

Implementation of EnKF in a high resolution spectral wave model

- with application in the Southern North Sea

14TH INTERNATIONAL ENKF WORKSHOP IN VOSS

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Agenda

- Motivation and ideas
- Spectral wave modeling (MIKE 21 SW)
- DA in MIKE FM
- Implementation DA in MIKE 21 SW
- Case study: Dutch Coast
- Closing remarks and future work

Motivation

- Accurate prediction of wave conditions
 - Design of offshore and coastal structures (hindcast)
 - Operations at sea (forecast)
- SW + EnKF = better wave models
- Is EnKF necessary? – or is it enough to use static error covariance?
- Can we reduce model complexity and rely on data and EnKF instead?

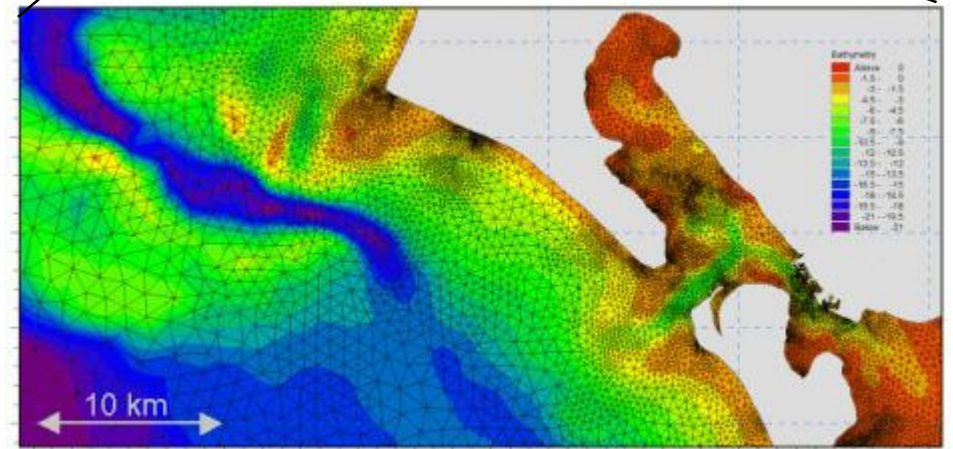
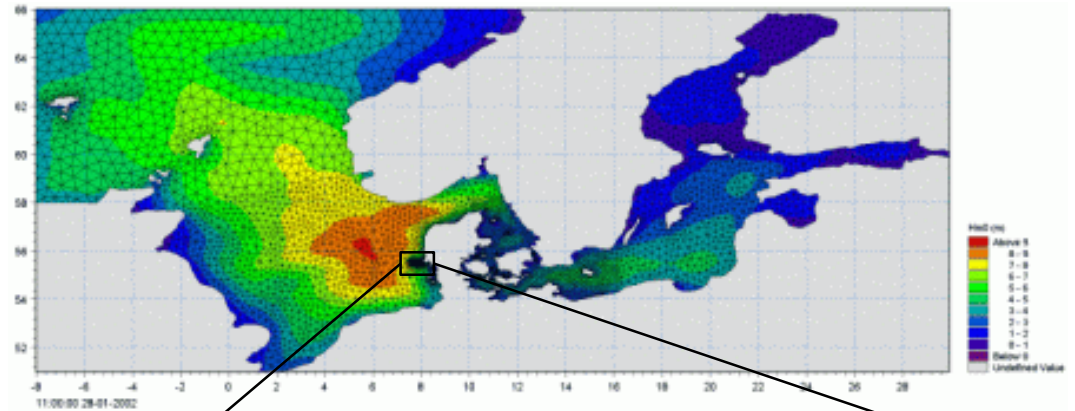


Spectral wave modelling

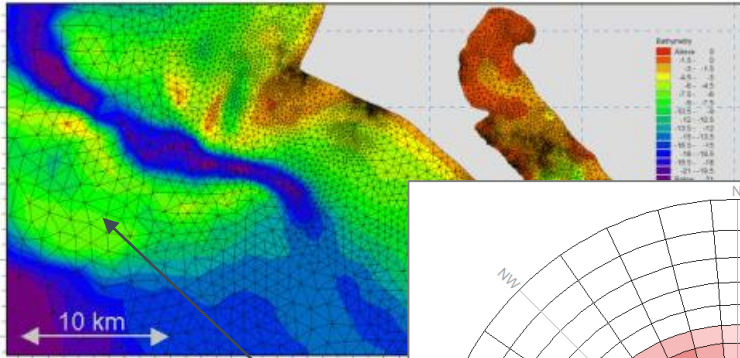
MIKE 21 SW

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

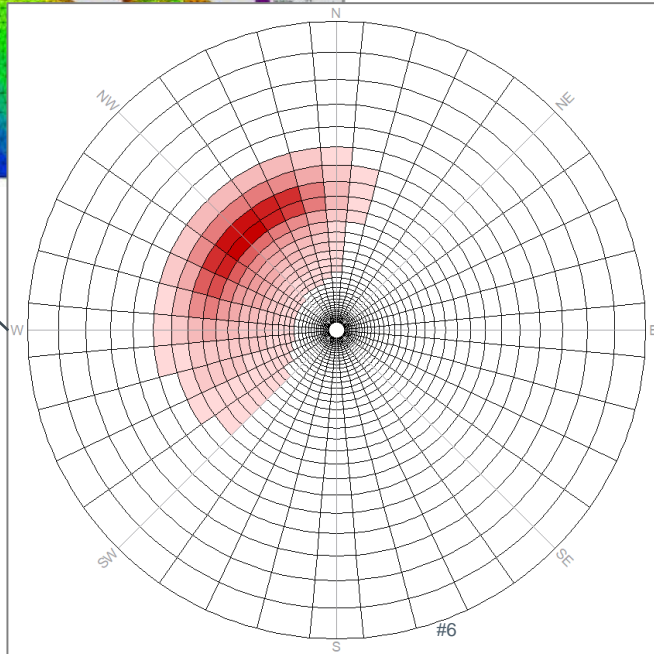
$$\frac{\partial N}{\partial t} + \nabla \cdot (\vec{v}N) = \frac{S}{\sigma}$$



