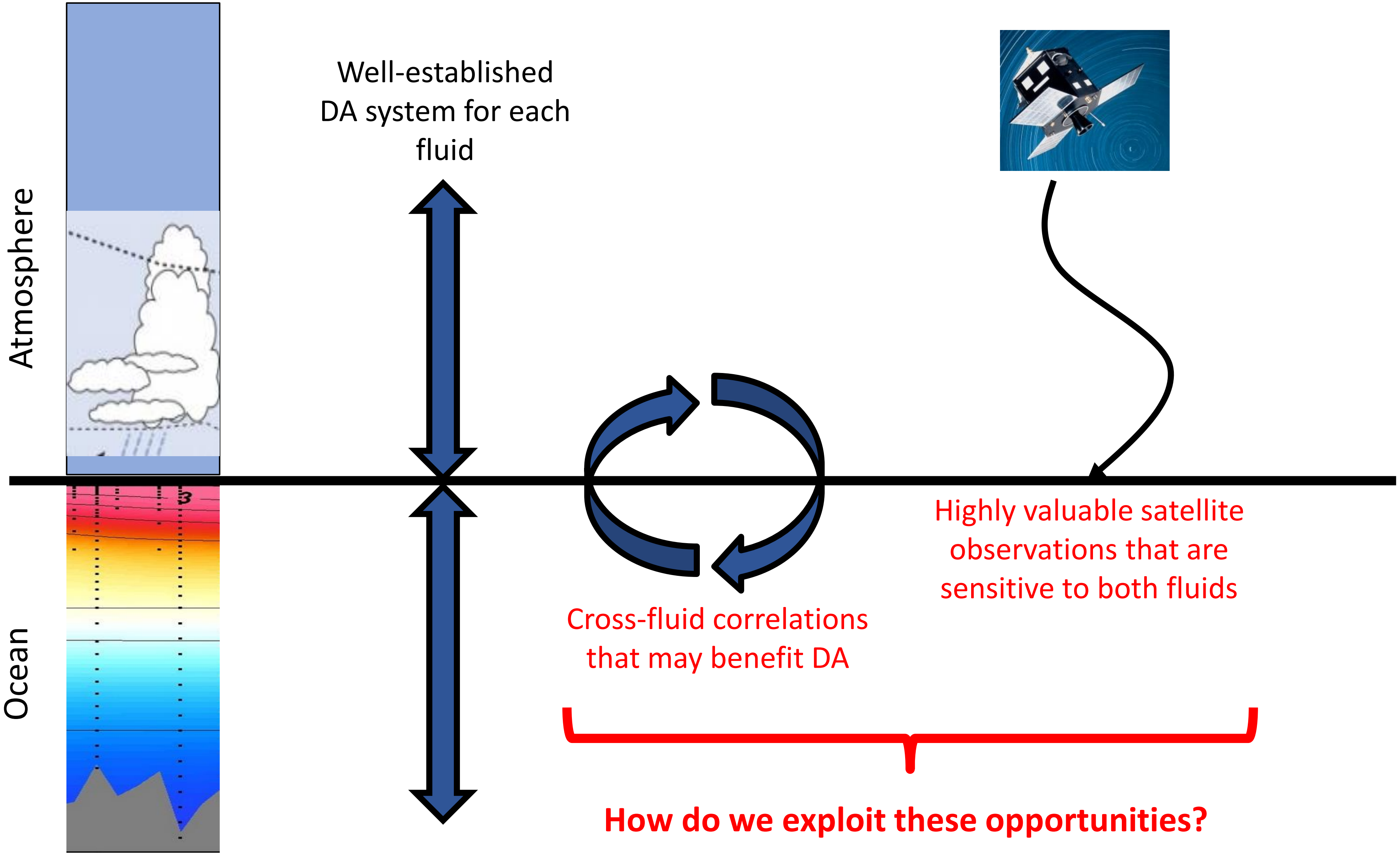
U.S. NAVAL RESEARCH LABORATORY

Comparison of data assimilation coupling strategies for Earth system models

Prepared: Sergey Frolov (NRL), with contributions from:
NRL: B. Ruston, W. Campbell, J. McLay, M. Flatau, D. Kuhl, N. Barton, OM. Smedstad, C. Rowley, C. Barron, P. Hogan, and T. Townsend
U Melbourne: C. Bishop
ECMWF: P. Laloyaux, M. Bonavita, J. Bidlot
ECMWF annual seminar, Reading, UK, September 2018

The coupled DA opportunity: effective use of observations



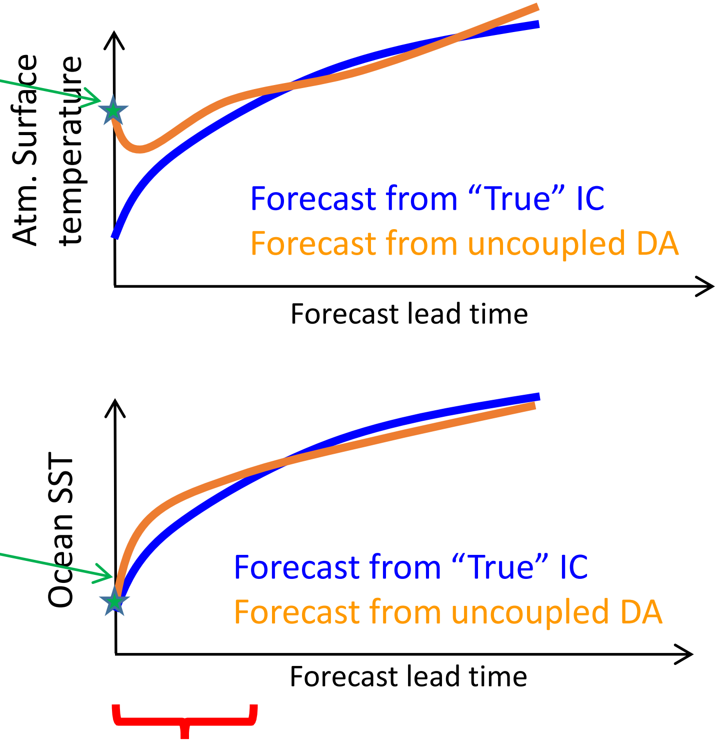
Outline

- The coupled DA opportunity and challenge
- Part 1: Algorithmic consideration for coupled DA
  - **Challenge 1: Approximations to the strongly coupled data assimilation**
  - Challenge 2: Mitigating for differences in space and time scales between Earth system components
- Part 2: Recent insights in to the coupling of atmospheric and oceanic temperatures
- Part 3: Low hanging fruit for coupled DA

The coupled DA challenge 1: Synchronization of the forecast

Atm. temp. analysis is away from truth because few direct observation of low-level atmospheric temperature are available over the ocean

Ocean temp. analysis is closer to truth because plentiful SST observations are available over the ocean



How long does it take for the ocean and atmospheric models to synchronize (balance) and converge on “truth”

Key questions addressed by methods development:

- How long does it take to synchronize?
- Can the synchronization time be moved within the data assimilation window?
- Is it sufficient to rely on the forecast model for synchronization or do we need coupled DA?

Coupled DA: a couple of definitions

For didactic purposes, lets start with something simple:

- Observational space estimator with one outerloop

$$x_k^a = \mathscr{M}(x_{k-1}^a) + \underbrace{\mathbf{P}_0\mathbf{M}^T\mathbf{H}^T\left(\mathbf{H}\mathbf{M}\mathbf{P}_0\mathbf{M}^T\mathbf{H}^T + \mathbf{R}\right)^{-1}}_{\text{Kalman gain: maps observation misfits to model space}}\left[y - \mathscr{H}(\mathscr{M}(x_{k-1}^a))\right]$$

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Definitions: strongly coupled DA

Strongly coupled data assimilation

$$x_k^a = \mathscr{M}(x_{k-1}^a) + \mathbf{P}_0\mathbf{M}^T\mathbf{H}^T\left(\mathbf{HMP}_0\mathbf{M}^T\mathbf{H}^T + \mathbf{R}\right)^{-1}\left[y - \mathscr{H}(\mathscr{M}(x_{k-1}^a))\right]$$

Coupled forecast model:

$$x_{k+1}^{coupled} = \begin{bmatrix} x_{k+1}^{atm} \\ x_{k+1}^{oce} \end{bmatrix} = \mathscr{M}^{coupled}\left(\begin{bmatrix} x_k^{atm} \\ x_k^{oce} \end{bmatrix}\right)$$

Coupled TLM/ADJ of the forecast model:

$$\mathbf{M}^{coupled} = \begin{bmatrix} \mathbf{M}^{AA} & \mathbf{M}^{AO} \\ \mathbf{M}^{OA} & \mathbf{M}^{OO} \end{bmatrix}$$

Coupled TLM/ADJ of the observation operator:

$$y^{radiance} = \mathbf{H}^{rtm-coupled} x^{coupled} = \begin{bmatrix} \mathbf{J}^{atm} \\ \mathbf{J}^{ocean} \end{bmatrix}\begin{bmatrix} x^{atm} \\ x^{ocean} \end{bmatrix}$$

Coupled initial-time covariance:

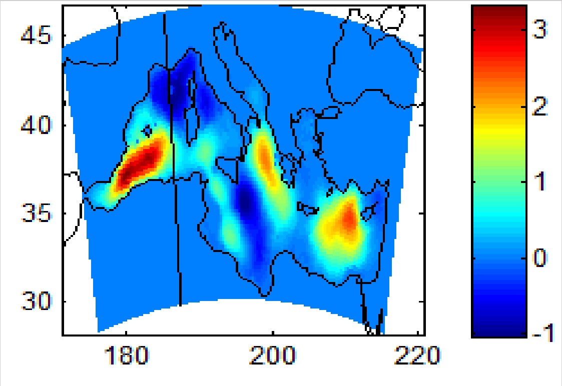
$$\mathbf{P}_0^{coupled} = \begin{bmatrix} \mathbf{P}^{AA} & \mathbf{P}^{AO} \\ \mathbf{P}^{OA} & \mathbf{P}^{OO} \end{bmatrix}$$

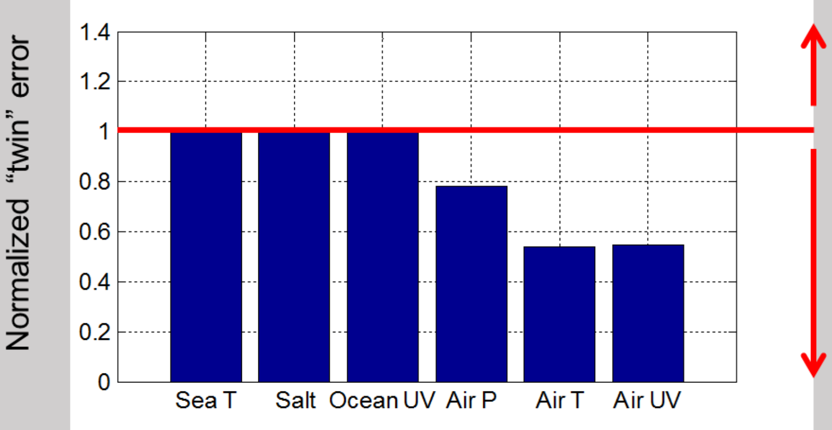
Examples of strongly coupled DA

- None so far in the models of operational complexity

- Early indications of promise in simplified models
  - Lu et al. (2015), Sluka (2016), Smith et al. (2015, 2017)

- Early indications of caution against strong coupling
  - Lu et al. (2015), Frolov et.al. (2016)





Strongly coupled is better

Intermediate coupling is better

Frolov et al. (2016) MWR

Definitions: weakly coupled DA

Weakly coupled data assimilation

$$x_k^a = \mathcal{M}(x_{k-1}^a) + \mathbf{P}_0\mathbf{M}^T\mathbf{H}^T\left(\mathbf{H}\mathbf{M}\mathbf{P}_0\mathbf{M}^T\mathbf{H}^T + \mathbf{R}\right)^{-1}\left[y - \mathcal{H}(\mathcal{M}(x_{k-1}^a))\right]$$

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TLM/ADJ of the forecast model:

$$\mathbf{M} = \begin{bmatrix} \mathbf{M}^{AA} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} \end{bmatrix}$$

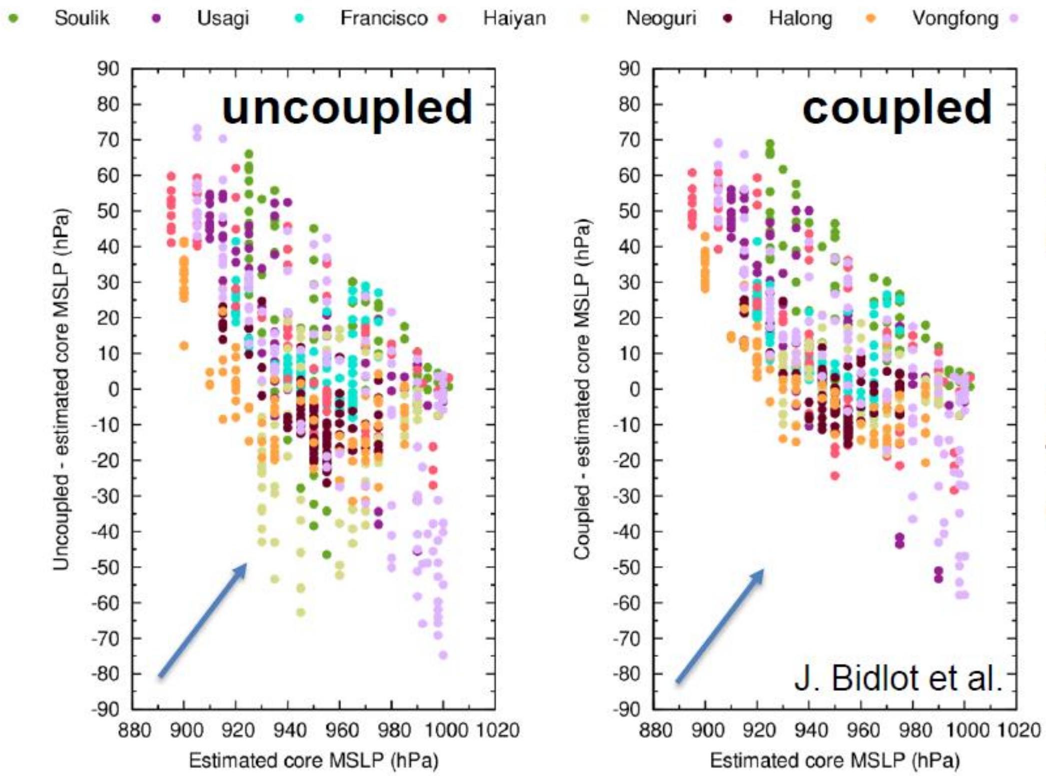
TLM/ADJ of the observation operator:

$$y^{radiance} = \mathbf{H}^{rtm} x^{atm} = \begin{bmatrix} \mathbf{J}^{atm} \\ 0 \end{bmatrix}\begin{bmatrix} x^{atm} \\ 0 \end{bmatrix}$$

Initial-time covariance:

$$\mathbf{P}_0 = \begin{bmatrix} \mathbf{P}^{AA} & \mathbf{0} \\ \mathbf{0} & \mathbf{P}^{OO} \end{bmatrix}$$

An example of a weakly coupled DA



MSLP forecast error versus the estimated core MSLP

→ In the uncoupled case, too deep TCs (no cold wake feedback effect, infinite source of energy)

- Impact of coupled forecast models have been widely documented:
    - TC strength (ECMWF above)
    - Tropical wind-SST coupling
    - Ice extent prediction

