Estimating forecast error covariances for strongly coupled atmosphere-ocean 4D-Var data assimilation

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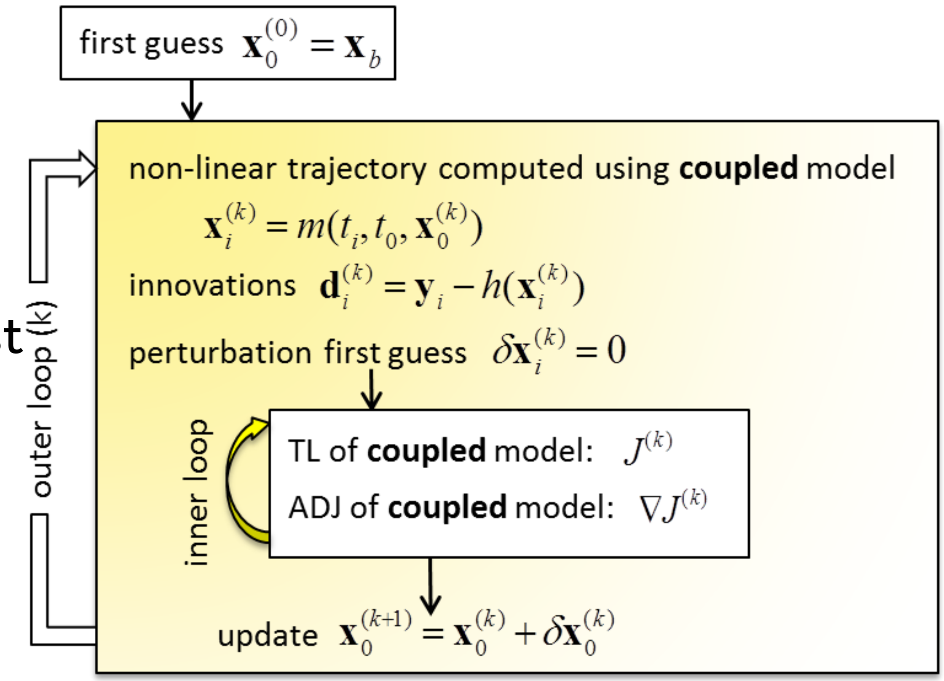
Strongly coupled incremental 4D-Var

- control vector contains both atmosphere & ocean model variables
- fully coupled tangent linear & adjoint models
- allows for cross-domain covariances between atmosphere & ocean forecast errors

$$\mathbf{B}_0 = \begin{pmatrix} \mathbf{B}_{\mathrm{AA}} & \mathbf{B}_{\mathrm{AO}} \\ \mathbf{B}_{\mathrm{AO}}^{\mathrm{T}} & \mathbf{B}_{\mathrm{OO}} \end{pmatrix}$$



- atmosphere observations can influence ocean analysis and vice versa
- leads to greater balance

Idealised system

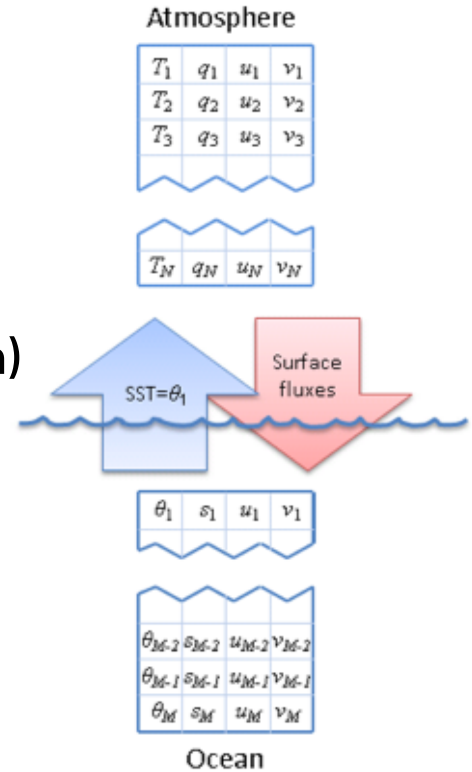
single-column, coupled atmosphere-ocean model

Atmosphere

- simplified version of the ECMWF single column model
  adiabatic component + vertical diffusion (no convection)
- 4 state variables on 60 model levels (surface to ~0.1hPa)
- forced by large scale horizontal advection

Ocean

- K-Profile Parameterisation (KPP) mixed-layer model
- 4 state variables on 35 model levels (1-250m)
- forced by short and long wave radiation at surface



coupled via SST and surface fluxes of heat, moisture & momentum

Smith et al 2015, doi:10.3402/tellusa.v67.27025

This talk

cross-domain forecast error covariances in strongly coupled 4D-Var atmosphere-ocean data assimilation

1. **Coupled error covariance estimation**
   - analysis-ensemble method
2. **Implementation**
   - single & double observation experiments
   - full **B** vs. block diagonal **B**

