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A Mesoscale Modelling over the Southern North Sea: Impacts of Data Assimilation and Model Uncertainity

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Outline

- Introduction and background
- Data description
- Mesoscale modelling and data assimilation
- Model uncertainity: Background error matrix
- Conclusions

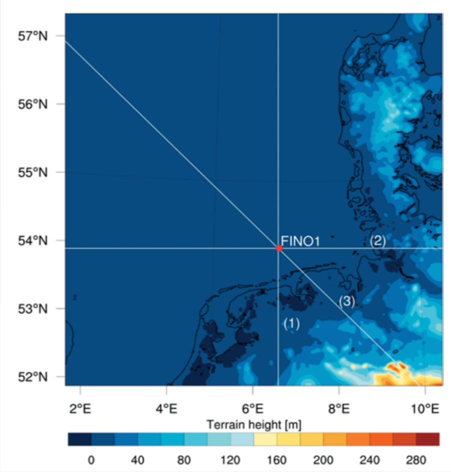
Introduction and background

- Setting and maintaning dense obs. are practically impossible. Therefore, numerical models with ability to provide consistent spatiotemporal predictions are desirable.
- In order to provide accurate short term forecast, we need to develop more reliable numerical weather precdiction (NWP) models.
- Data assimilation can improve the initial and lateral boundary conditions of the mesoscale model and significantly reduce the negative spin-up effect.
- DA with Lidar is more challenging compared to other traditional meteorological measurements.

Data description

topography map of the simulation

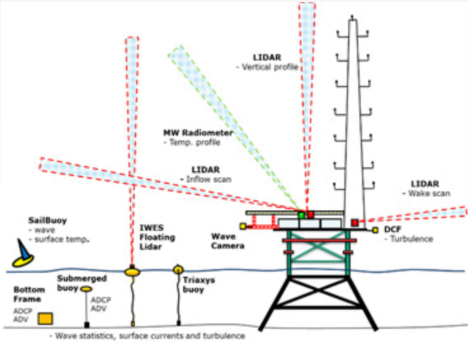
Windcube 100s wind Lidarin pulsed Doppler Beam Swing (DBS) collected from May 2015 to September 2016 at FINO1 offshore platform. In this study, we focus on 5 days between 1-5 July 2015 where we have a clear low level jet event.



We use only data for heights between 75m and 1km.

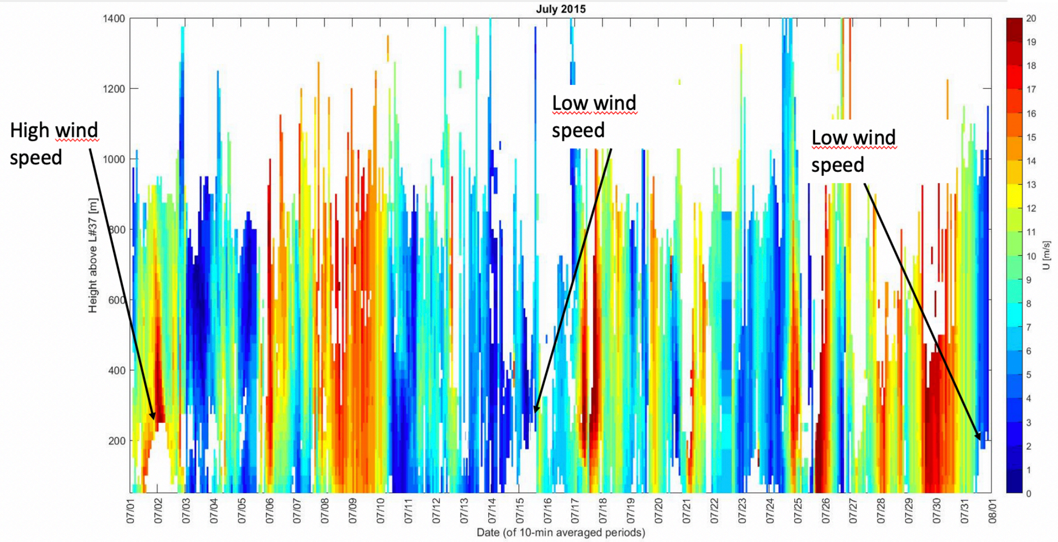
We use cap anemometer data collected at heights 33 m and 90 m as reference measurements to conduct quality control of data.

