



Applications of data assimilation and current challenges

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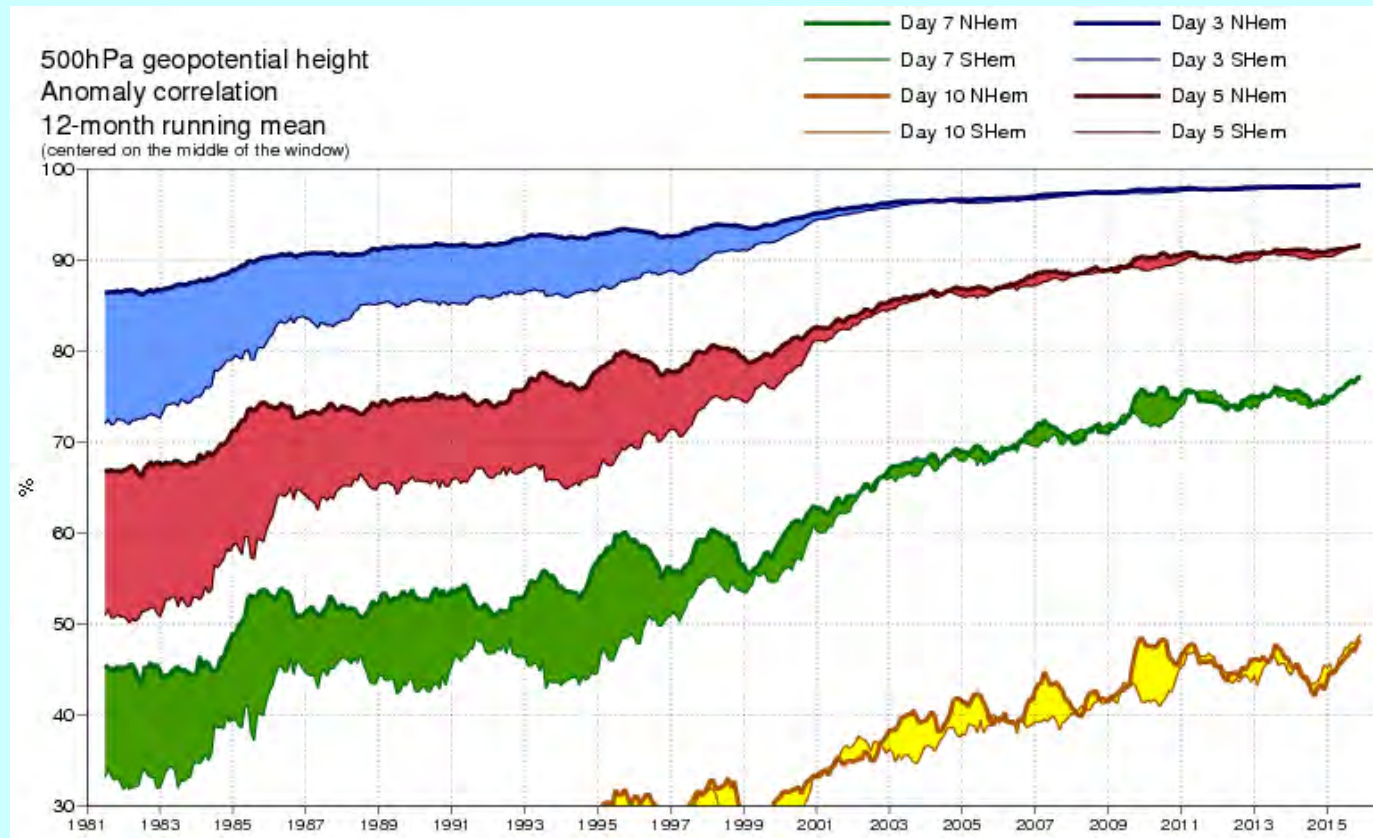
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Numerical weather prediction

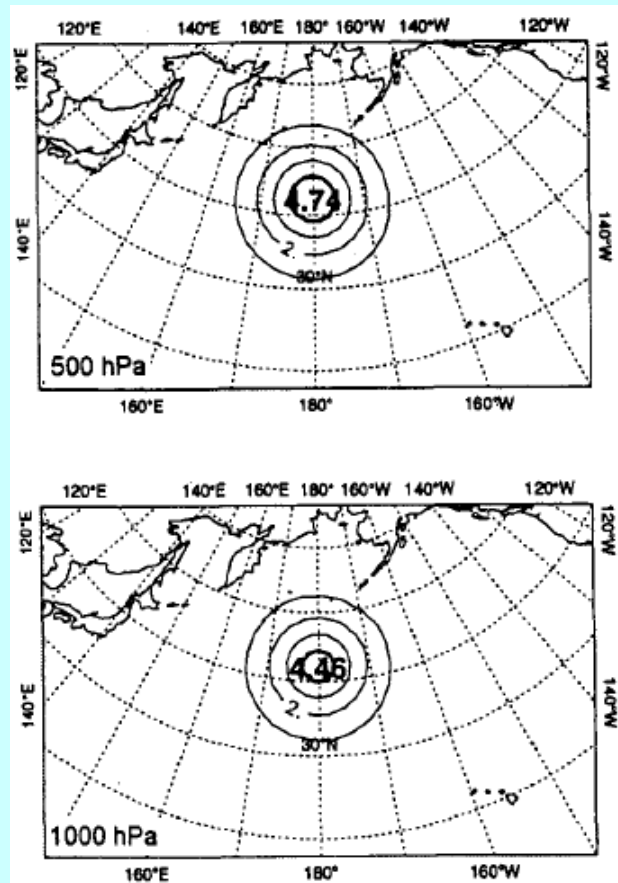


↑
4D-Var
introduced

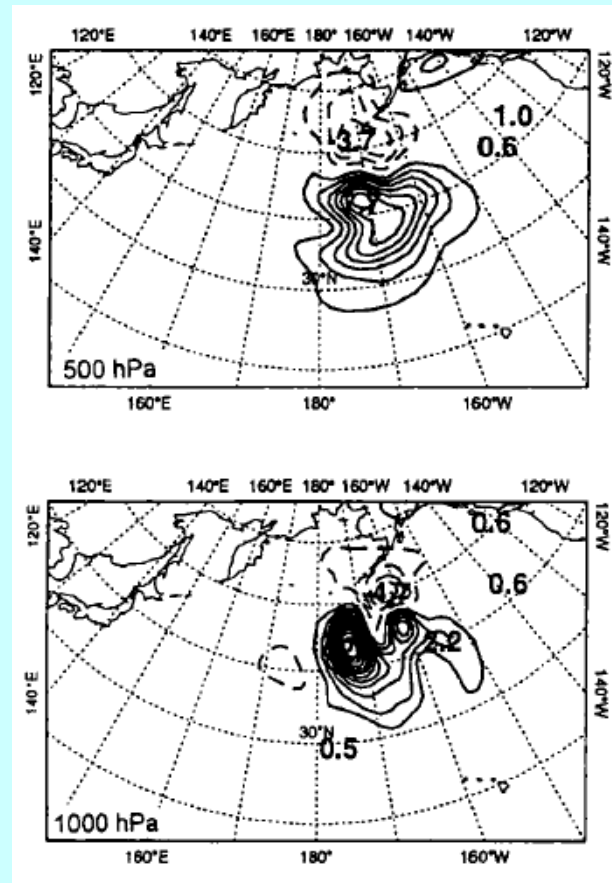
↑
Assimilation
update

From www.ecmwf.int

Flow-dependent covariances



3D-Var



4D-Var

Increments from single observation of height at 500 hPa.

Thepaut et al. (1996)