Definitions: coupling through an outerloop

Data assimilation coupled through 4DVAR outerloop

$$x_k^{a[i]} = \mathcal{M}\left(x_{k-1}^a + \sum_i \delta x_{k-1}^{[i]}\right) + \mathbf{P}_0\mathbf{M}^T\mathbf{H}^T\left(\mathbf{H}\mathbf{M}\mathbf{P}_0\mathbf{M}^T\mathbf{H}^T + \mathbf{R}\right)^{-1}\left[y - \mathcal{H}\left(\mathcal{M}\left(x_{k-1}^a + \sum_i \delta x_{k-1}^{[i]}\right)\right) - \mathbf{H}\sum_i \delta x_{k-1}^{[i]}\right]$$

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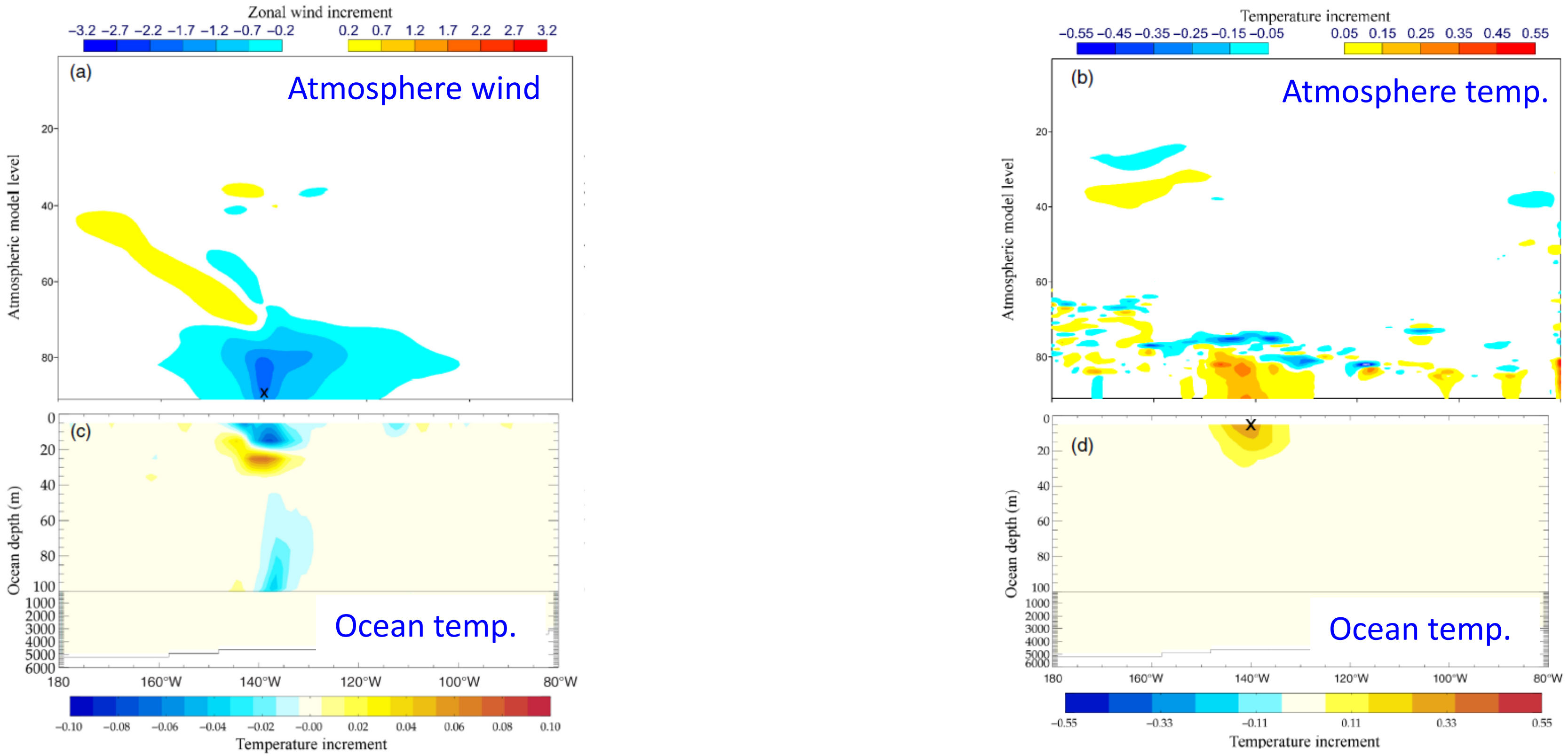
Initial-time covariance:

$$\mathbf{P}_0 = \begin{bmatrix} \mathbf{P}^{AA} & \mathbf{0} \\ \mathbf{0} & \mathbf{P}^{OO} \end{bmatrix}$$

An example of DA coupled through an outerloop



- Laloyaux et al. (2016) showed that outerloop coupling is effective at propagating information between assimilated fluids: E.g.
  - (left) Impact of wind observation on the mixed layer depth
  - (right) Impact of SST assimilation on the boundary layer depth
  - (Later in this talk) is outerloop enough?

Definitions: coupling through observation operator

Data assimilation coupled through observation operator

$$x_k^a = \mathcal{M}(x_{k-1}^a) + \mathbf{P}_0\mathbf{M}^T\mathbf{H}^T\left(\mathbf{H}\mathbf{M}\mathbf{P}_0\mathbf{M}^T\mathbf{H}^T + \mathbf{R}\right)^{-1}\left[y - \mathcal{H}(\mathcal{M}(x_{k-1}^a))\right]$$

Coupled forecast model:

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Initial-time covariance:

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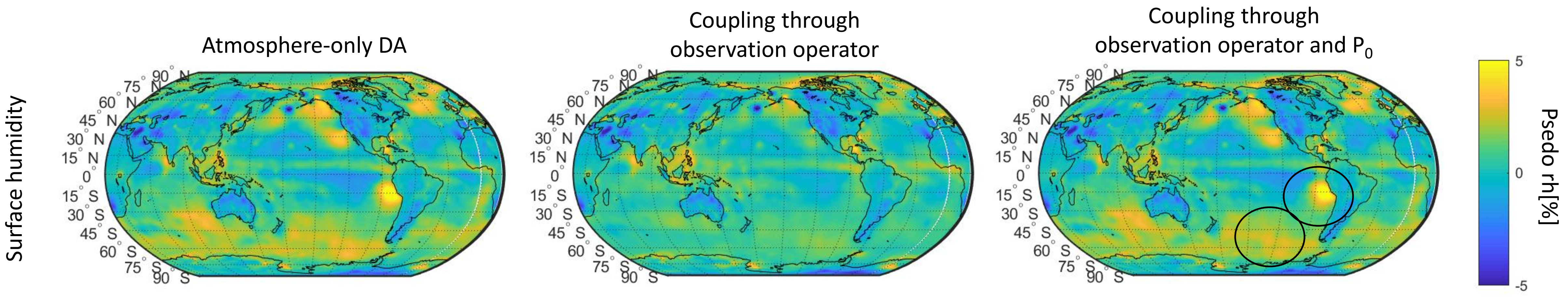
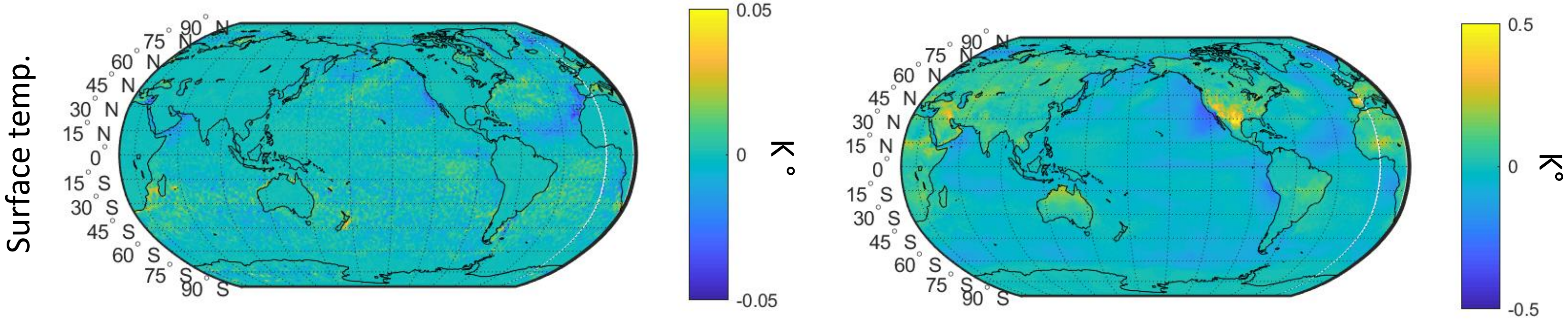
A version of this system is currently (pre-)operational at UKMO and NCEP

Example of coupling through observation operator

Average increment (July-August 2016)



- Preliminary results suggests that coupling through observation operator alone might further alias atmospheric signal into the ocean.



In collaboration with: B. Campbell,C. Bishop, B. Ruston, D. Kuhl, N. Barton. J. McLay, M. Flatau,

Definitions: coupling through initial time error covariance

Data assimilation coupled through initial time covariance

$$x_k^a = \mathcal{M}(x_{k-1}^a) + \mathbf{P}_0\mathbf{M}^T\mathbf{H}^T\left(\mathbf{H}\mathbf{M}\mathbf{P}_0\mathbf{M}^T\mathbf{H}^T + \mathbf{R}\right)^{-1}\left[y - \mathcal{H}(\mathcal{M}(x_{k-1}^a))\right]$$

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Coupled initial-time covariance:

$$\mathbf{P}_0^{coupled} = \begin{bmatrix} \mathbf{P}^{AA} & \mathbf{P}^{AO} \\ \mathbf{P}^{OA} & \mathbf{P}^{OO} \end{bmatrix}$$

Modification to the P_0 coupling: the interface solver

Data assimilation coupled through initial time covariance

$$x_k^a = \mathcal{M}(x_{k-1}^a) + \mathbf{P}_0\mathbf{M}^T\mathbf{H}^T\left(\mathbf{H}\mathbf{M}\mathbf{P}_0\mathbf{M}^T\mathbf{H}^T + \mathbf{R}\right)^{-1}\left[y - \mathcal{H}(\mathcal{M}(x_{k-1}^a))\right]$$

Initial-time covariance:
Full coupling

$$\mathbf{P}_0^{coupled} = \begin{bmatrix} \mathbf{P}^{AA} & \mathbf{P}^{AO} \\ \mathbf{P}^{OA} & \mathbf{P}^{OO} \end{bmatrix}$$

Initial-time covariance:
Coupling at the interfaces

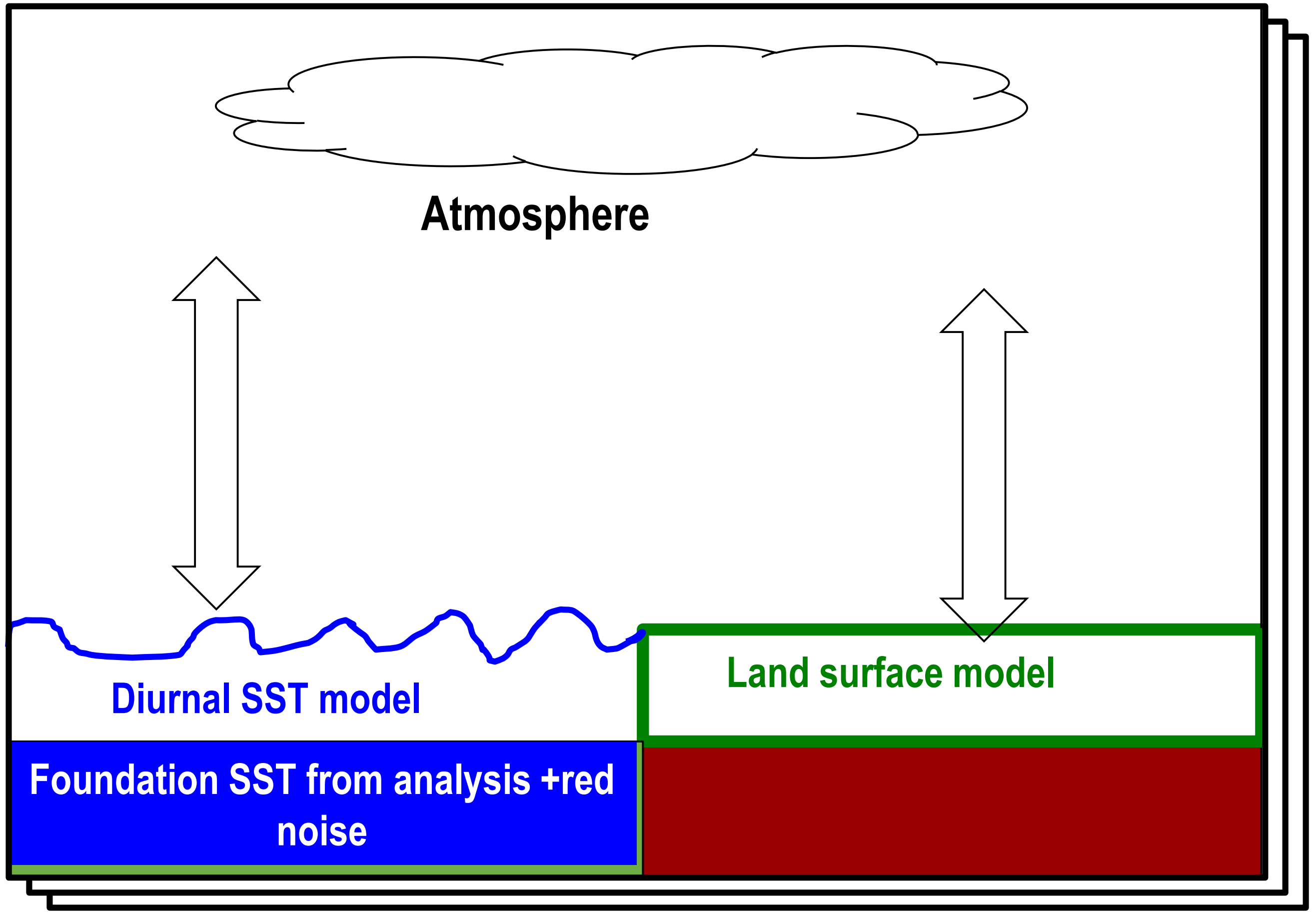
$$\mathbf{P}_0^{coupled} = \begin{bmatrix} \mathbf{P}^{\mathrm{fA|fA}} & \mathbf{P}^{\mathrm{fA|BL}} & \mathbf{0} & \mathbf{0} \\ \mathbf{P}^{\mathrm{BL|fA}} & \mathbf{P}^{\mathrm{BL|BL}} & \mathbf{P}^{\mathrm{BL|ML}} & \mathbf{0} \\ \mathbf{0} & \mathbf{P}^{\mathrm{ML|BL}} & \mathbf{P}^{\mathrm{ML|ML}} & \mathbf{P}^{\mathrm{ML|dO}} \\ \mathbf{0} & \mathbf{0} & \mathbf{P}^{\mathrm{dO|ML}} & \mathbf{P}^{\mathrm{dO|dO}} \end{bmatrix}$$

- Assume that within the DA cycle
  - Atmospheric boundary layer (BL) and ocean mixed layer (ML) are coupled
  - Free atmospheric (fA) and deep ocean (dO) are NOT coupled
- Implement "interface solver" approximation by extending existing DA systems using ensemble covariances.

Frolov et al. (2016)

An example of the interface solver

Ensemble of coupled atmospheres



- Hybrid-4DVAR maintains an ensemble of 80 cycling atmospheric states.
- Each atmospheric member cycles their own version of diurnal SST and land surface model.
- Additional time-space-correlated noise is added to the foundational SST to simulate the lack of a dynamic ocean model.

