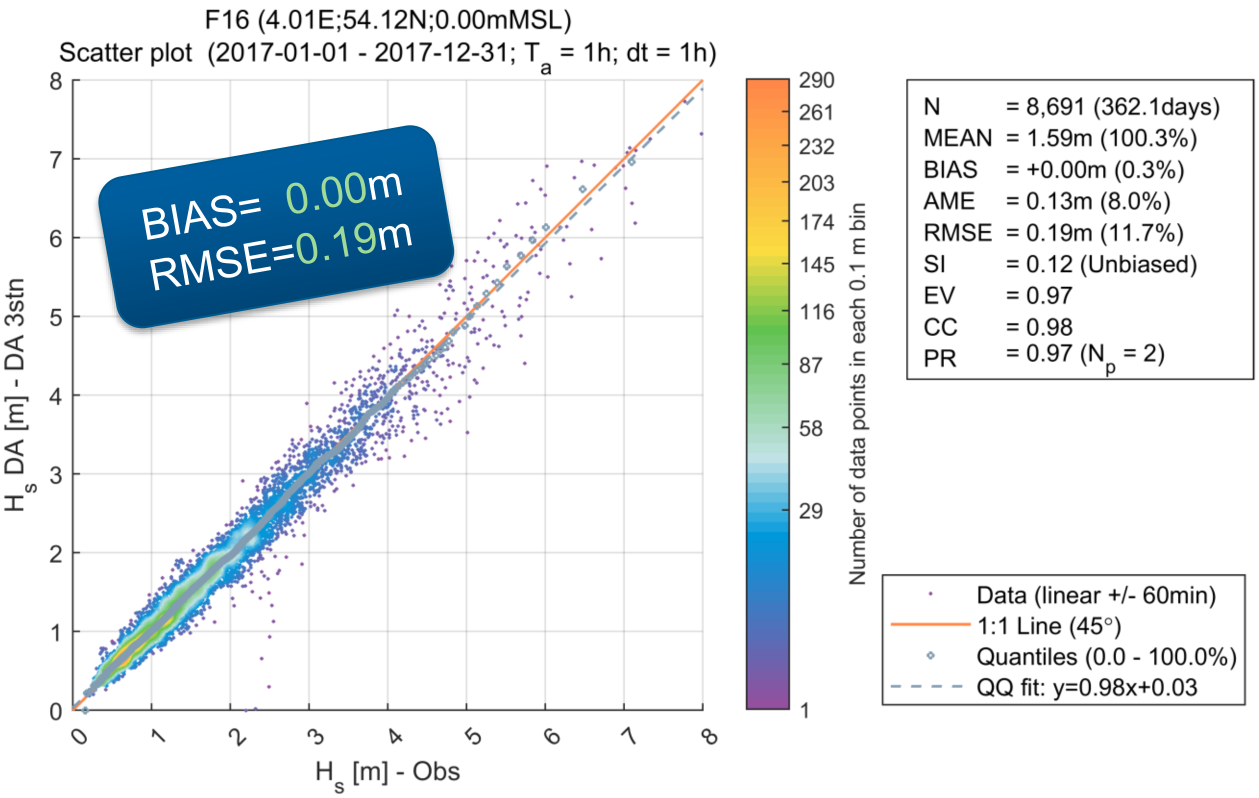
Station F16 – DA Sentinel 3A, bad input

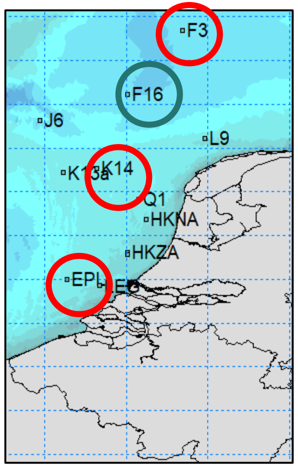






