Multiple timescale coupled atmosphere-ocean data assimilation

(for climate prediction & reanalysis)

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Motivation

Context: climate forecasting & reanalysis

- Interannual to decadal : External forcing & initial conditions important (Meehl et al. 2009, Hawkins & Sutton 2009)
- Uninitialized hindcasts: skill limited to externally forced variability over continental & larger scales (Sakaguchi et al. 2012)
- Coupled system: fast atmosphere & slow (deep) ocean

Still unclear how to best initialize the coupled

system (Meehl et al. 2014)

- Slow has the memory (source of predictability) but much fewer observations than fast
- Requires coherent analyses of fast & slow
 components

Strongly (& multiscale) coupled DA?



predictions



Challenges / overarching questions

- Coherence between initial conditions of slow & fast relies on "cross-media" error covariances
 - <u>Q1</u>: What do these look like? How to reliably estimate? Fast component is "noisy" (i.e. high-frequencies)...
- Coupled system with wide variety of scales
 - <u>Q2</u>: Any benefits of multi-timescale DA?
- Slow has the memory but fewer observations than in fast
 - Q3: What role atmospheric obs. in initializing fast & slow components of a poorly observed ocean? ... a one-way coupling perspective

Approach

How to efficiently test ideas, prototype & evaluate strategies?

• Complex Earth system models problematic for such basic research

 Extremely expensive, especially for ensemble DA (small ensembles & limited experimentation, realizations, etc.)

• Motivates using simplified approach:

- Low-order analog of the coupled N. Atlantic climate system
 - -> few state variables: obtained from comprehensive AOGCM output
- Offline (i.e. "no cycling") ensemble DA
 - -> prior ensemble members drawn from states of long climate simulations
 - -> same prior used at every analysis times
 - :: uninformed prior (other than climatology of the model)

Cheap: Allows extensive numerical experimentation

Low-order analogue of N. Atlantic coupled system

[Inspired by Roebber (1995) & used in Tardif et al (2014, 2015)]

Subpolar N

Africa

Europe

Equator

65°

Ν

40°N

Eddy heat

flux

AMOC

Amei

- State variables:
 - Atmosphere:
 - MSLP along 40°N transect ("NAO" winds -> gyre) ←
 - Meridional eddy

heat flux across 40°N

Ocean:

- subpolar upper temperature & salinity

- AMOC index (max. overturning streamfunction in N. Atlantic)
 [taken as unobserved!]

S. Amer.

• Data derived by coarse-graining of state-of-the-art AOGCM gridded output

-> Simplified system but w/ complex underlying (fast/slow) dynamics

 $\circ~$ Monthly data for above variables as basis for DA experimentation

-> truth, observations (truth + random noise) & prior

Low-order analogue of N. Atlantic coupled system

- Analogue data derived from:
 - Community Climate System Model version 4 (CCSM4) gridded output from CMIP5 archives
 - o 1000-yr "Last Millennium" simulation (pre-industrial natural variability)



Low-order analogue of N. Atlantic coupled system



*** How much of this *unobserved* component of the coupled system can we recover using coupled multiple timescale DA? *** (by assimilating obs from other components of the low-order analogue)

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(Strongly) Coupled atmosphere-ocean DA

Ensemble Kalman filter:



Coupled atmosphere-ocean DA

- Ensemble DA & cross-media update
 - Assimilation of atmospheric obs. updating the ocean ...



Consider assimilation of **time-averaged obs.**

=> Averaging over the noise -> increase cov. w/ slow component
=> Increase "observability" -> reduce obs. error variance (R) ~1/sqrt(N)

[Tardif et al. 2014, 2015; Lu et al. 2015]

Time-average DA

• Assimilation of time-averaged observations

[State vector] [Observations]
$$\mathbf{x} = \overline{\mathbf{x}} + \mathbf{x}'$$
 $\mathbf{y} = \overline{\mathbf{y}} + \mathbf{y}'$