In collaboration with: C. Bishop, B. Ruston, D. Kuhl, N. Barton. J. McLay, M. Flatau, B. Campbell

An example of a coupled increment from the interface solver

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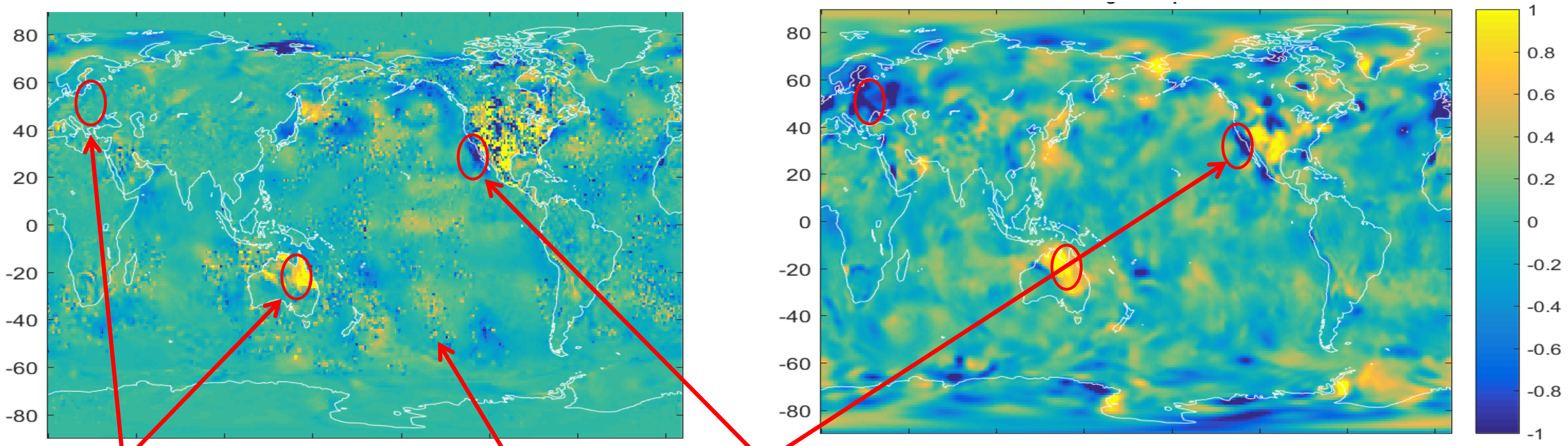
Earth surface temperature increment

Surface air temperature increment



Large changes over land. Coupling of increments over land has likely diurnal signal

Some changes to ocean temperature are likely generated to balance atmospheric increments

Correction of EST is "speckly" because we used overly simplified static error covariance

In collaboration with: C. Bishop, B. Ruston, D. Kuhl, N. Barton. J. McLay, M. Flatau, B. Campbell

Definitions: coupling through tangent Linear and Adjoint

Data assimilation coupled through Tangent Linear and Adjoint

$$x_k^a = \mathcal{M}(x_{k-1}^a) + \mathbf{P}_0\mathbf{M}^T\mathbf{H}^T\left(\mathbf{H}\mathbf{M}\mathbf{P}_0\mathbf{M}^T\mathbf{H}^T + \mathbf{R}\right)^{-1}\left[y - \mathcal{H}(\mathcal{M}(x_{k-1}^a))\right]$$

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Initial-time covariance:

$$\mathbf{P}_0 = \begin{bmatrix} \mathbf{P}^{AA} & \mathbf{0} \\ \mathbf{0} & \mathbf{P}^{OO} \end{bmatrix}$$

Outline

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- Part 1: Algorithmic consideration for coupled DA
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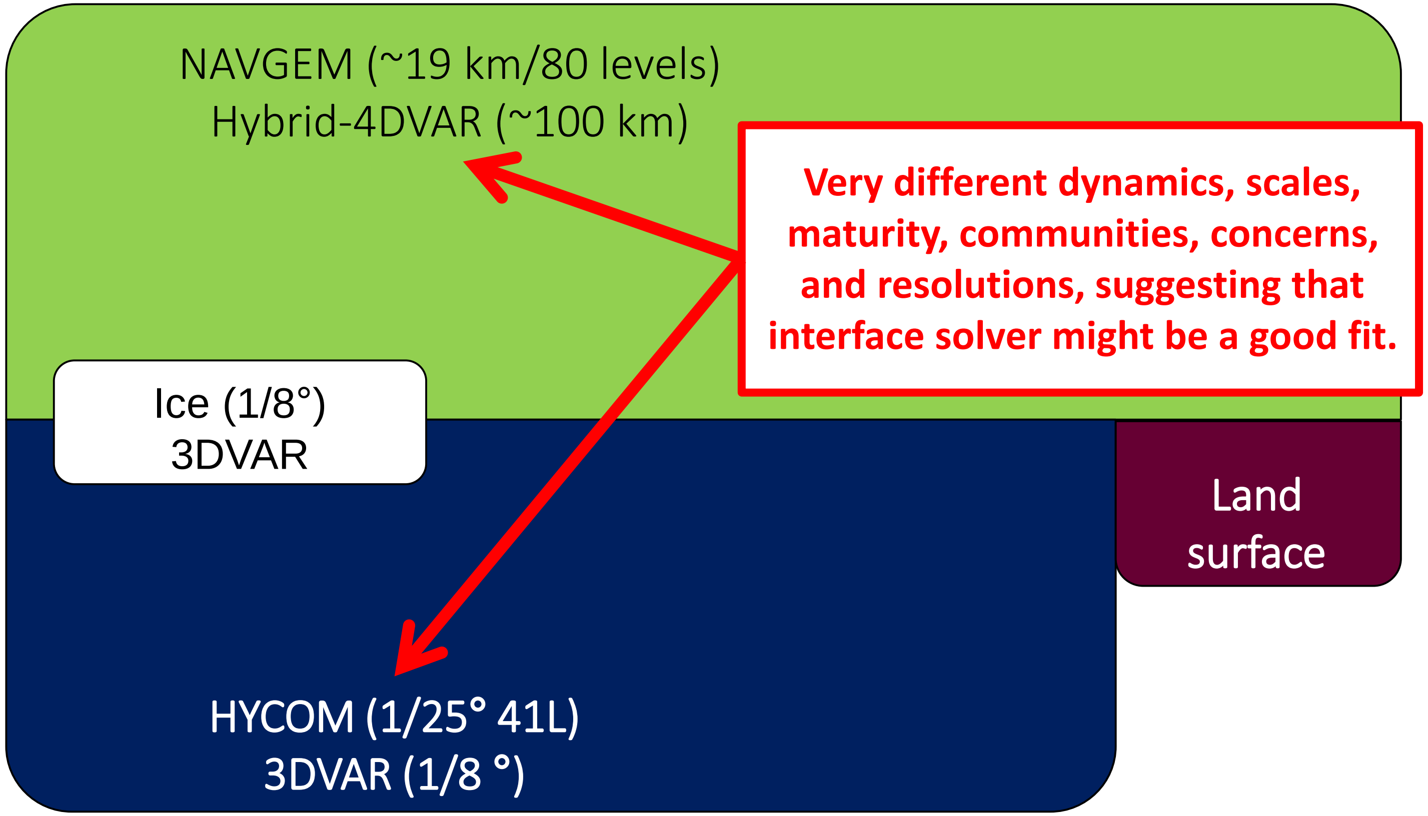
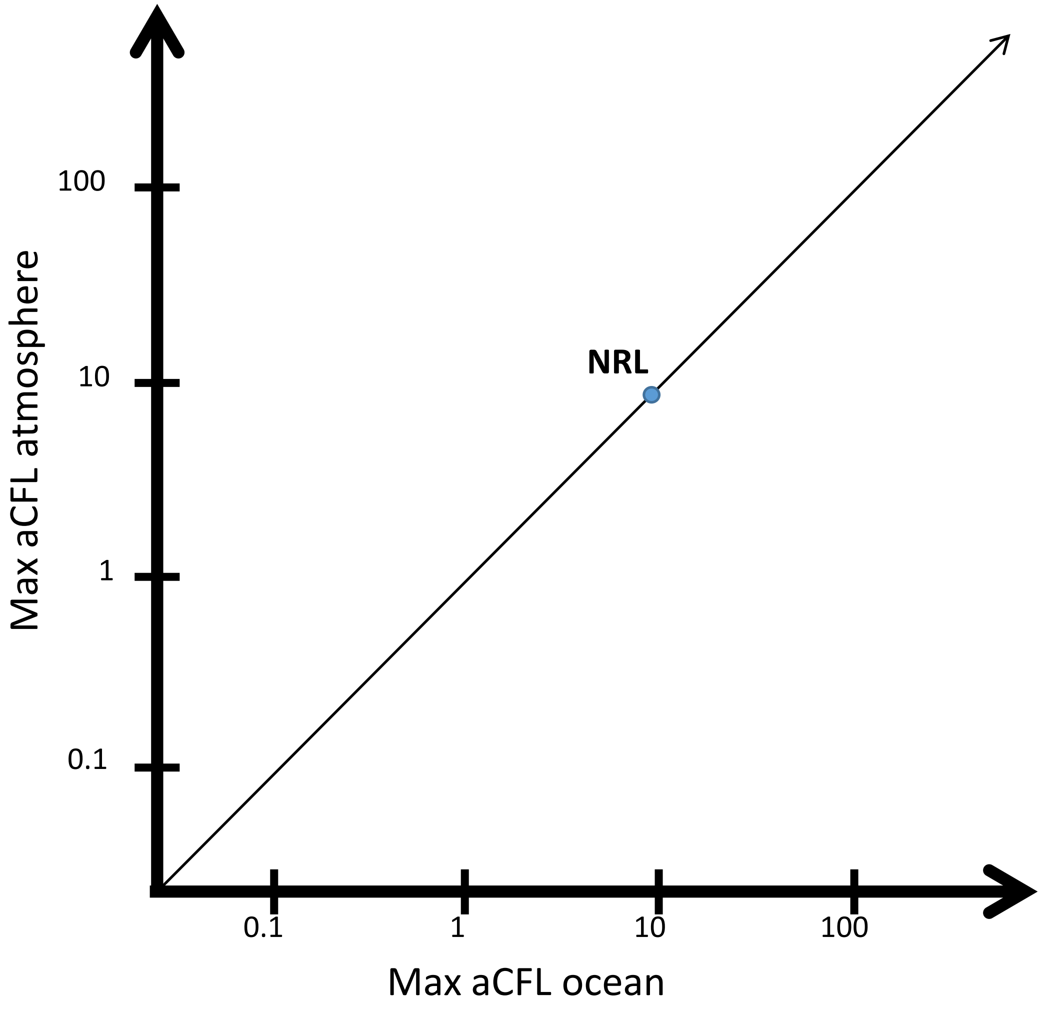
An example of a real system (US NRL)



- Length scales differ an order of magnitude:
  - Gulfstream: max of 2 m/s, av. 0.2 m/s
  - Jet stream: max of 50 m/s; av. 10 m/s
- Observation data delays:
  - Atmosphere: ~1 hours
  - Ocean: Altimeter can be ~24 hours
- Observation coverage:
  - Atmosphere: almost complete coverage in 12 hours
  - Ocean: complete coverage for ARGO in 10 days
- Global forecast and model resolution differ
  - Atmosphere: 13km forecast and 33km anal.
  - Ocean: 4km forecast and 12km anal.

Coupled DA challenge 2: Interplay between resolution and timescales

Best guess at the appropriate DA algorithm



aCFL—analysis Courant-Fletcher Levy number:

$$aCFL = \frac{\max(wind\_speed)}{analysis\_\Delta x / analysis\_window\_length}$$

For NRL atm. Hybrid-4DVAR

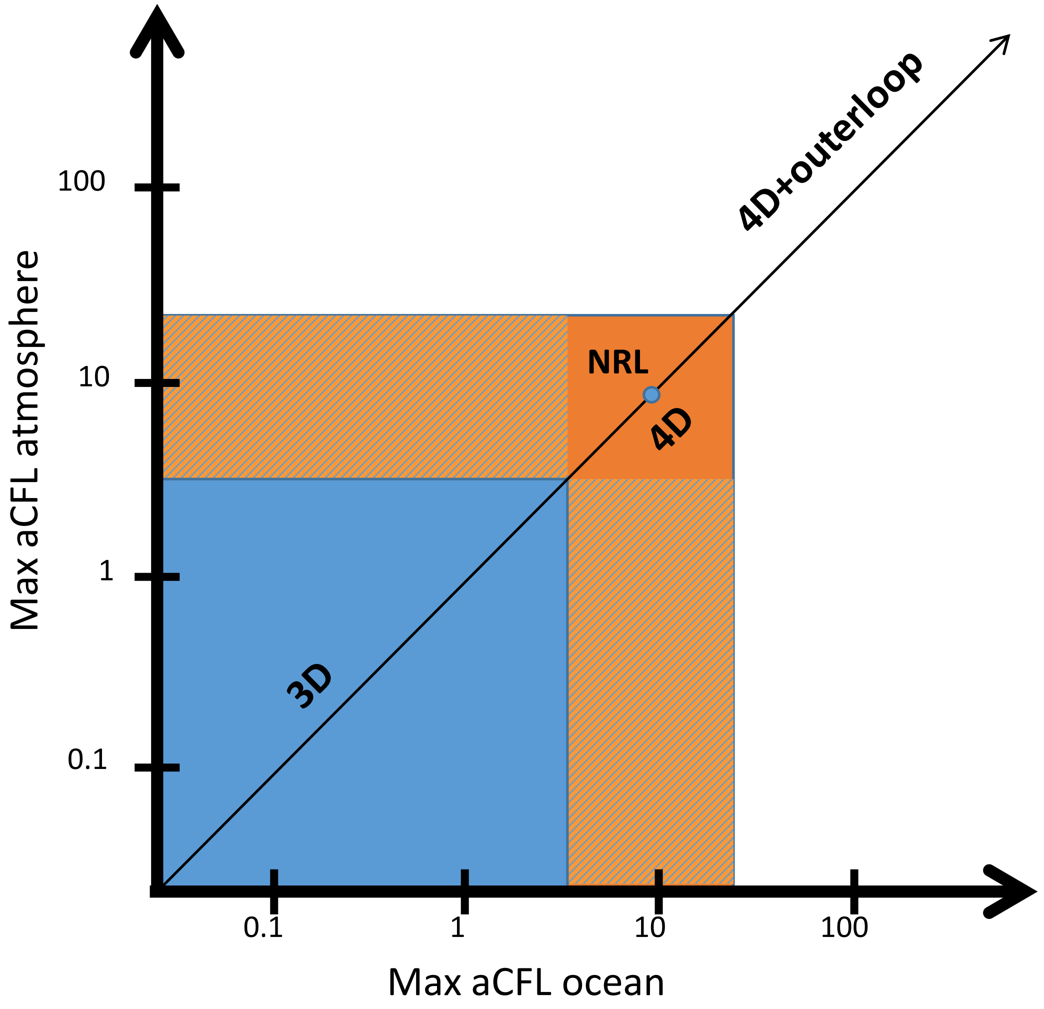
$$aCFL = \frac{50\ [m/s]}{100\ [km] / 6\ [hours]} = 10.8$$