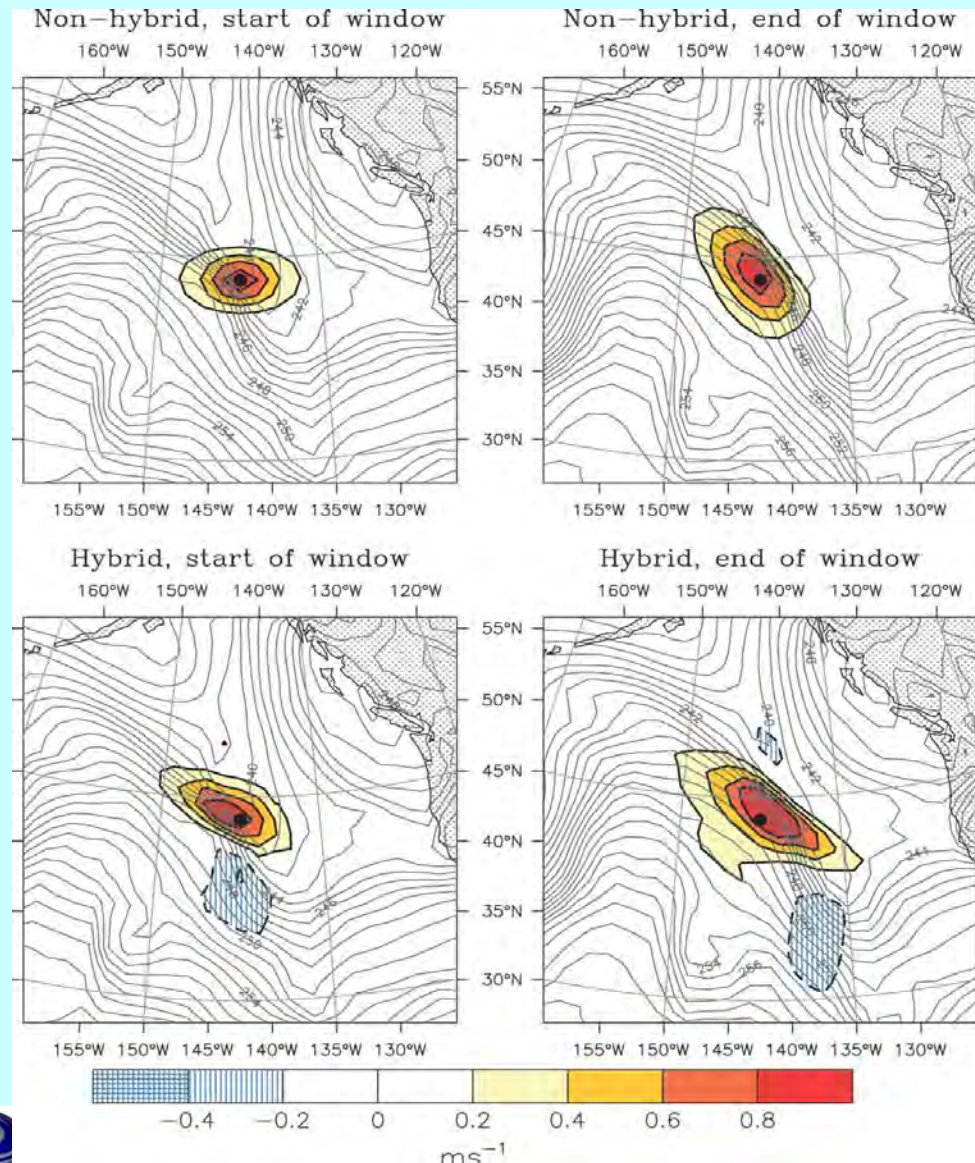
Next generation NWP assimilation

Can we get more flow dependence by combining variational and ensemble methods?

Various proposals:

- En4DVar
- 4DEnVar
- Ensembles of 4DEnVar
- ...

Met office implementation



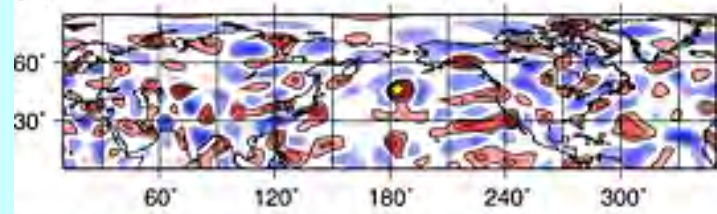
Zonal wind responses (filled thick contours, with negative contours dashed) to a single zonal wind observation.

The unfilled contours show the background temperature field.

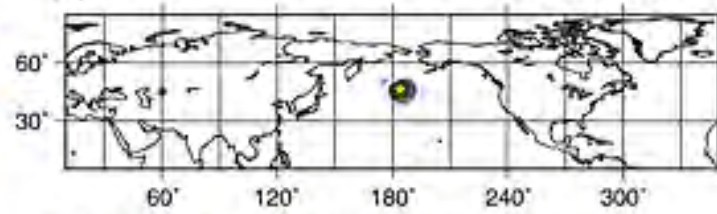
Clayton et al. (2012)

Localisation

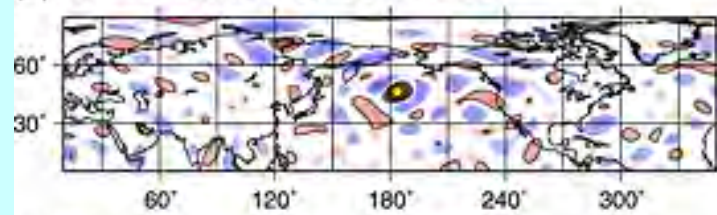
(a) 20 members w/o localization



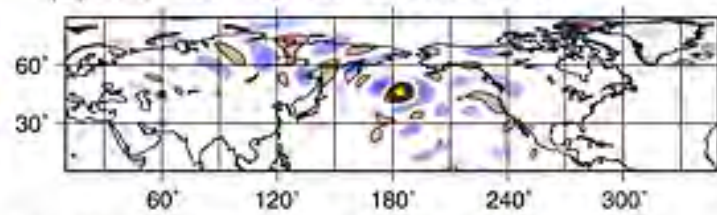
(b) 20 members w/ 700-km localization



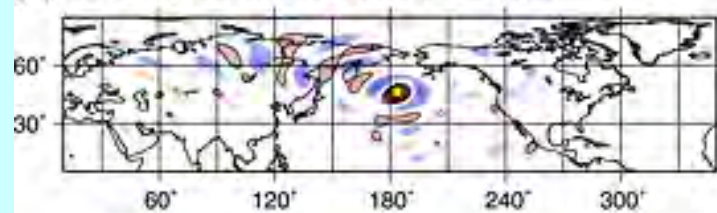
(c) 80 members w/o localization



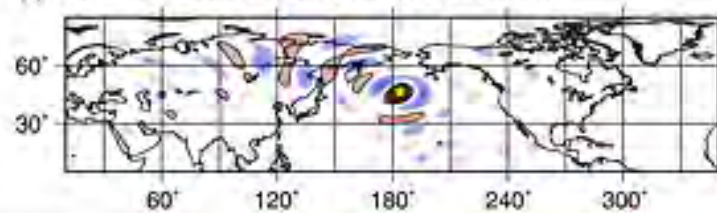
(d) 320 members w/o localization



(e) 1280 members w/o localization



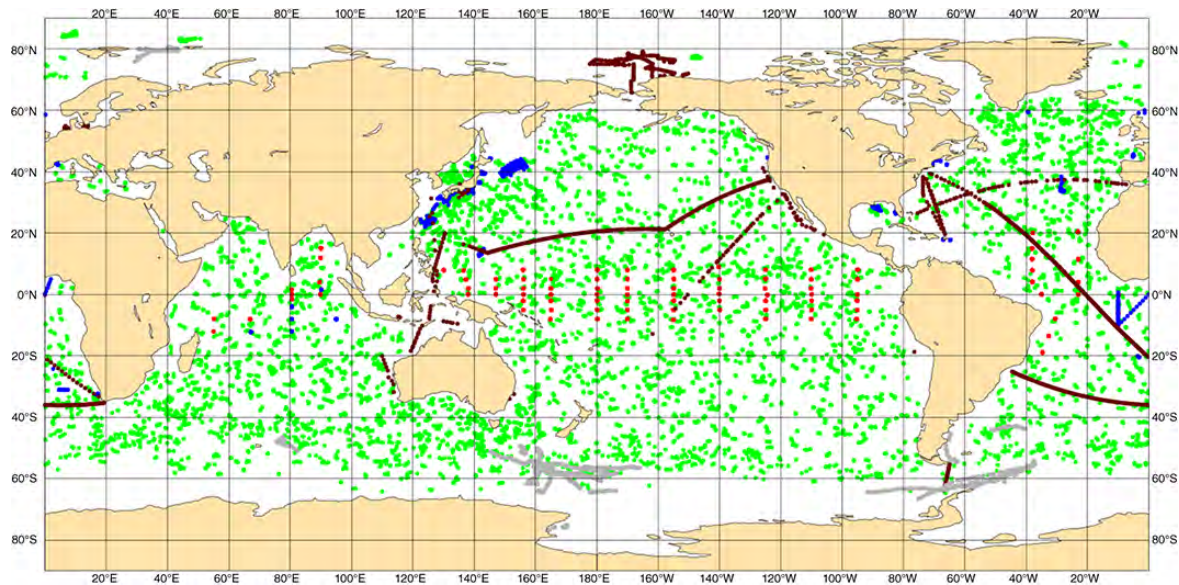
(f) 10240 members w/o localization



Experiments on 10 Petaflop ‘K’ supercomputer! *Miyoshi et al. (2014)*

Ocean DA

A coupled data assimilation system for climate reanalysis



Quarterly Journal of the Royal Meteorological Society
Volume 142, Issue 694, pages 65-78, 24 SEP 2015 DOI: 10.1002/qj.2629
<http://onlinelibrary.wiley.com/doi/10.1002/qj.2629/full#qj2629-fig-0013>

