Department of Meteorology

University of Reading

Using lagged covariances to assimilate RAPID data

Chris Thomas | Keith Haines | Irene Polo | Jon Robson

Introduction

Our objective is to assimilate RAPID data into a high-resolution ocean model in order to produce more dynamically consistent ocean states for use in coupled forecasting. To do this we will make use of robust covariance relationships between the AMOC at 26°N and high-latitude density anomalies. The strongest relationships are found at multi-year lags which cannot be used in a standard variational assimilation framework. We describe the methodology that has been developed to achieve this and show some preliminary results from the RAPID assimilation.

Methodology and idealised study

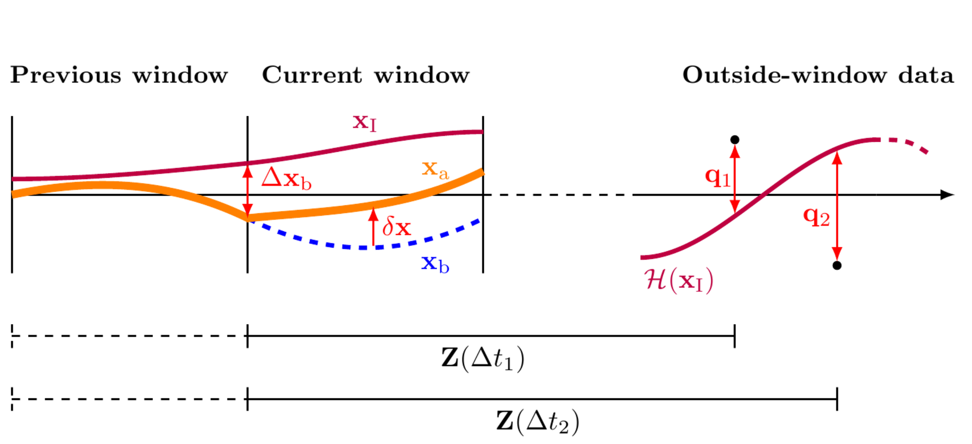

Figure 1: Schematic of two-stage assimilation procedure as described in the text.

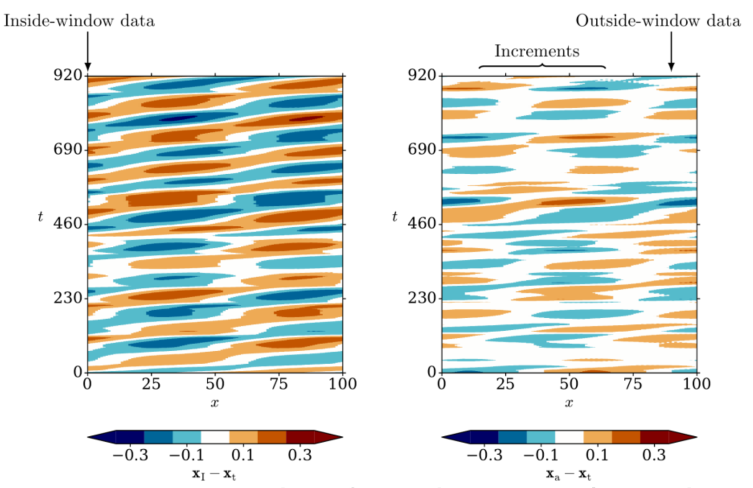

Figure 2: Results of simulation study: analysis errors for (left) first (right) second stage.

- Two-stage assimilation procedure (schematic in Fig. 1).
- Stage 1 is a standard short-window 3DVar assimilating other time-coincident data, producing trajectory $\mathbf{x}_\mathrm{I}$.
- Stage 2 repeats 1, also assimilates lagged data from several years in the future.
- Use robust time-lagged covariances to augment standard variational scheme, which cannot deal with such long lags.
- New cost function term:

$$J_c(\delta\mathbf{x}) = \frac{1}{2}\sum_i [\mathbf{q}_i - \mathbf{Z}_i(\delta\mathbf{x} + \Delta\mathbf{x}_\mathrm{b})]^\mathrm{T}\mathbf{R}_i^{-1}[\mathbf{q}_i - \mathbf{Z}_i(\delta\mathbf{x} + \Delta\mathbf{x}_\mathrm{b})]$$

where the index i runs over the lags used, $\mathbf{q}_i$ are the innovations between RAPID data and the initial trajectory, $\mathbf{R}_i$ are error covariance matrices, $\mathbf{Z}_i$ incorporate the lagged covariances, $\mathbf{x}_\mathrm{b}$ is the background trajectory in the second run and $\Delta\mathbf{x}_\mathrm{b} = \mathbf{x}_\mathrm{b} - \mathbf{x}_\mathrm{I}$ always references the AMOC innovations to the trajectory $\mathbf{x}_\mathrm{I}$, enabling consistent influence from $\mathbf{q}_i$ over several windows. The increments $\delta\mathbf{x}$ are used to produce the final analysis $\mathbf{x}_\mathrm{a}$.

- The lag-covariance matrix $\mathbf{Z}_i$ plays the role of $\mathbf{H}_i\mathbf{M}_i$ term in classical 4DVar and can be determined by applying linear regression to *e.g.* a long model run.
- This method avoids need for a computationally expensive adjoint.
- Methodology tested in simple advection model (Thomas and Haines, 2017).
- First stage assimilates standard data using 3DVar-FGAT, and second stage also assimilates future data using lagged regressions.
- Results (Fig. 2) indicate improved analysis errors after second stage.

RAPID assimilation configuration

- We have implemented the lagged regression methodology in NEMOVAR code which is used operationally at Met Office & ECMWF.
- First stage is similar to GloSea5 reanalysis (Jackson *et al*., 2016). The following data sets are assimilated: GHRSST and in-situ SST (ICOADS), altimetry, EN4 profiles and sea ice (OSI-SAF).
- The second stage additionally assimilates RAPID data.

Lagged regressions

- Regressions determined using 120y HadGEM3-GC2 coupled ocean-atmosphere run; 0.25° ocean (same as GloSea5).
- Fig. 3 shows AMOC anomalies from this run.

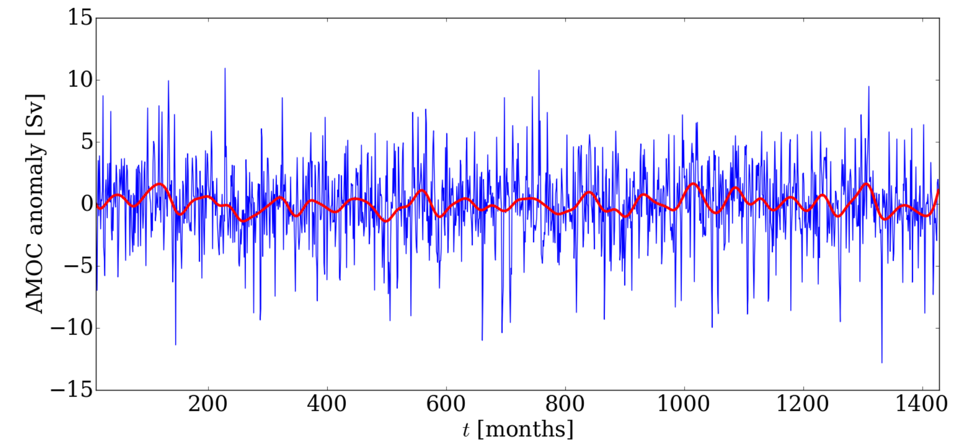

Figure 3: AMOC anomaly at 26°N in 120 years HadGEM3-GC2. The blue line shows the value every month and the red line is the two-year running mean.

- Fig. 4 shows **Z** matrix at a lag of 4 years between 3D Lab. Sea T and 26N AMOC. Regression uses EOF of T that explains most variance.