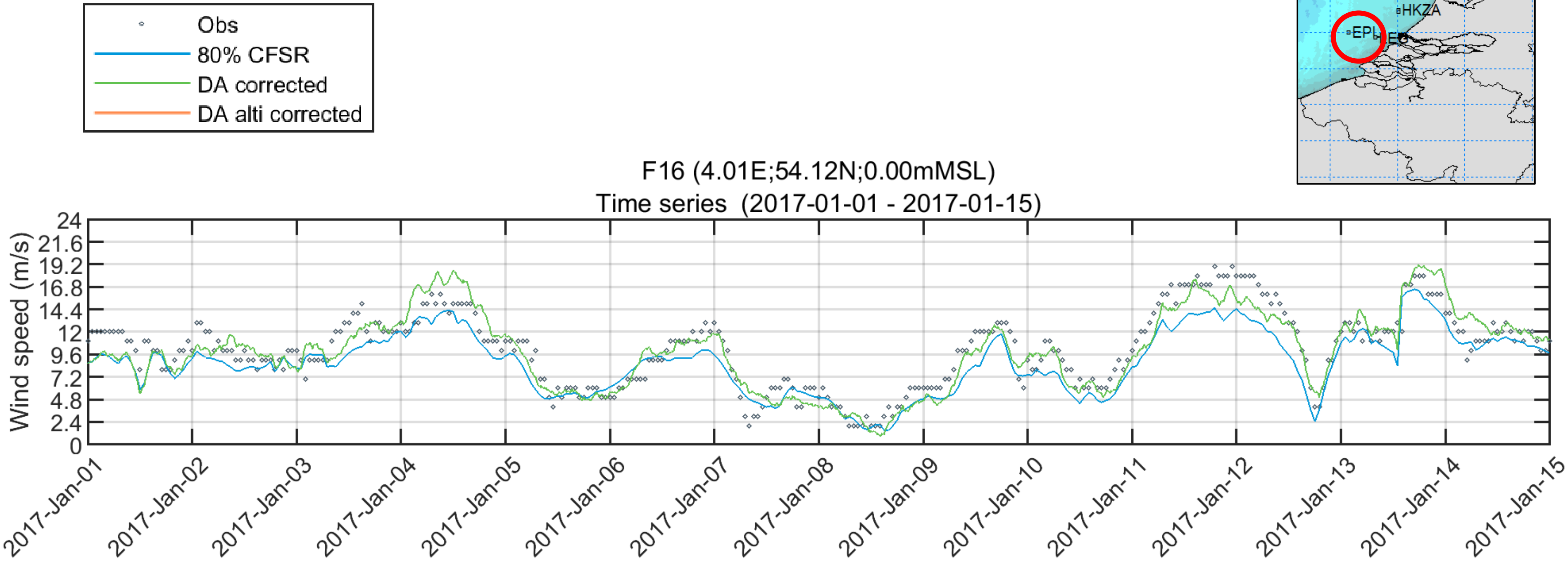
Station F16 – DA with 3 stations, bad input