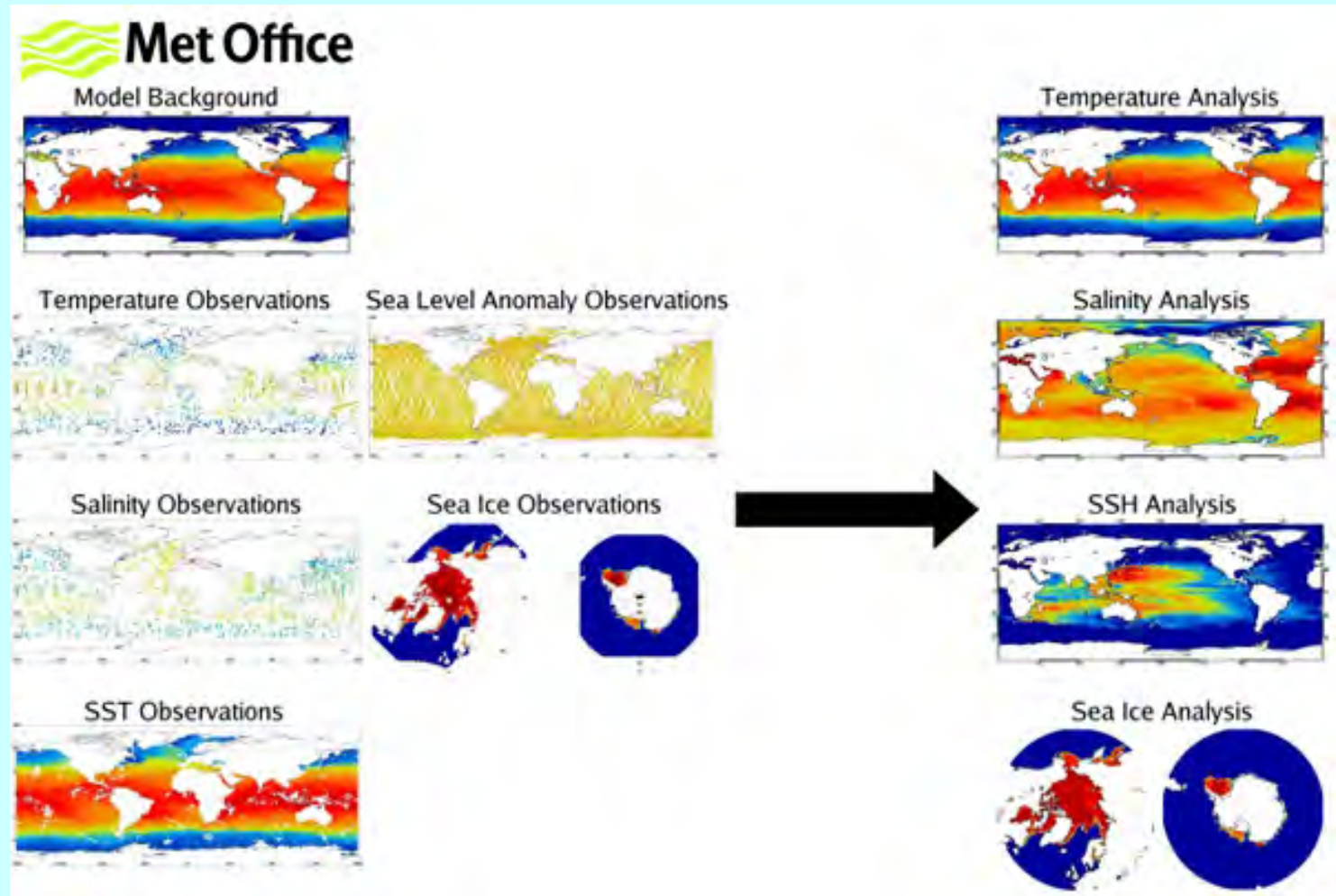
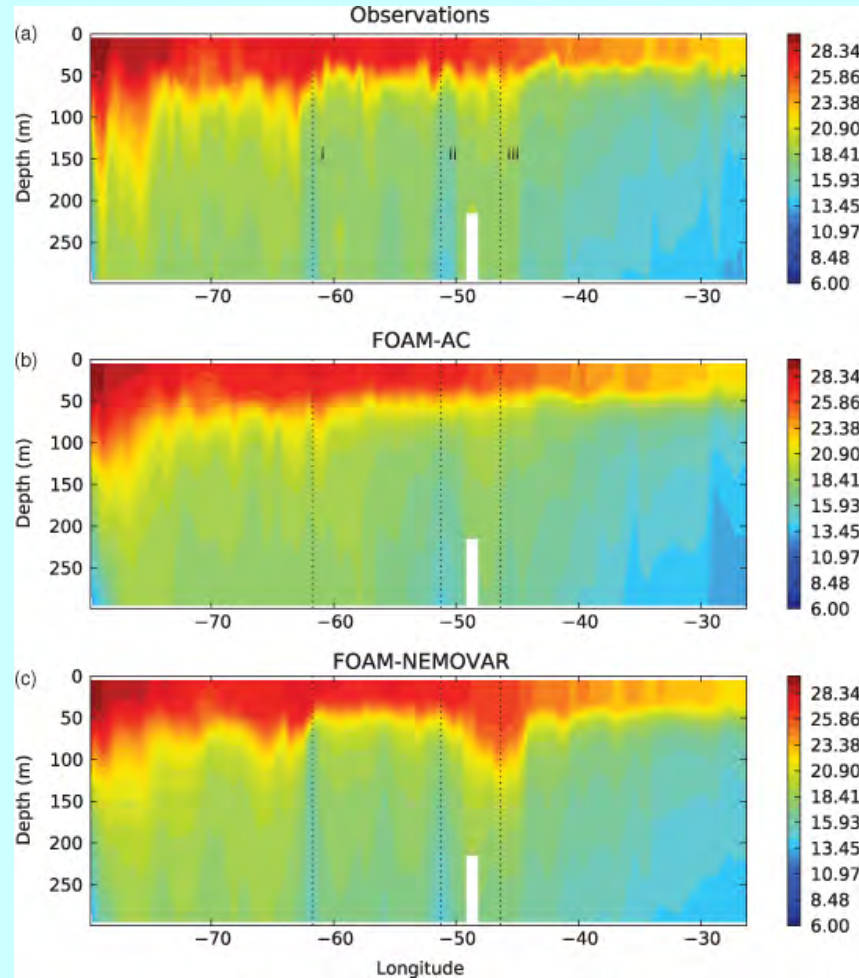
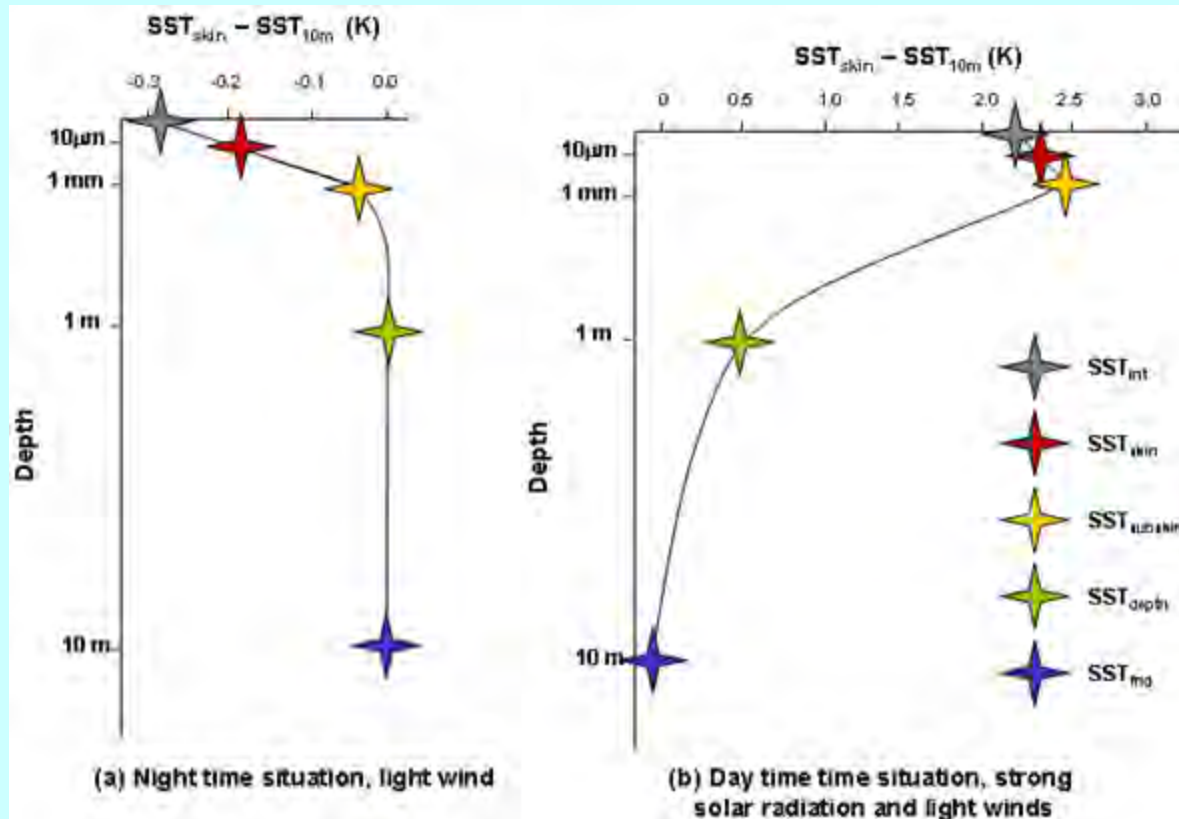