Ensemble error covariances

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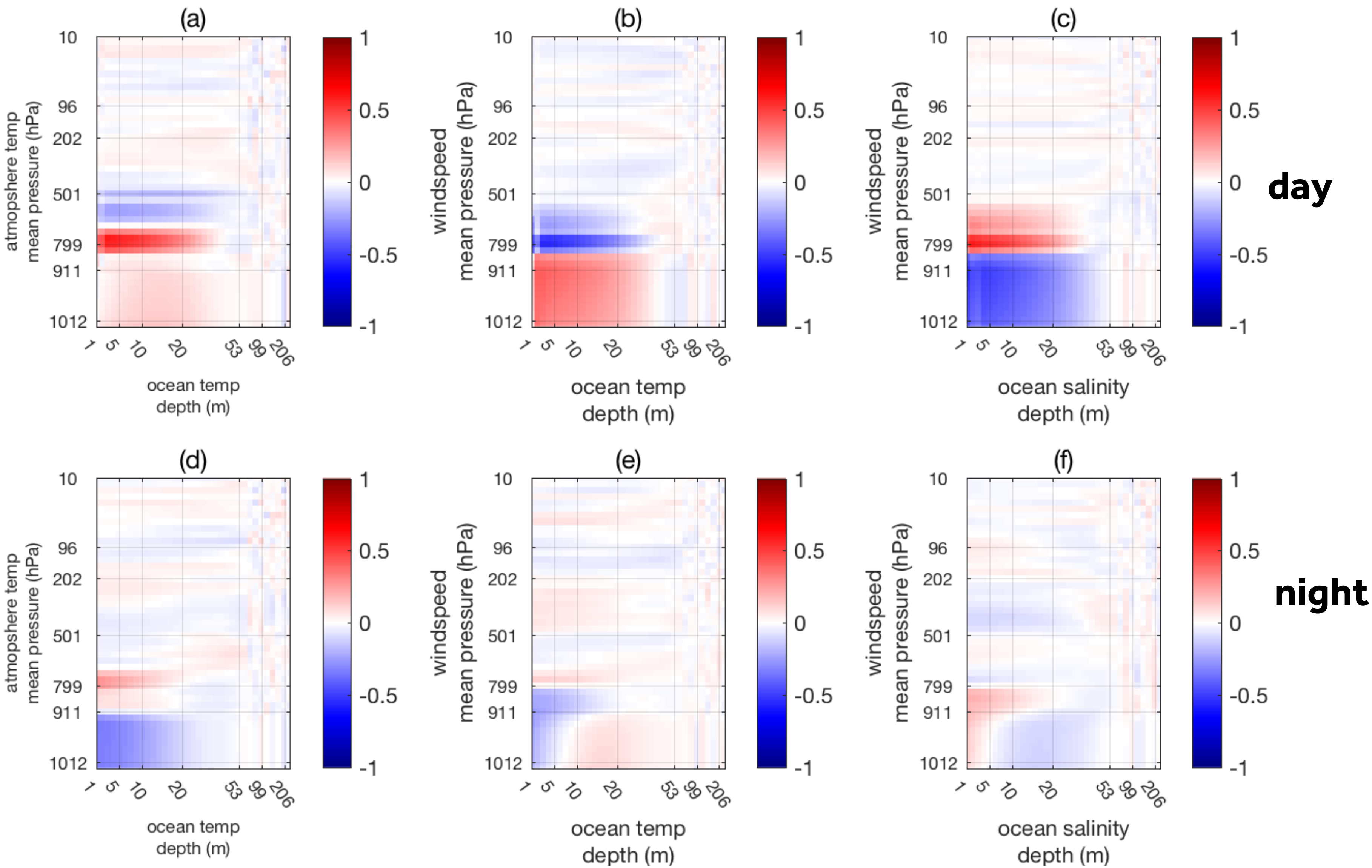
- experiments are identical twin, repeated using data for June & December 2013, point in NW Pacific Ocean.
- estimate background error covariance from a 500 member ensemble of perturbed strongly coupled 4D-Var analyses.
- average over a several assimilation cycles to increase effective ensemble size.
- 8 cycles, each uses 12 hour assimilation window.
- each cycle starts at either 12 UTC or 00 UTC which corresponds to the early hours of the morning and early afternoon local time.
- allows comparison of day-night plus summer-winter error correlations.

Questions: part 1

- where are the atmosphere-ocean cross-domain forecast error correlations strongest?
- how do the structures vary between summer and winter, and between day and night?
- can we explain our results by considering the underlying model physics, forcing and known atmosphere-ocean feedback mechanisms?
- what impact does using ensemble correlations to prescribe $\mathbf{B}_0$ have on a strongly coupled 4D-Var assimilation?