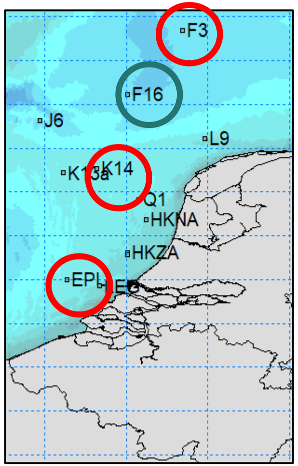




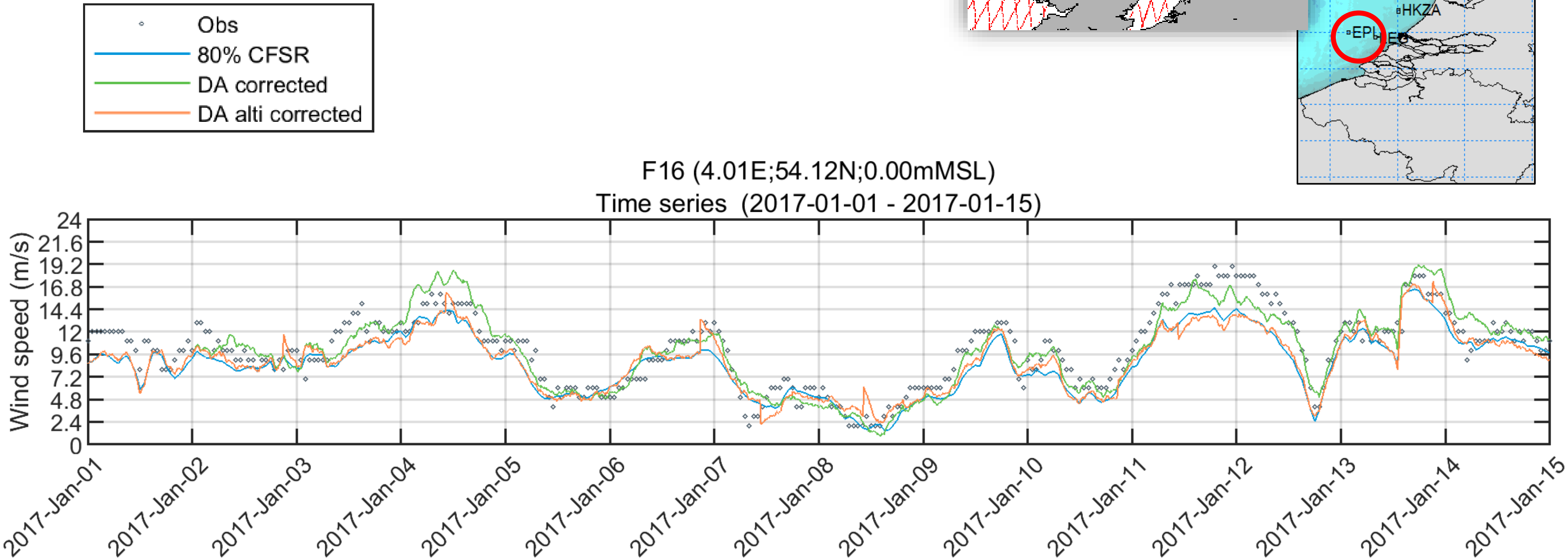
What about estimation of wind?