Figure from www.metoffice.gov.uk

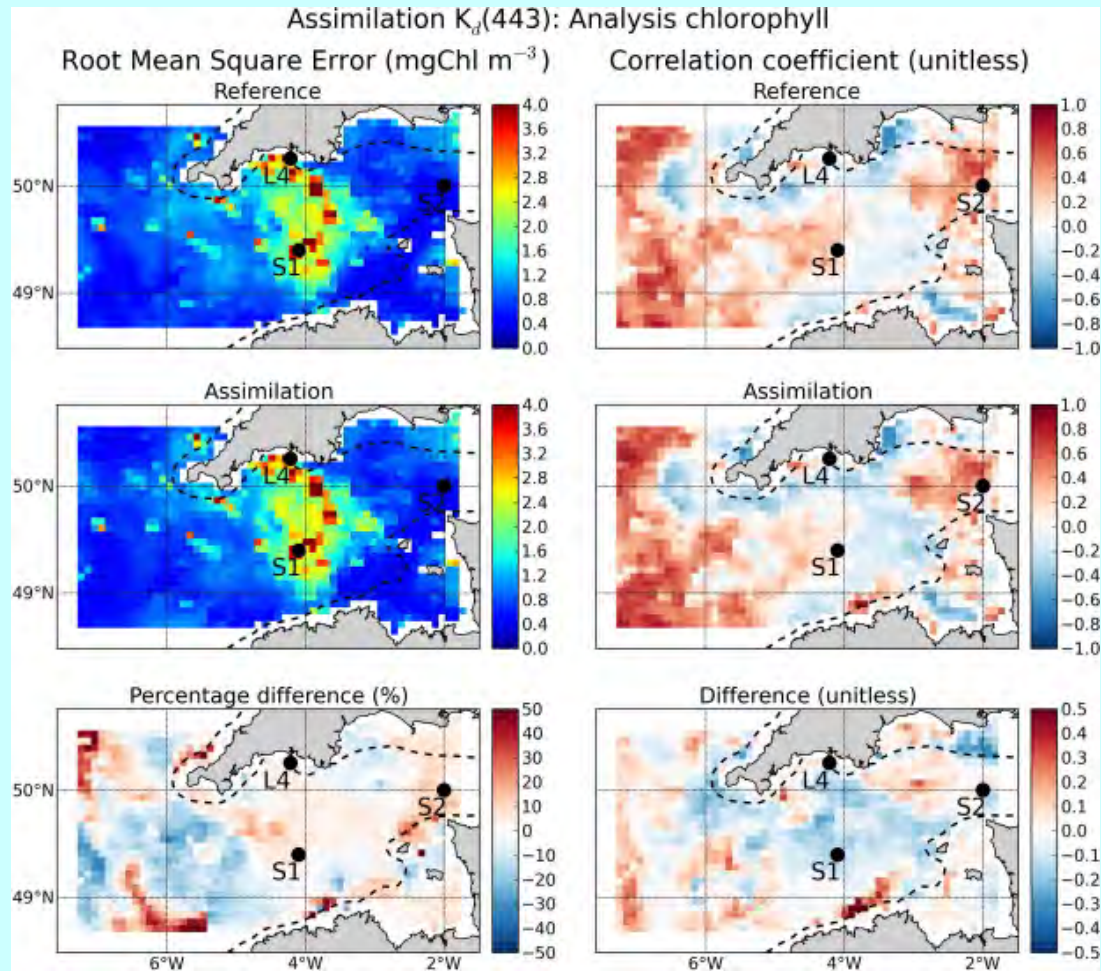
Implementing a variational data assimilation system in an operational 1/4 degree global ocean model