Sensor	Parameter	Heights (m AMSL)
Wind LiDAR	u,v,w	72–518, every 23.5
Cup Anemometer	ws (u, v)	33,
Wind vane	wd (u, v)	33.



Data description

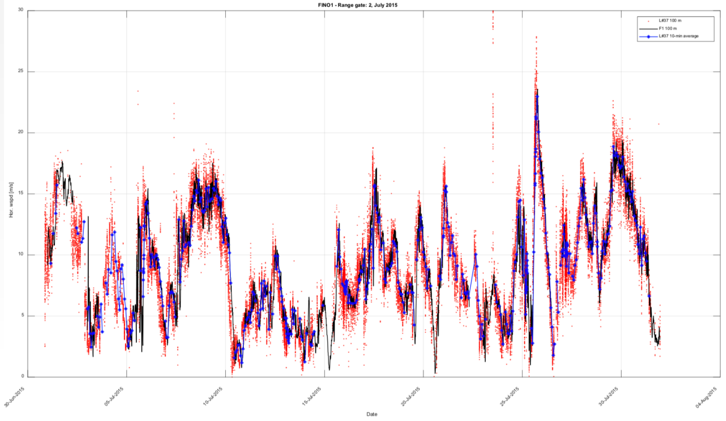
- Lidar measurements enable wind information at higher altitudes.
- Data availability in this measuring technique reduces with increasing altitude due to a decrease in aerosol density required for the backscattering of the lidar signal.
- High-frequency fluctuations cannot be properly measured by lidar.
- Estimated turbulence intensity from Lidar correlates with sonic turbulence data at lower altitudes

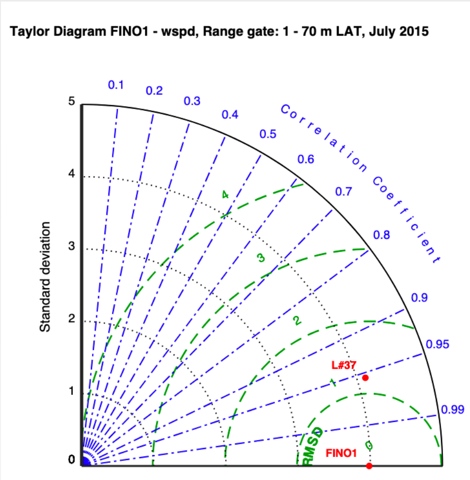


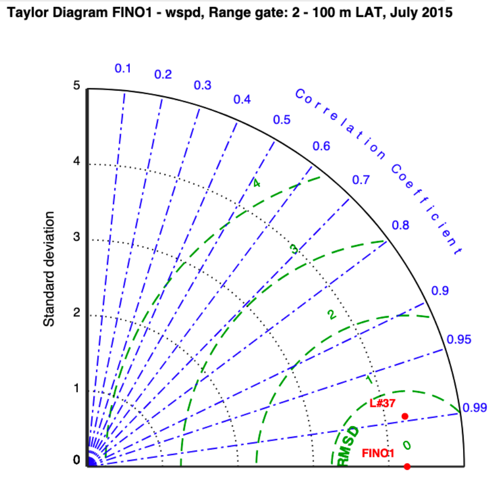
Data description

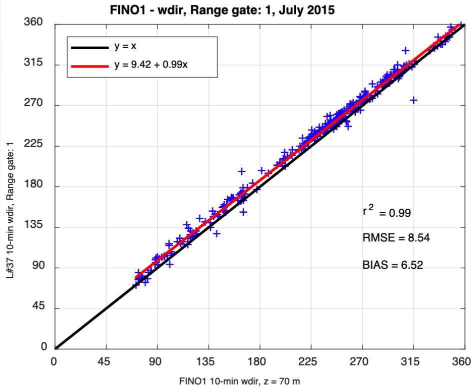
Comparisons between cup-anemometers at 70 m and 90 m showes very good agreement