December case:

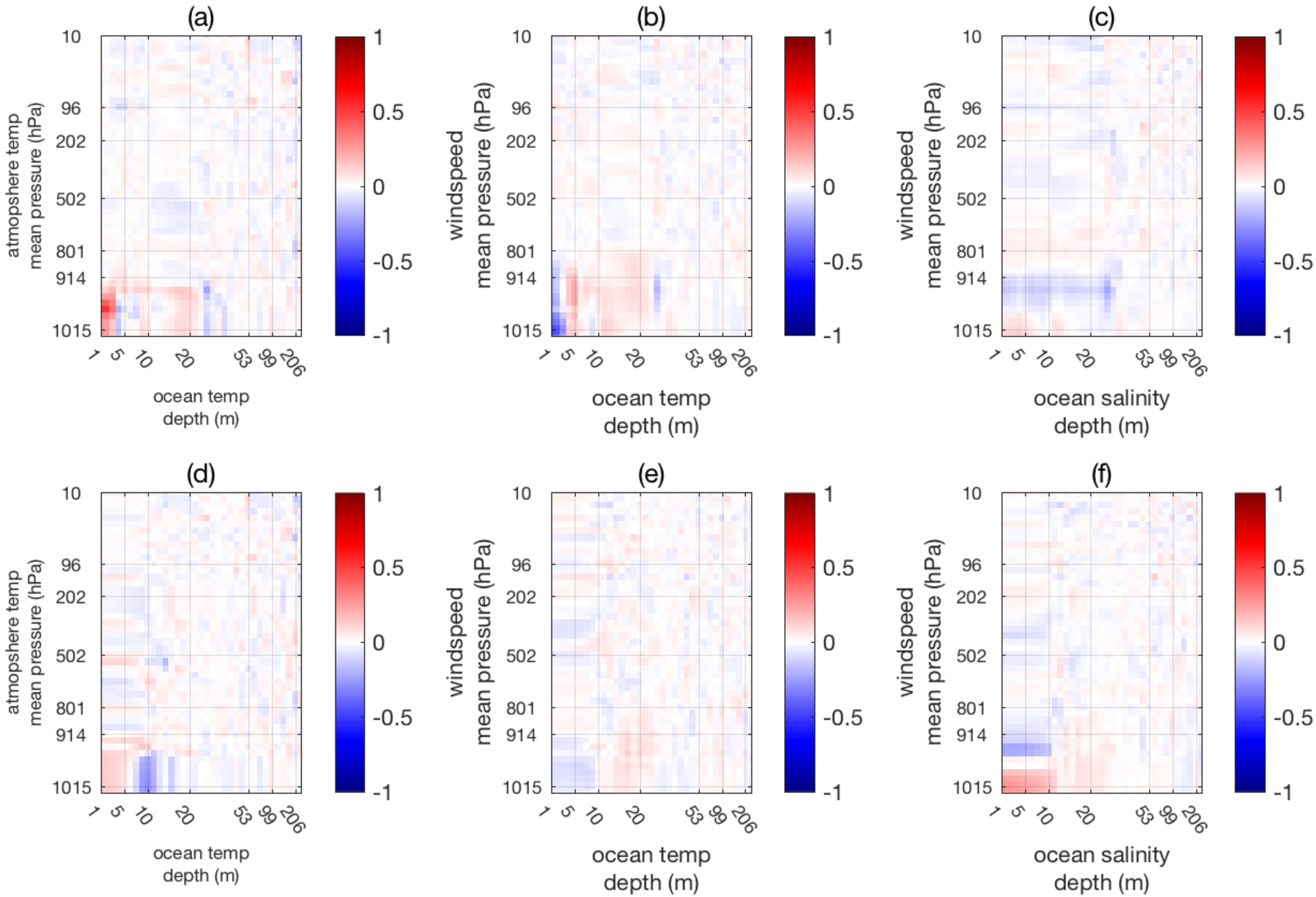
atmosphere-ocean error cross-correlations



left to right: atmosphere-ocean temp, wind speed-ocean temp, wind speed-ocean salinity

June case:

atmosphere-ocean error cross-correlations



day

night

left to right: atmosphere-ocean temp, wind speed-ocean temp, wind speed-ocean salinity

Key points: part 1

- strongest cross-domain error correlations are in near surface atmosphere-ocean boundary, beyond this atmosphere-ocean errors appear to be mostly uncorrelated.
- significant variation in cross-domain forecast error correlation structures between summer & winter, and between day & night.
- error correlation structures are most distinct in the winter case: effect of solar insolation on ocean stability is reduced, surface winds are high and the atmosphere-ocean surface temperature difference is large; these combine to produce turbulent heat fluxes of greater magnitude so that air-sea coupling is strong.
- results can be explained by consideration of the underlying model physics, forcing and known atmosphere-ocean feedback mechanisms: full details in Smith et al, MWR (2017).