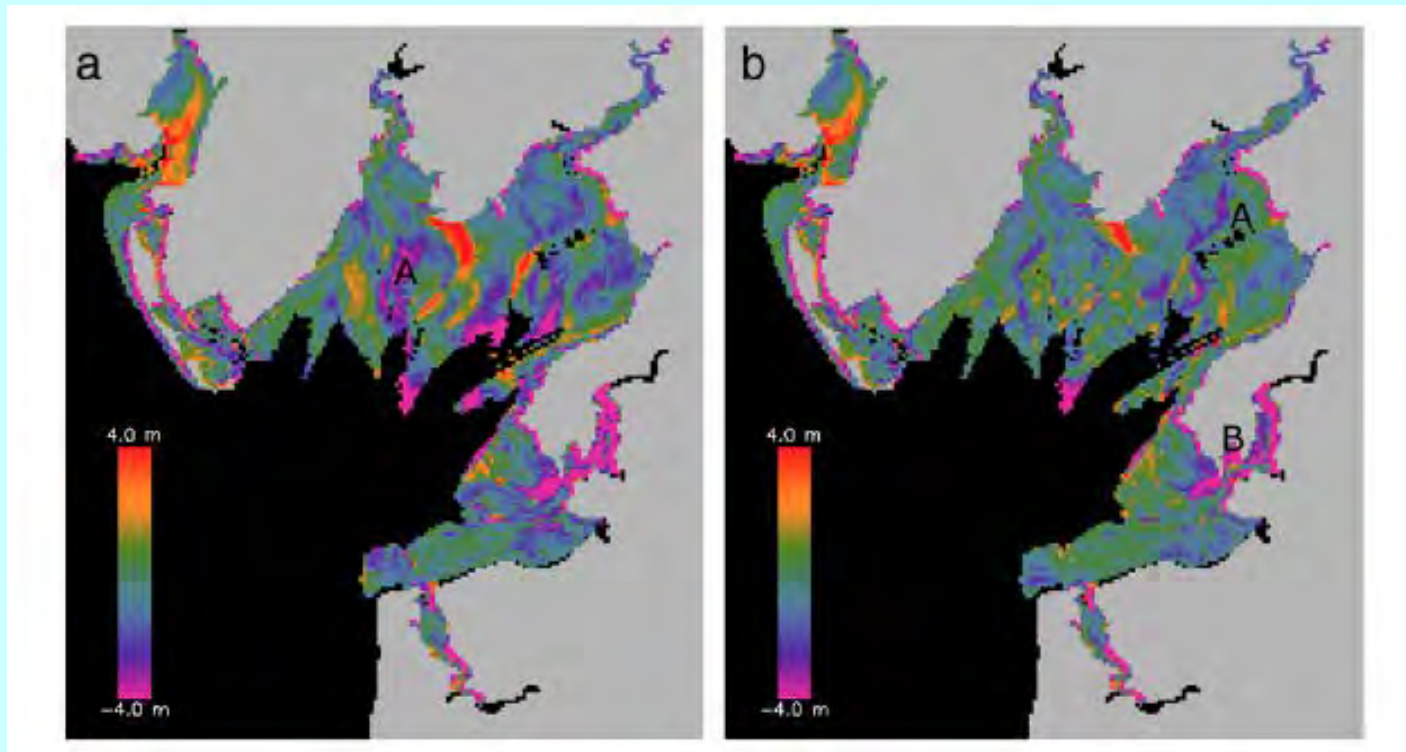
Sea surface temperature



Ocean colour - Chlorophyll

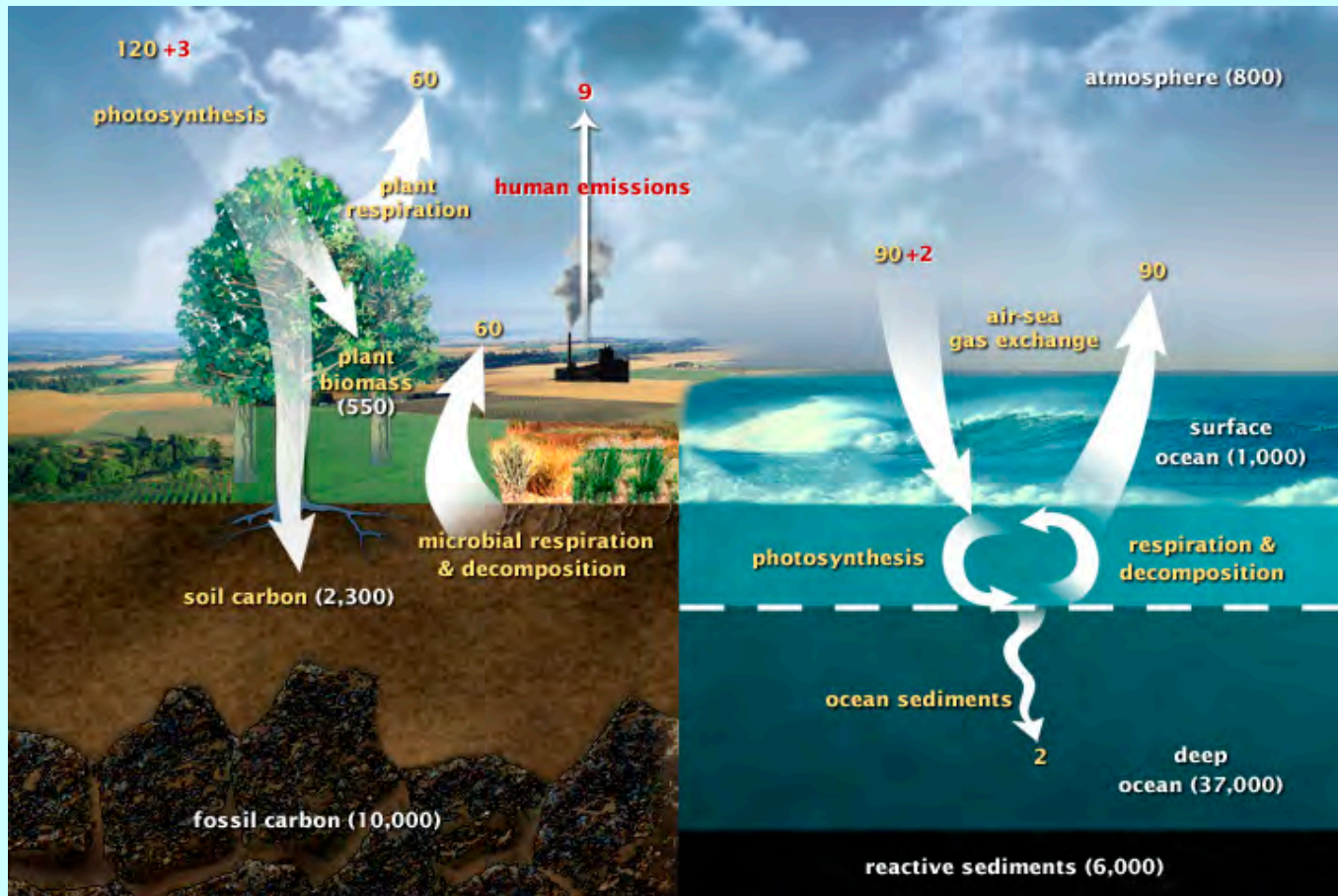


Coastal bathymetry

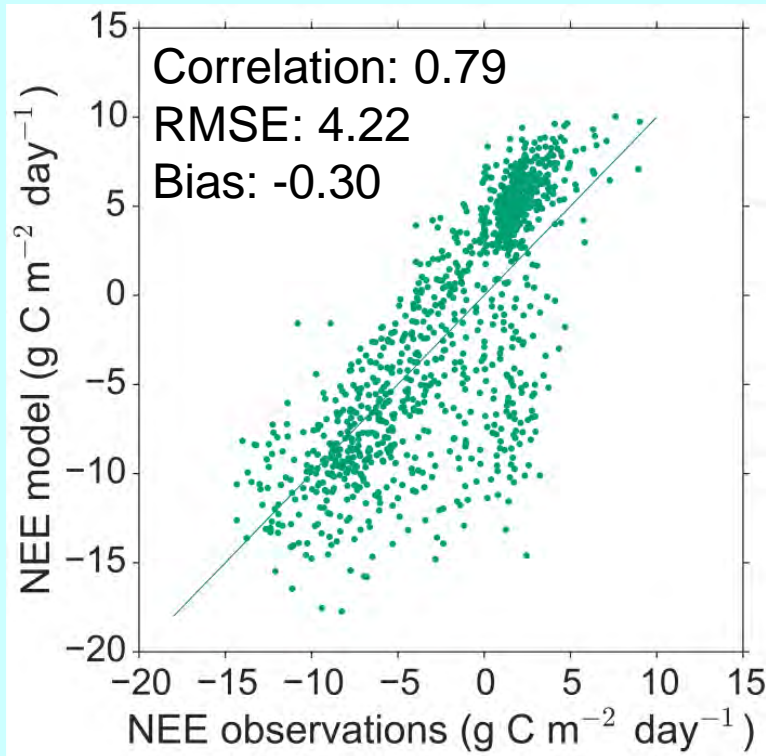


Errors in predicted bathymetry (a) without assimilation and (b) with assimilation, from *Thornhill et al (2012)*

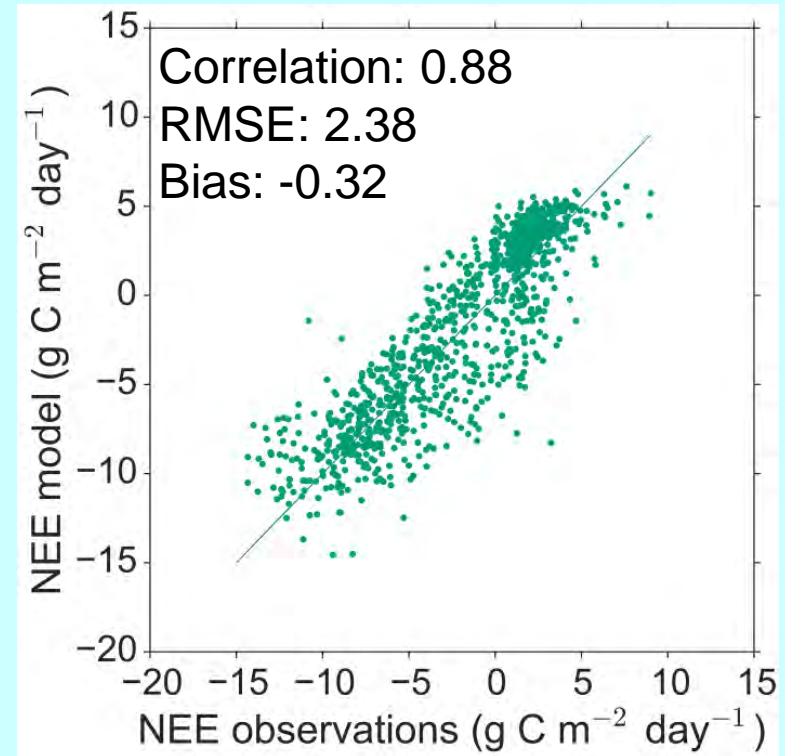
Carbon cycle



Assimilation of Net Ecosystem Exchange observations into a carbon cycle model – Forecast 2000-2013



No correlations



With correlations

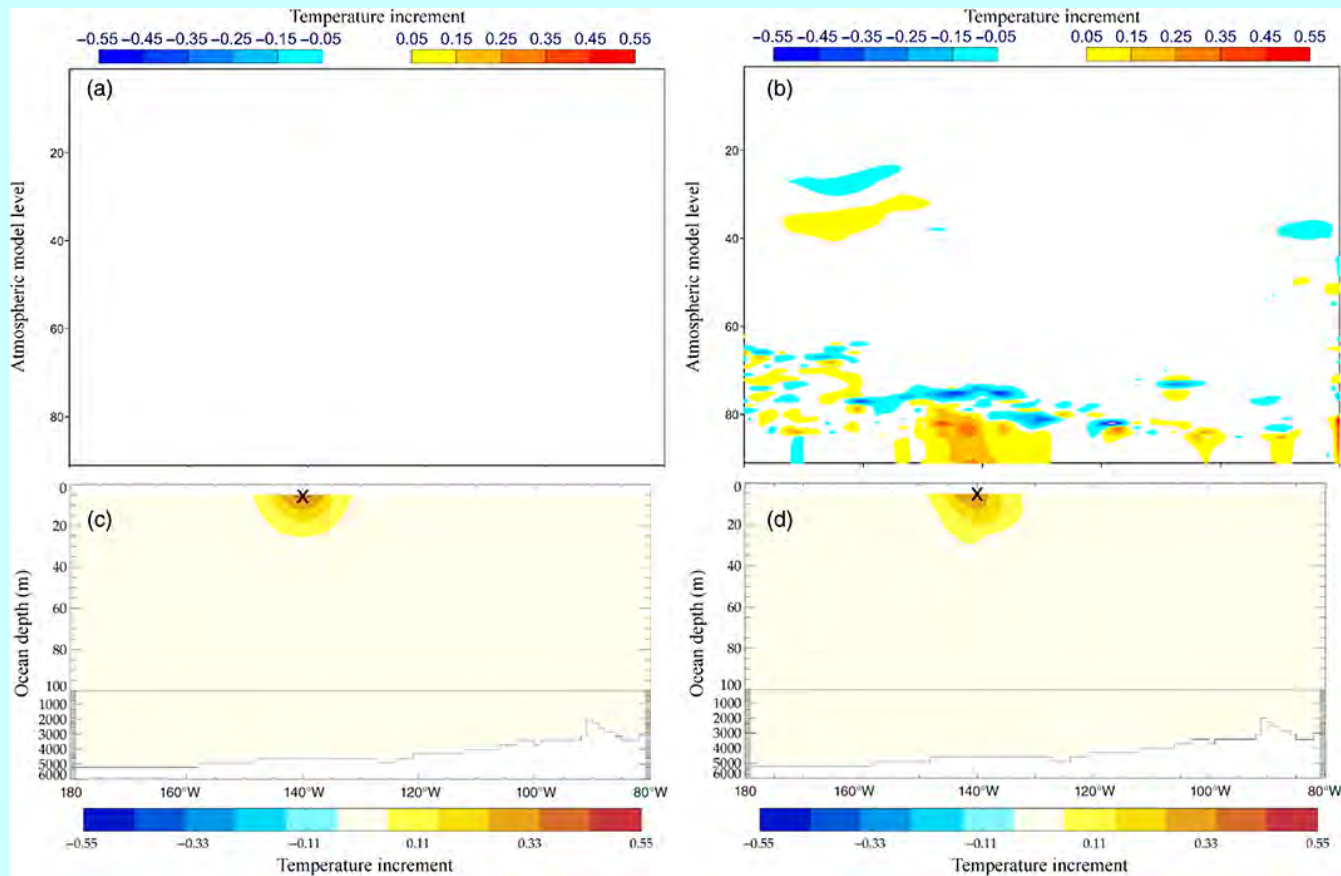
Coupled atmosphere-ocean DA

- Seasonal to decadal forecasting requires initialisation of coupled atmosphere-ocean models
- Currently atmosphere and ocean systems are initialised separately using data assimilation.
- Forecasting centres want to move towards more coupled data assimilation
- Variational or ensemble methods?

Coupled atmosphere-ocean DA

Atmos

Ocean

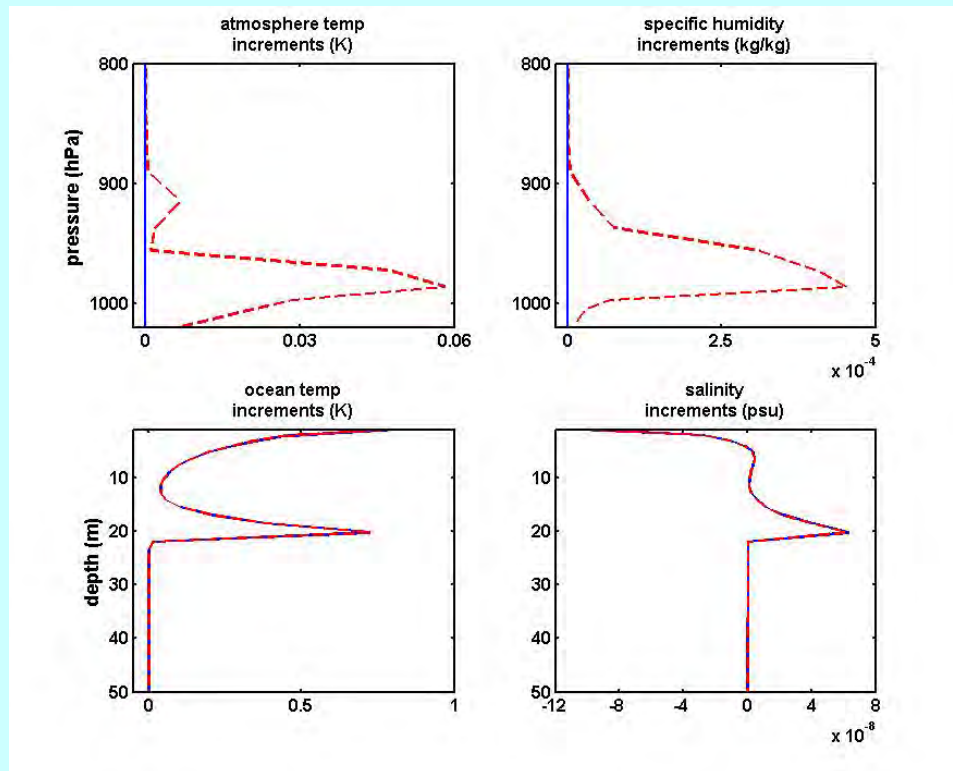


Start of assimilation window

End of assimilation window

Transfer of information

How well can the schemes transfer information across the coupling interface?