MIKE 21 SW – discretization and variables



- Each cell: Energy density with e.g. 16 directions and 25 frequencies



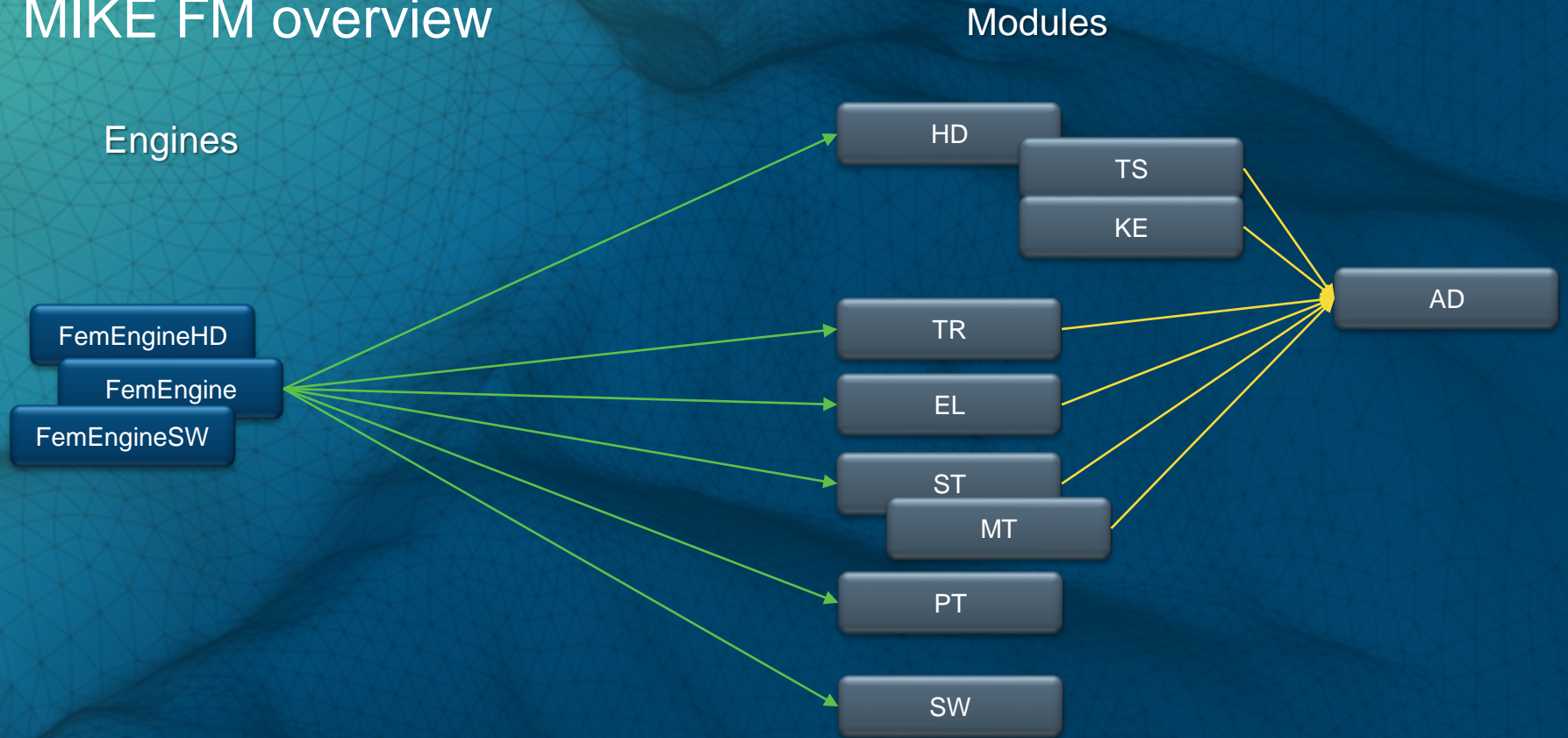
MIKE 21 SW - Source terms

$$S = S_{wind} + S_{nl} + S_{ds} + S_{bot} + S_{surf}$$

- Wind generation (*wind*)
- Non-linear energy transfer (*nl*)
- Dissipation by white capping (*ds*)
- Dissipation due to bottom friction (*bot*)
- Surf zone dissipation/wave breaking (*surf*)

MIKE FM

MIKE FM overview



DA in MIKE FM

Modules

Engines

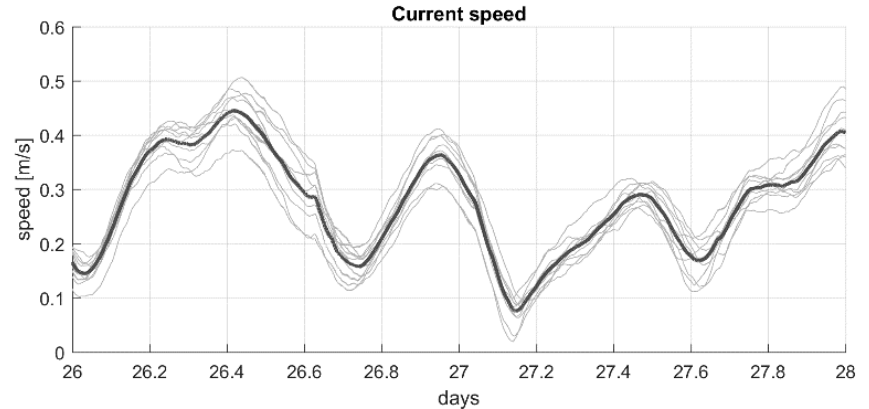


Ensemble models

- Ensemble consisting of m *members*

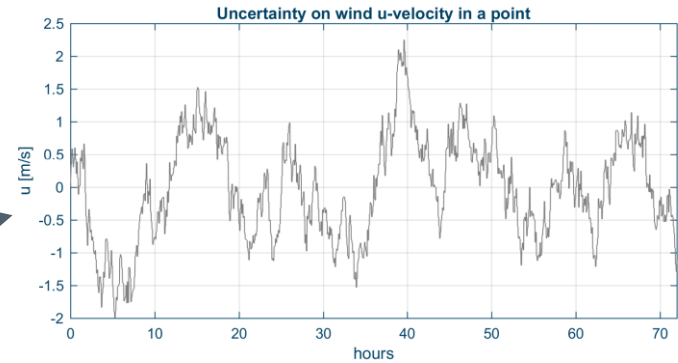
How to introduce variability in model?

- Add small “errors” (=perturbations) to...
 - Initial conditions
 - Forcings
 - Parameters

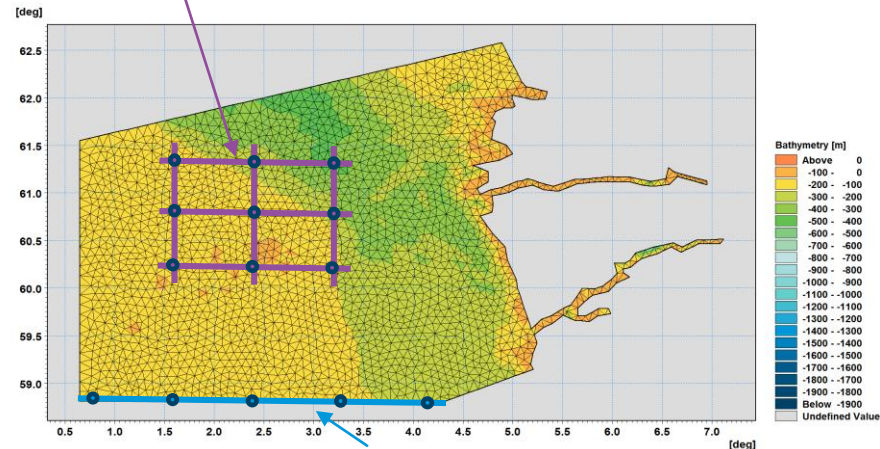


Uncertainty modelling in MIKE FM

- 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 21/3 FM

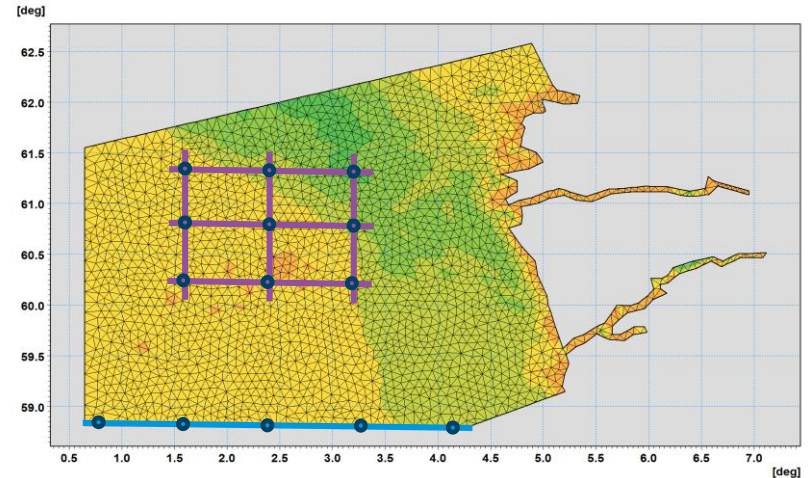
- Model variables according to selected modules
 - State variables $x_{model} = (wl, u, v, \dots)$

- Model errors

- Types: open bc, wind-u, wind-v, ...
- Discretized on a grid: ϵ

- Augmented state

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



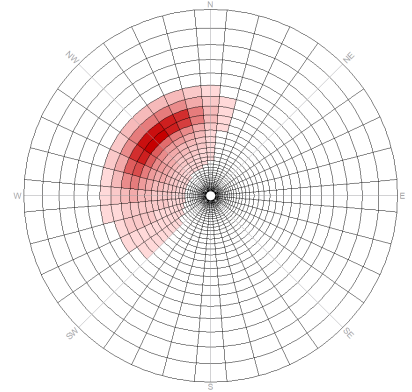
DA scheme

- ESRF (no perturbation of measurements)
 - Serial-ESRF ("Potter scheme")
 - ETKF
- R-factor for inflation

Data assimilation for **MIKE 21 SW**

State representation

- Action density!
- And... variables that we would like to assimilate
 - H_m0 , T_p
- Model errors