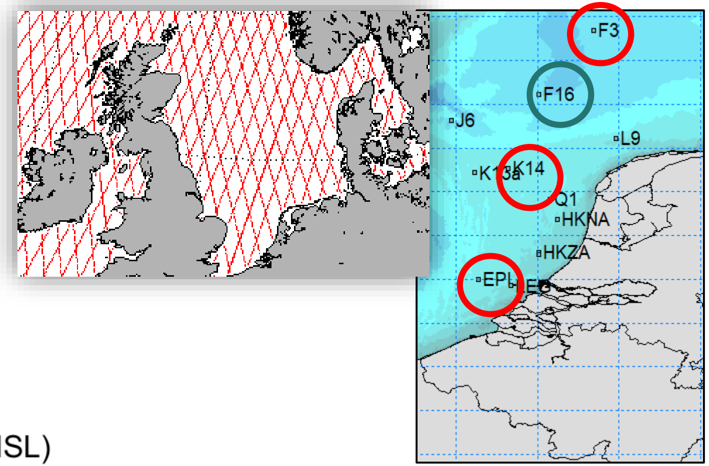
Time series of wind speed at F16



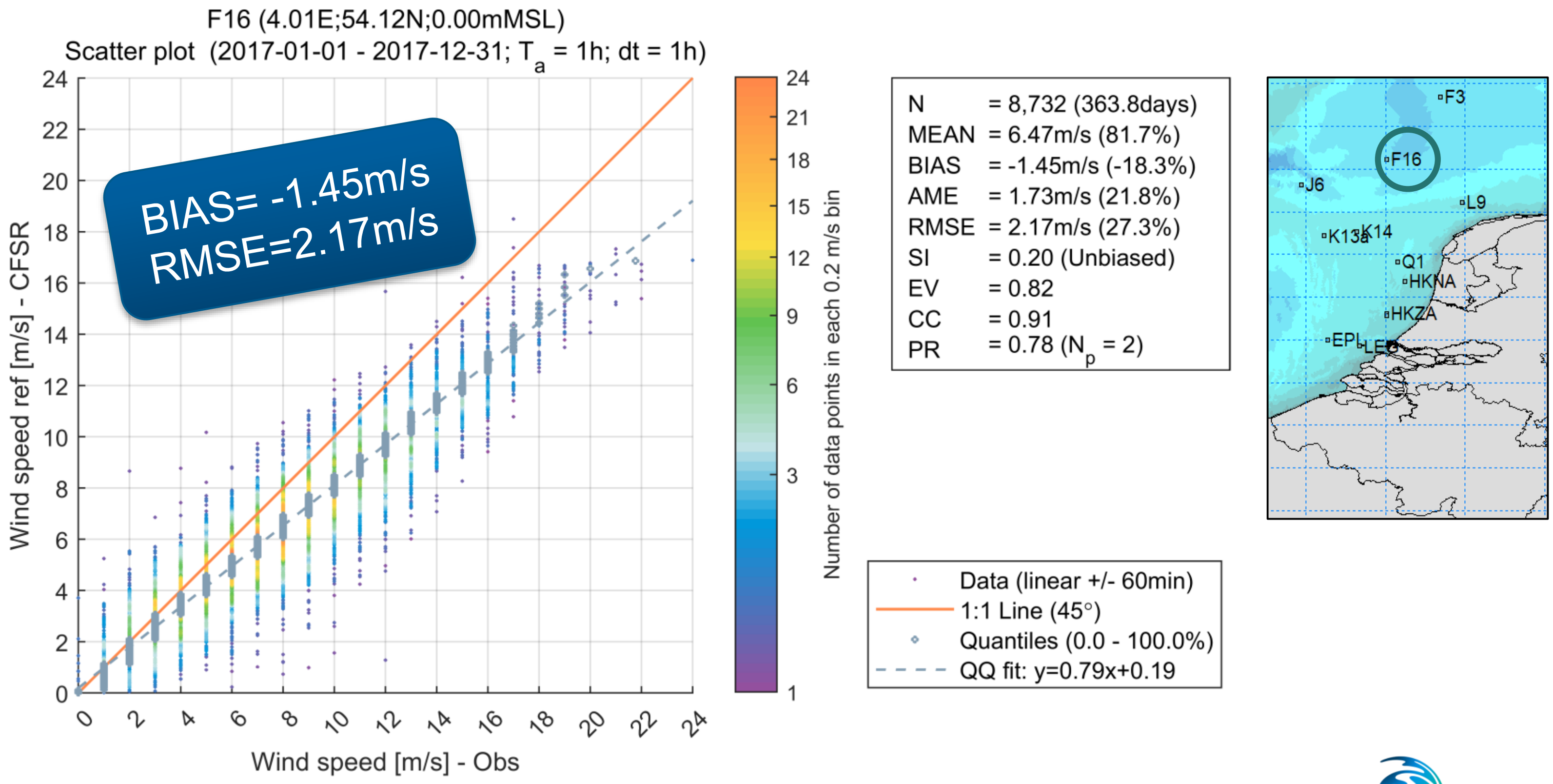


Time series of wind speed at F16