--- Strongly coupled
--- Weakly coupled

Increments at initial time from single observation of SST at end of window

From *Smith et al (2015)*

Reanalysis

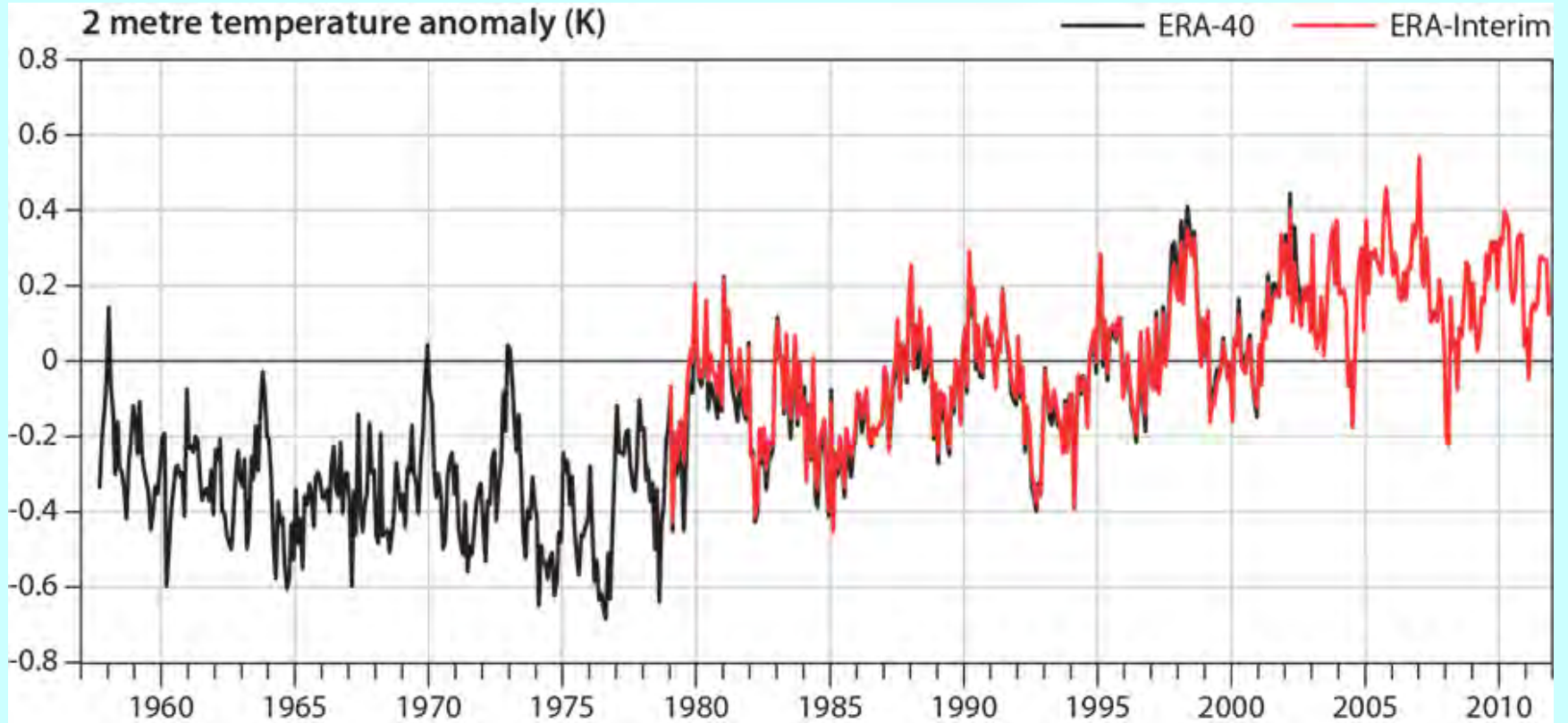
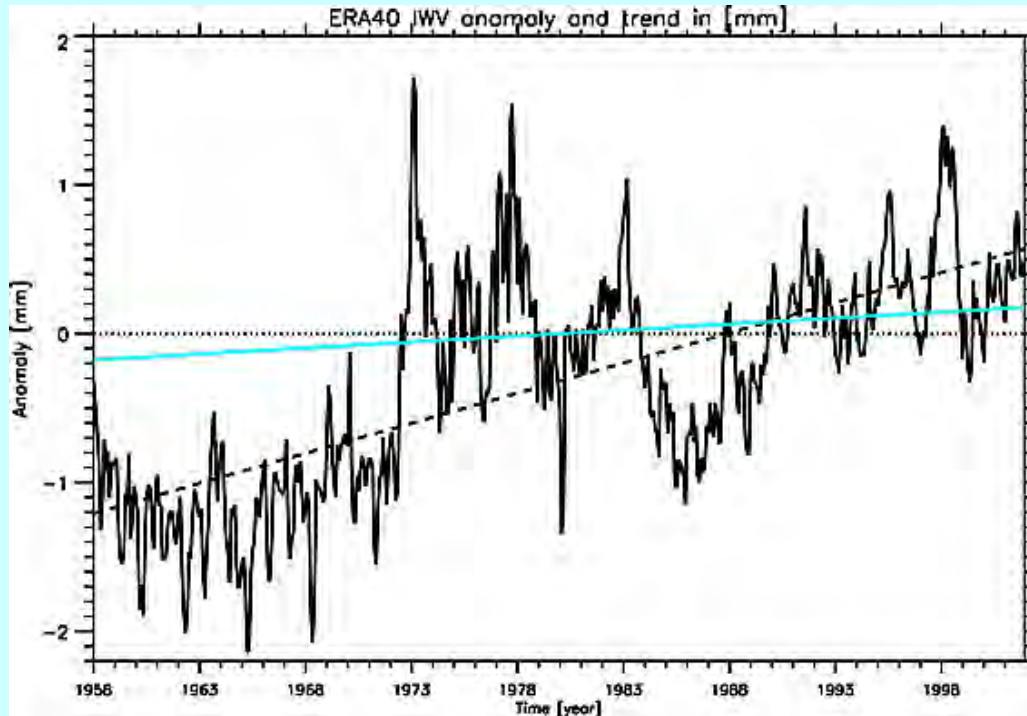


Figure from www.ecmwf.int

Can climate trends be calculated from reanalysis data?



Vertically integrated water vapour, IWV, of ERA40 for the period 1958–2001.
From *Bengtsson et al (2004)*

Observation System Simulation Experiments (OSSEs)

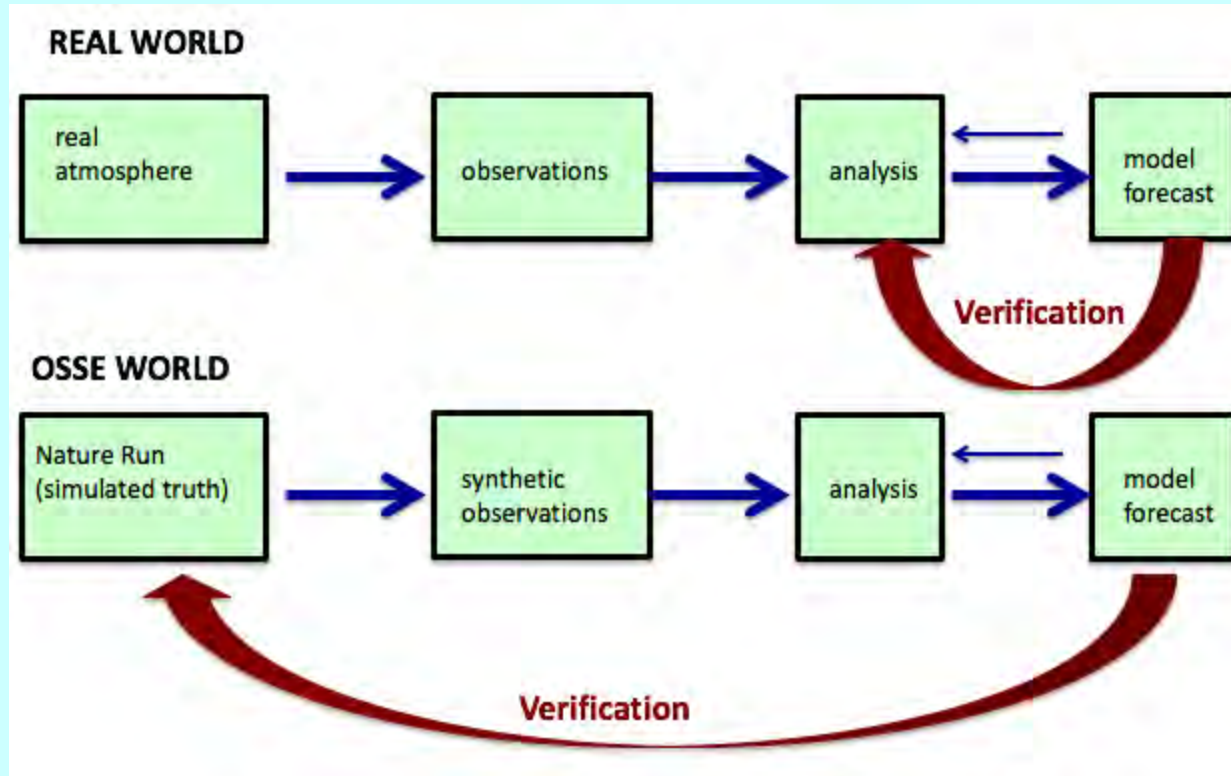


Figure from <http://www.esrl.noaa.gov/gsd/gosa/ose-osse.html>

Observation System Simulation Experiments (OSSEs)

- Useful for estimating the potential impact of new instruments.
- Must be carried out with great care, e.g. calibration of nature run.
- Results must be interpreted with care, especially for potential new satellite instruments – the observing system and assimilation method may be very different by the time the satellite flies.

