Applications of data assimilation and current challenges

Amos S. Lawless

Data Assimilation Research Centre
University of Reading

a.s.lawless@reading.ac.uk

@amoslawless

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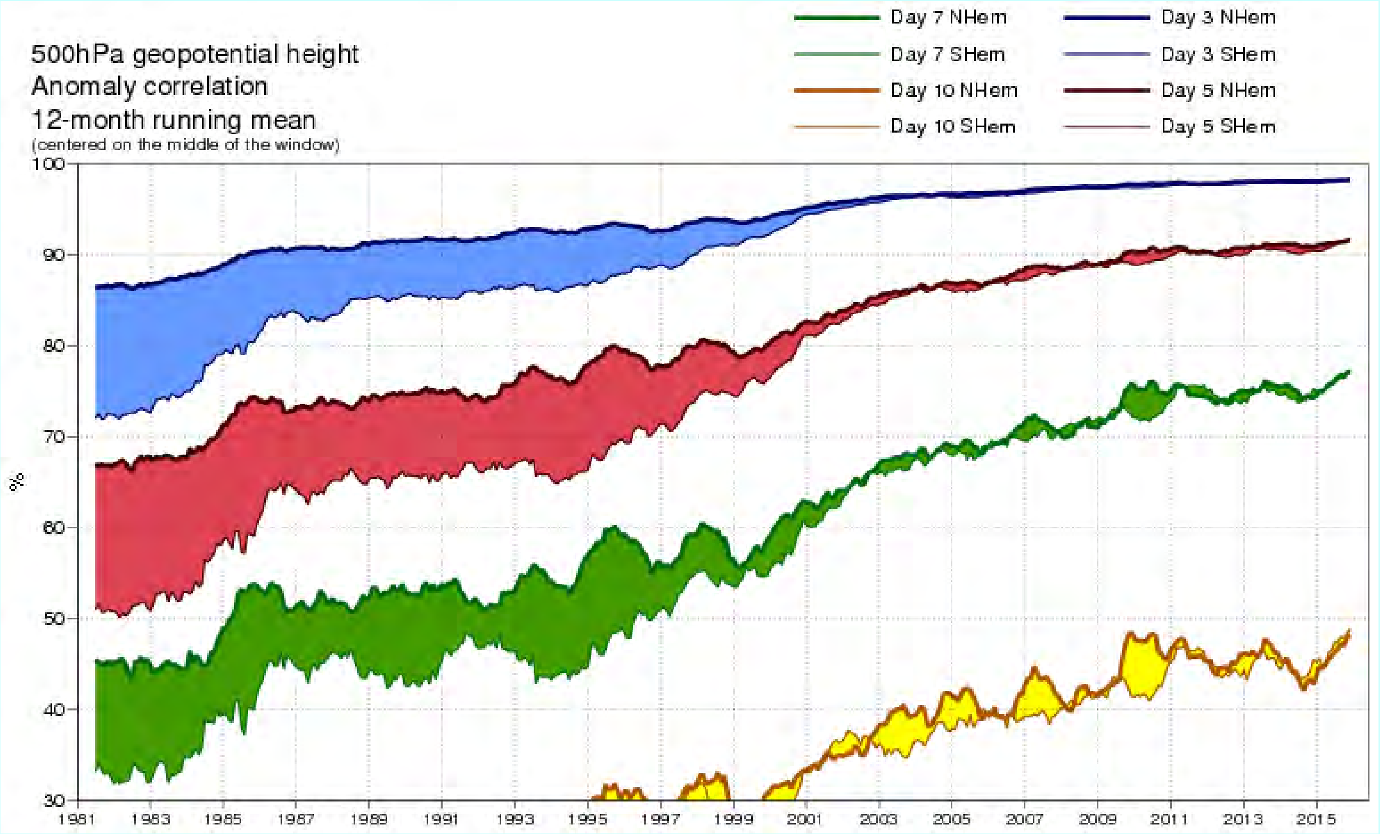
Numerical weather prediction



4D-Var introduced

Assimilation update

From www.ecmwf.int

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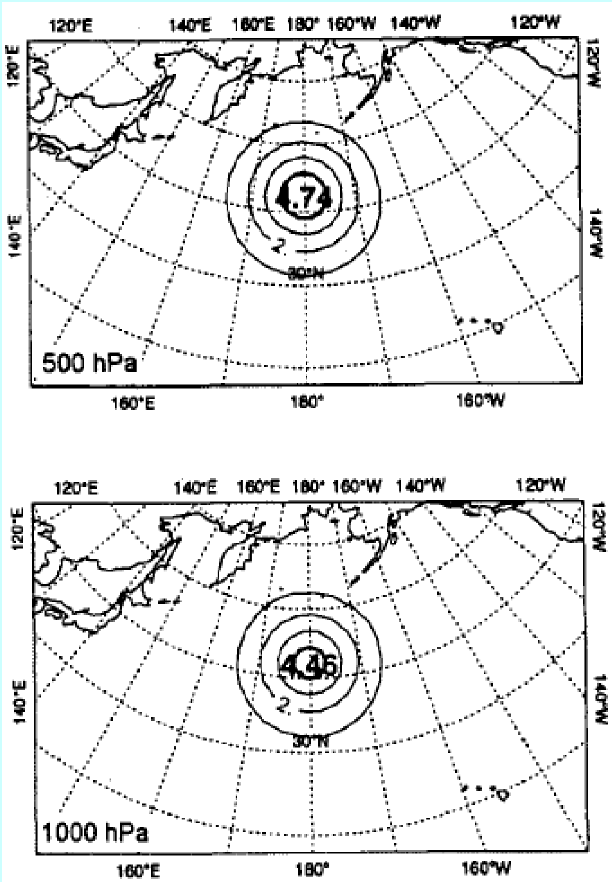
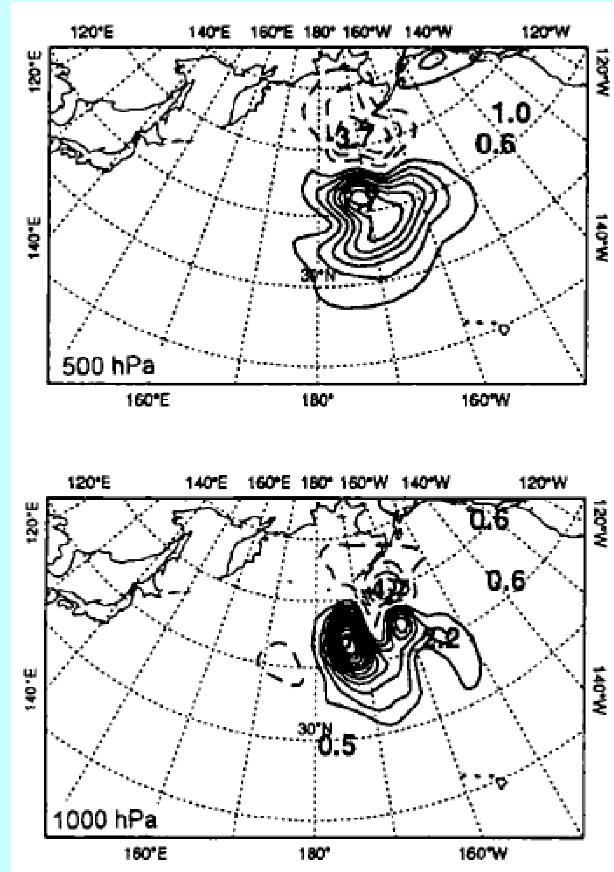
Flow-dependent covariances





3D-Var 4D-Var

Increments from single observation of height at 500 hPa.

Thepaut et al. (1996)

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Next generation NWP assimilation

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

Various proposals:

- En4DVar
- 4DEnVar
- Ensembles of 4DEnVar
- …

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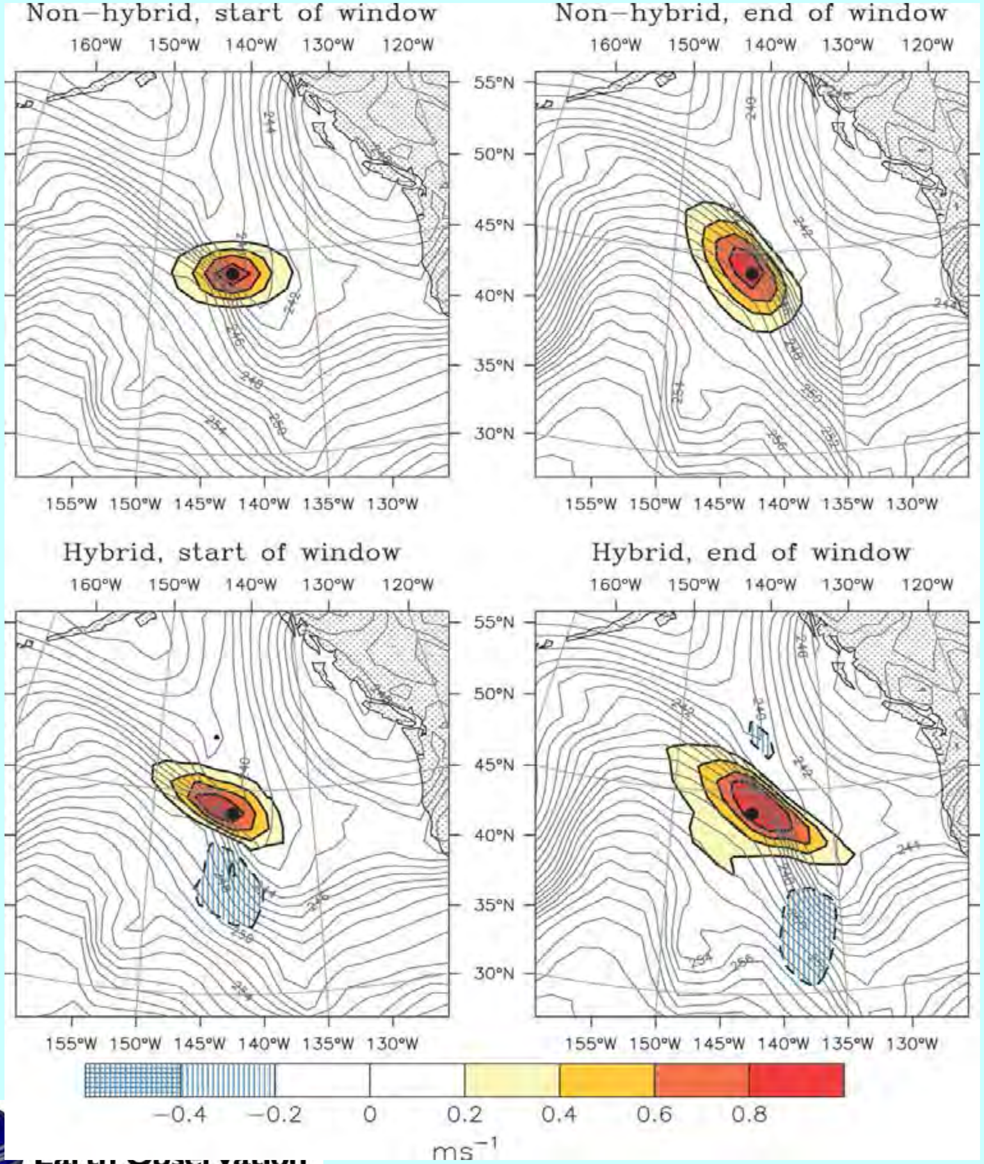
Met office implementation



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)

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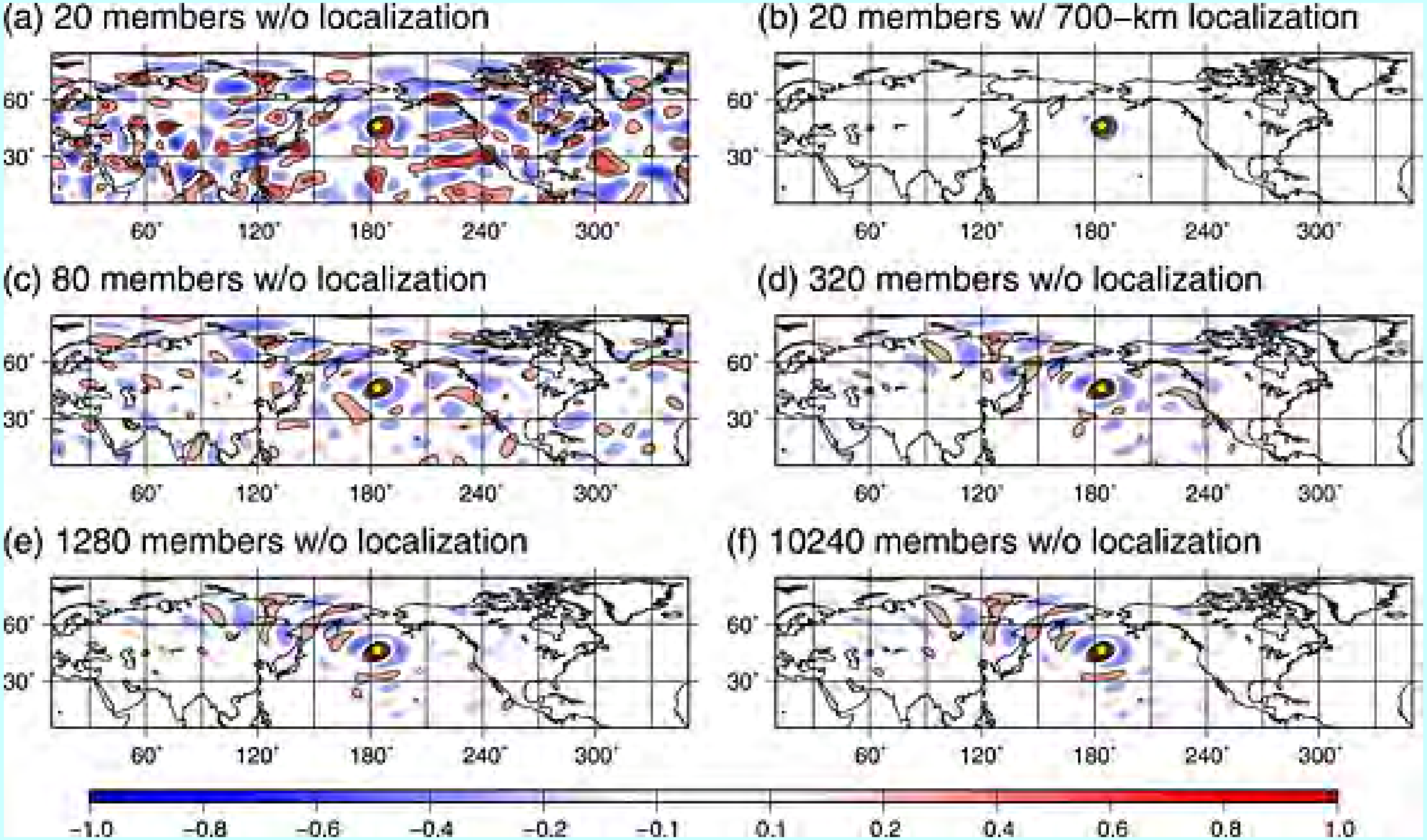
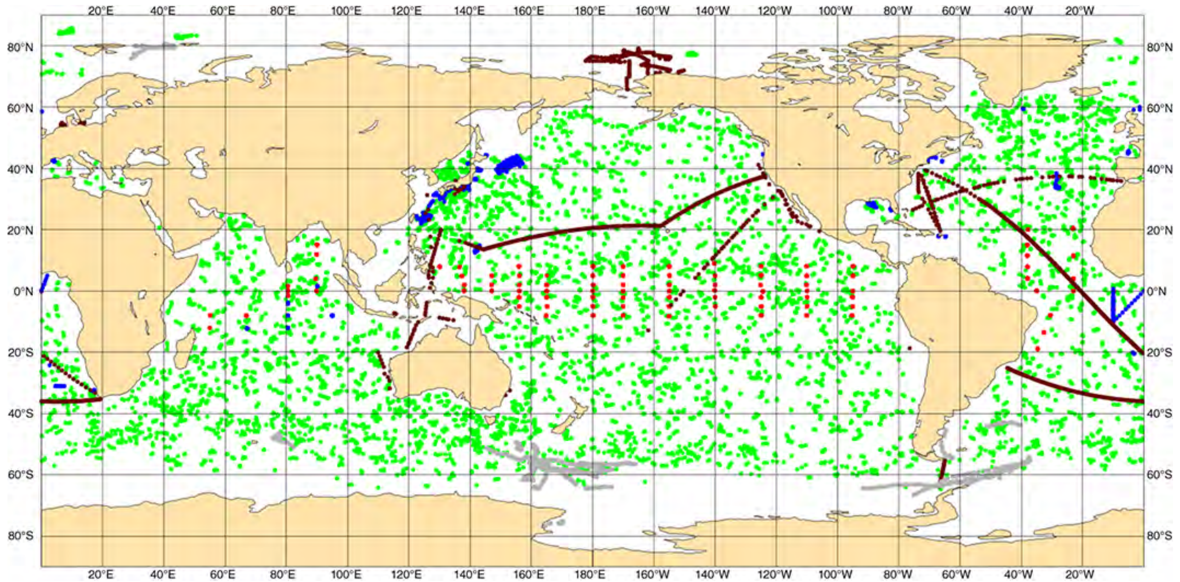
Localisation



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

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Figure from *Lalayoux et al (2016)*