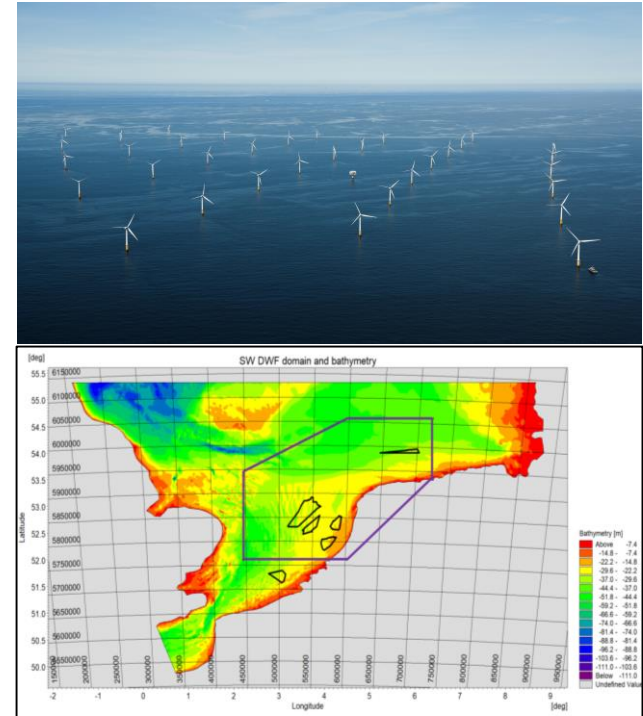
Creating the MIKE 21 SW ensemble

- Forcings
 - Wind
 - Windspeed
- Parameters
 - Whitecapping CDIS
 - Bottom friction (Nikuradse roughness)
- Boundary conditions (later)

Case study

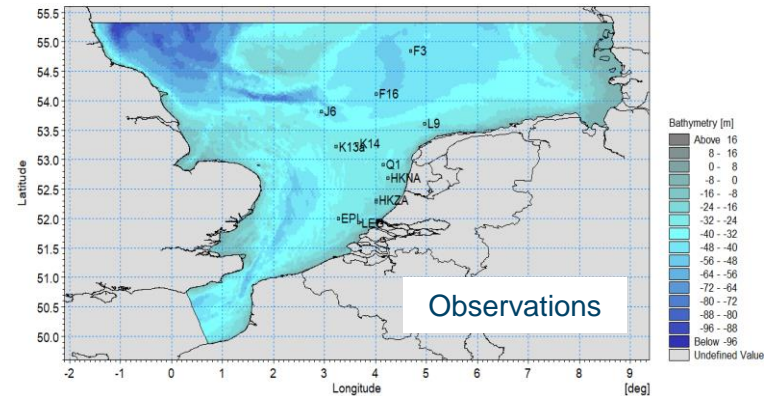
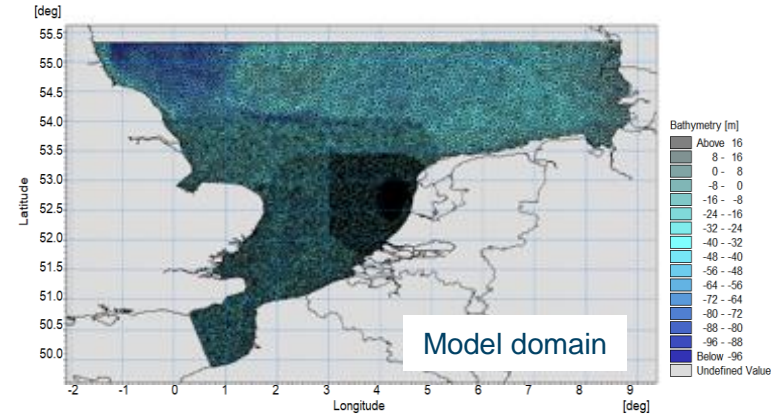
Case Study: Dutch Coast Metocean Desk Study

- Project within DHI from 09.2018-01.2019
- Provide meteorological and oceanographic (metocean) conditions for the Dutch Coast wind Farm zone
- Based on numerical modelling over 39 years



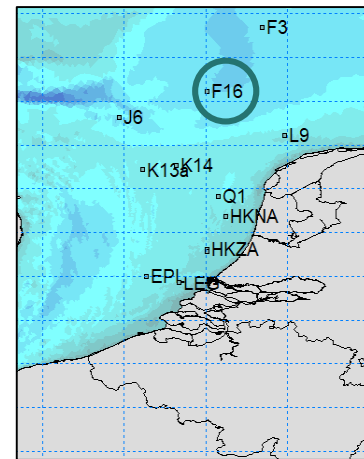
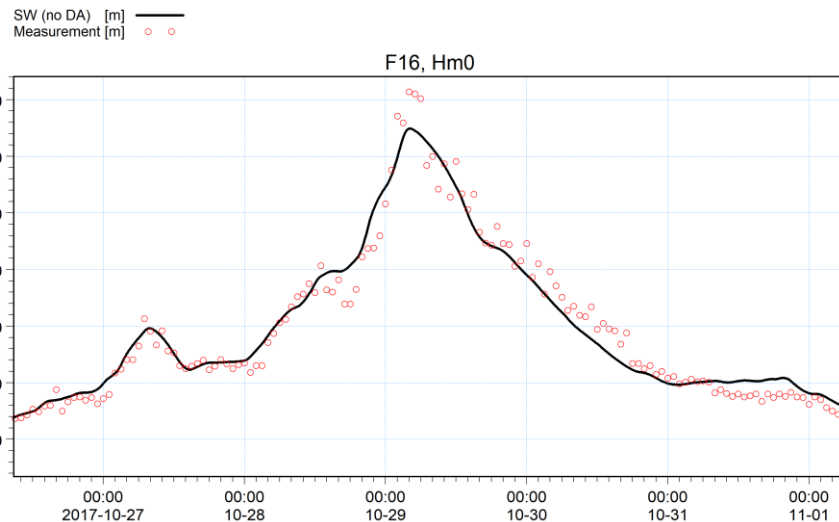
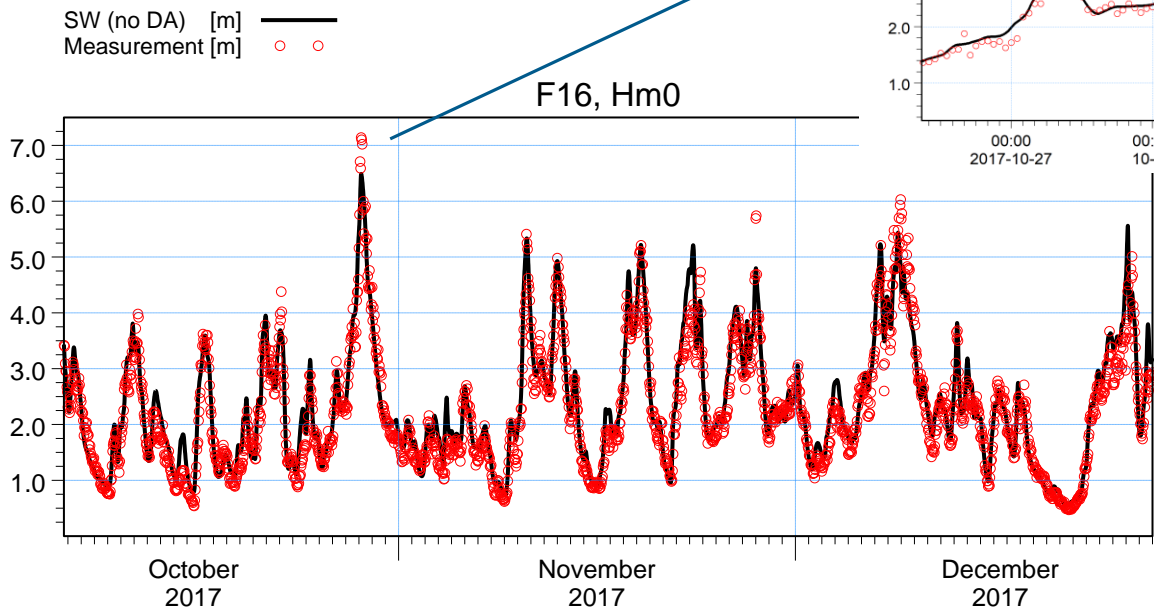
Case Study: MIKE 21 SW settings

- Coarse-resolution edition of existing SW model setup
- Default calibration
- CFSR wind
- Boundary conditions from well-calibrated regional model
- **Study period** October-December 2017
 - Including a severe NW storm October 29



Base model is already good!