Questions: part 2

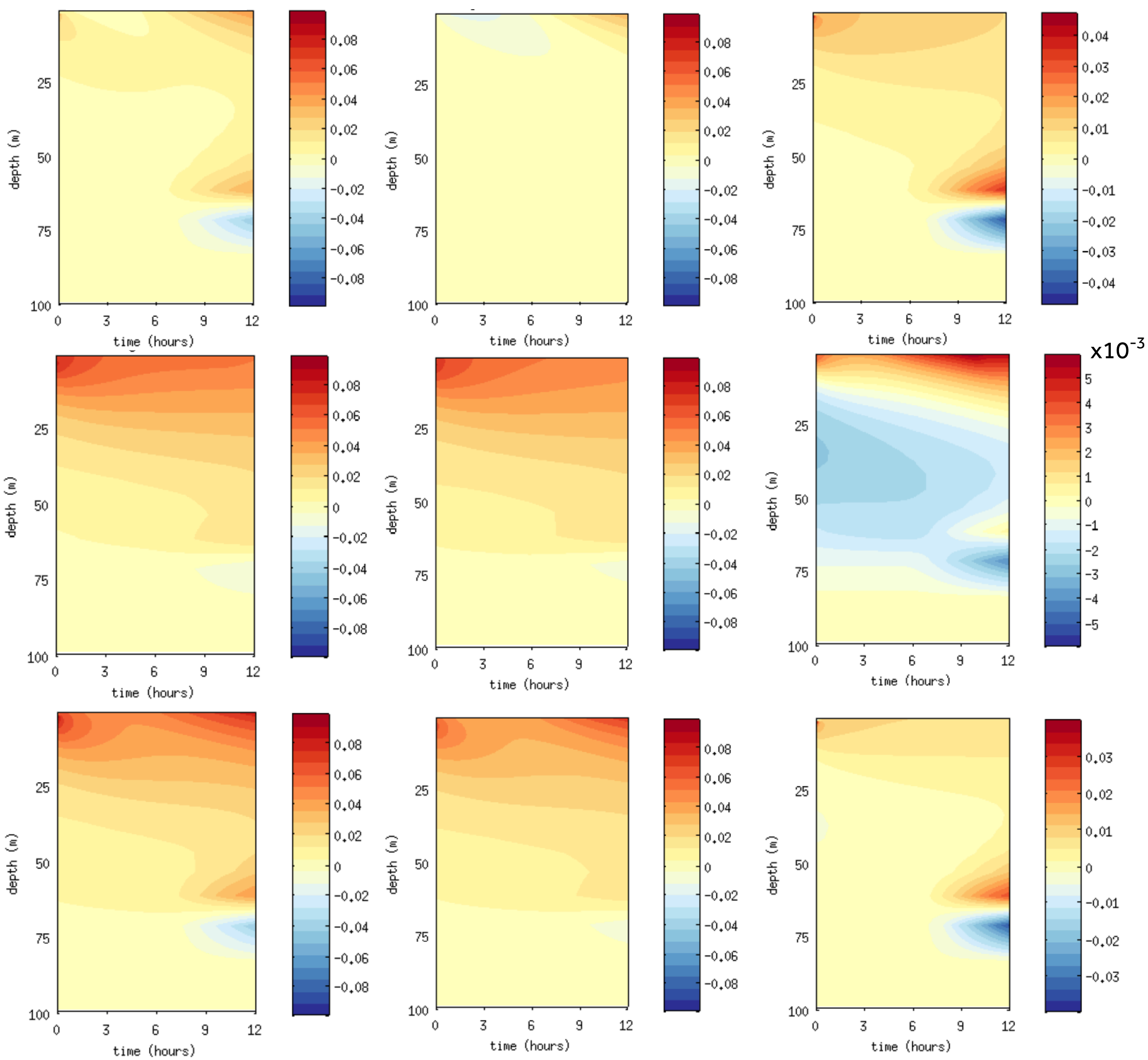
- where are the atmosphere-ocean cross-domain forecast error correlations strongest?
- how do the structures vary between summer and winter, and between day and night?
- can we explain our results by considering the underlying model physics, forcing and known atmosphere-ocean feedback mechanisms?
- what impact does using ensemble correlations to prescribe $\mathbf{B}_0$ have on a strongly coupled 4D-Var assimilation?