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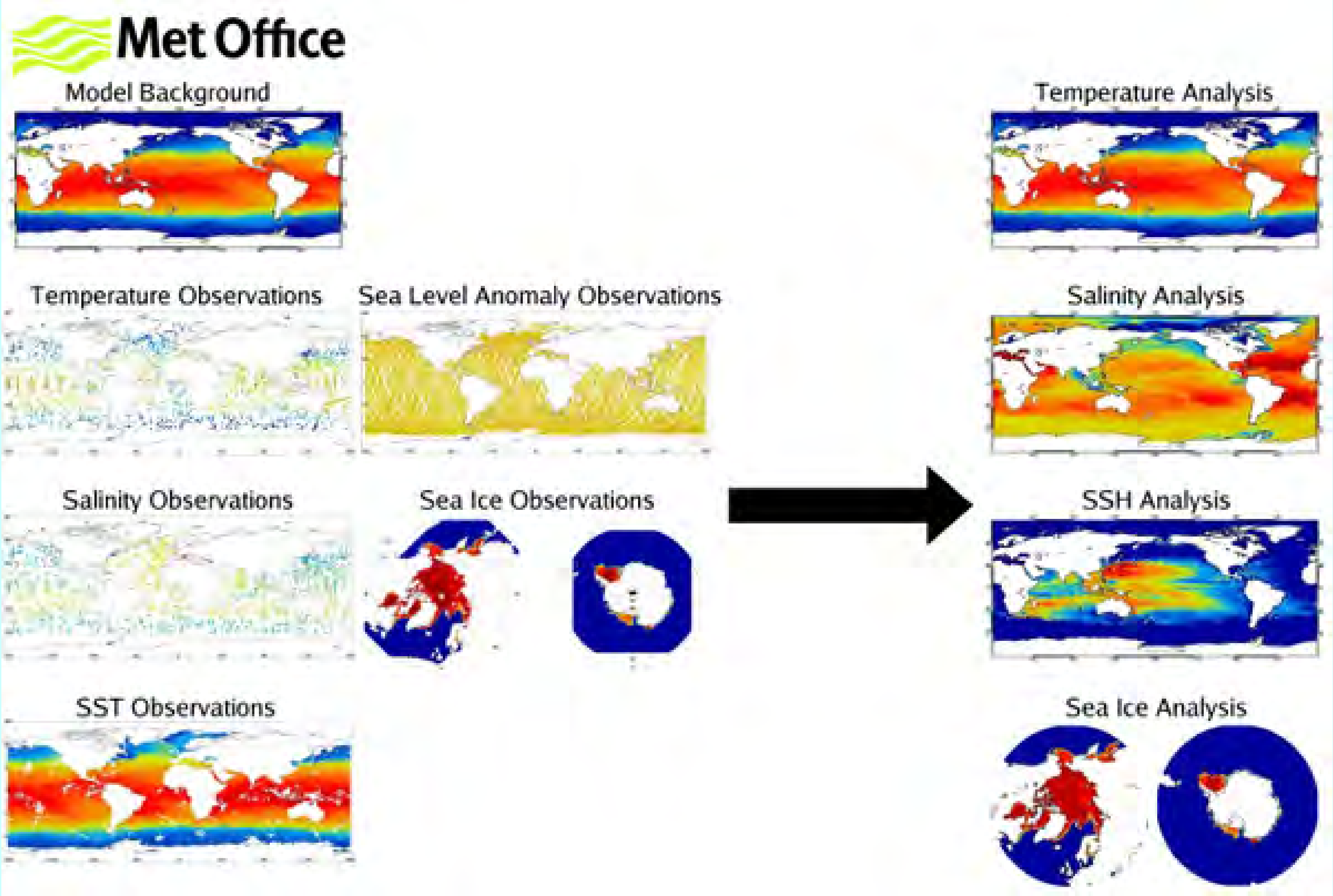

Figure from www.metoffice.gov.uk

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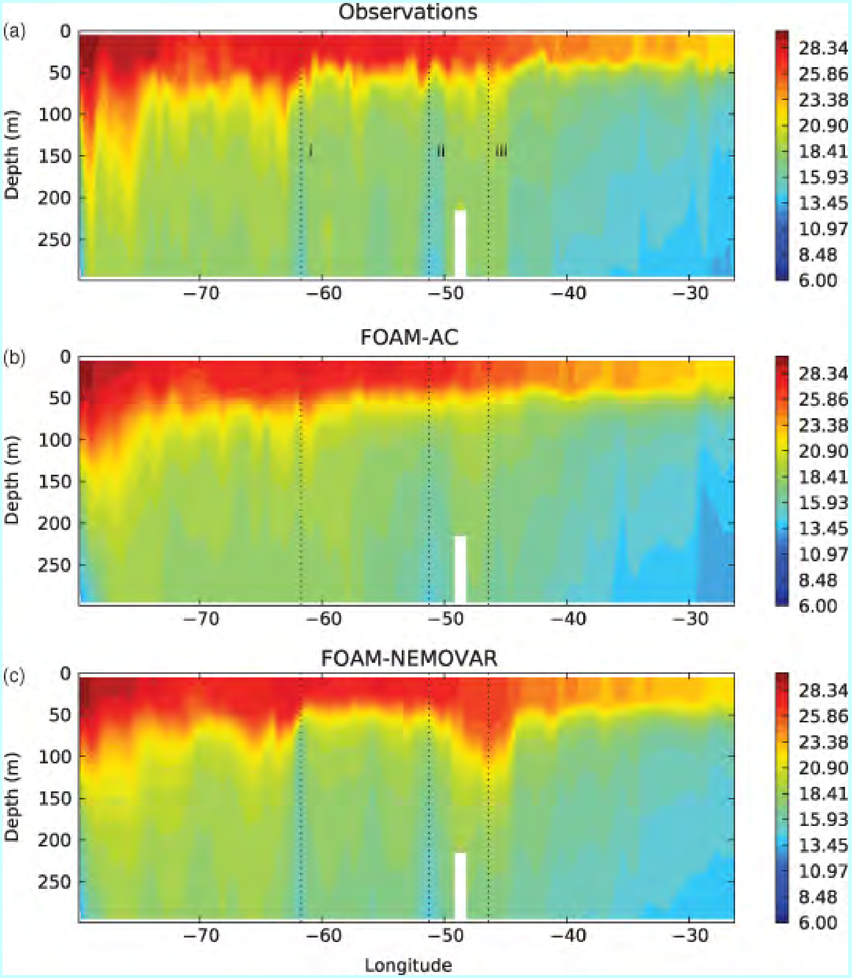
Implementing a variational data assimilation system in an operational 1/4 degree global ocean model



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Waters et al (2015)

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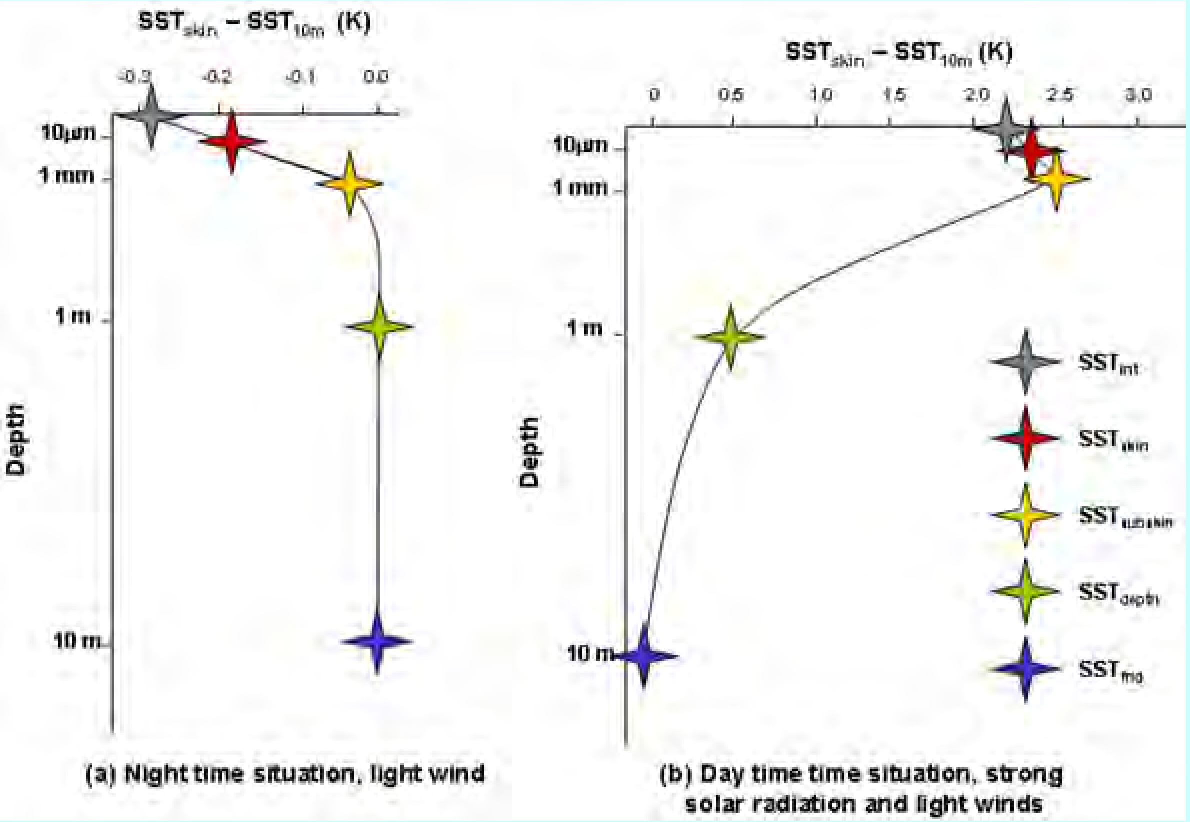
Sea surface temperature