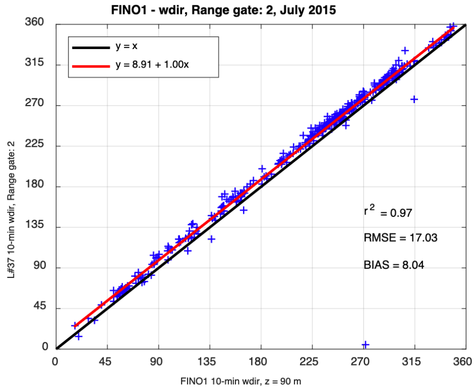
Comparison between 10-min averaged lidar and ref. wind at 33 m heights







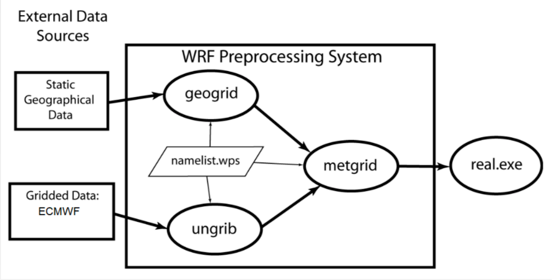


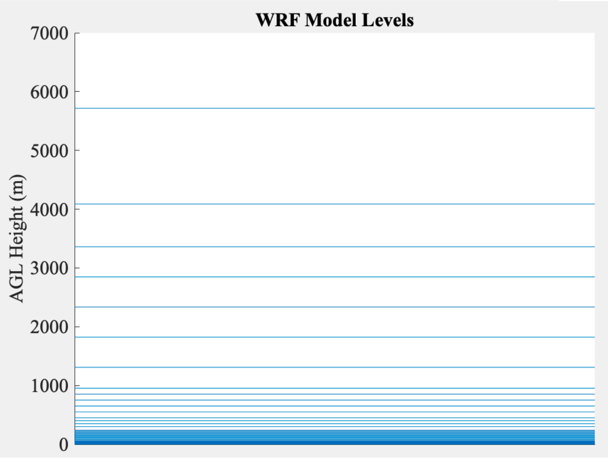


The continuous line represents the linear regression of the data

Mesoscale modelling & data assimilation

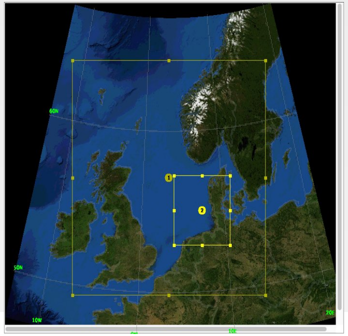
- Initial and boundary conditions of all simulations are based on the ERA5 reanalysis data set by the European Centre for Medium-Range Weather Forecasts.
- Turbulent kinetic energy (TKE) closure within the ABL was achieved by using the Mellor–Yamada–Nakanishi–Niino (MYNN) 2.5 scheme.
- The Noah-MP land-surface model and MYNN surface layer scheme are used.
- The Rapid Radiative Transfer Model (RRTM) longwave radiation and Dudhia shortwave radiation scheme are used.