Single & double observation exp

analysis increments: ocean temperature

(a) full B | (b) $\mathbf{B}_{AO} = 0$ | difference (a)-(b)

$$\mathbf{B}_0 = \begin{pmatrix} \mathbf{B}_{AA} & \mathbf{B}_{AO} \\ \mathbf{B}_{AO}^{T} & \mathbf{B}_{OO} \end{pmatrix}$$



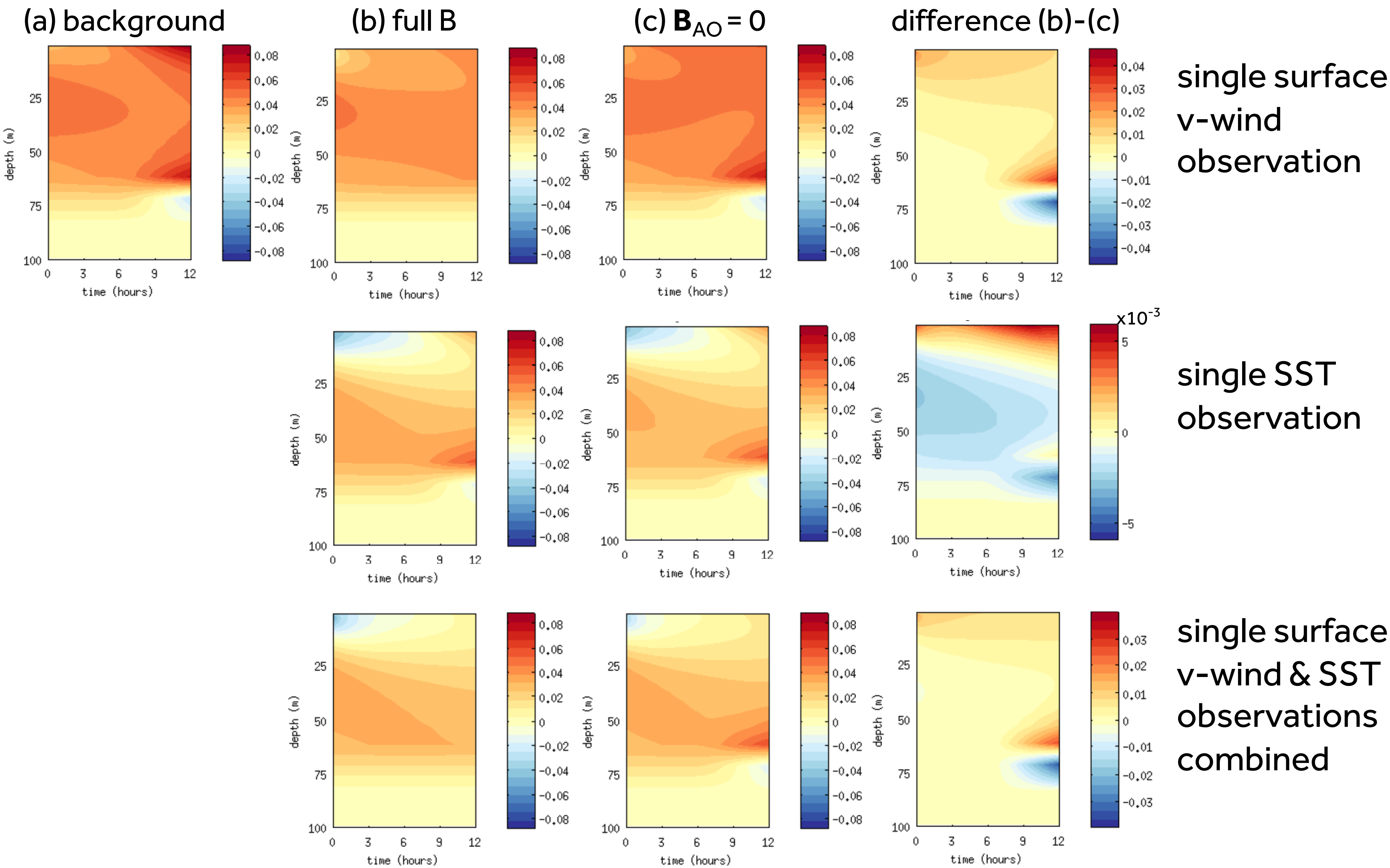
single surface v-wind observation (at end of 12hr window)

single SST observation

single surface v-wind & SST observations combined

Single & double observation exp

analysis errors: ocean temperature



Key points: part 2

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If only a single domain is observed:

- including explicit cross-domain forecast error covariances ($\mathbf{B}_{AO} \neq \mathbf{0}$) mostly impacts the unobserved domain.
- if $\mathbf{B}_{AO} = \mathbf{0}$ the initial increments in the unobserved domain rely on the implicitly generated cross-domain error covariances, which in turn depend on the strength of coupling in the TL model.
- setting $\mathbf{B}_{AO} = \mathbf{0}$ will always lead to a loss of information; the unobserved domain is unable to influence the structure of the increments in the observed domain and so is unlikely to produce a balanced initial state.

If both domains observed:

- a block diagonal **B** may be sufficient when the coupling in the TL model is strong and $\mathbf{B}_{AA}$, $\mathbf{B}_{OO}$ are consistent with coupled background state.

Summary

- a key motivation for strongly coupled atmosphere-ocean DA is the ability to increase information exchange across the modelled air-sea interface by enabling observations in one domain to directly influence the analysis in the other.
- for 4D-Var this is info exchange can be maximised by specification of *a priori* cross-domain forecast error covariances.
- cross-domain error correlations are state and model dependent; naturally vary depending on factors such as location and time of day and year, but also depend on features of the model and assimilation system design.
- for strongly coupled 4D-Var it will be important to introduce an element of flow dependence to the traditional static forecast error covariance matrix.