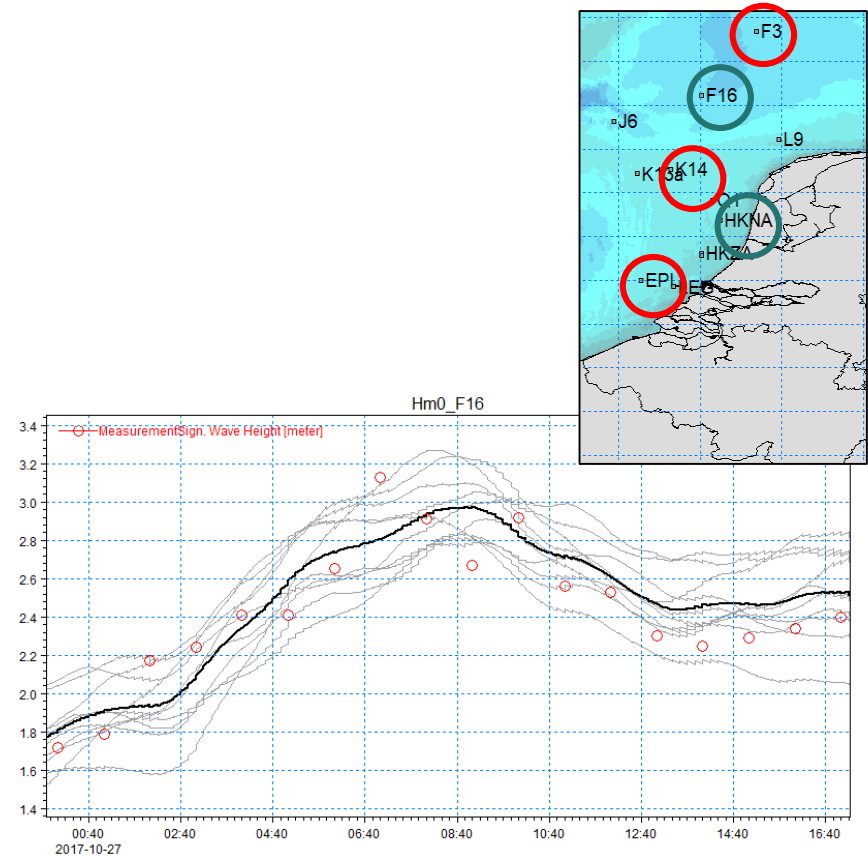
But with some room for improvement...



Case Study: DA settings

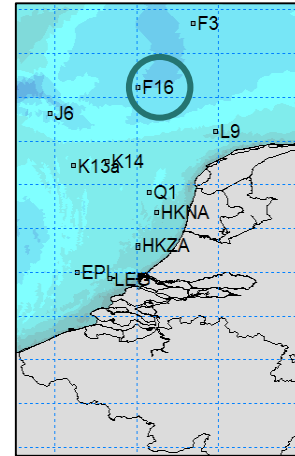
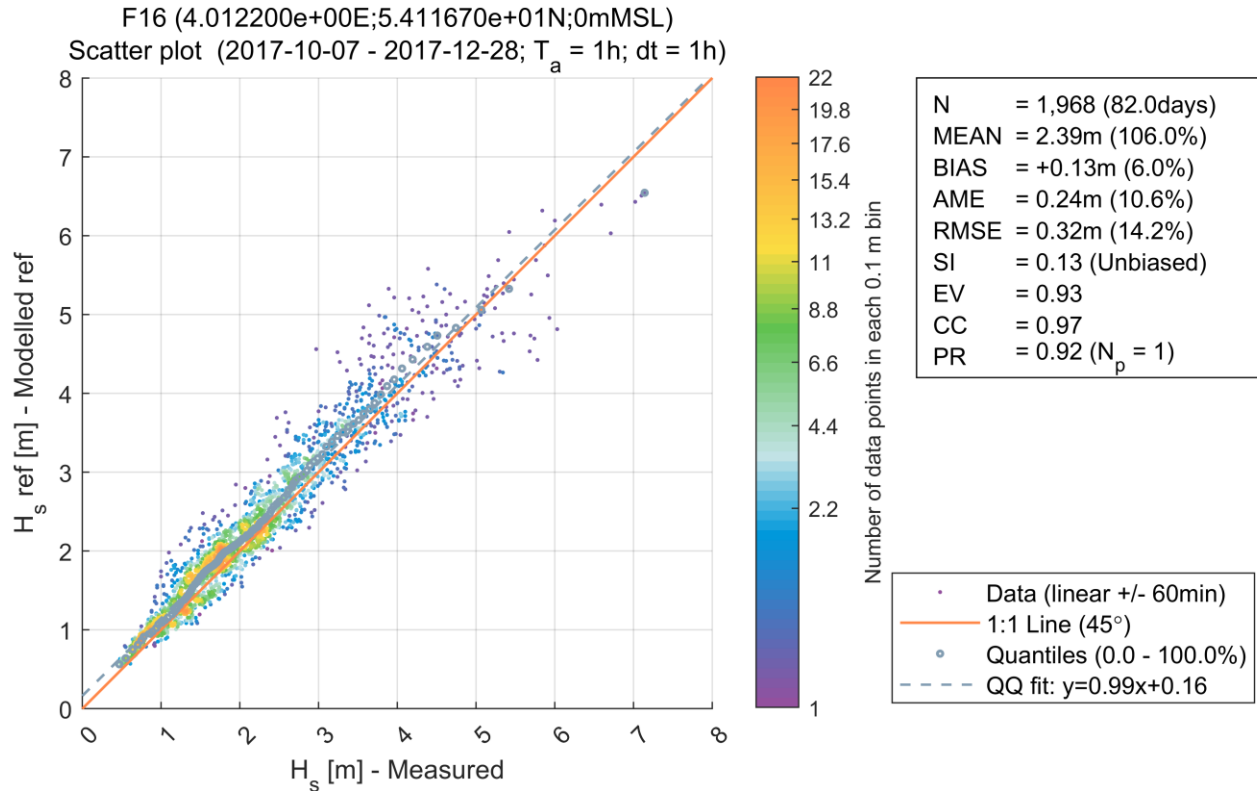
DA reference model

- Ensemble size: 10
- Perturbation of wind forcing:
 - 1.5m/s additive error on 80km grid
 - Horizontal correlation: 500km
 - AR(1) half-time: 3 hours
- Serial ESRF (potter scheme)
- Assimilation stations (Hm0): 3
- Assimilation every 10 minutes
- Observation uncertainty: st.dev=0.7m
- R-factor: 3
- No localization



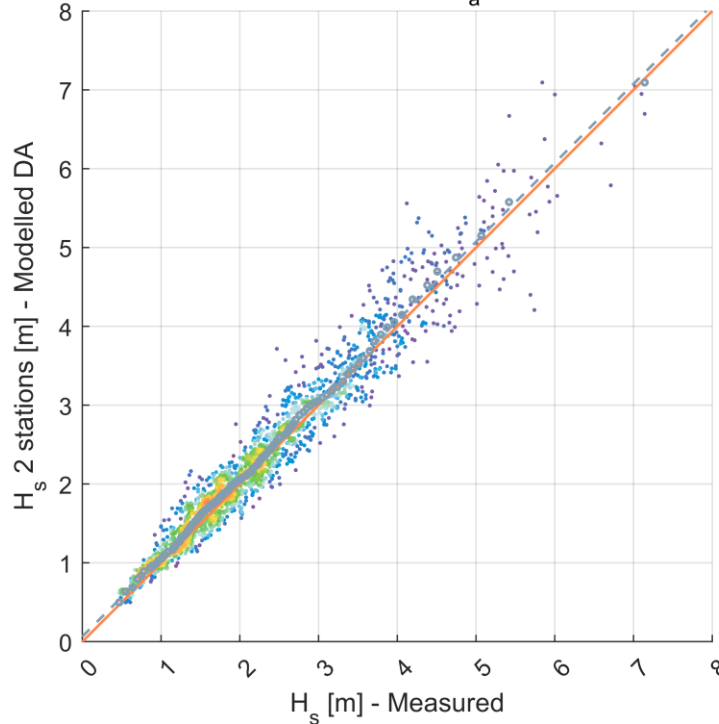
Let's check Hm0 at the F16 station

Station F16 – no DA



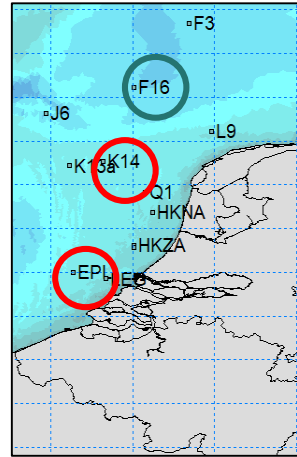
Station F16 – DA with 2 stations

F16 (4.012200e+00E;5.411670e+01N;0mMSL)
 Scatter plot (2017-10-07 - 2017-12-28; $T_a = 10\text{min}$; $dt = 1\text{h}$) 2 stations