For NRL ocean. 3DVAR

$$aCFL = \frac{2\ [m/s]}{12.5\ [km] / 24\ [hours]} = 13.8$$

Coupled DA challenge 2:
Interplay between resolution and timescales

Best guess at the appropriate DA algorithm



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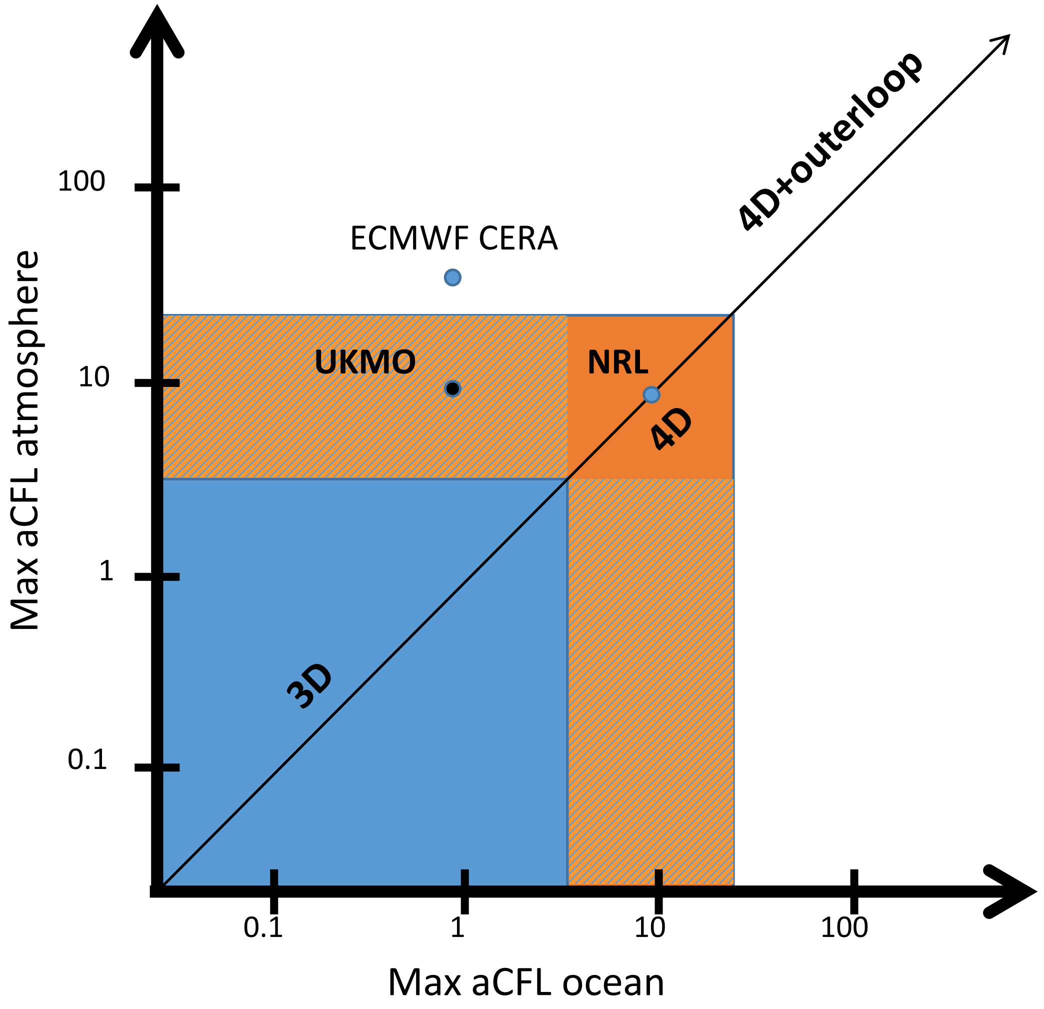
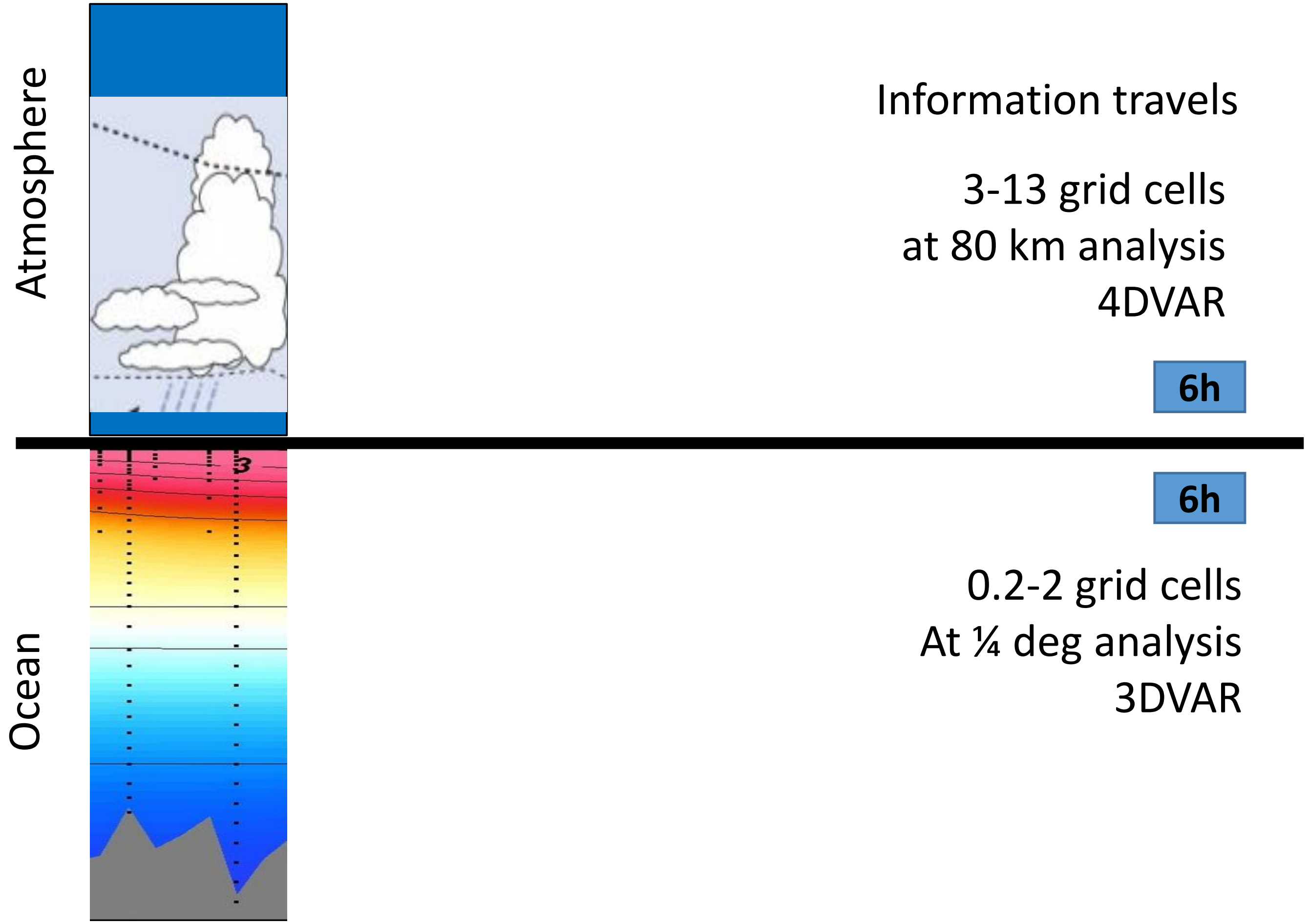


Used the following information for existing systems

System	Fluid	dx	T_{win}	Alg.
NRL	Ocean	12	24	3DVAR
	Atm	100	6	H4DVAR
CERA	Ocean	100	24	3DVAR
	Atm.	100	24	ol-4FVAR
UKMO	Ocean	25	6	3DVAR
	Atm.	80	6	4DVAR

Based on reports at the CDA workshop, Toulouse (2016)

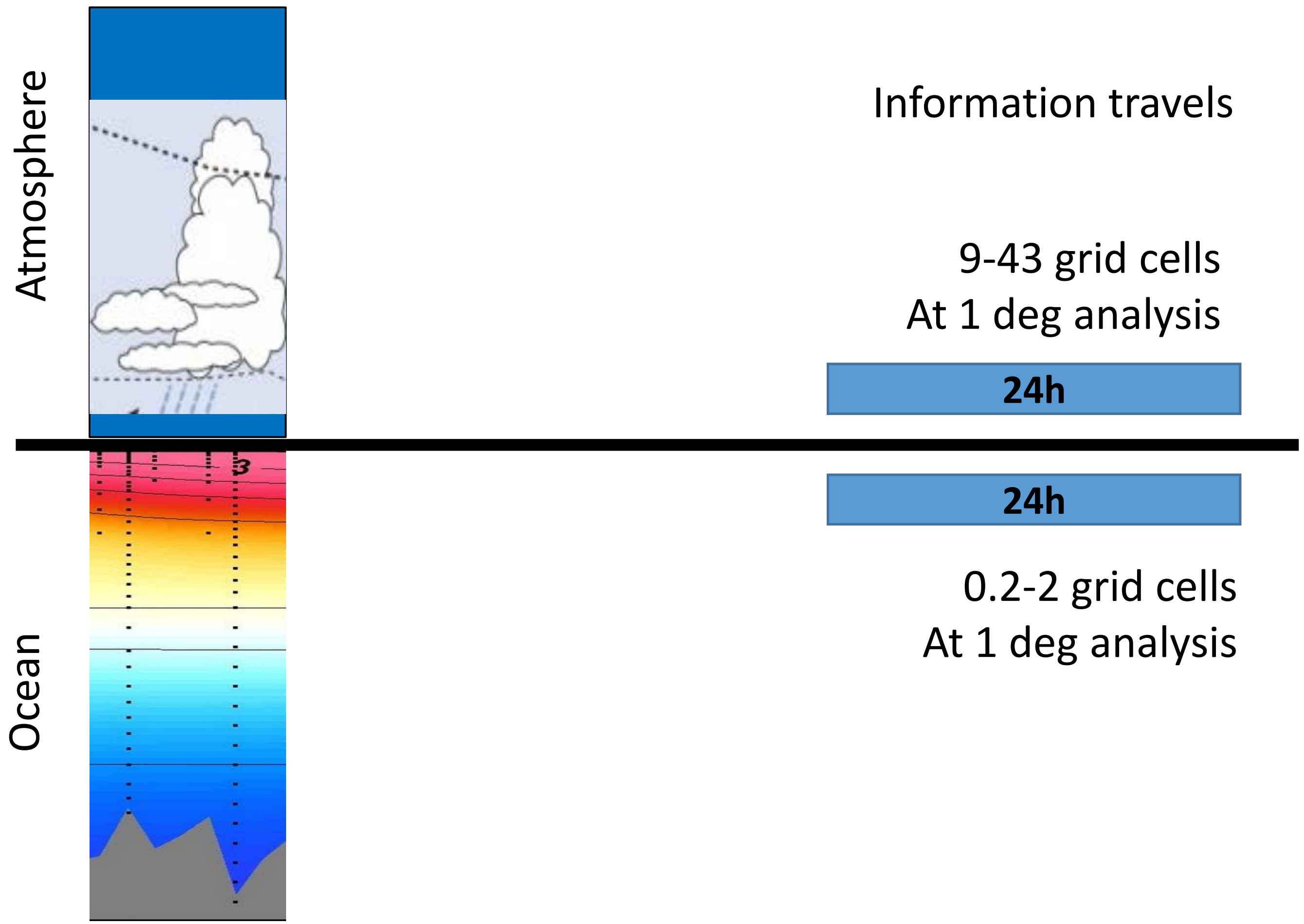
Timescales in Coupled DA: UKMO



- Single (shortest) cycle:
  - Atm: 4DVAR single outerloop
  - Ocean: 3DVAR
- Results at NRL show that 6-h ocean 3DVAR degrades forecast skill in Western boundary conditions
- Degraded skill because of the delays in the delivery of the altimeter data makes this system impractical for the Navy application

Based on reports at the CDA workshop, Toulouse (2016)

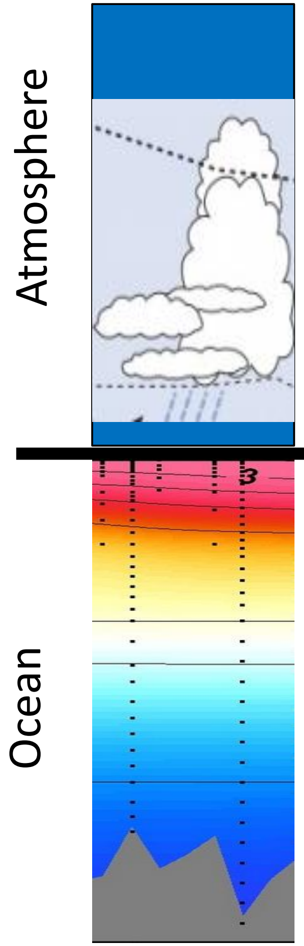
Timescales in Coupled DA: ECMWF reanalysis



- Single (longest) cycle:
  - Atm: 4DVAR multiple outerloops
  - Ocean: 3DVAR
- Special case of a CERA-centenial reanalysis with a 1 degree model
- Does not assimilate satellite observations (e.g. not competitive with operational NWP)

Based on reports at the CDA workshop, Toulouse (2016)

Timescales in CDA: NRL ESPC system



Information travels

10-2 grid cells
at 100 km analysis
Hybrid-4DVAR

6h | 6h | 6h | 6h

24h

10-1 grid cells
At 16 km analysis
3DVAR

- Mixed cycles:
  - Atm: 6-h 4DVAR single outerloop
  - Ocean: 3DVAR
- Goal is to deliver a system with at least as good performance as the operational atmospheric and oceanic systems
- This analysis suggests that both DA systems have room for an upgrade:
  - Atm: higher resolution increment
  - Ocean: Aspects of flow-dependent analysis can be beneficial in WBC

Based on reports at the CDA workshop, Toulouse (2016)

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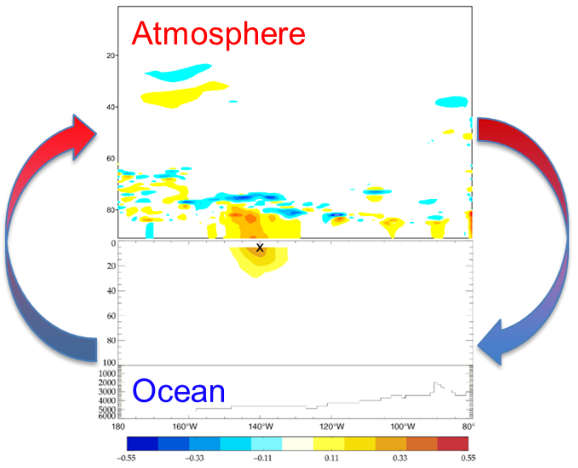
    - Role of the outerloop in coupling
- Part 3: Low hanging fruit for coupled DA

Role of the outerloop in coupling

The coupling in the CERA assimilation system



Ocean and atmospheric increments are transferred between the components

How much coupling in CERA?