References

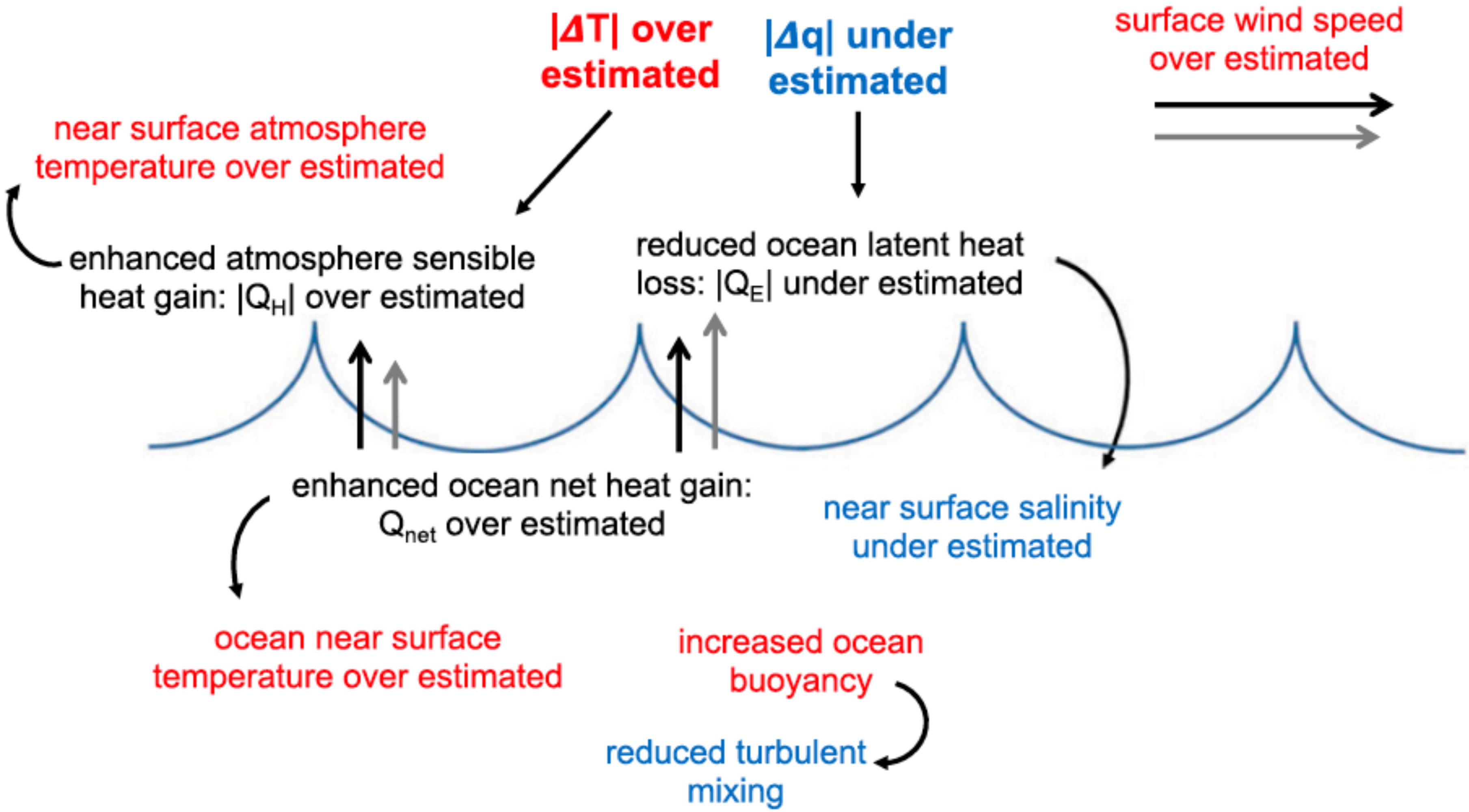
1. Smith et al. (2018), Geophys. Res. Lett., doi: 10.1002/2017GL075534
2. Smith et al. (2017), Mon. Wea. Rev., doi: 10.1175/MWR-D-16-0284.1
3. Smith et al (2015), Tellus A, doi: 10.3402/tellusa.v67.27025