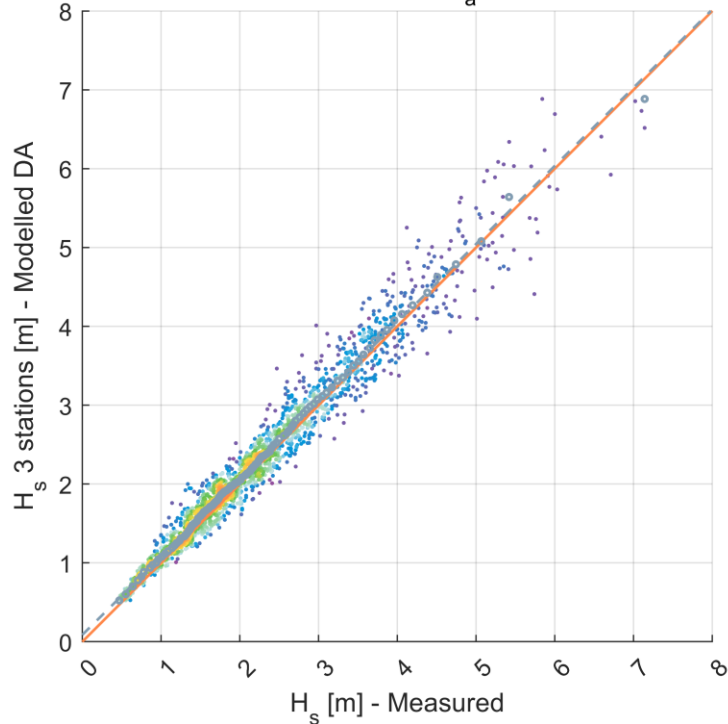
N	= 1,968 (82.0days)
MEAN	= 2.32m (103.1%)
BIAS	= +0.07m (3.1%)
AME	= 0.19m (8.4%)
RMSE	= 0.26m (11.5%)
SI	= 0.11 (Unbiased)
EV	= 0.95
CC	= 0.97
PR	= 0.99 ($N_p = 1$)

- Data (linear +/- 60min)
- 1:1 Line (45°)
- Quantiles (0.0 - 100.0%)
- - - QQ fit: $y=1.00x+0.07$



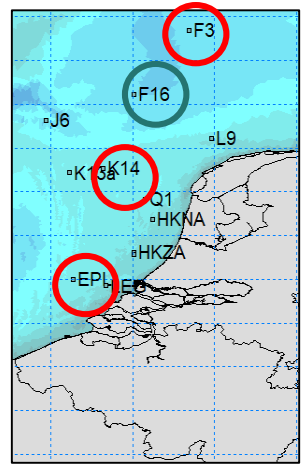
Station F16 – DA with 3 stations

F16 (4.012200e+00E;5.411670e+01N;0mMSL)
 Scatter plot (2017-10-07 - 2017-12-28; $T_a = 10\text{min}$; $dt = 1\text{h}$) 3 stations



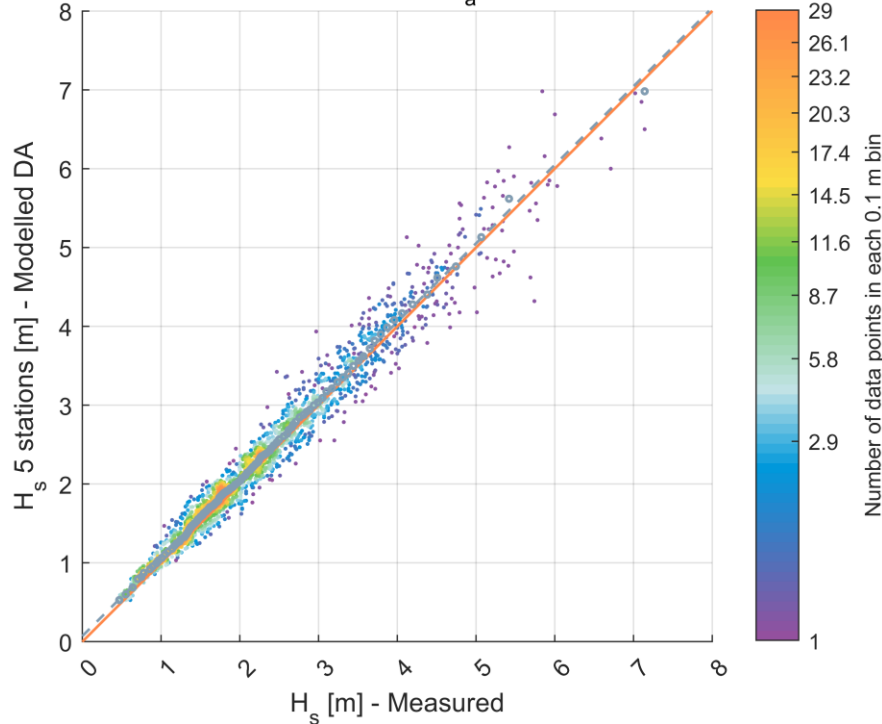
N	= 1,968 (82.0days)
MEAN	= 2.32m (103.1%)
BIAS	= +0.07m (3.1%)
AME	= 0.17m (7.4%)
RMSE	= 0.23m (10.1%)
SI	= 0.10 (Unbiased)
EV	= 0.96
CC	= 0.98
PR	= 0.96 ($N_p = 1$)

- Data (linear +/- 60min)
- 1:1 Line (45°)
- Quantiles (0.0 - 100.0%)
- - - QQ fit: $y=0.99x+0.09$



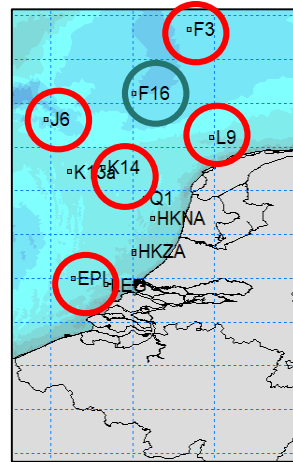
Station F16 – DA with 5 stations

F16 (4.012200e+00E;5.411670e+01N;0mMSL)
 Scatter plot (2017-10-07 - 2017-12-28; $T_a = 10\text{min}$; $dt = 1\text{h}$) 5 stations



N	= 1,968 (82.0days)
MEAN	= 2.32m (102.8%)
BIAS	= +0.06m (2.8%)
AME	= 0.15m (6.7%)
RMSE	= 0.21m (9.2%)
SI	= 0.09 (Unbiased)
EV	= 0.97
CC	= 0.98
PR	= 0.98 ($N_p = 1$)

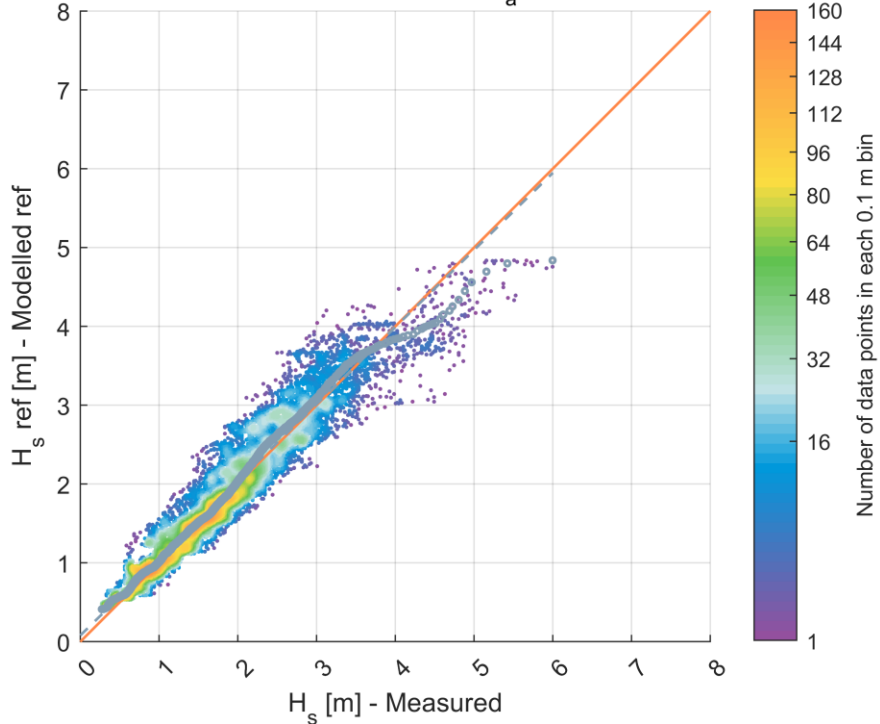
•	Data (linear +/- 60min)
—	1:1 Line (45°)
•	Quantiles (0.0 - 100.0%)
- - -	QQ fit: $y=1.00x+0.07$



Let's check another station...