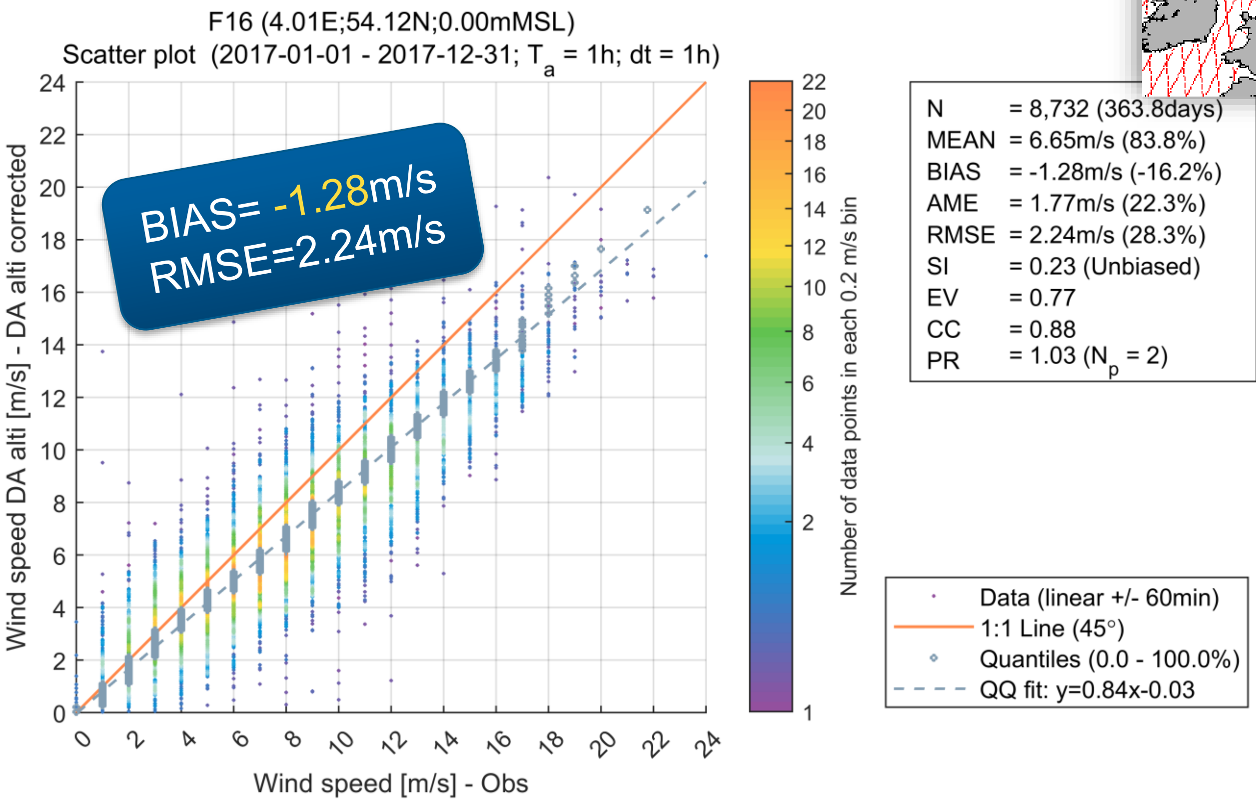


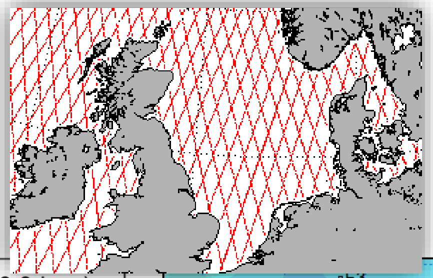


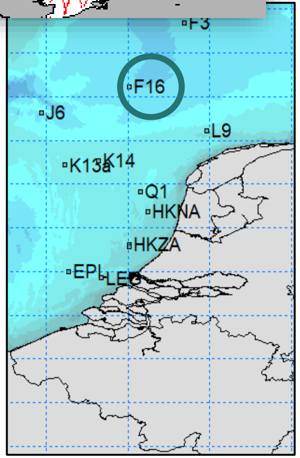
F16 wind speed – 80% CFSR (bad input)