2016

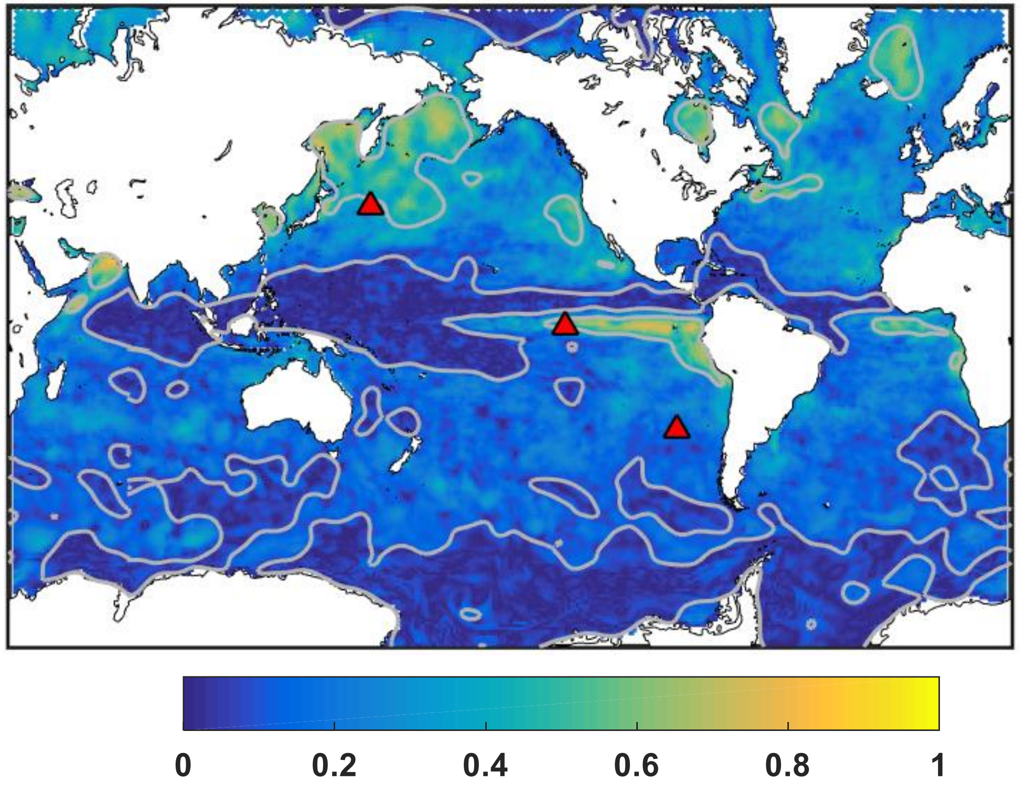
How much coupling in CERA?

2017

Slide borrowed from P Laloyaux

Global patterns of coupling between SST and 2m air temp: regional patterns

Average ensemble correlation for August 2005



Absolute value of the correlation between SST and the surface air temperature

Dataset:

- ECMWF CERA reanalysis
- In-situ data is assimilated using 24-hour assimilation cycle
- Both ocean and atmosphere is 1 deg resolution

Methods:

- Using 25 coupled ensemble members (Feb and Aug 2005), compute instantaneous 24-hour forecast error correlations
- Average instantaneous correlations.

Laloyaux et al. (2018) QJ

Original insight Feng et .al.2016

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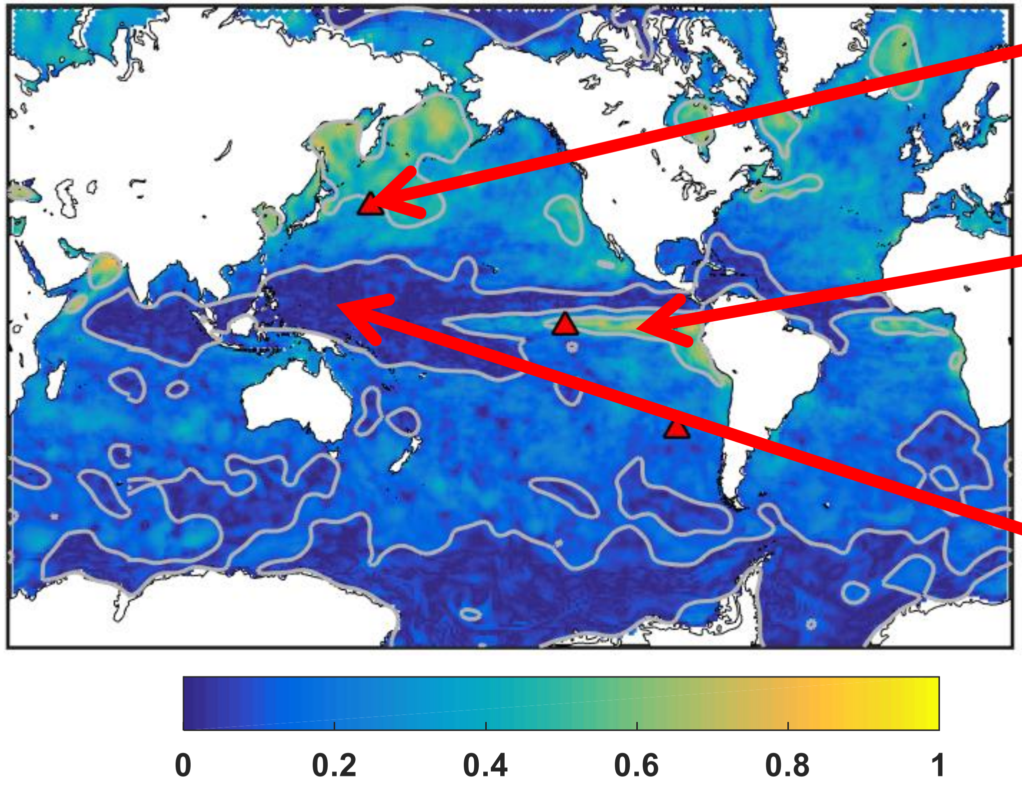


Absolute value of the correlation between SST and the surface air temperature

(c) Seasonal coupling in mid-latitudes

- Stronger coupling in summer hemisphere, when MLD is shallower.

(a) Strong coupling in eastern tropical Pacific and Atlantic

- Shallow MLD (ocean can respond to atmosphere)
- Precipitation is modulated by strong gradients in the SST

(b) No coupling in the Warm Pool

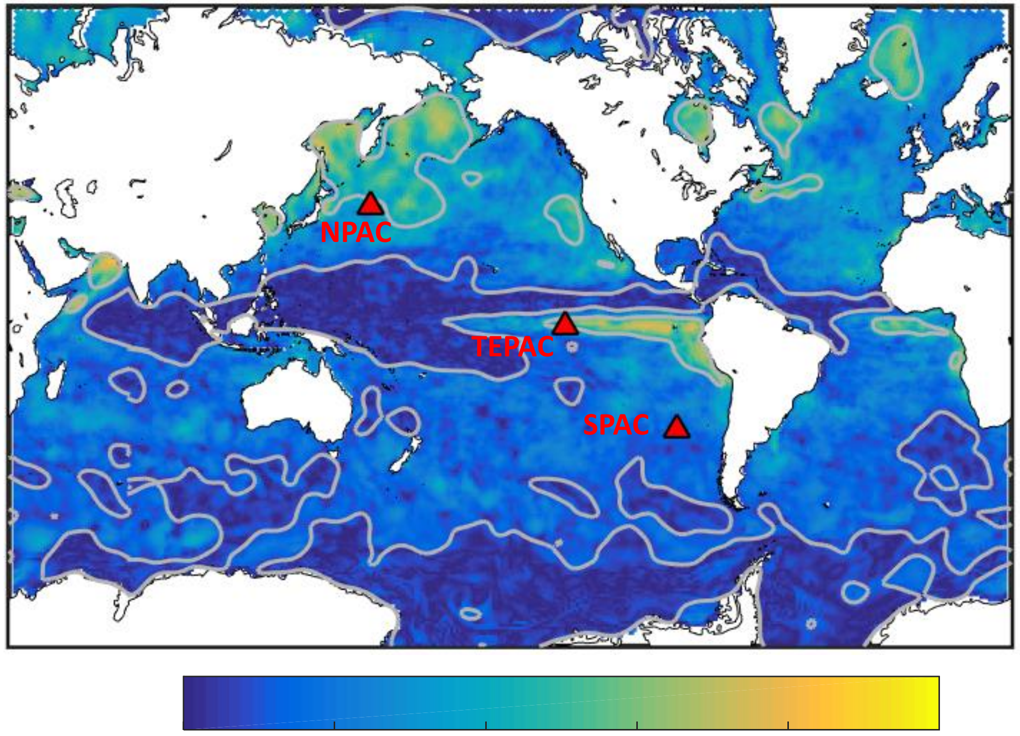
- Deeper MLD
- Weaker gradients in the SST
- Omnipresent convection acts like white noise to the ocean with deep mixed layer
- Weak lagged coupling when clouds shade SST following a convective event

Laloyaux et al. (2018) QJ

Original insight Feng et .al.2016

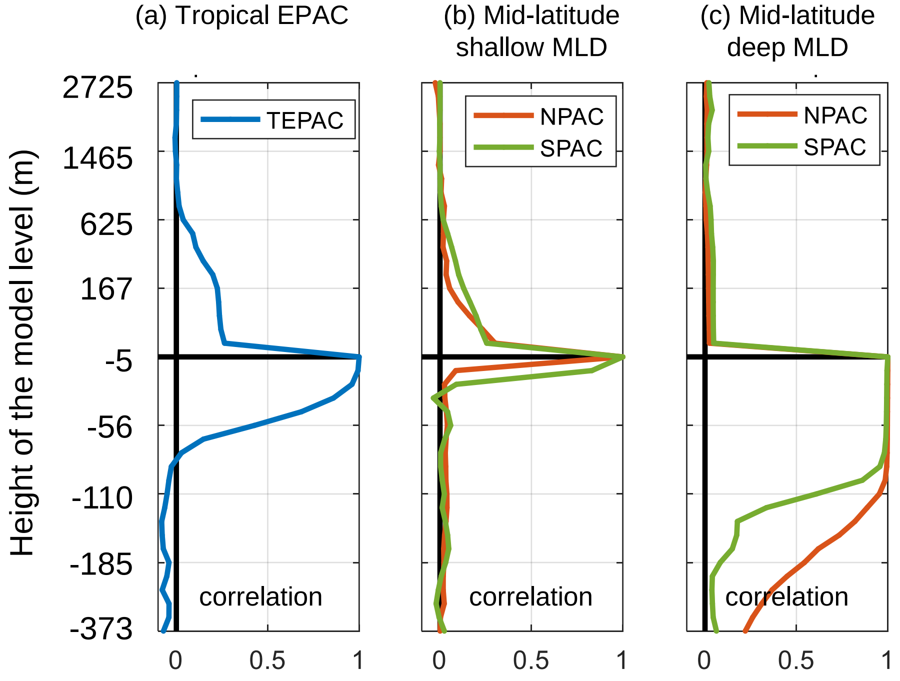
Global patterns of coupling between SST and 2m air temp: vertical extent of coupled correlations

Average ensemble correlation for August 2005



Absolute value of the correlation between SST and the surface air temperature

Average, localized ensemble correlations between SST and coupled state

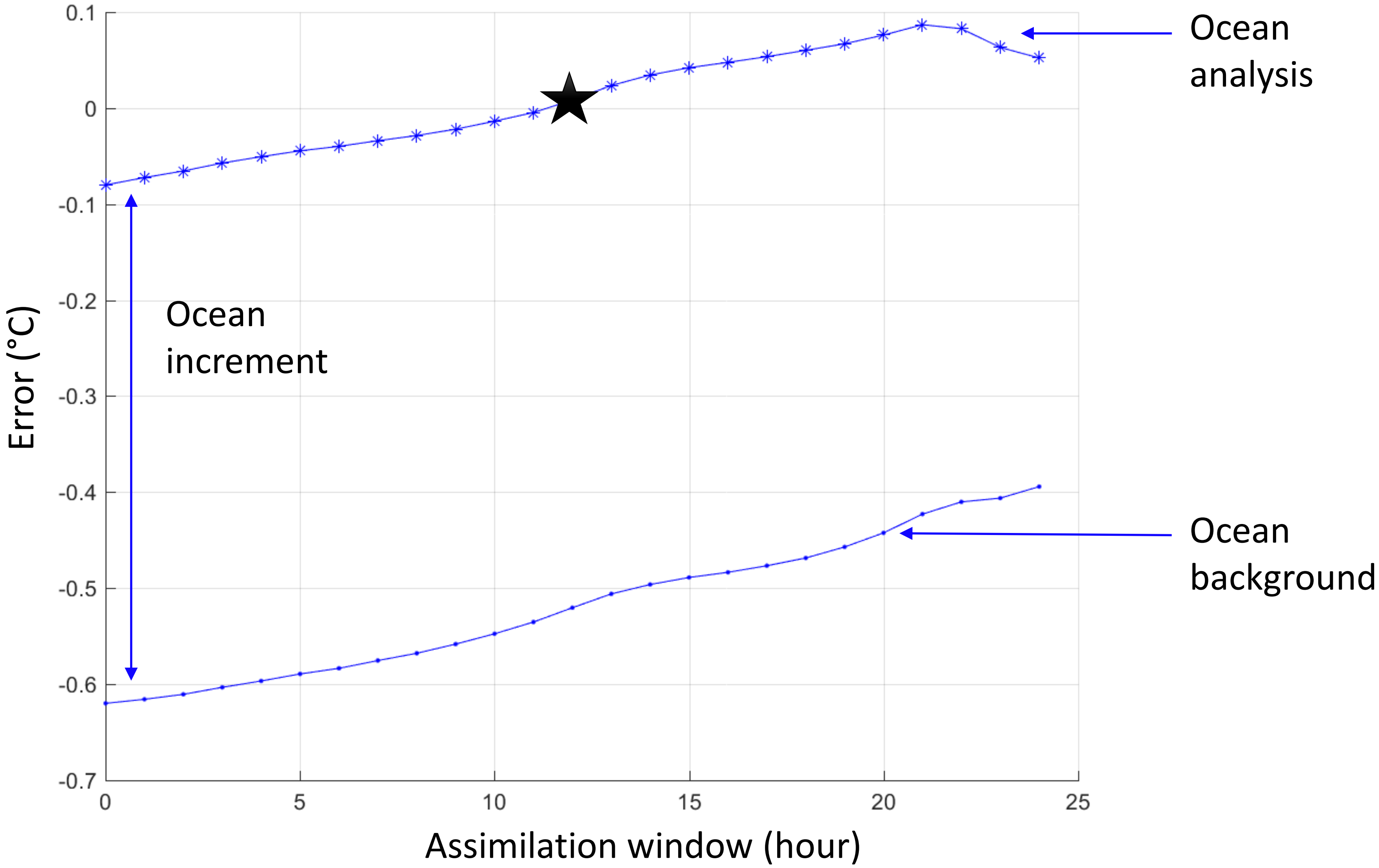


For the three locations and 6 dates (3 in Aug. and 3 in Feb.), we conducted single observation studies where we evaluated impact of assimilating 5m ocean temperature on the atmospheric analysis.