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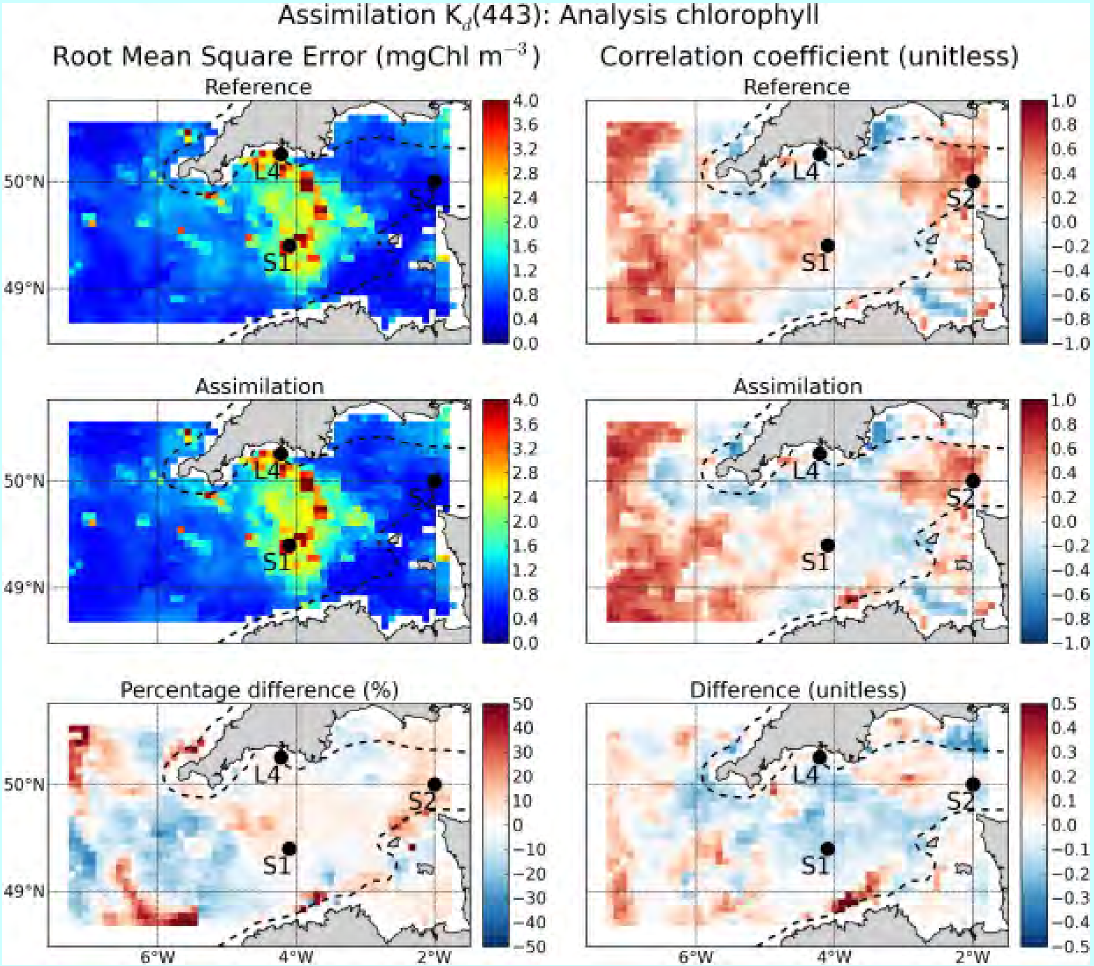
Ocean colour - Chlorophyll



Ciavatta et al (2014)

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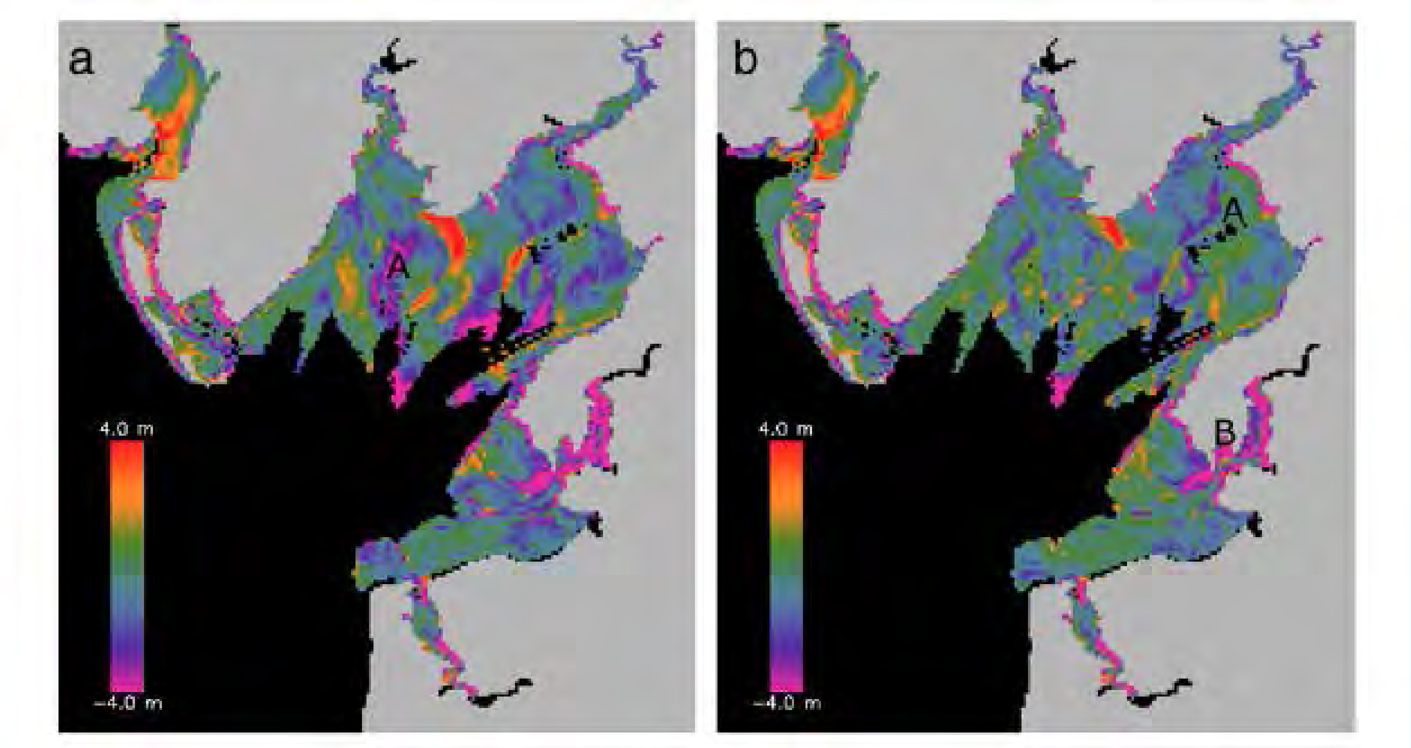
Coastal bathymetry