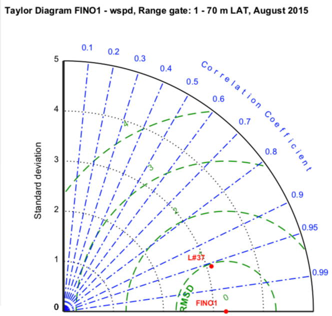




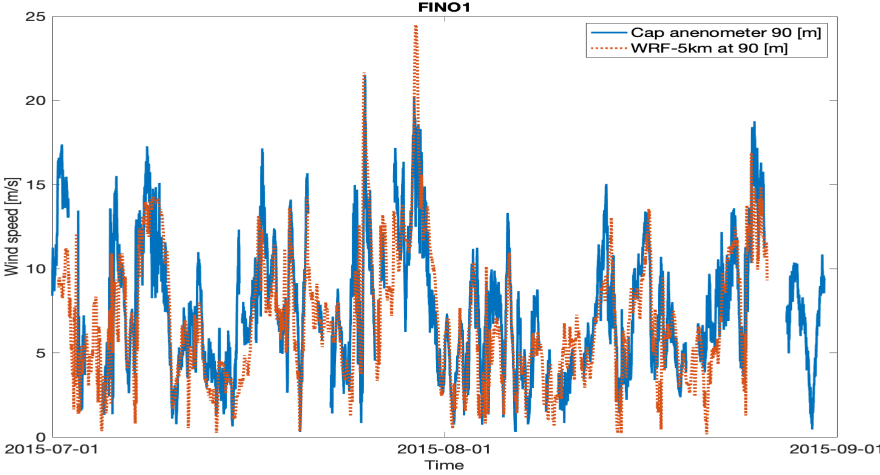
Mesoscale modelling and data assimilation

Validation versus reference observation: Multi-domain WRF simulations, a Taylor Diagram for the WRF simulation at 9000 m resolution vs. cup-anemometer data at 90 m hight for hourly wind speed.

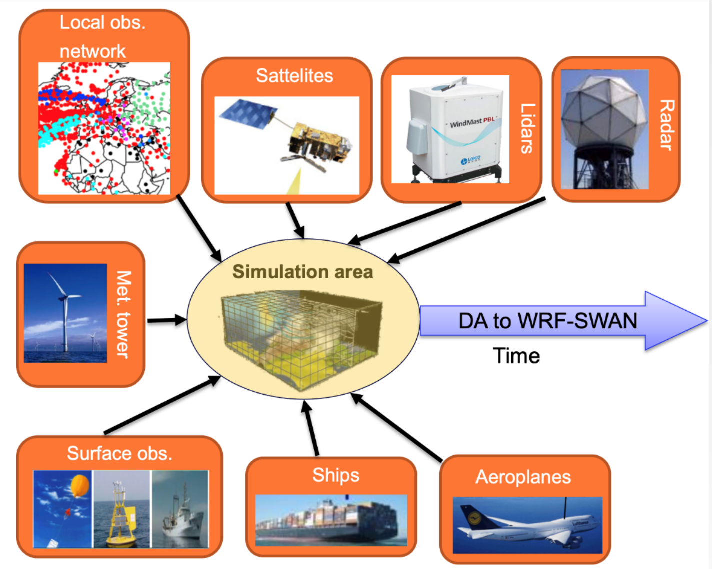


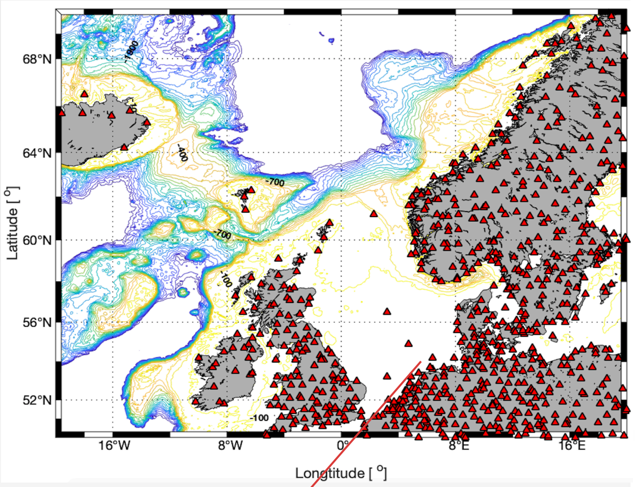


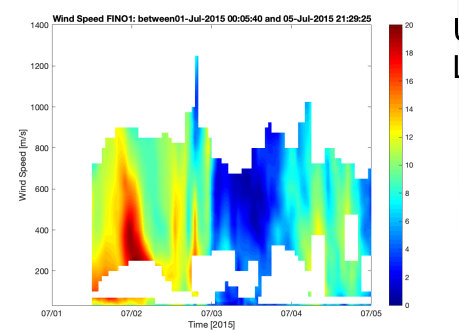
Red represents WRF (no assimilation) simulations, and blue represents time series of reference measurement at 90 m height.