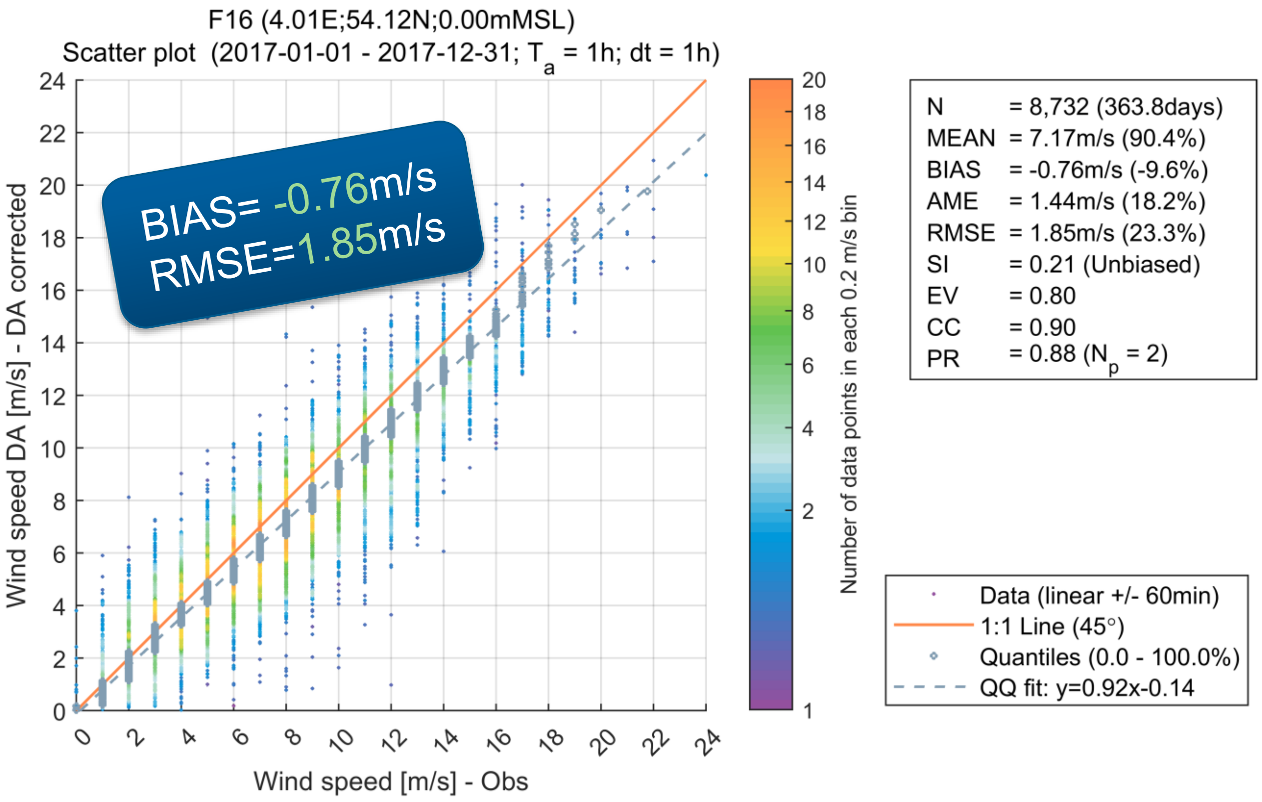
F16 wind speed – DA Sentinel 3A, bad input

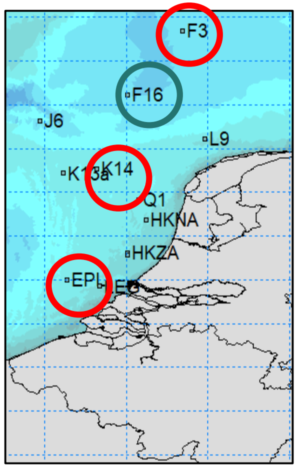






F16 wind speed – DA with 3 stations, bad input





Concluding remarks

Conclusion

- EnKF succesfully implemented for MIKE 21 SW
- Demonstrated on real metocean case
  - Station DA improved Hm0 RMSE 30%
  - Altimetry DA didn’t help in this case
- Demonstrated on case with reduced-quality input (wind biased low)
  - Altimetry DA improved Hm0 RMSE 20%
  - Station DA improved Hm0 RMSE 57%
  - Wind speeds improved by DA
- It could be feasible to EnKF in stead of high-resolution model with good forcings
  - Computation time (1yr simultion): 2hr on 20 cores (10 members)
  - Original high-resolution model: 25hr on 72 cores