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

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Carbon cycle

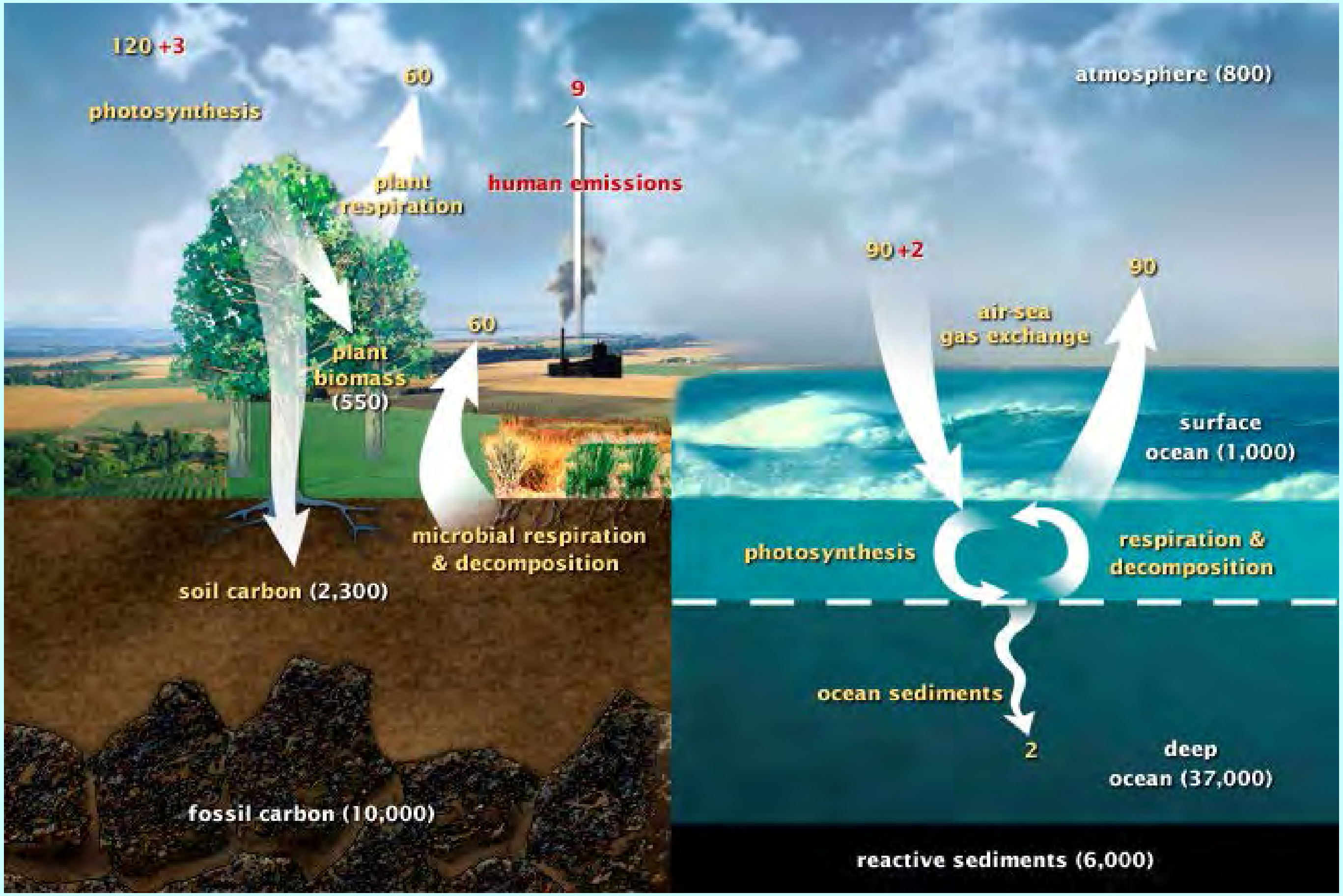

Figure from http://earthobservatory.nasa.gov

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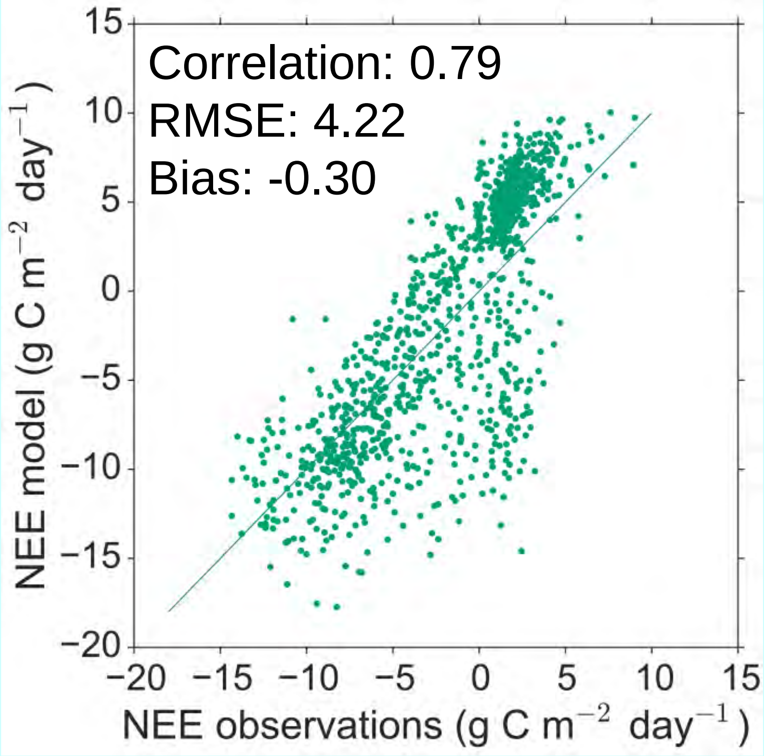
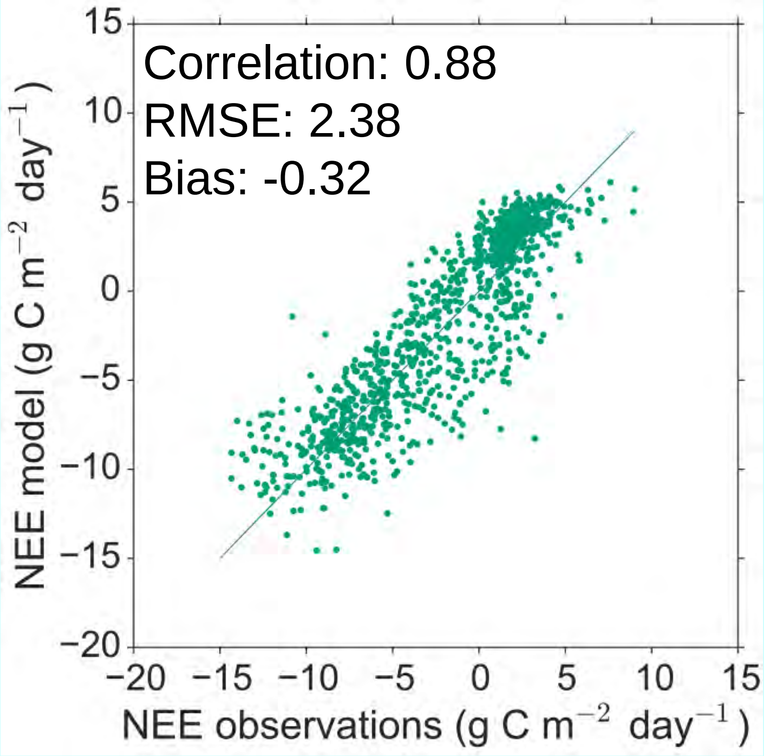
Assimilation of Net Ecosystem Exchange observations into a carbon cycle model – Forecast 2000-2013



No correlations



With correlations

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Pinnington et al (2016)

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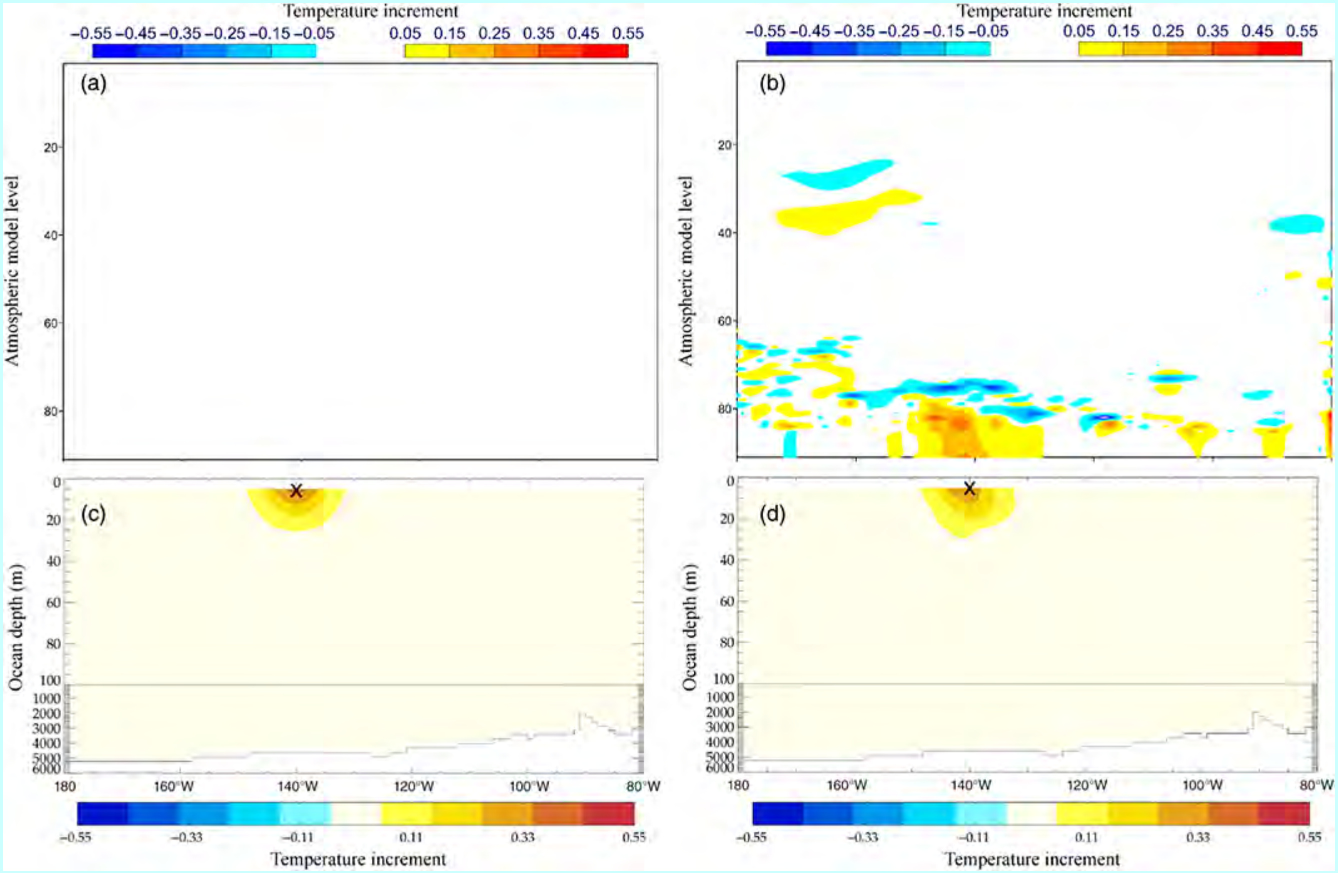
Coupled atmosphere-ocean DA

- The sea surface provides a lower boundary for the atmosphere – important for seasonal to decadal forecasts.
- Currently atmosphere and ocean systems are initialised separately using data assimilation.
- Forecasting centres want to implement coupled data assimilation, even for numerical weather prediction.
- Variational or ensemble methods?