Data assimilation







Upward-looking LiDAR wind

The conventional observations consisted of data from Meteorological Assimilation Data Ingest System (MADIS) combining data sources from the National Oceanographic and Atmospheric Administration (NOAA) as well as from non-NOAA sources. MADIS contains observations from surface METAR reports, radiosonde soundings, wind profilers, satellite wind, and dense surface observations from MesoWest.

Data assimilation

The following equation represents how the nudging term can be added into the governing equations:

In this work we study two types of assimilation

(i) NUDGING

$$\frac{\partial A}{\partial t} = F(A) + G_A W_A (A_o - A), \quad (1.1)$$

where $F(A)$ is the normal tendancy term due to physics, advection, etc. W_A the additional limits in time or space to constriant further nudging, and G_A denotes a time scale that control the strength of nudging.

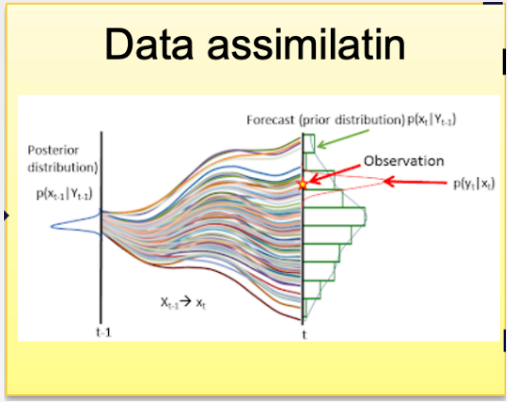
(ii) 3DVAR

In this method, previous forecast, observational data and their errors are used to produce the analysis increments x^a which will be added to the first guess x^b providing an updated analysis. This method aims to provide optimum values for the atmospheric state field x^a at any time by minimizing following cost function:

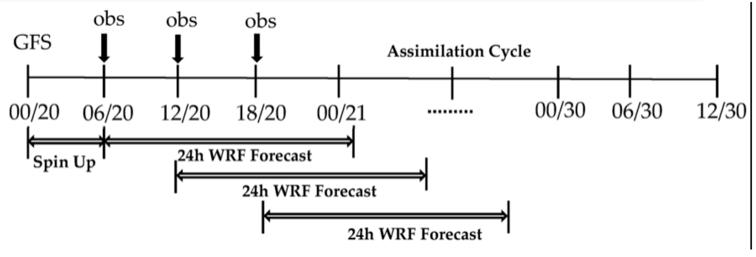
$$J(x) = J^b + J^o = \frac{1}{2}\left[(x - x^b)^T B^{-1}(x - x^b) + (y - y^o)^T (O + F)^{-1}(y - y^o)\right], \quad (1.2)$$

the analysis $x = x^a$ is an estimate for the true atmospheric state based on background data (previous forecast, x^b) and observations (y^o). B, O, and F denote the covariance matrices for background, observation, and representativeness, repectively.

Cold



Cyclic



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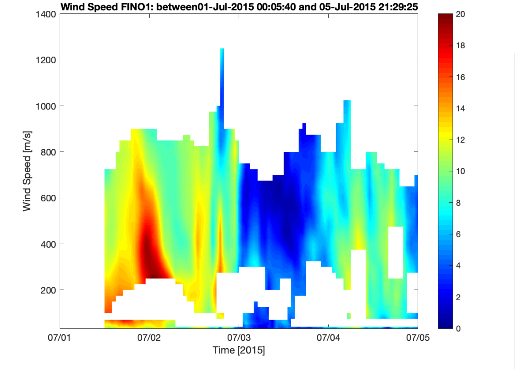
Data assimilation

Since nudging add nonphysical forcing term in prognostic equations, the tuneable parameters, nudging interval, and the number of altitudes at which nudging takes place are important.