Laloyaux et al. (2018) QJ

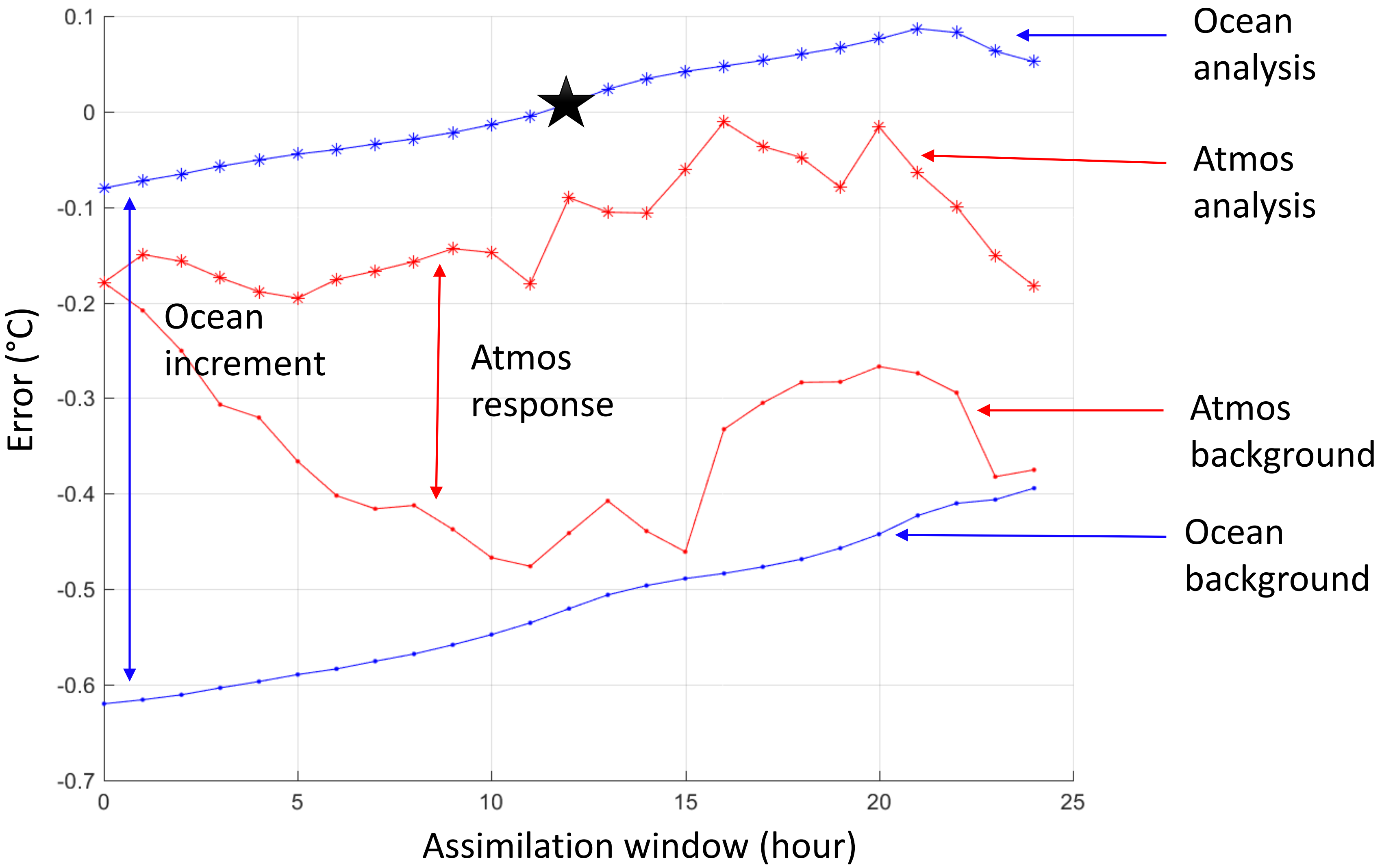
Role of the outerloop in coupling

Top level in the ocean and bottom level in the atmosphere



Role of the outerloop in coupling

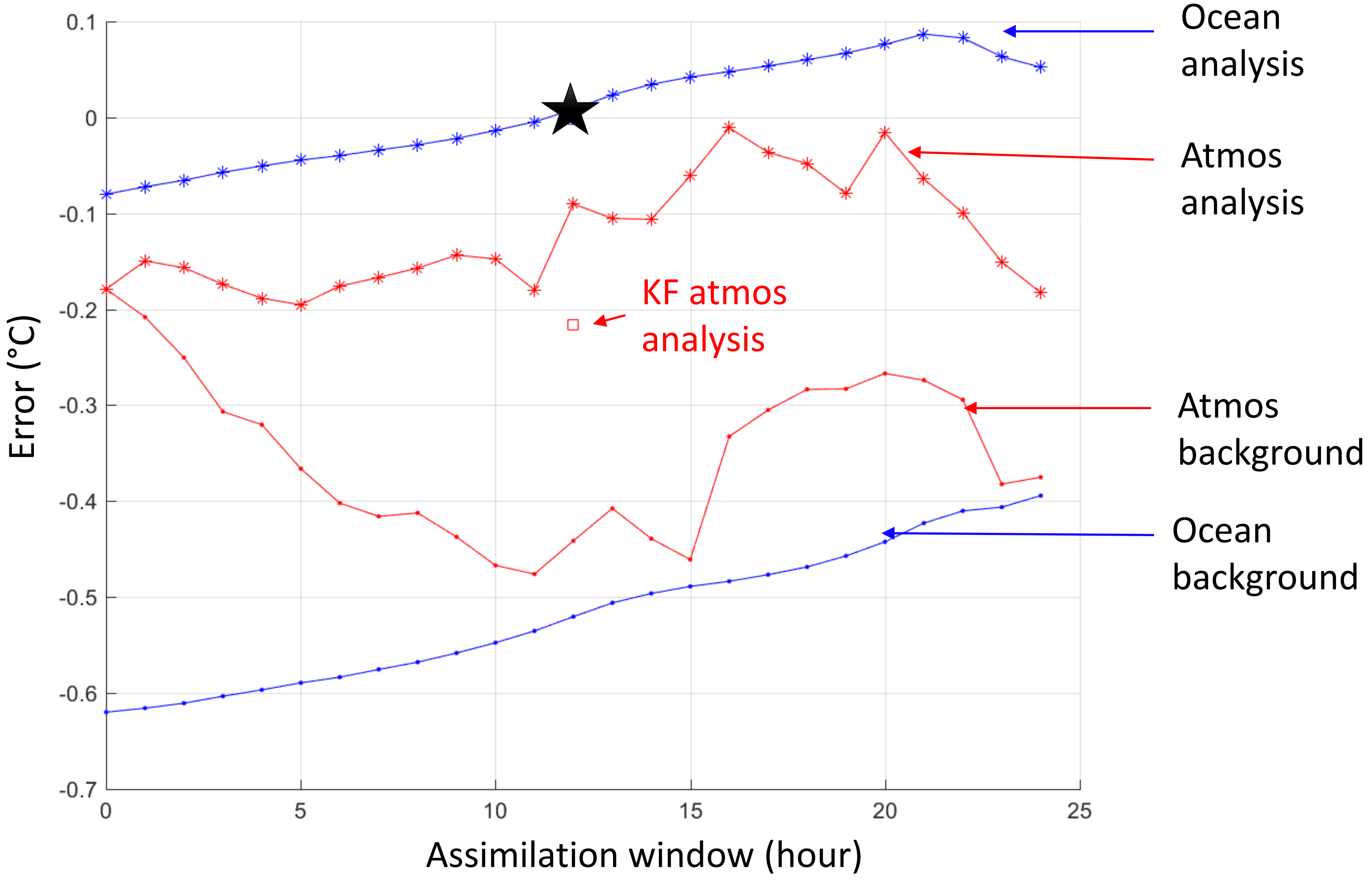
Top level in the ocean and bottom level in the atmosphere



Atmospheric response to the ocean observation happens in few hours

Comparing outerloop with strongly coupled KF

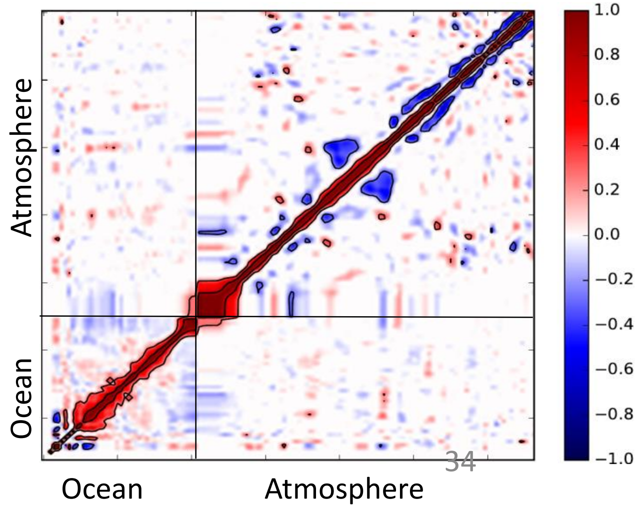
Top level in the ocean and bottom level in the atmosphere



$$x_{atm}^{a} = x_{atm}^{f} + \frac{\sigma_{air} c_{air|sst} \sigma_{sst}}{\sigma_{sst}^{2} + \sigma_{ob.error}^{2}} \left[y_{sst} - \mathcal{H}(x_{sst}^{f}) \right]$$

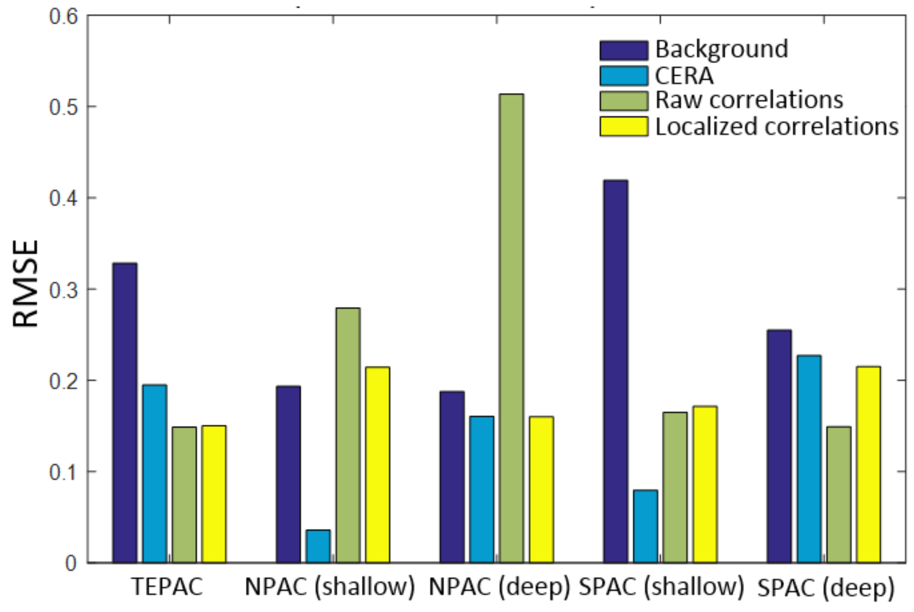
In addition to CERA outerloop results, we computed a two-point KF analysis based on covariance computed from 25 CERA members

Localized ensemble correlations

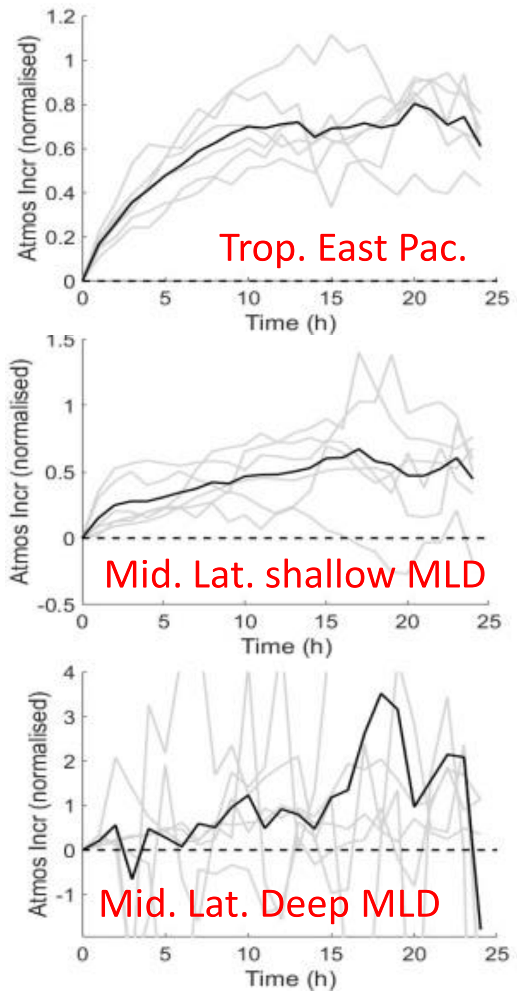


Comparing outerloop with strongly coupled KF

Average atmospheric surface temp. error



Response time of the atmosphere to assimilation of the SST ob.

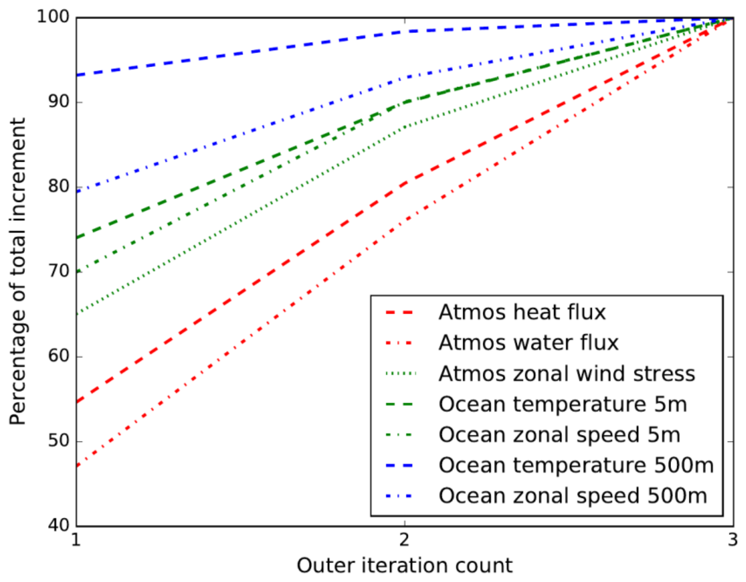


Forecast lead time

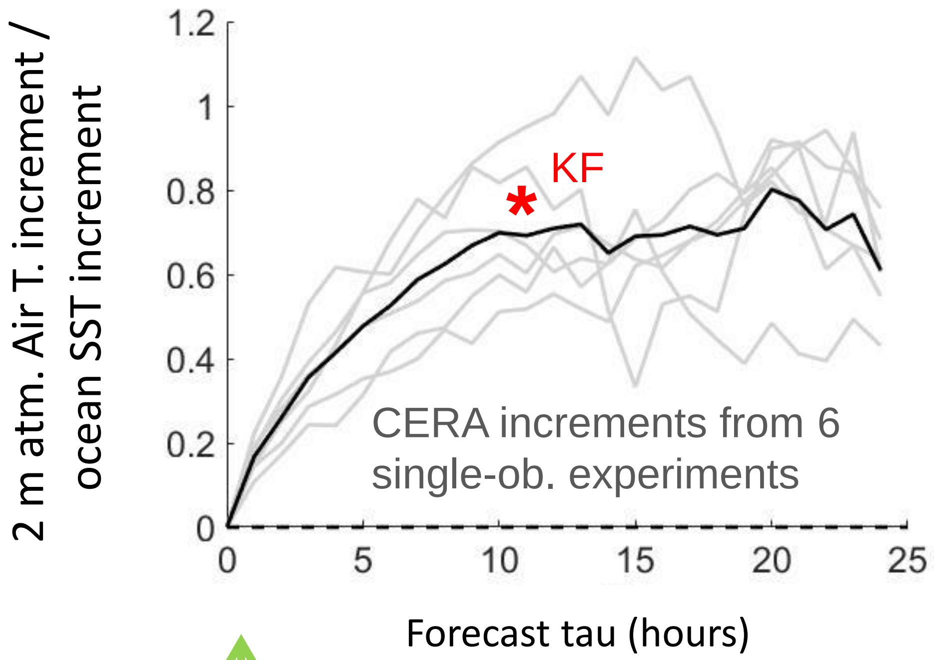
Results:

- (top) average performance of the strongly coupled and outerloop coupled DA is similar.
- (right) Ocean and atmosphere synchronize within the first 10-20 hours .

Role of the outerloop in coupled DA



Results of a single ob. experiment at the TEPAC location



Interpretation:

- (left) in CERA system, it takes multiple outerloop to converge on the atmospheric state, but only one iteration for the deep ocean. This suggests that outerloop is primarily needed to support atmospheric DA in CERA.
- (right) Outerloop is effective at moving synchronization within the DA window. However, this is best done with windows > 12 hours.