Coupled atmosphere-ocean DA

Atmos

Ocean



Start of assimilation window

End of assimilation window

ECMWF system - *Lalayoux et al (2016)*

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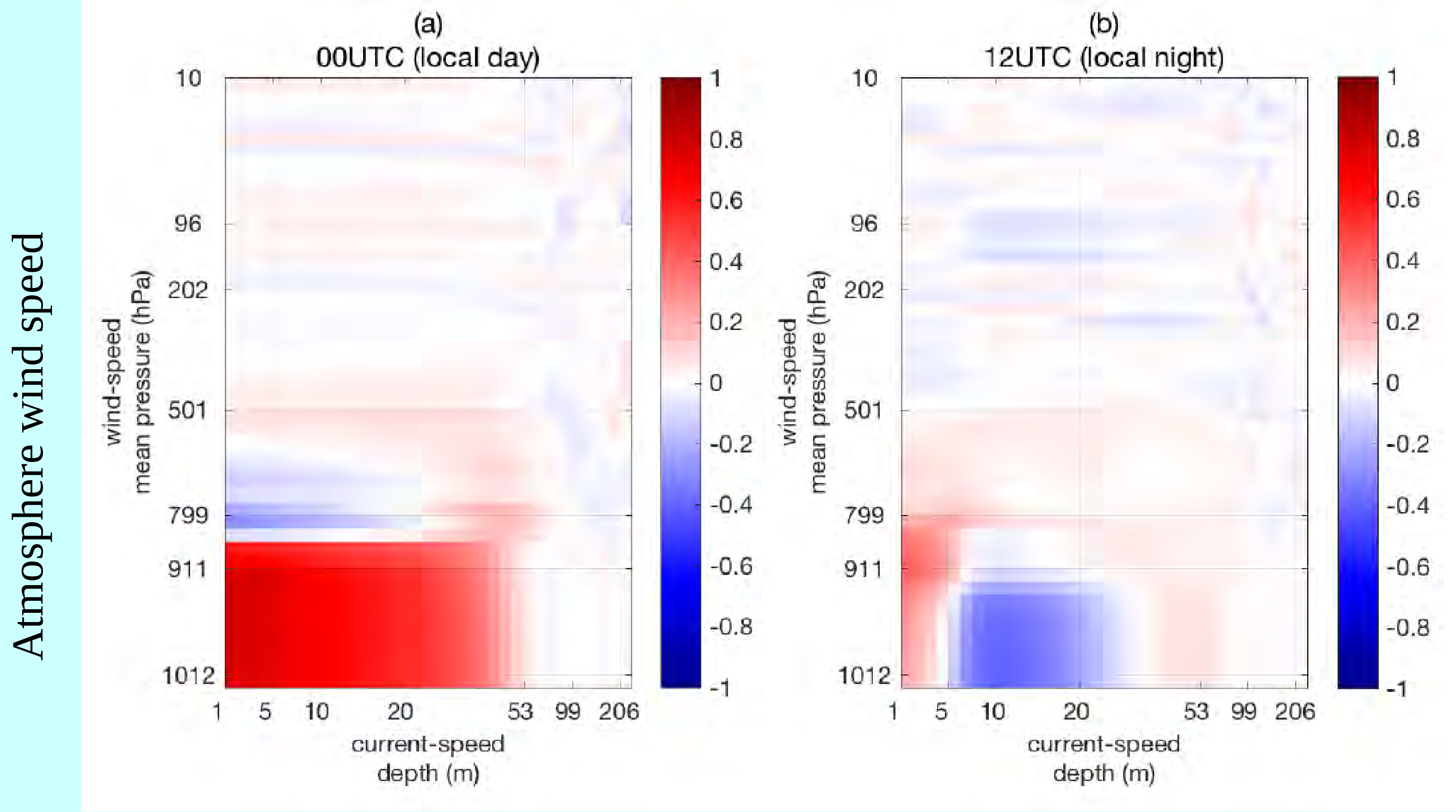
Atmosphere-ocean cross-correlations



Ocean current speed

Ocean current speed

Smith et al (2017)