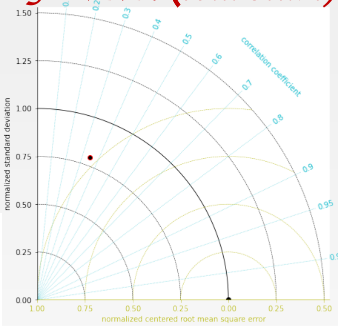
Here, we use 6-hour nudging for all altitude between 75 m and 900 m. This may constrain the simulation. Note that nudging is performed over available data.

3DVAR simulation has been done 6-hourly,

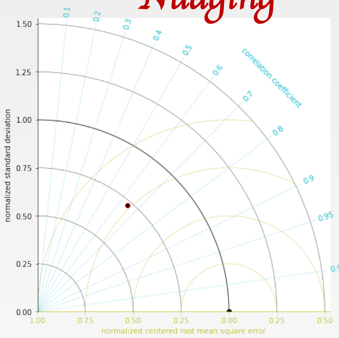


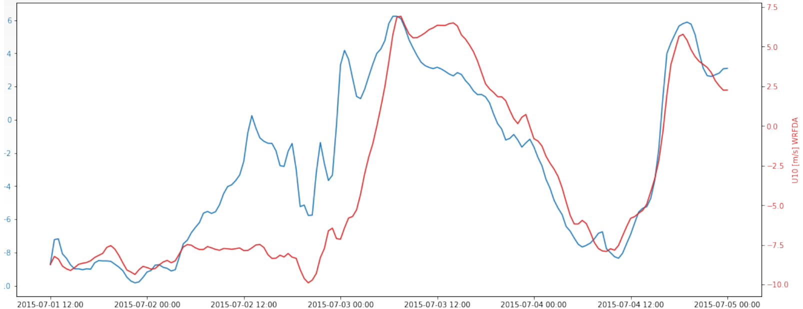
Upward-looking LiDAR wind

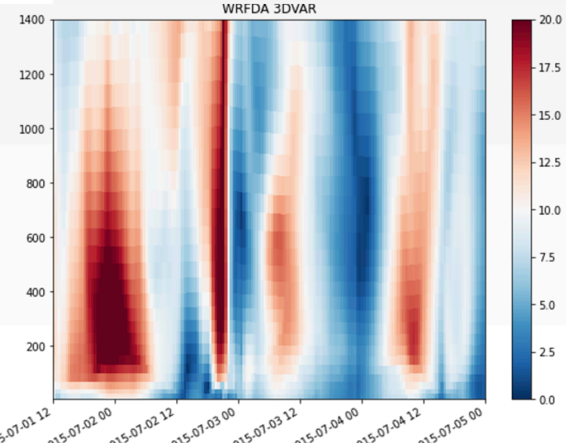
3DVAR (cold start)

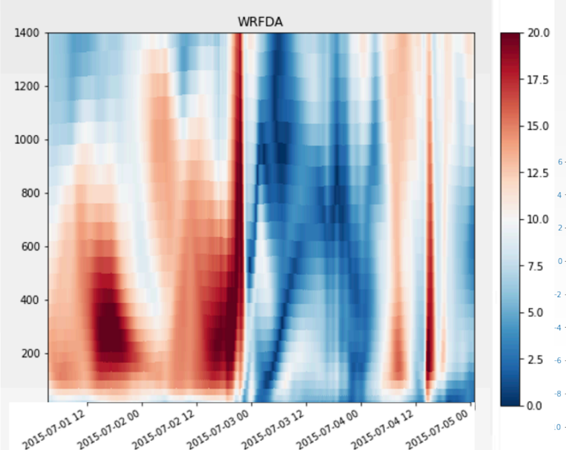


Nudging









Model uncertainity: Background error matrix

- Successful assimilation in variational DA depends on quality of two covariance matrices. Here, we focus on the background error.