Some current challenges

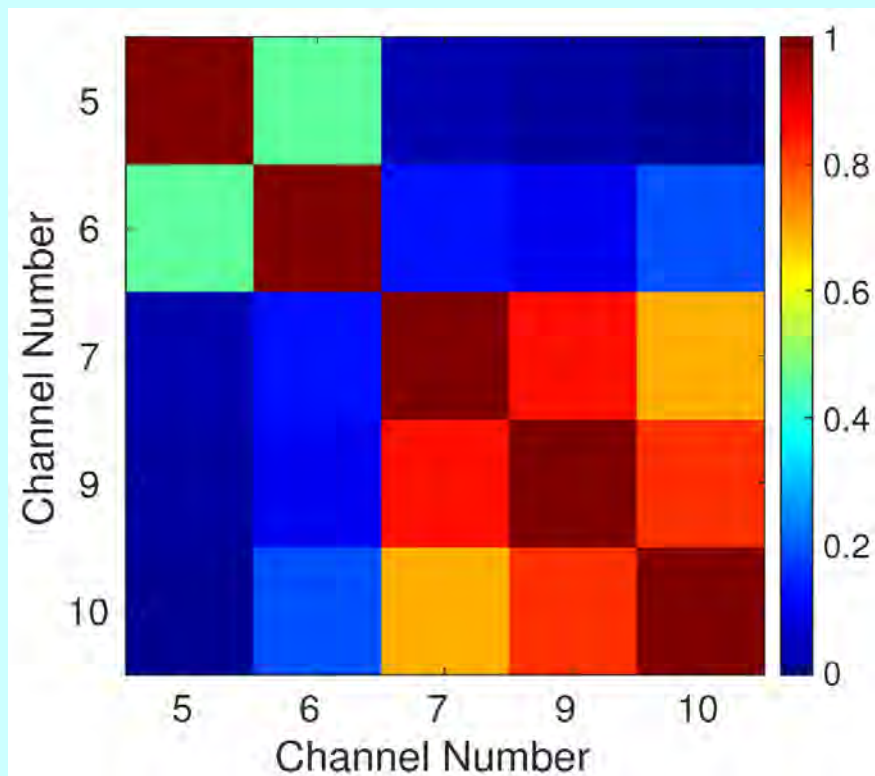
Challenges: Data amount

- Satellites produce a lot of data!
- Modern satellite instruments may have thousands of channels.
- Currently operational weather forecasting centres use less than 5% of the satellite data they receive.
- Lots of challenges in big data, data manipulation, etc.

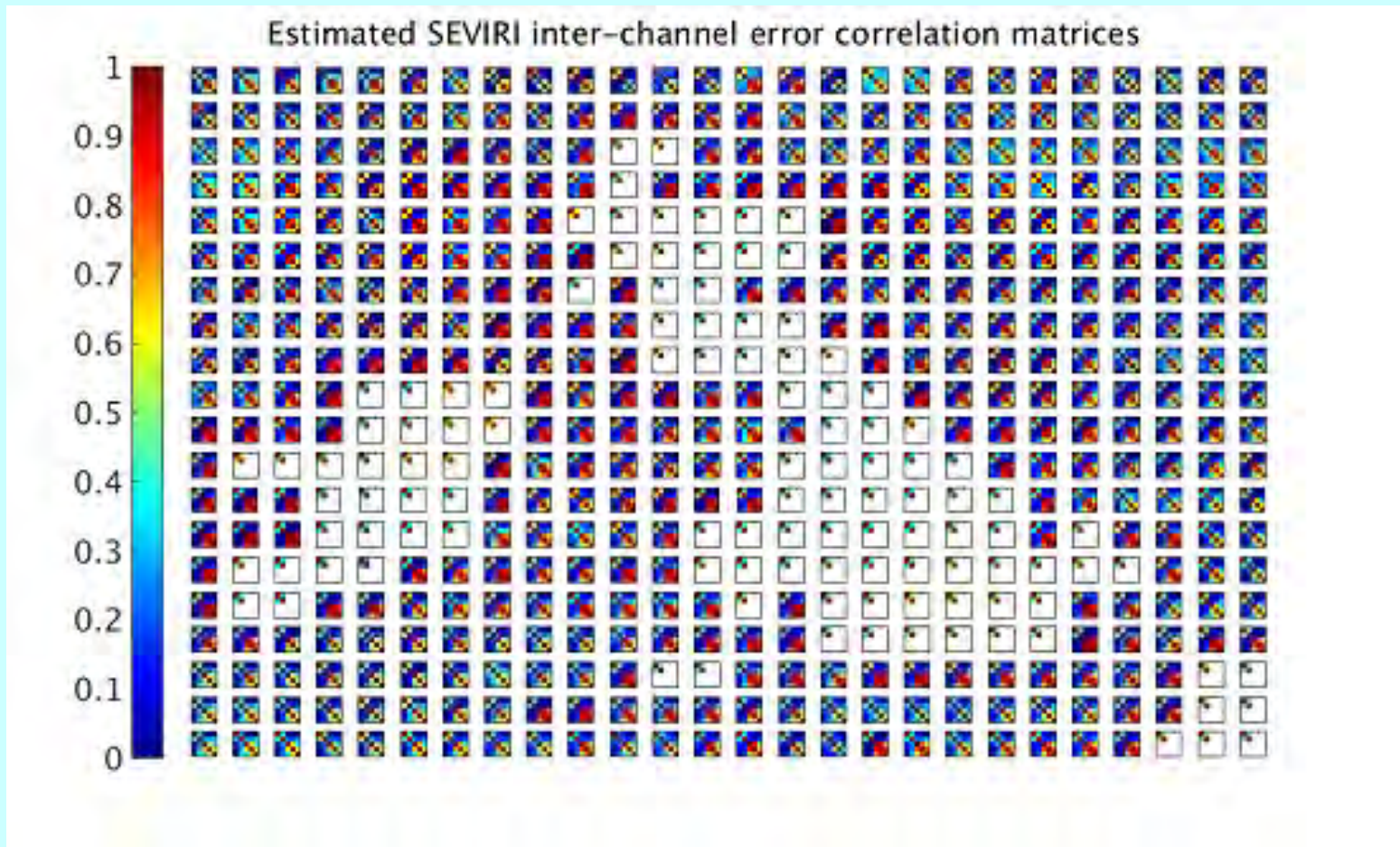
Challenges: Observation error correlations

- Part of the reason so much data is thrown away is that we don't know how to deal with correlations in the observation errors
 - Understanding what the correlations are.
 - Representing them in the matrix **R**.
- Much current work in this area.

Observation error correlations



Estimated observation error correlation matrix for assimilated SEVIRI channels.
From *Waller et al (2016)*



Spatial variation of estimated observation error correlation matrix for assimilated SEVIRI channels.