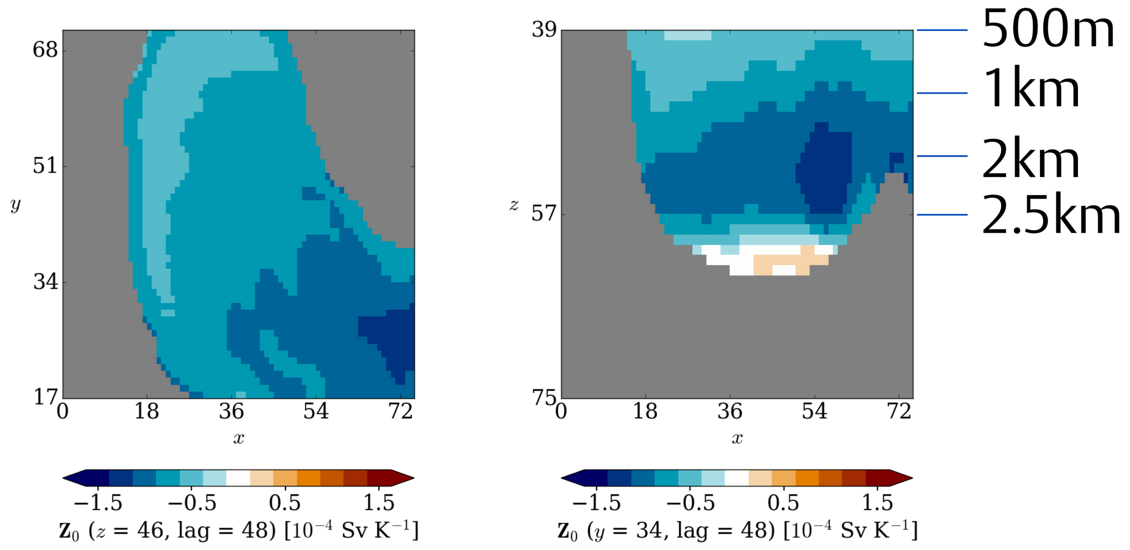

Figure 4: Regressions between 3D Lab. Sea T and AMOC with a 4-year lag: (left) 1km depth (right) 60°N.

- The negative T-AMOC correlation corroborates relationships observed previously in runs separating buoyancy and wind forcing (Polo *et al*., 2014), and other studies show similar relationships.

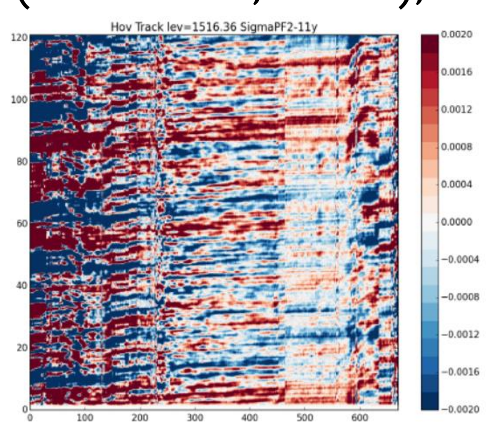

Figure 5: Hovmöller diagram of density along boundaries at 1500m depth.

- Labrador sea signals then propagate down Western boundary (Fig. 5, 6); differing vertical density structures and speeds (Polo *et al*., 2017).
- These low-freq. boundary signals can inform $\mathbf{q}_i$.

Figure 6: Boundary path used to study signal propagation.

Preliminary results

- So far have run a three-month test of two-stage methodology.
- Regression patterns from HadGEM3 used with assumed RAPID-model difference ($\mathbf{q}$) of 3±1Sv.
- Fig. 7 shows difference between the analysed T in the Labrador Sea region for the two stages after three months.
- Influence of lagged assimilation clearly observable, particularly at larger depth where noise is less important.