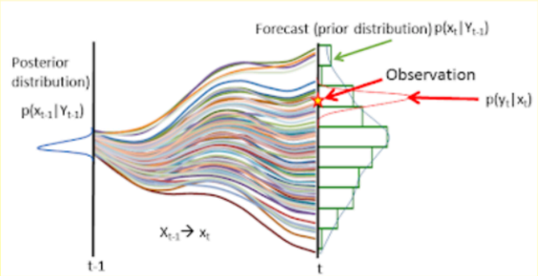
- Effect of nonlinearity appeared in the cost function:

$$J(x) = \frac{1}{2}(x - x_b)^T B^{-1}(x - x_b) + \frac{1}{2}(y - H(x))^T R^{-1}(y - H(x))$$

- The domain-dependent background error covariance can be estimated using the NMC method with T+24h minus T+12h forecasting difference.

$$B = \overline{(x_b - x_t)(x_b - x_t)^T}$$

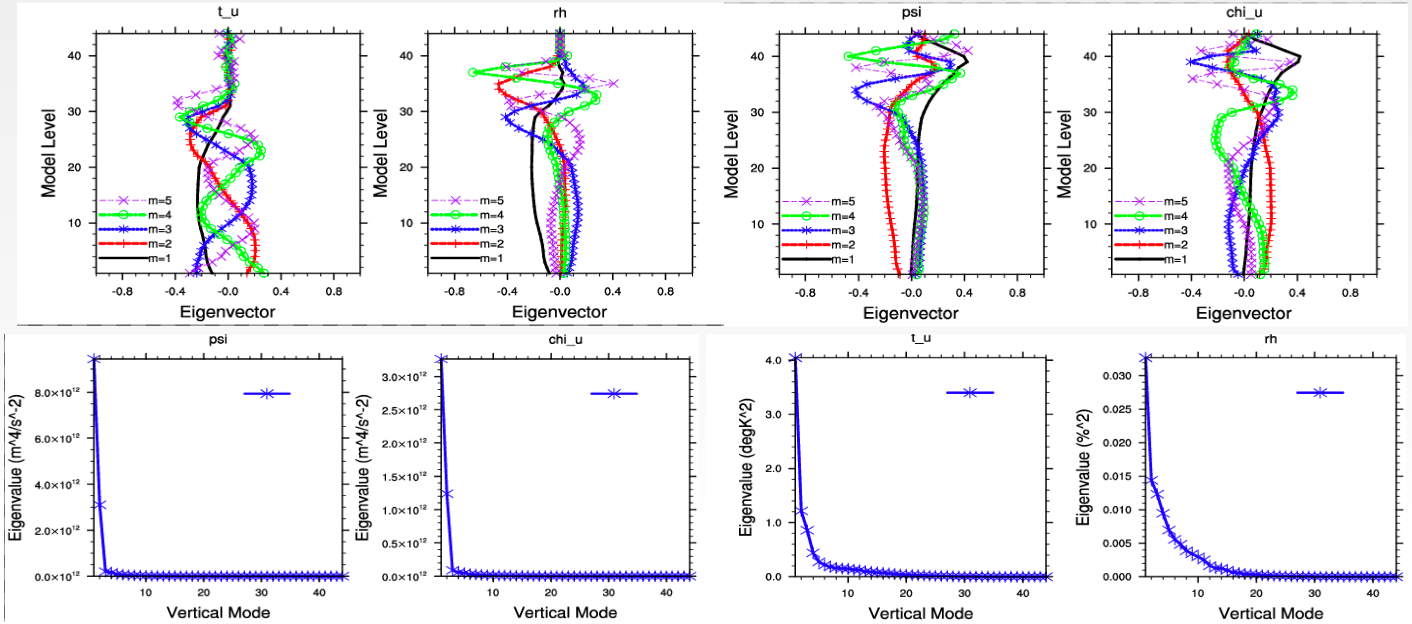
Data assimilatin



Model uncertainity: Background error matrix

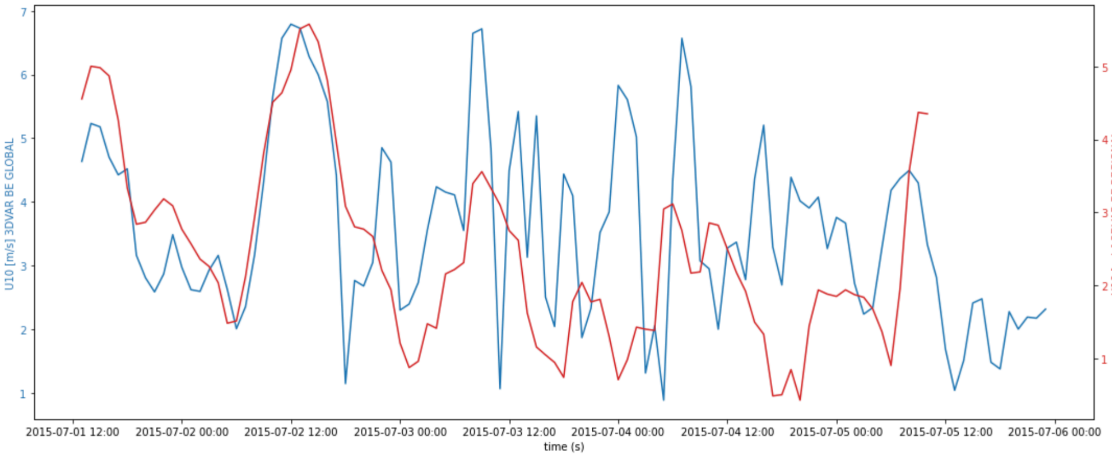
Control variables are: stream function, velocity potential, horizontal wind component along x-axis, and relative humidity.

The input data from WRF forecasts between 1th July 2015 and 4th July 2015 are used to statistically generate the background errors.

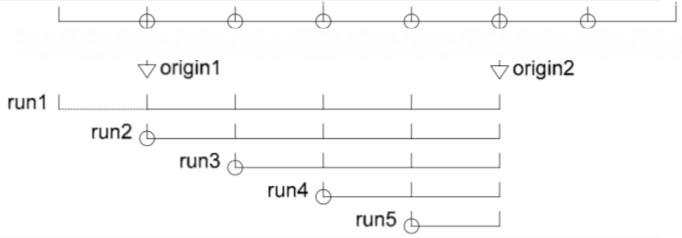


Model uncertainity: Background error matrix

Comparison between cyclic forecast for horizon of 1h and cycle length of three hours. The regional BE is just an example based on 5 days forecast procedure as mentioned earlier (just to highlight the importance of this matrix)



Cyclic forecast for hourly forecast horizon



Conclusions and further works

- Lidar data measured at FINO1 platform has been assimilated in WRF using two DA techniques.
- Tentative results suggests that nudging provides reliable agreement versus observations. Deviation between numerical results and obs. can be reduced if appropriate site-specific values are set.
- Variational DA is sensitive to the choice of BE and observational error matrices.
- Regional BE was calculated for the study area just for the sensitivity analysis.
- Further validation-verification needs to be conducted to improve the quality of DA techniques.

References

1. **Barker, D. M., Huang, W., Guo, Y. R., Bourgeois, A., and Xiao, Q. N.: A three-dimensional variational data assimilation system for MM5: implementation and initial results, Mon. Weather Rev., 132, 897–914, 2004.**

2. Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Barker, D. M., Duda, M. G., Huang, X. Y., Wang, W., and Powers, J. G.: A Description of the Advanced Research WRF Version 3, NCAR Technical Note, NCAR/TN-475+STR, 2008.

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