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Reanalysis

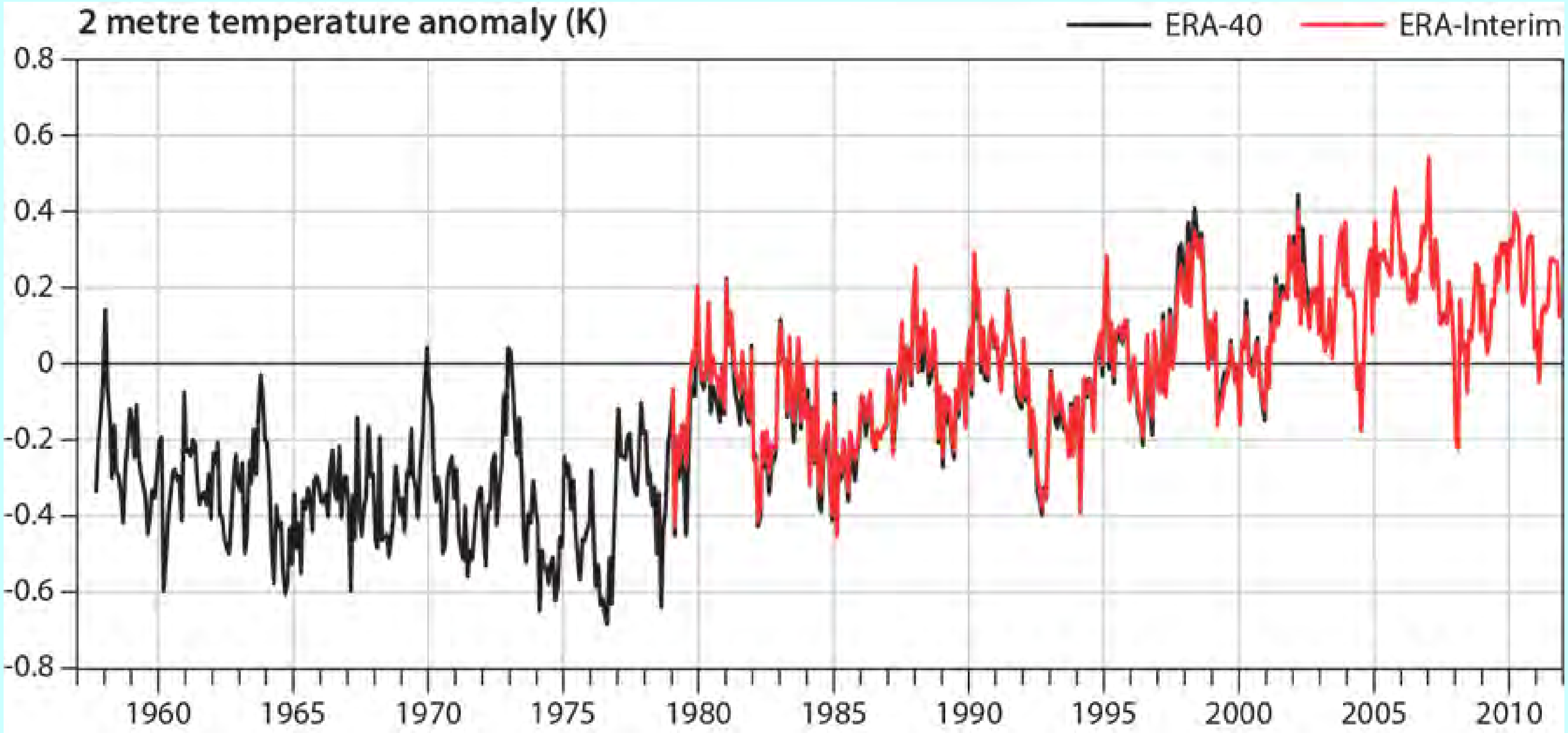

Figure from www.ecmwf.int

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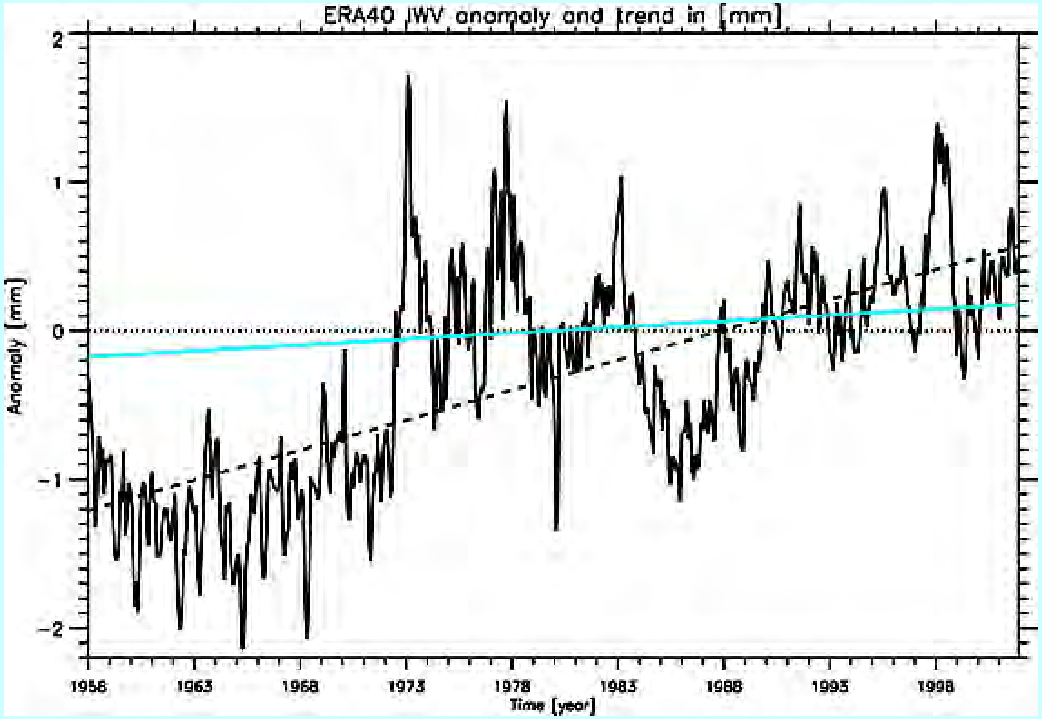
Can climate trends be calculated from reanalysis data?



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

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Observation System Simulation Experiments (OSSEs)

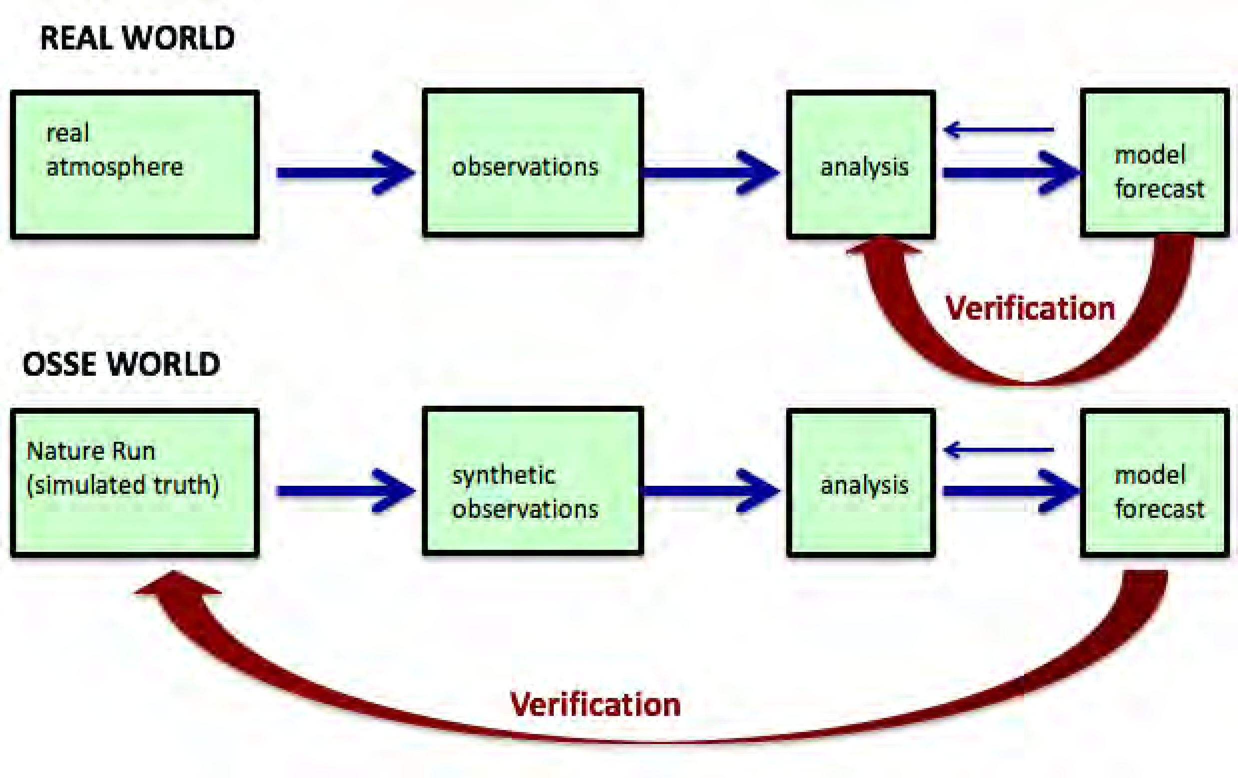

Figure from http://www.esrl.noaa.gov/gsd/gosa/ose-osse.html

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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.