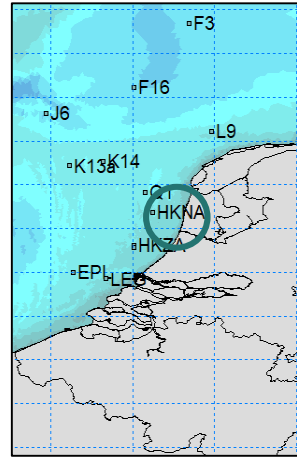
Station HKNA – no DA

HKNA (4.242000e+00E;5.268870e+01N;0mMSL)
 Scatter plot (2017-10-07 - 2017-12-28; $T_a = 10\text{min}$; $dt = 10\text{min}$)

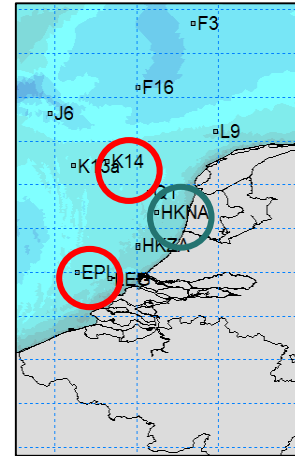
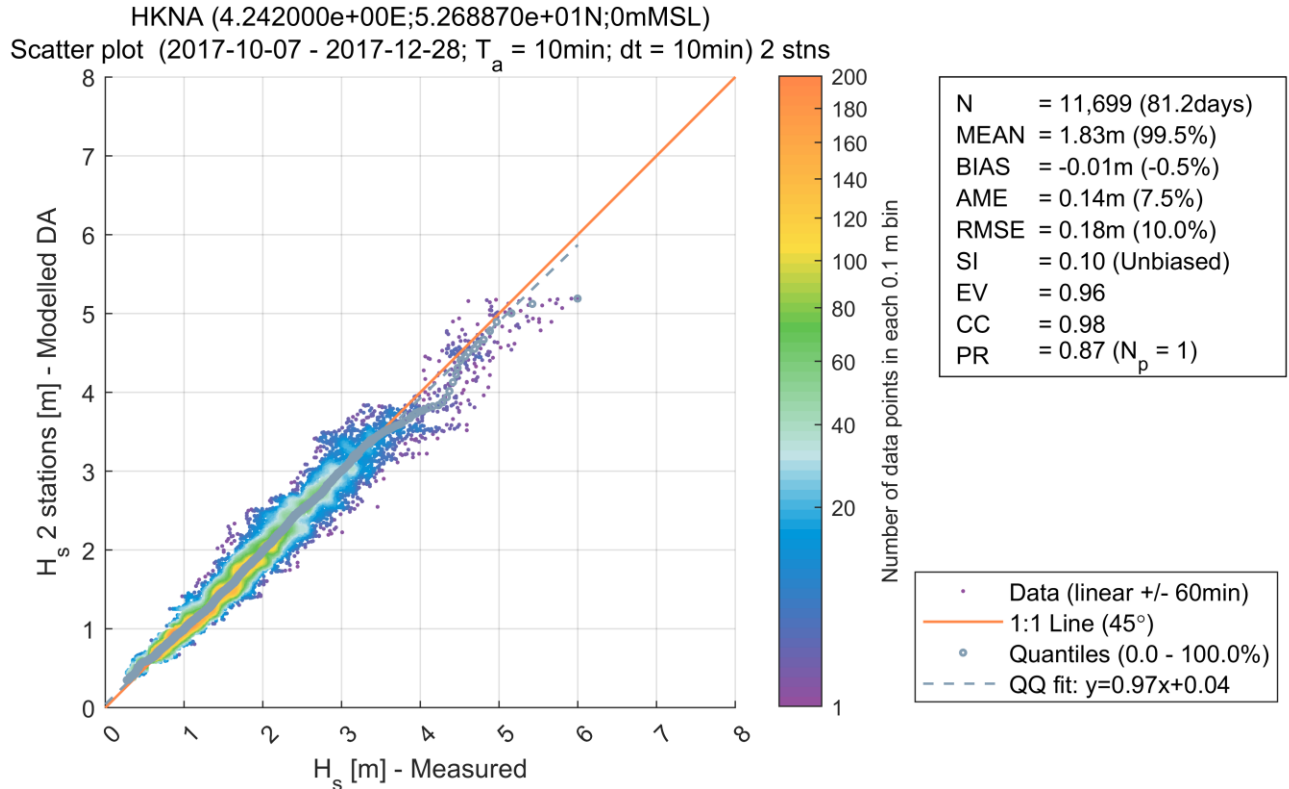


N	= 11,699 (81.2days)
MEAN	= 1.87m (102.2%)
BIAS	= +0.04m (2.2%)
AME	= 0.20m (10.8%)
RMSE	= 0.27m (14.7%)
SI	= 0.15 (Unbiased)
EV	= 0.91
CC	= 0.96
PR	= 0.81 ($N_p = 1$)

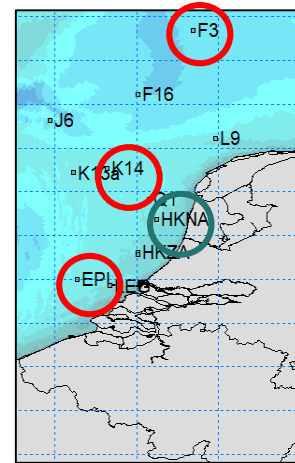
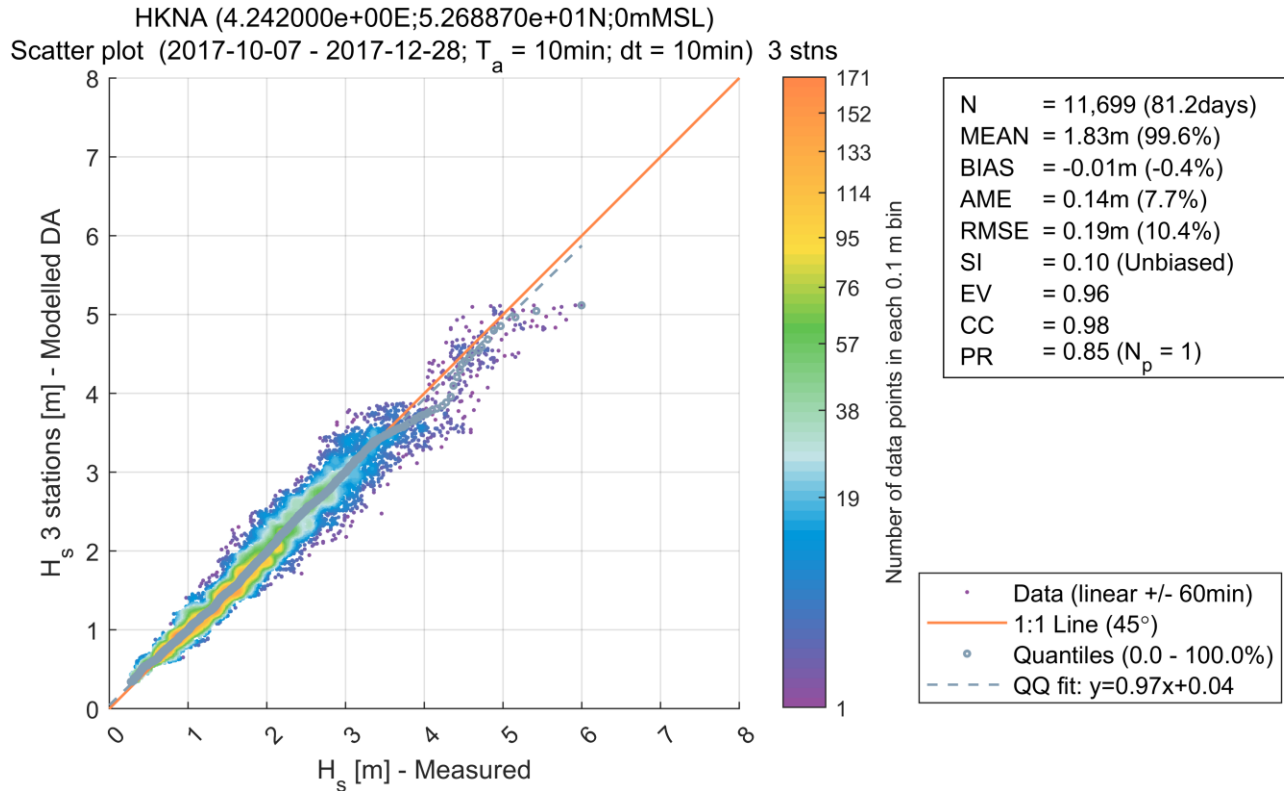
- Data (linear +/- 60min)
- 1:1 Line (45°)
- Quantiles (0.0 - 100.0%)
- - - QQ fit: $y=0.98x+0.08$