Extra slides

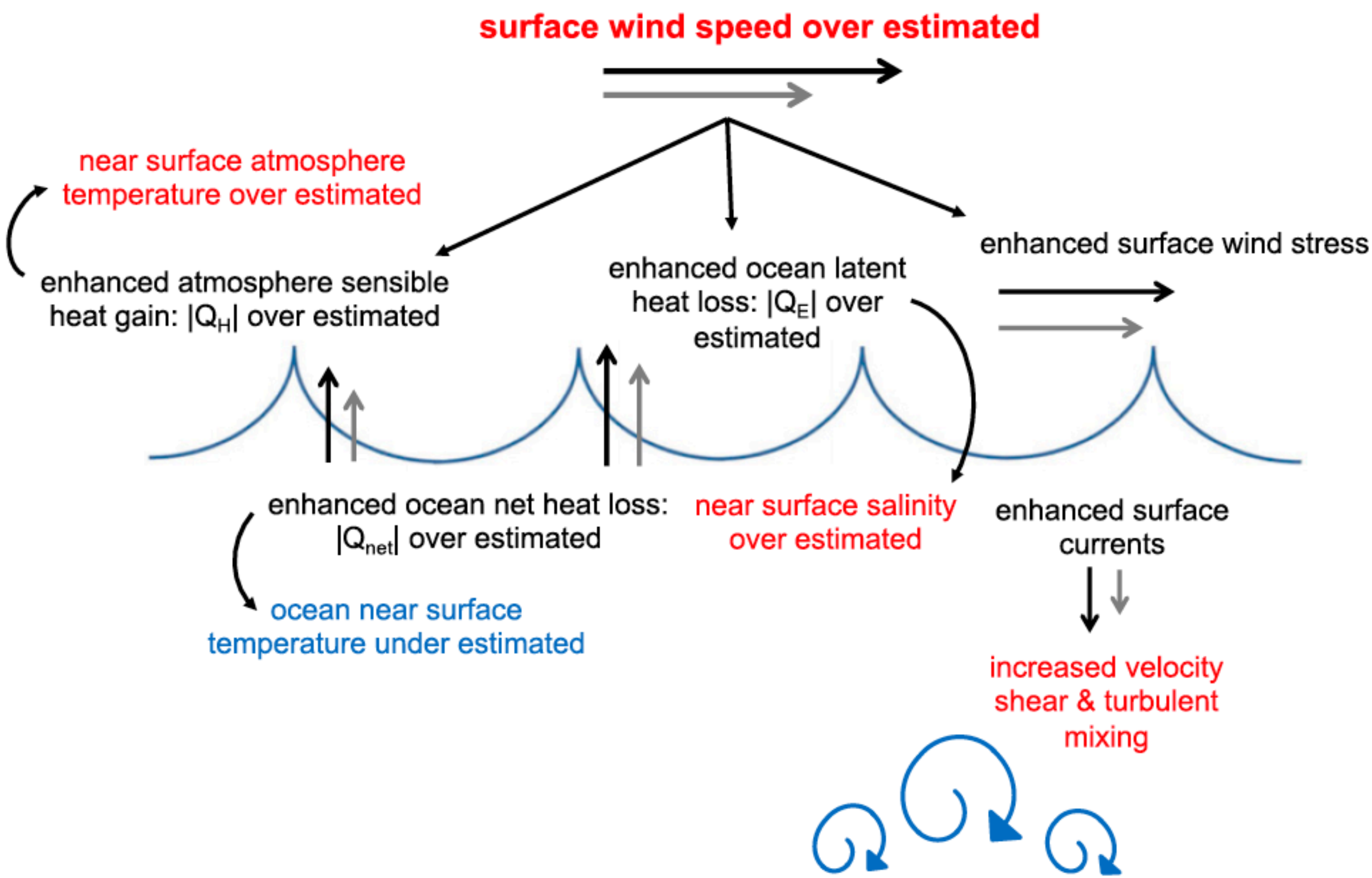
Identical twin experiments: details

- 12 hour assimilation window, 3 outer-loops, 8 cycles
- experiments repeated using data for June 2013 & Dec 2013 (point is 188.75°E, 25°N, N Pacific Ocean)
- 'true' initial state is coupled model forecast initialised using ERA Interim and Mercator Ocean data
- initial background state is a perturbed coupled model forecast
- 3 hourly observations are generated by adding random noise to 'truth'
- error covariance matrices **B** and **R** are diagonal (same for all cycles)
- ensemble of 500 members - generated by perturbing initial background state and observations
- average pairs over a several assimilation cycles to increase effective ensemble size