Next steps

Case study

- Parameter errors
- Testing of EnOI (static ensemble)
- Assess forecasting skill
- Assimilation of wind

Development

- Boundary forcing errors
- Ensemble Kalman Smoother (EnKS)

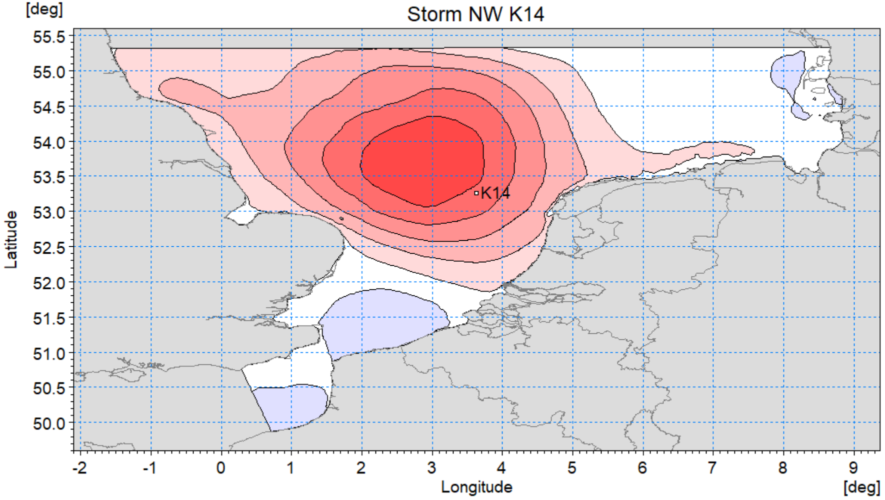
Questions?

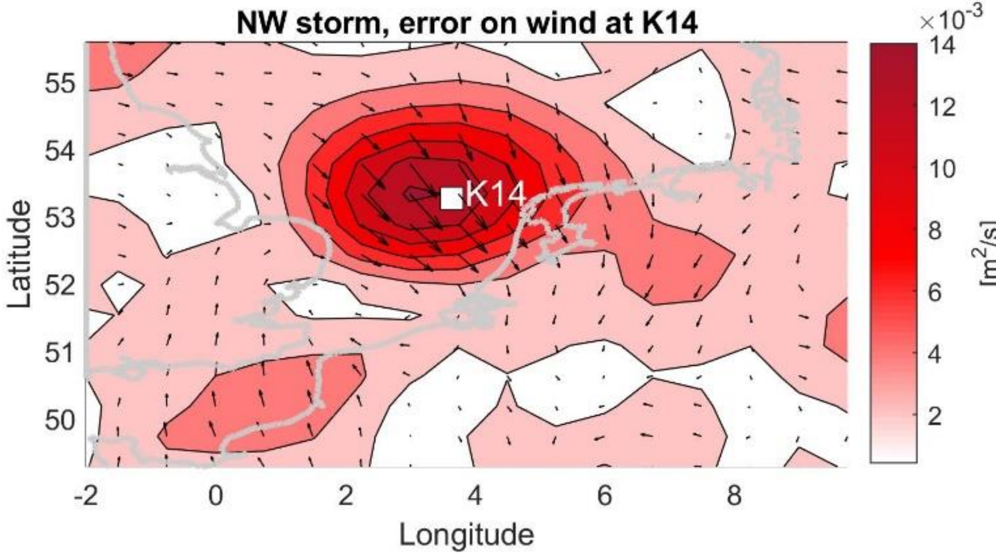
Jesper Sandvig Mariegaard, DHI

Error covariance

Error covariance

- Covariance of Hm0 with Hm0 in K14 during NW storm





Error covariance