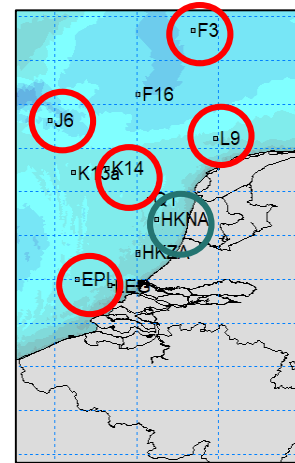
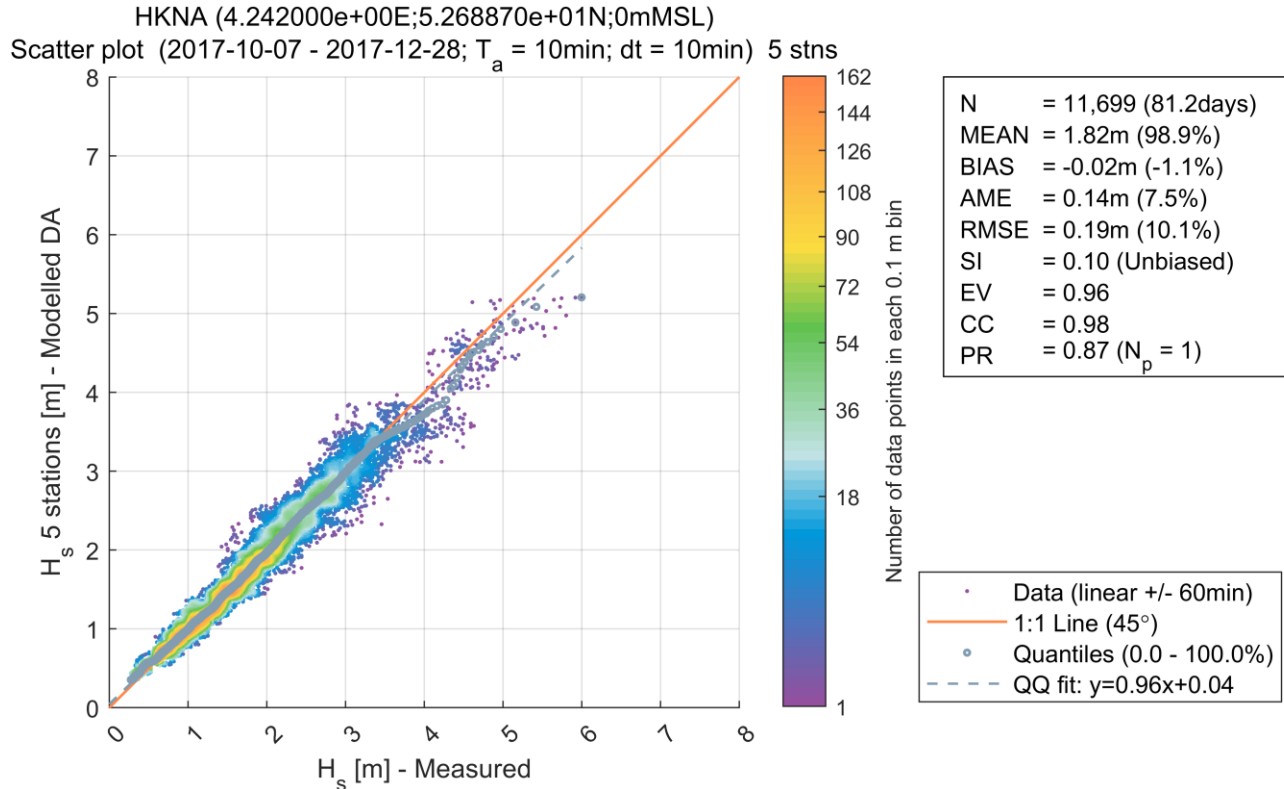
Station HKNA – DA with 2 stations



Station HKNA – DA with 3 stations



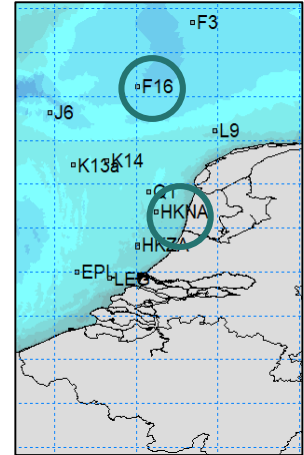
Station HKNA – DA with 5 stations



How about other DA parameters

Improvement in Hm0 RMSE

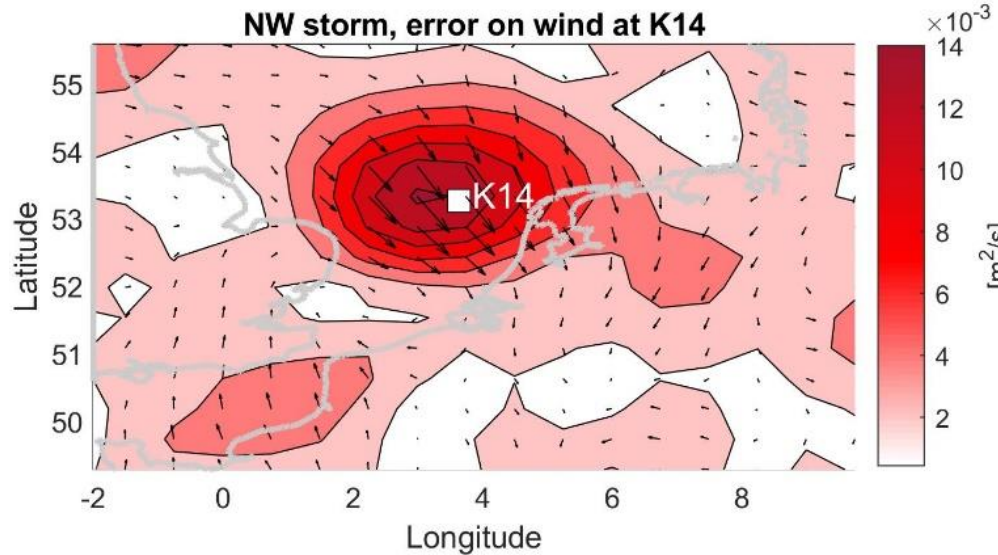
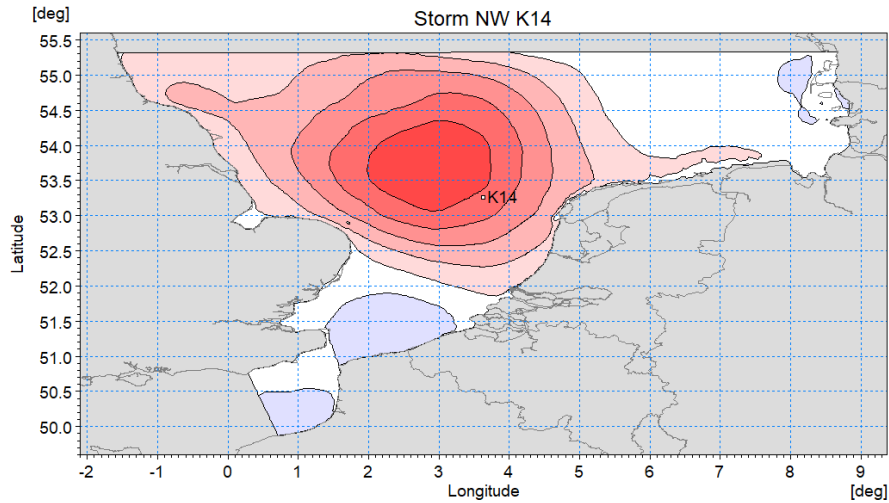
	F16	HKNA
DA Reference (10mem, 3stn, additive 3hour wind)	30.6%	30.0%