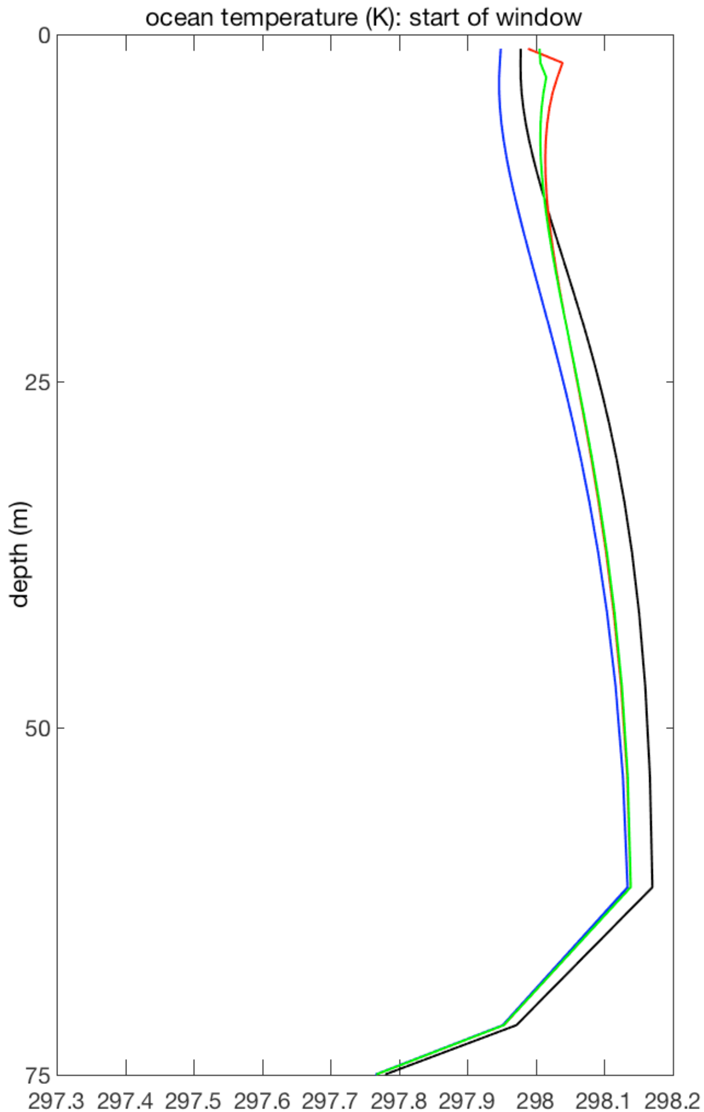
(a) December day (ΔT & Δq driven errors)



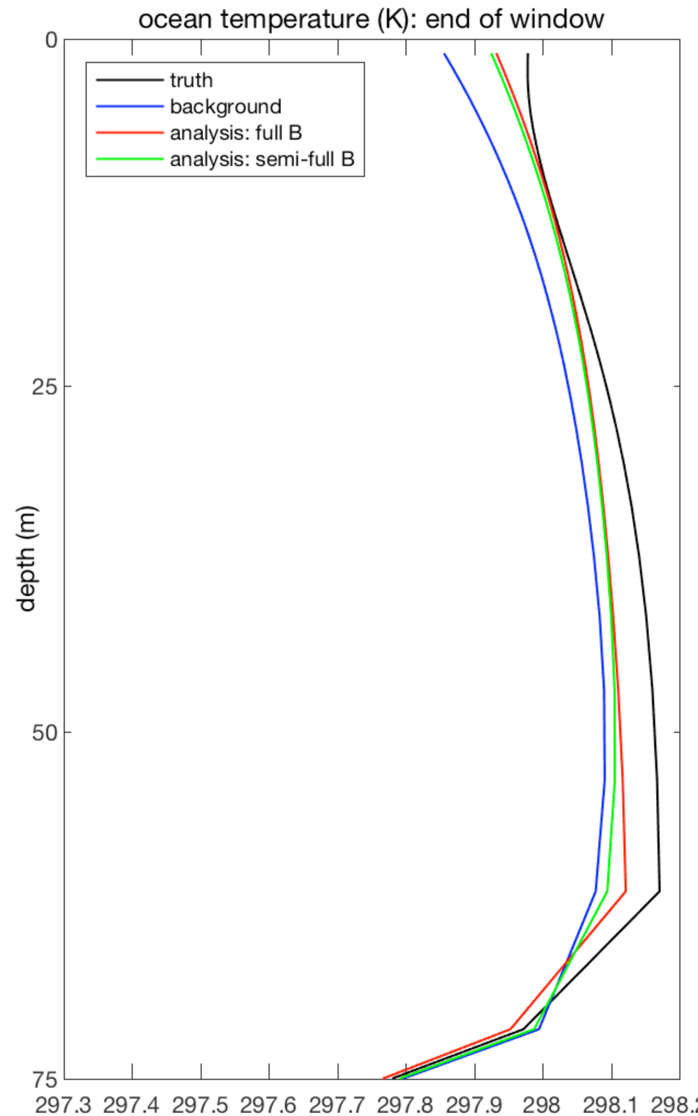
(b) December night (wind-driven errors)



Mixing leads to counter-balancing errors below



ocean temperature (K): start of window
depth (m)
0
25
50
75
297.3
297.4
297.5
297.6
297.7
297.8
297.9
298
298.1
298.2



ocean temperature (K): end of window
truth
background
analysis: full B
analysis: semi-full B
depth (m)
0
25
50
75
297.3
297.4
297.5
297.6
297.7
297.8
297.9
298
298.1
298.2