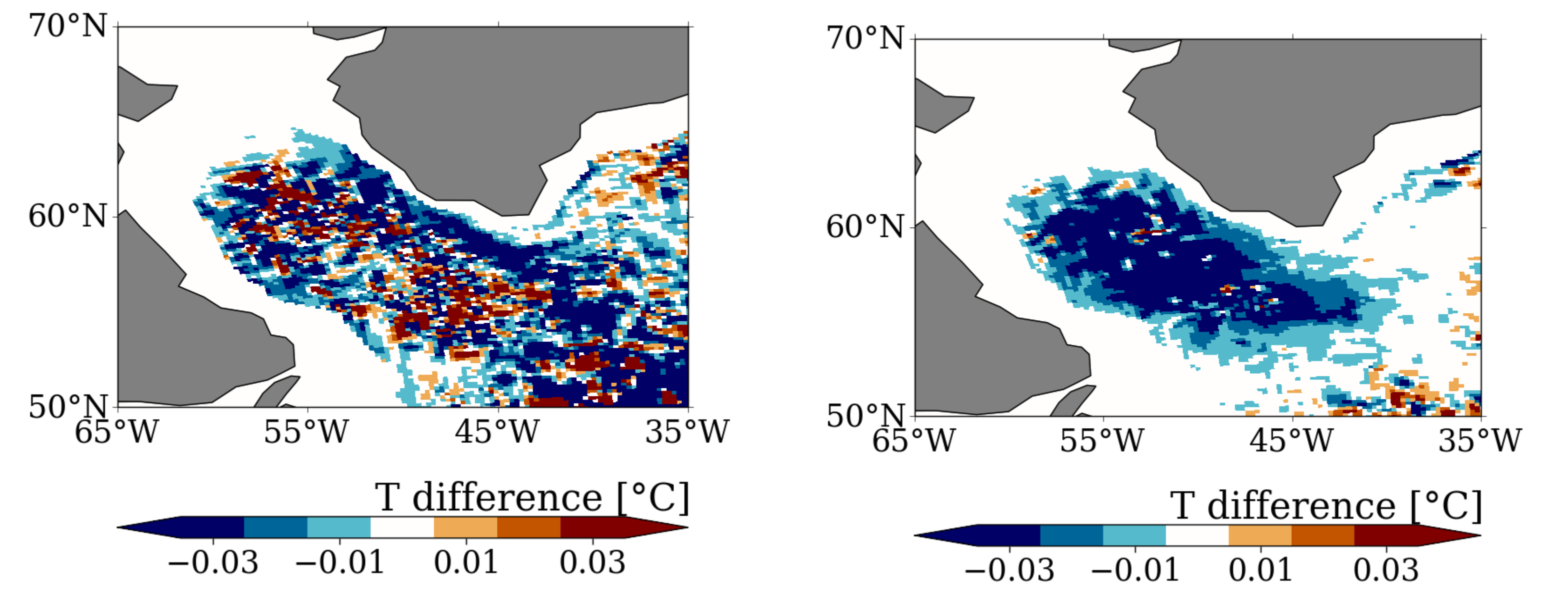

Figure 7: Difference between analysed T in Lab Sea region at depth (left) 1km (right) 2km.

Future work

- Finalise choice of lags and spatial patterns.
- Study boundary EOFs at 26°N which enable propagating signal related to low-frequency AMOC to be identified.
- Perform full assimilation spanning multiple years (2007-2015).
- Evaluate performance (e.g. AMOC impact).
- Output will be used to initialise coupled decadal climate prediction experiments.

References

1. Thomas and Haines (2017), Using lagged covariances in data assimilation, submitted to Tellus A.
2. Polo *et al.* (2014), The importance of wind and buoyancy forcing for the boundary density variations and the geostrophic component of the AMOC at 26°N, J. Phys. Oceanogr., 44, 2387-2408.
3. Polo *et al.* (2017), Signature of buoyancy forced AMOC signals at 26°N in NEMO 1 degree model, in preparation.
4. Jackson *et al.* (2016), Recent slowing of Atlantic overturning circulation as a recovery from earlier strengthening, Nat. Geo. 9, 518-522.

Acknowledgements

- We gratefully acknowledge support from NERC under the RAPID program.

Contact information

- Department of Meteorology, University of Reading, Whiteknights, RG6 6AH, UK
- Email: c.m.thomas@reading.ac.uk

NERC SCIENCE OF THE ENVIRONMENT