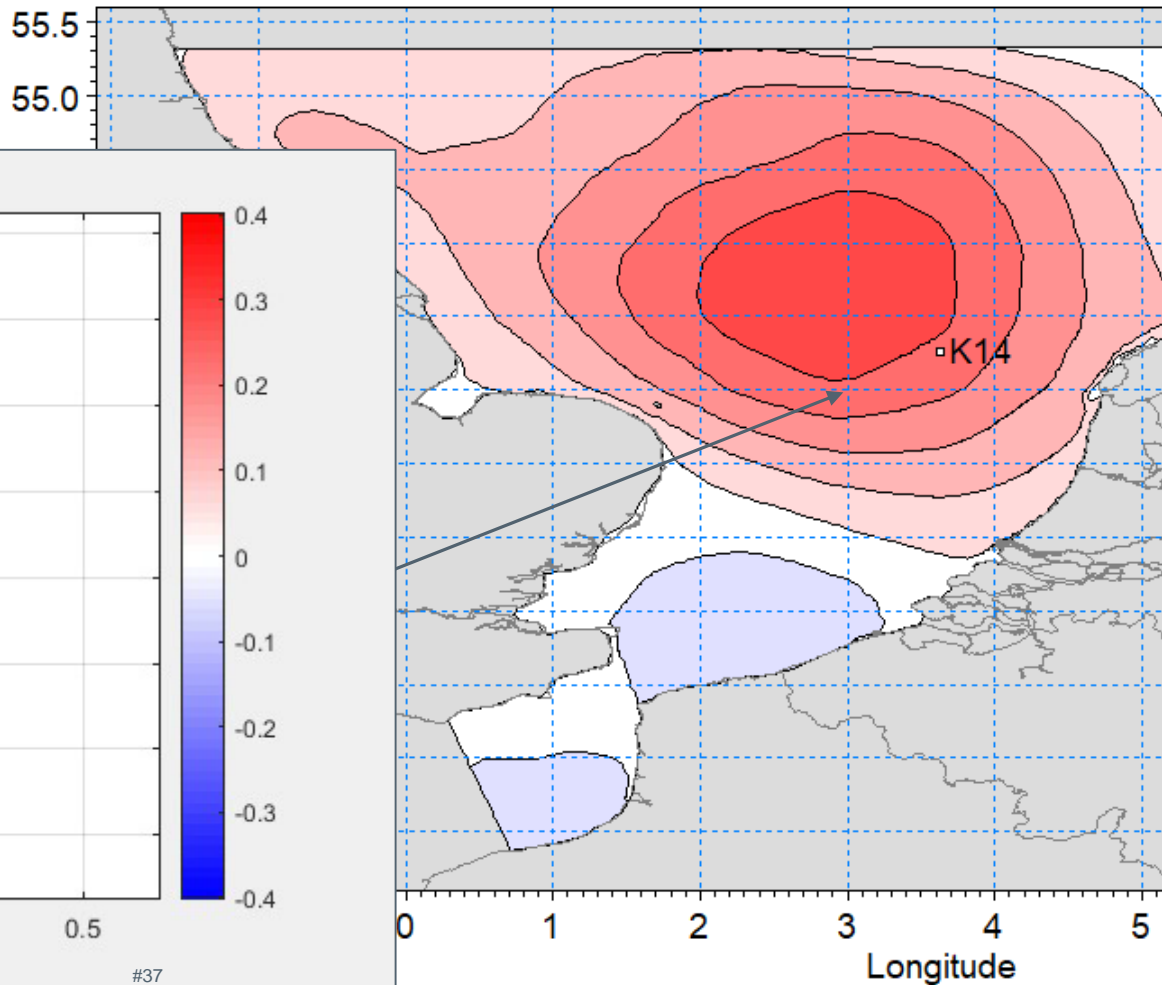
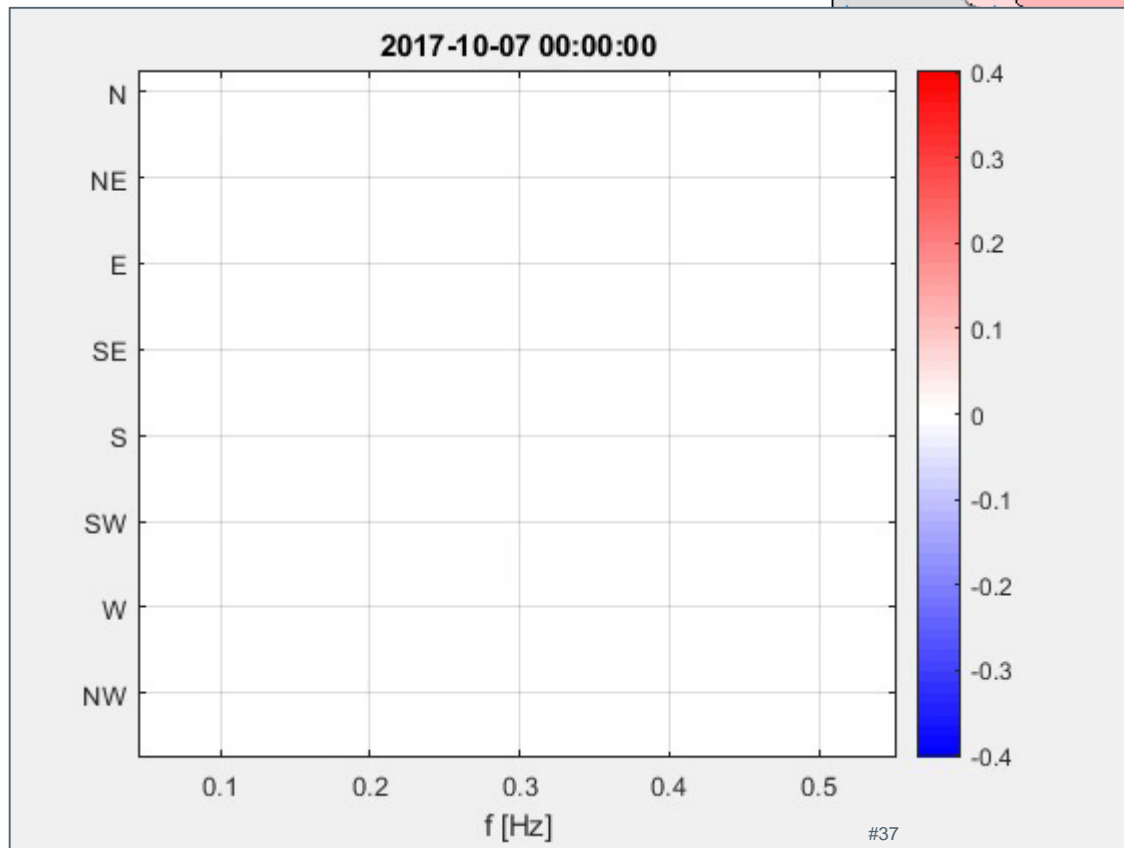
Error covariance

Error covariance

- Covariance of Hm0 with Hm0 in K14 during NW storm



Error covariance



Concluding remarks

Conclusion

- EnKF successfully implemented for MIKE 21 SW
- Demonstrated on real metocean case
 - Improvement in Hm0 RMSE 30%
 - Not sensible to DA settings
 - More data improves the results
 - Analysis of error covariance suggests that EnKF is a good choice

Next steps

Case study

- Compare to wind measurements
- Parameter errors
- Use lower quality boundary conditions
- Testing of “steady” and EnOI
- Forecasting skill

Development

- Assimilation of wind
- Boundary forcing errors
- Ensemble Kalman Smoother (EnKS)

Questions?

Jesper Sandvig Mariegaard, DHI

Greatfully acknowledging support from NordForsk NCoE EmbIA project