Outerloop approximates strong coupling poorly at the begining of the window

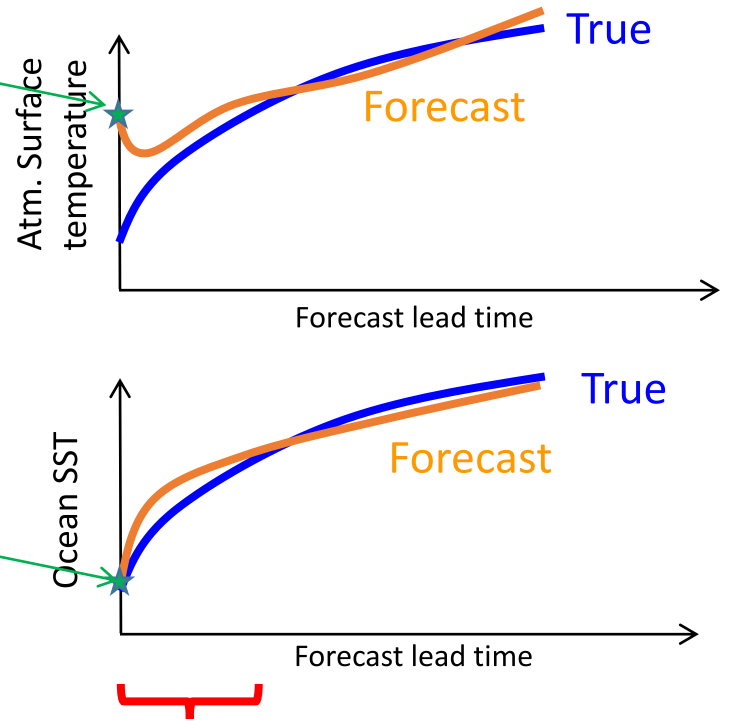
Outerloop approximates strong coupling well after 12 hours

Laloyaux et.al. (2018) QJ

The coupled DA challenge 1: Synchronization of the forecast

Atm. temp. analysis is away from truth because few direct observation of low-level atmospheric temperature are available over the ocean

Ocean temp. analysis is close to truth because plentiful SST observations are available over the ocean



How long does it take for the ocean and atmospheric models to synchronize (balance) and converge on “truth”

Key questions addressed by methods development:

- How long does it take to synchronize?
- Can the synchronization time be moved within the data assimilation window?
- Is it sufficient to rely on the forecast model for synchronization?

Outline

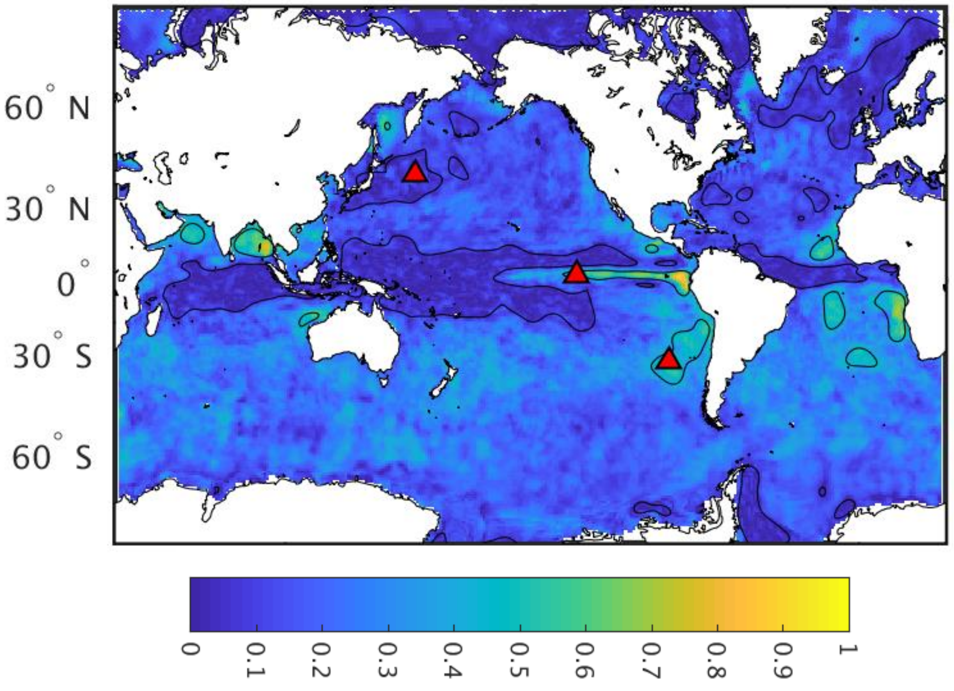
- The coupled DA opportunity and challenge
- Part 1: Algorithmic consideration for coupled DA
  - Challenge 1: Approximations to the strongly coupled data assimilation
  - Challenge 2: Mitigating for differences in space and time scales between Earth system components
- Part 2: Recent insights in to the coupling of atmospheric and oceanic temperatures

Part 3: Low hanging fruit for coupled DA

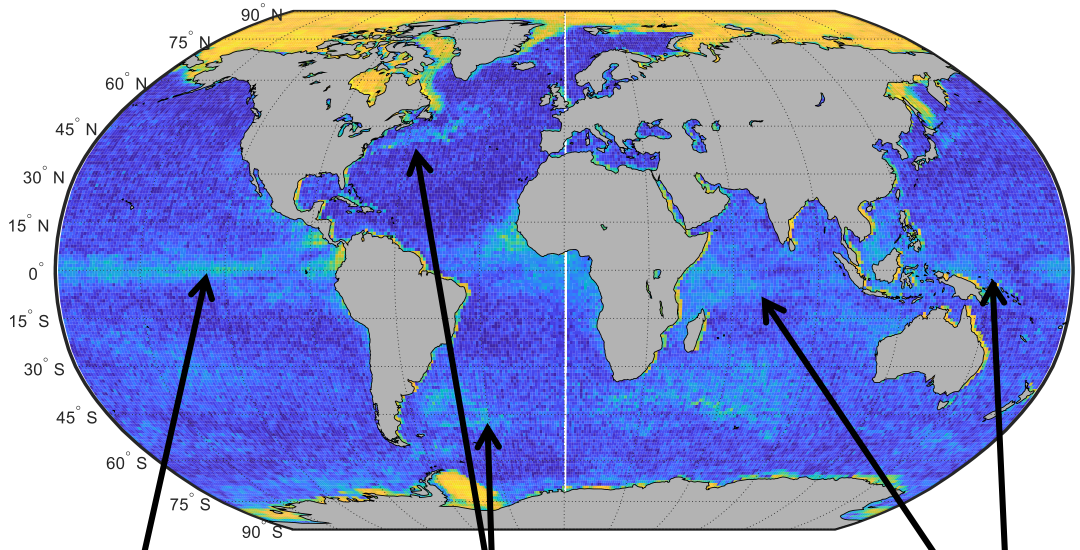
Low hanging fruit

Absolute value of air temperature-Earth surface correlation

ECMWF ensemble correlation (1 deg)
February 2005



ESPC ensemble correlation (on NAVGEM grid)
February 2017



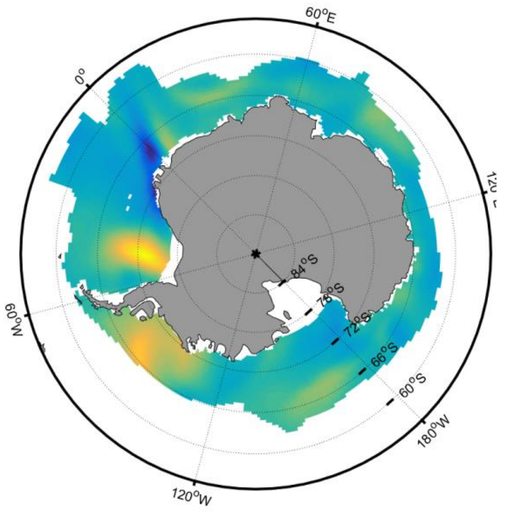
Same features in TEPAC

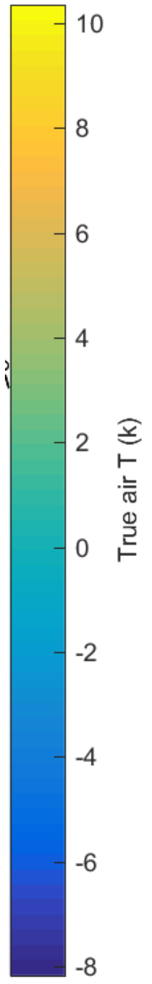
New features due to ocean mesoscale fronts

New features in the WPAC and Indian ocean (salinity boundary layer?)

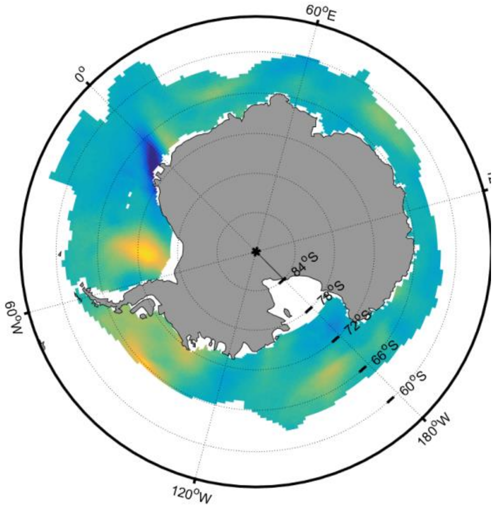
Lightweight Coupled DA OSSE

True state of the air T over sea ice





Predicted air T from “observed” ice T



for each point i,j solve the following scalar eq:

$$T^{a}_{air} = \bar{T}_{air} + \mathbf{k}\left[\left(T^{true}_{ice} + \varepsilon\right) - \bar{T}_{ice}\right]$$

$$\mathbf{k} = \frac{\sigma_{air} c_{air|ice} \sigma_{ice}}{\sigma^{2}_{ice} + \sigma^{2}_{ob.error}}$$

- **First guess**: ensemble mean
- **True state**: an out-of-sample ensemble member
- **Observation error**: added to the truth and accounted for in the KF
- **Covariance**: based on 25 CERA ensemble members
- **Forecast lead**: 24 hour forecast

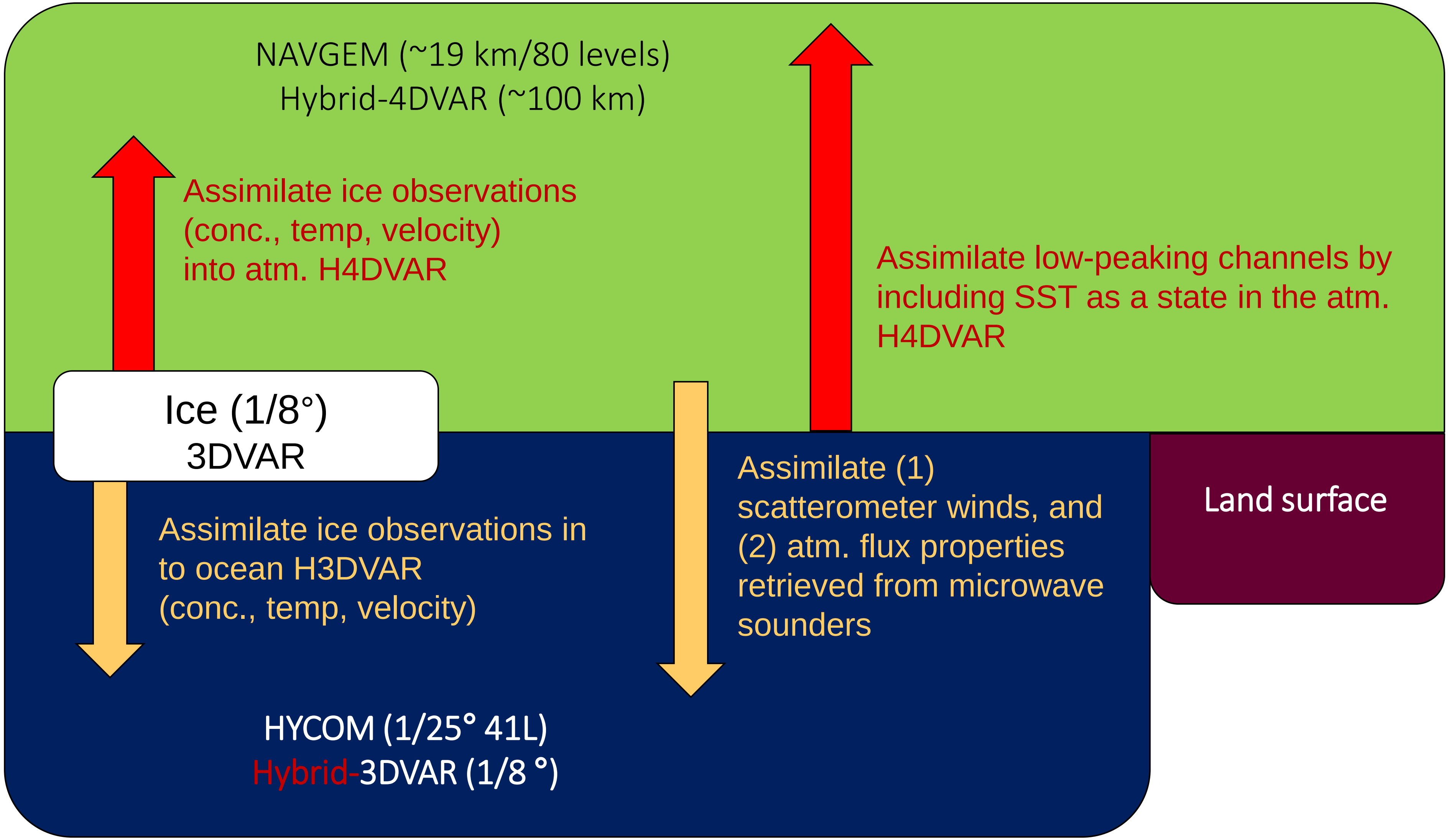
OSSE results using the CERA ensemble

Observations	Predicted state	RMSE red.(%)	Comments
SST	Surface air temp.	2% globally	Significant error reduction (20%) in marginal seas, around the ice edge, and TEPAC region
Significant wave height (from altimeter)	Surface wind speed	10%	Improvements are localized to large winter storms
Significant height of wind waves (currently not observable)	Surface wind speed	50-60%	This observation might be available from the next-generation SAR
Ice temperature	Surface air temp.	40-60%	Significantly better in winter, when the temperatures are below freezing
Ice velocity	Surface wind	40-60%	Good year round, better in S. Hemisphere where errors are larger.

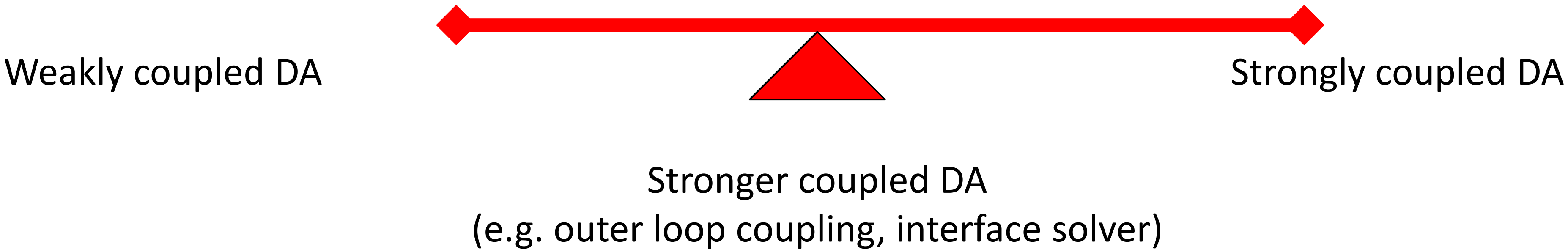
- How will these results change in a high-resolution ensemble (e.g. NRL's ESPC)?
- Do we have any indication that coupled DA can help constrain MLD or ocean velocities?