From *Waller et al (2016)*

Challenges: Bias correction

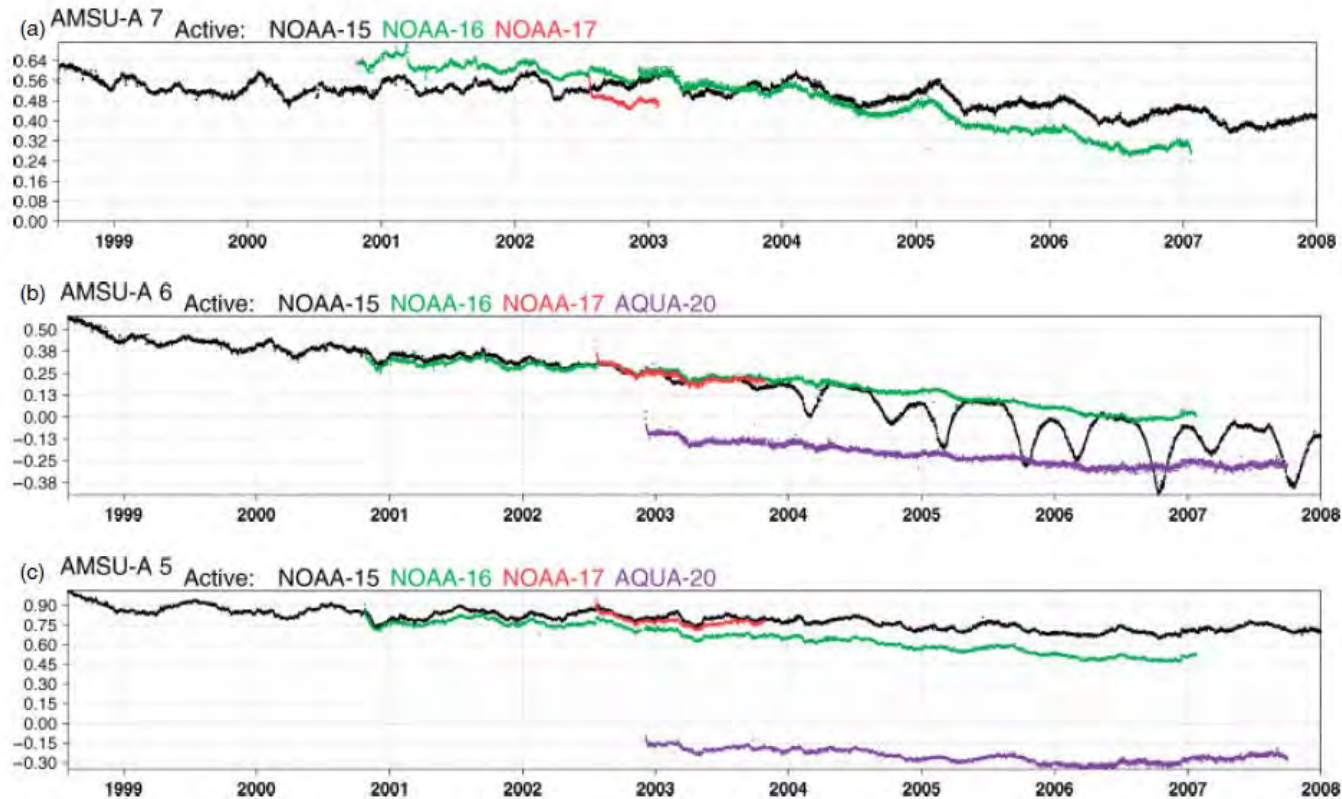


Figure 7. Globally averaged 12-hourly bias estimates (K) from NOAA-15, NOAA-16, NOAA-17, and AQUA for AMSU-A (a) channel 7, (b) channel 6, and (c) channel 5.

Challenges: Model error

We consider that the model has unknown errors:

$$\mathbf{x}_{i+1} = \mathcal{M}_i(\mathbf{x}_i) + \boldsymbol{\eta}_i, \quad \boldsymbol{\eta}_i \sim \mathcal{N}(0, \mathbf{Q}_i)$$

State formulation

$$\begin{aligned} & \mathcal{J}(\mathbf{x}_0, \mathbf{x}_1, \dots, \mathbf{x}_N) \\ = & \mathcal{J}_b + \mathcal{J}_o + \frac{1}{2} \sum_{i=0}^{N-1} (\mathbf{x}_{i+1} - \mathcal{M}_i(\mathbf{x}_i))^T \mathbf{Q}_i^{-1} (\mathbf{x}_{i+1} - \mathcal{M}_i(\mathbf{x}_i)) \end{aligned}$$

Error formulation

$$\mathcal{J}(\mathbf{x}_0, \boldsymbol{\eta}_0, \dots, \boldsymbol{\eta}_{N-1}) = \mathcal{J}_b + \mathcal{J}_o + \frac{1}{2} \sum_{i=0}^{N-1} \boldsymbol{\eta}_i^T \mathbf{Q}_i^{-1} \boldsymbol{\eta}_i$$

Implementation of weak-constraint formulation

- Size of the control vector is greatly increased.
- The two formulations may behave quite differently, even though they appear to be equivalent.
- We need to specify the model error covariances \mathbf{Q} . It is not obvious how this should be done.

Can we distinguish model and observation bias?

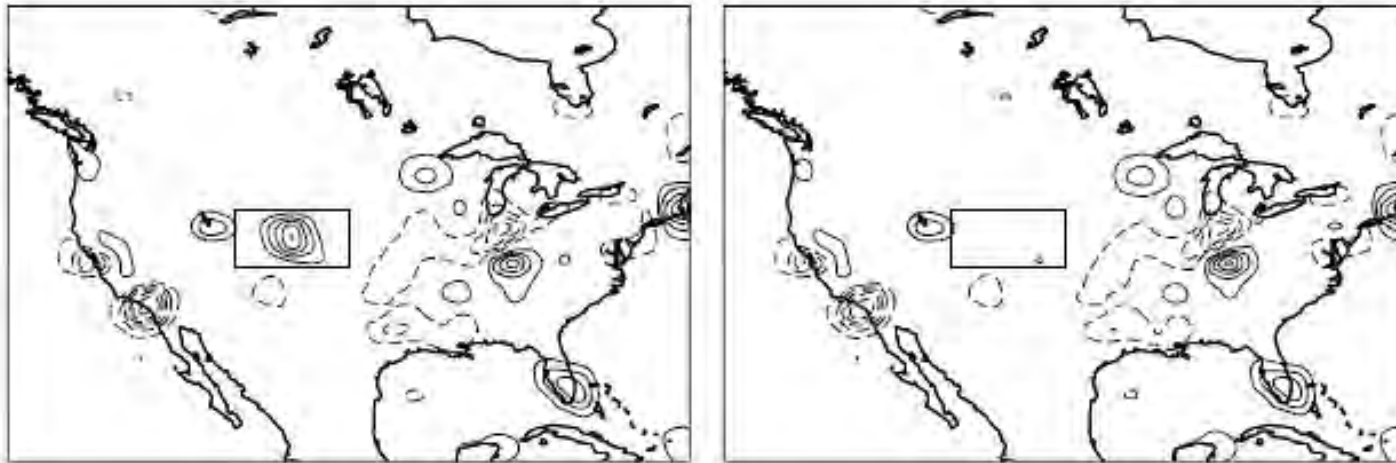


Figure 11. Average temperature forcing at the lowest model level over North America; with all data (left panel), and without aircraft data in the marked area (right panel). The contour interval is 0.01 K h^{-1} .

Estimated model bias using all data (left) and without aircraft data (right).
Trémolet (2007)

Challenges: New algorithms

- Data assimilation of the future will have to take account of new computer architectures.
- Massively parallel architectures seem more suited to ensemble-based methods.
- Desire to move to non-Gaussian methods such as particle filters.
- The best algorithm will depend on your application.

Concluding remarks

- Data assimilation is potentially useful whenever you have data and a model.
- DA is now being applied to many different areas of Earth science.
- Launch of new satellites will provide many more data available for assimilation, but this brings its own challenges.
- Many research questions remain as to how best to implement DA for different applications.

References

- Bengtsson, L., Hagemann, S., & Hodges, K. I. (2004). Can climate trends be calculated from reanalysis data?. *Journal of Geophysical Research: Atmospheres*, 109(D11).
- Ciavatta, S., Torres, R., Martinez-Vicente, V., Smyth, T., Dall’Olmo, G., Polimene, L., & Allen, J. I. (2014). Assimilation of remotely-sensed optical properties to improve marine biogeochemistry modelling. *Progress in Oceanography*, 127, 74-95.
- Clayton, A. M., Lorenc, A. C. and Barker, D. M. (2013), Operational implementation of a hybrid ensemble/4D-Var global data assimilation system at the Met Office. *Q.J.R. Meteorol. Soc.*, 139: 1445–1461.
- Dee, D. P. and Uppala, S. (2009), Variational bias correction of satellite radiance data in the ERA-Interim reanalysis. *Q.J.R. Meteorol. Soc.*, 135: 1830–1841.
- Laloyaux, P., Balmaseda, M., Dee, D., Mogensen, K. and Janssen, P. (2016), A coupled data assimilation system for climate reanalysis. *Q.J.R. Meteorol. Soc.*, 142: 65–78.
- Miyoshi, T., K. Kondo, and T. Imamura (2014), The 10,240-member ensemble Kalman filtering with an intermediate AGCM, *Geophys. Res. Lett.*, 41, 5264–5271.
- Pinnington, E.M., Casella, E., Dance, S.L., Lawless, A.S., Morison, J.I., Nichols, N.K., Wilkinson, M. and Quaife, T.L., 2016. Investigating the role of prior and observation error correlations in improving a model forecast of forest carbon balance using Four-dimensional Variational data assimilation. *Agricultural and Forest Meteorology*, 228, pp.299-314.

References

- Smith, P.J., Fowler, A.M. and Lawless, A.S. (2015), Exploring strategies for coupled 4D-Var data assimilation using an idealised atmosphere-ocean model. *Tellus A*, 67, 27025.
- Thépaut, J. N., Courtier, P., Belaud, G., & Lemaître, G. (1996). Dynamical structure functions in a four-dimensional variational assimilation: A case study. *Quarterly Journal of the Royal Meteorological Society*, 122(530), 535-561.
- Thornhill, G.D., Mason, D.M., Dance, S.L., Lawless, A.S. and Nichols, N.K. (2012), Integration of a 3D Variational data assimilation scheme with a coastal area morphodynamic model of Morecambe Bay. *Coastal Engineering*, 69, 82-96.
- Trémolet, Y. (2007), Model-error estimation in 4D-Var. *Q.J.R. Meteorol. Soc.*, 133: 1267–1280.
- Waller, J. A., Ballard, S. P., Dance, S. L., Kelly, G., Nichols, N. K., & Simonin, D. (2016). Diagnosing Horizontal and Inter-Channel Observation Error Correlations for SEVIRI Observations Using Observation-Minus-Background and Observation-Minus-Analysis Statistics. *Remote Sensing*, 8(7), 581.
- Waters, J., Lea, D. J., Martin, M. J., Mirouze, I., Weaver, A., & While, J. (2015). Implementing a variational data assimilation system in an operational 1/4 degree global ocean model. *Quarterly Journal of the Royal Meteorological Society*, 141(687), 333-349.