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Some current challenges

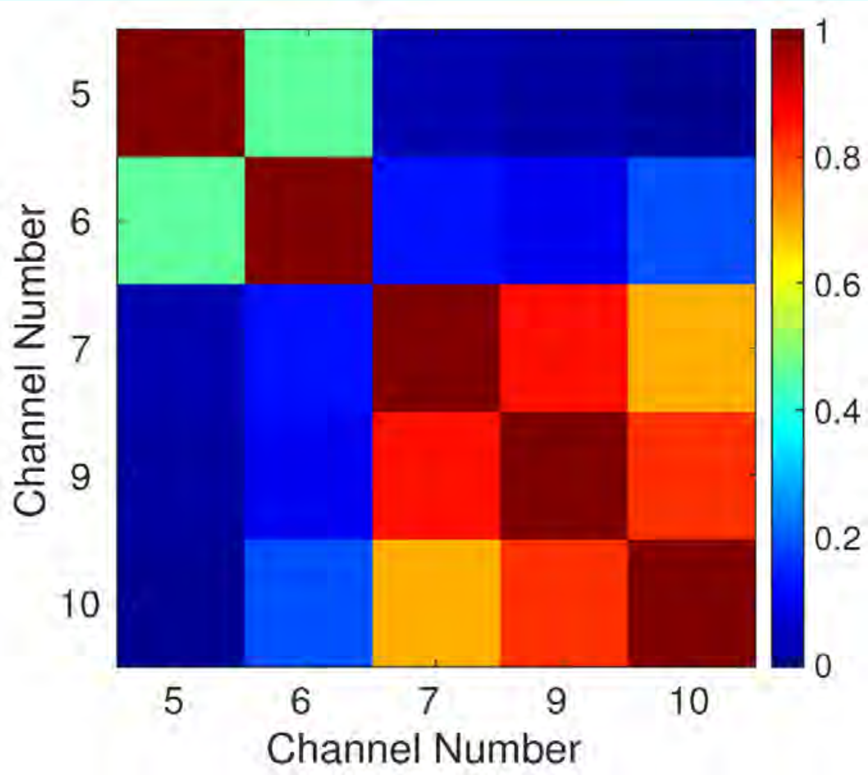
Challenges: Data amount

- 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)*

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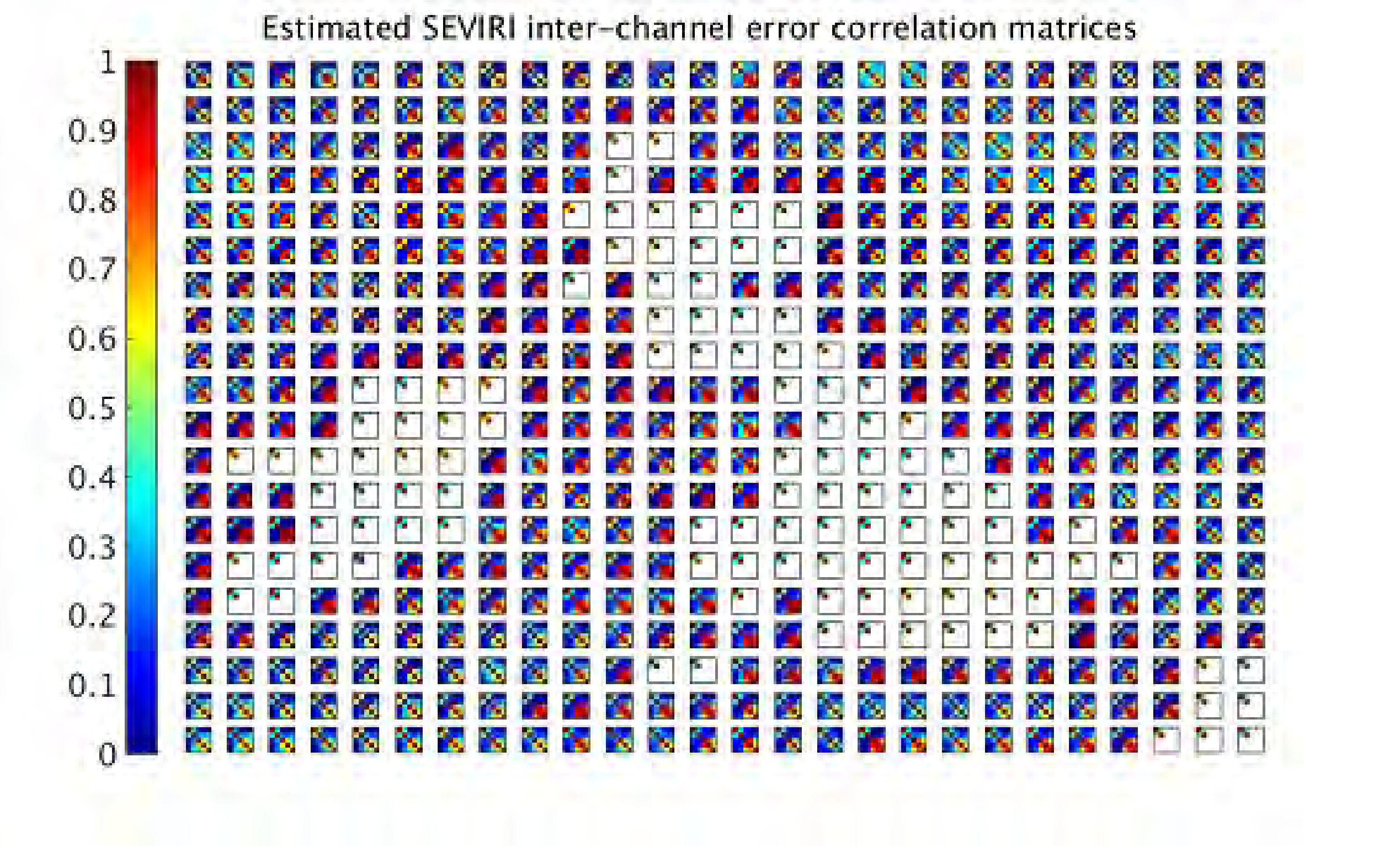

Spatial variation of estimated observation error correlation matrix for assimilated SEVIRI channels.

From *Waller et al (2016)*

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Challenges: Bias correction

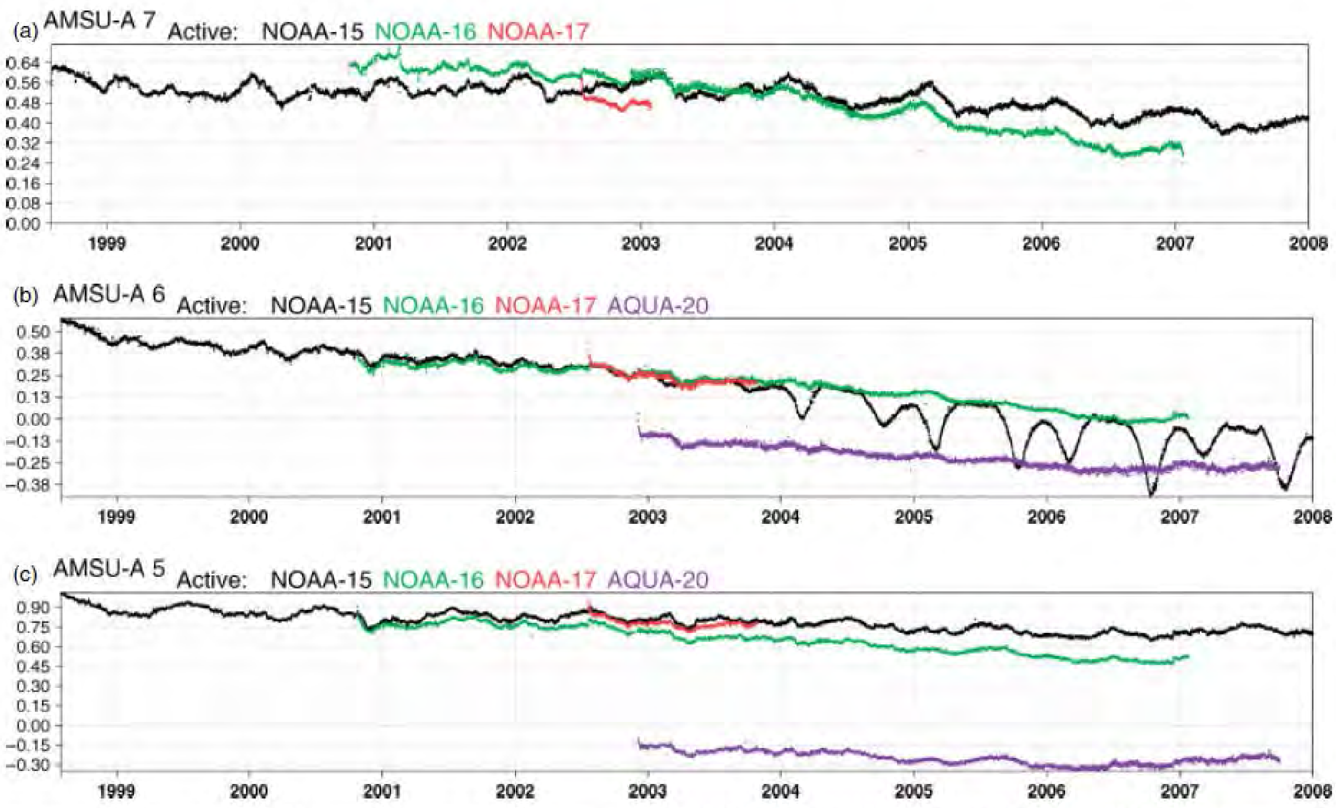

Figure 7. Globally averaged 12-hourly bias estimates (K) from NOAA-15, NOAA-16, NOAA-17, and AQUA for AMSU-A (a) channel 7, (b) channel 6, and (c) channel 5.

From *Dee and Uppala (2009)*

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Challenges: Model error

We consider that the model has unknown errors:

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

State formulation

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

Error formulation

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

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 **Q**. It is not obvious how this should be done.

Can we distinguish model and observation bias?

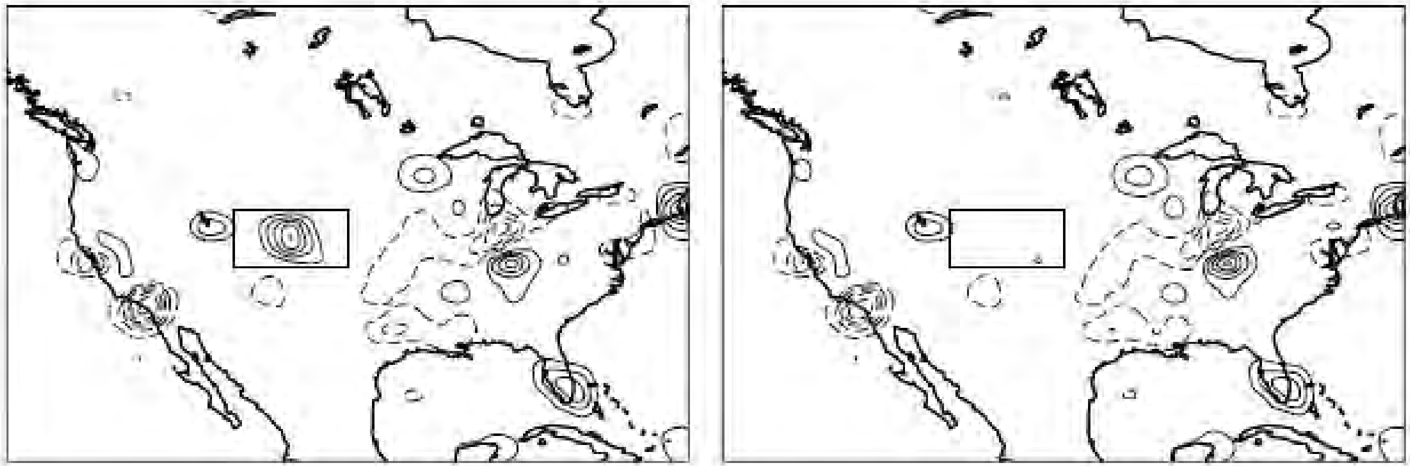

Figure 11. Average temperature forcing at the lowest model level over North America; with all data (left panel), and without aircraft data in the marked area (right panel). The contour interval is 0.01 Kh^{-1}.

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

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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.
- Move towards coupled Earth system models.
- 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.

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