In collaboration with: P Laloyaux; JR. Bidlot

Plans for the NRL coupled system (2019-2022)



Conclusions

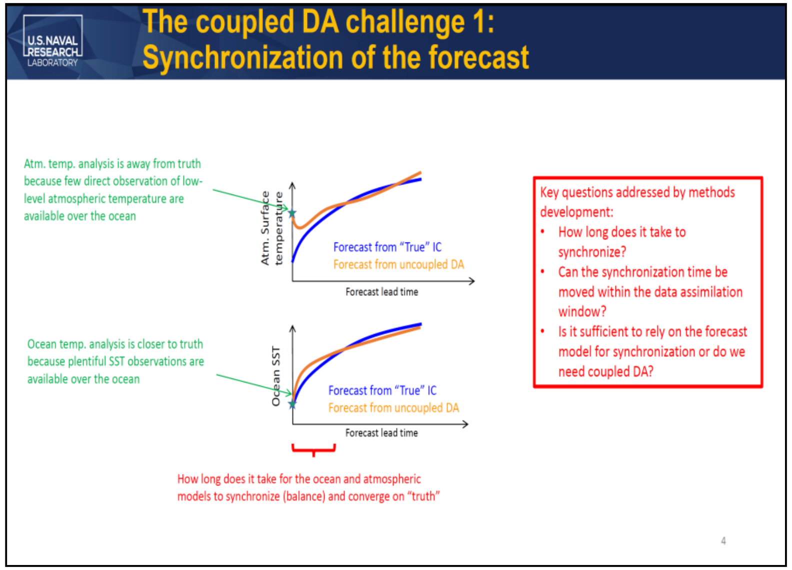


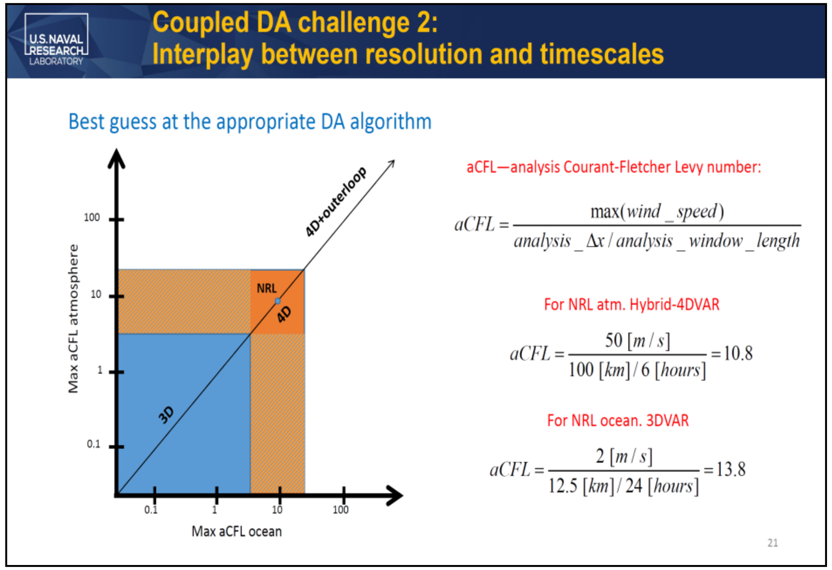
Working hypothesis:

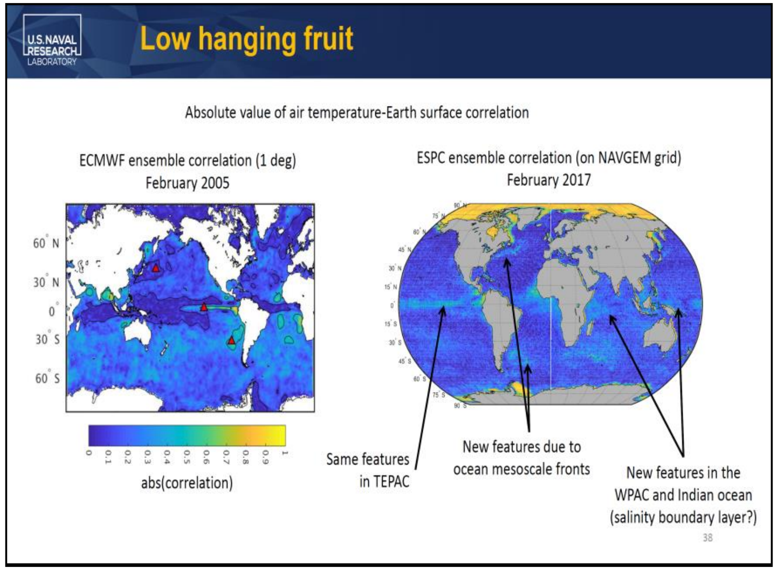
- **Currently**: The forecast skill will degrade if we implement strongly-coupled DA right now (due to our poor knowledge of the coupled error covariance).
- **In 3-7 years:** Implement approximations to the strongly coupled DA that will allow us to refine the coupled error covariance and, at the same time, control the strength of the coupling.
- **In 7+ years**: Merge the software environment for ocean/ice/atmosphere DA. Even if we choose to use different solvers in ocean and atmosphere, it would be good if we can borrow components from either system at will.

End

Summary







1) Coupling through dynamics along requires large assimilation windows (12-24 hours)

- Additional benefits are realized when DA is also coupled through observational operator and initial time-covariance

2) One algorithms is unlikely to be appropriate for all fluids at the same time

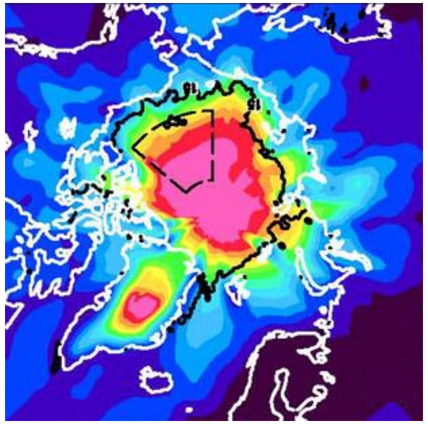
- In practical applications, synchronization of assimilation windows is the key challenge

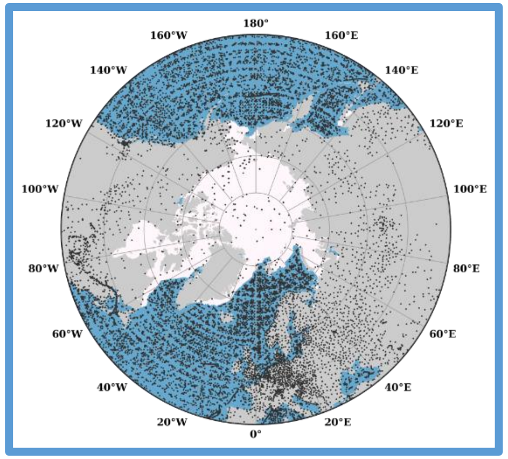
3) Correlations from coupled ensembles can be used to focus the development of CDA applications

- With large gains to be realized in the polar regions, over land, parts of the oceans.

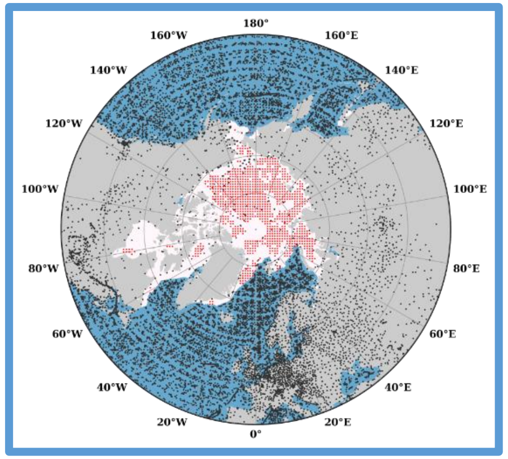
Coupled DA over ice is an obvious low-hanging fruit

Ensemble spread for surface pressure
is largest over the Arctic





Arctic is poorly observed
In current NWP systems



Red dots show locations of ice velocity measurements that can help to constrain the Artic forecast

Status-quo:

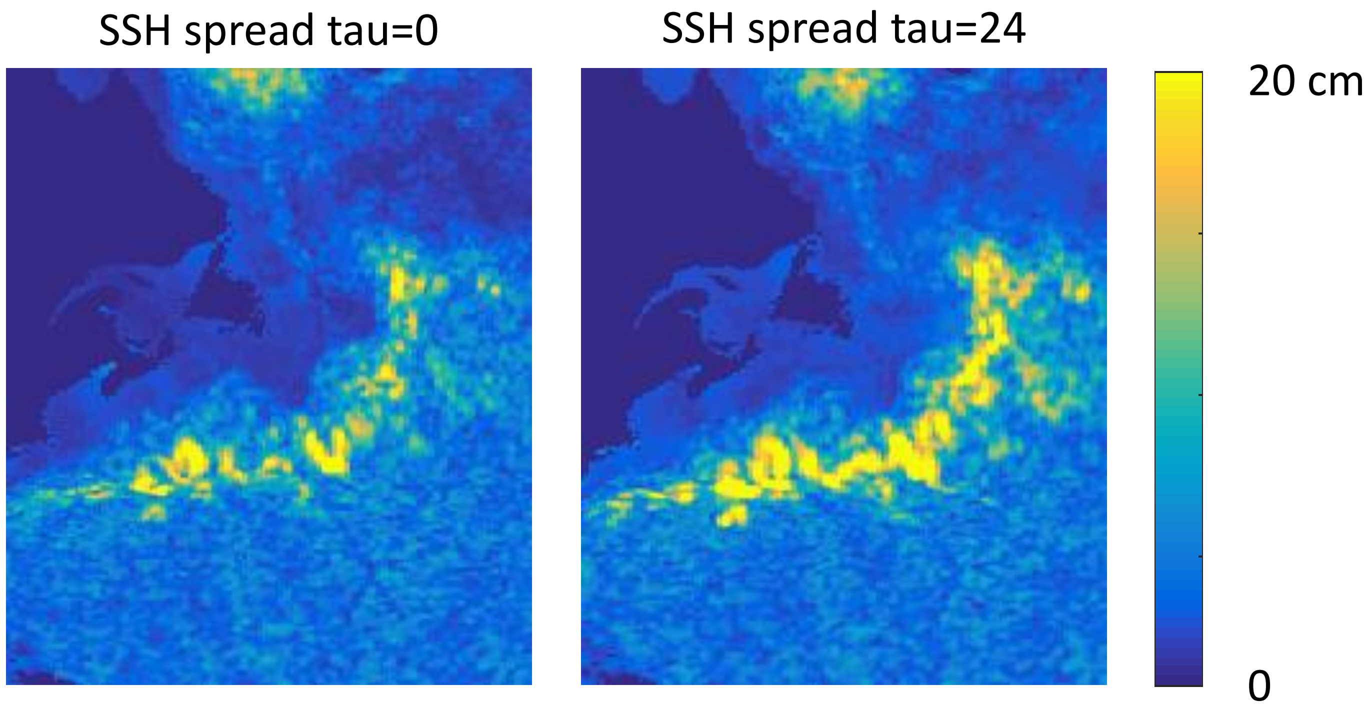
- Polar regions currently have very poor observing networks.
- Current DA systems use very little of the existing and abundant ice observations.

Opportunity:

- Assimilate ice drift and surface ice temperature to fully exploit
- Understand impact of the additional constrain on high impact weather events (rapid ice loss and sever winter storms)

In collaboration with: N. Barton, R. Allard, and P. Posey

Opportunity for Hybrid ocean DA



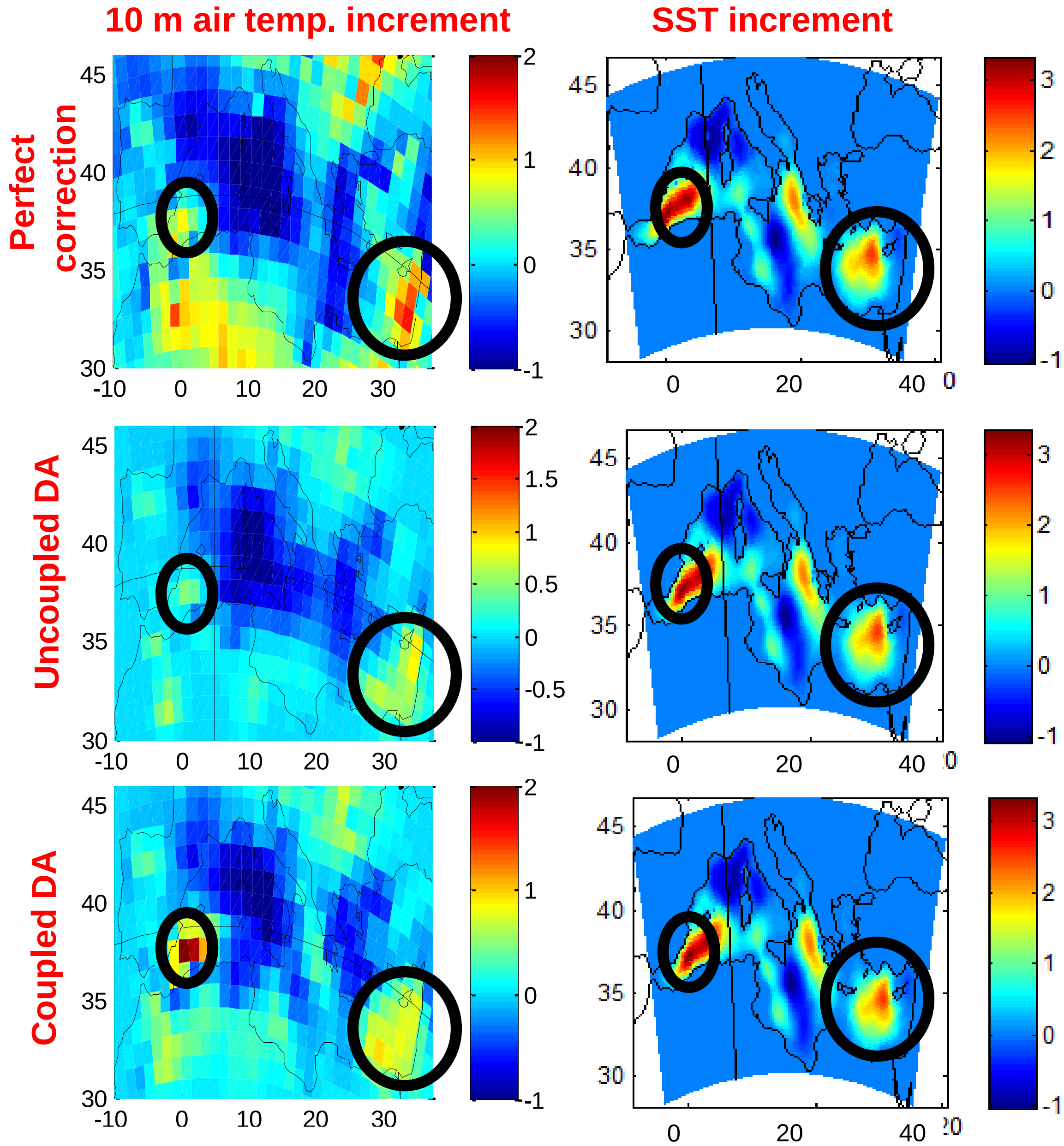
$$\mathbf{P}^{f}_{hybrid} = \alpha^{static}\mathbf{P}^{f}_{NCODA} + \alpha^{ens}\mathbf{C}_{loc} \odot \mathbf{P}^{f}_{ens}$$

New addition to NCODA, available since 2014

- ESPC ensembles (an early look of ensemble spread for SSH from 10 members above) show promise at characterizing uncertainty in location and strength of fronts in highly-energetic ocean boundary currents
- This information can be exploited at very little additional cost by the Hybrid-NCODA

In collaboration with: C. Bishop, OM. Smedstad, C. Rowley, P. Hogan, and C. Baron

Our early results with NCOM-COAMPS coupled DA (circa 2014)



- Early results (Frolov et.al. 2016) showed that strongly-coupled DA can transfer information from the SST observation into lower atmosphere.
- However, we struggled to see any patterns to coupling in such a small regional domain.