Time averaging & Kalman-filter-update operators linear and commute

Time-mean:
$$\overline{\mathbf{x}}_a = \overline{\mathbf{x}}_b + \mathbf{K}_A (\overline{\mathbf{y}} - \mathbf{H}\overline{\mathbf{x}}_b) \ \mathbf{K}_A = \overline{\mathbf{x}}_b \mathbf{y}_e^T [\mathbf{y}_e \mathbf{y}_e^T + \mathbf{R}]^{-1}$$

Deviations

ons:
$$\mathbf{x}'_a = \mathbf{x}'_b + \mathbf{K}_P(\overline{\mathbf{y}} - \mathbf{H}\overline{\mathbf{x}}_b) \ \mathbf{K}_P = \mathbf{x}'_b \mathbf{y}_e^T [\mathbf{y}_e \mathbf{y}_e^T + \mathbf{R}]^{-1}$$

 $\mathbf{x}_b' \mathbf{y}_e^T pprox 0 o \mathbf{x}_a' = \mathbf{x}_b'$ just update time-mean

Full state:
$$\mathbf{x}_a = \overline{\mathbf{x}}_a + \mathbf{x}_b'$$

(Dirren & Hakim 2005; Huntley & Hakim 2010)

Multiple timescale DA

• Assimilate obs. at "appropriate" time scale

$$\mathbf{x}_{b} = \overline{\mathbf{x}}_{b}^{\tau_{1}} + \mathbf{x}_{b}'$$

$$\mathbf{x}_{a} = \overline{\mathbf{x}}_{b}^{\tau_{1}} + \mathbf{K}_{A}(\underline{\overline{\mathbf{y}}}_{1}^{\tau_{1}} - \mathbf{H}\overline{\mathbf{x}}_{b}^{\tau_{1}})$$
Do update
$$\mathbf{x}_{a} = \overline{\mathbf{x}}_{a}^{\tau_{1}} + \mathbf{x}_{b}'$$
Recover full state
$$\mathbf{x}_{b} = \overline{\mathbf{x}}_{b}^{\tau_{2}} + \mathbf{x}_{b}'$$
Decompose at scale $\tau_{\underline{\mathbf{z}}}$

$$\mathbf{x}_{a} = \overline{\mathbf{x}}_{b}^{\tau_{2}} + \mathbf{x}_{b}'$$
Decompose at scale $\tau_{\underline{\mathbf{z}}}$

$$\mathbf{x}_{a} = \overline{\mathbf{x}}_{b}^{\tau_{2}} + \mathbf{x}_{b}'$$
Recover full state
$$\mathbf{x}_{a} = \overline{\mathbf{x}}_{a}^{\tau_{2}} + \mathbf{x}_{b}'$$
Recover full state

If at last step (i.e. \mathbf{y}_2 shares same time scale as \mathbf{x}_b : $\mathbf{x}'_b = 0$ \mathbf{y} End product is final analysis at time scale τ_2

CDA experiments

- Ensemble square root filter (Whitaker & Hamill 2002)
- Serial obs. processing
- Low-order system -> no localization
- Offline/no cycling -> no inflation
- "Reanalysis mode" -> all obs. available a-priori

- simplifications

- Perfect model experiments, i.e. same model for truth & observations
 -> obs.: random noise added (10% of climatological variance)
- Frequency of obs.: monthly
- Generate AMOC analyses over 1000 years
- Run DA experiment w/ various obs. availability scenarios

(atmosphere vs. ocean)

• Consider **2 time scales**: a **slow** (τ_1) and a **fast** (τ_2 = monthly)

Assimilated obs. vs. time scales

• Covariability w/ AMOC index vs averaging time scale



Single vs. multiple timescale DA

Coupled DA of MSLP (atmosphere) and upper subpolar ocean T, S



Verification metric

Coefficient of efficiency

(Nash and Sutcliffe 1970)



Single vs. multiple timescale DA

Verification vs. time scales

(calculated with analyses covering full 1000 yrs)

CE for ensemble mean AMOC analyses



Multi-time scale DA: ocean vs. atmosphere-only



Multi-time scale DA: ocean vs. atmosphere-only

Atmosphere-only DA: vs. long time scale



Toward application to real data...

- Last Millennium Reanalysis (LMR)
 - Offline assimilation of paleoclimate data
 - Tree rings



LMR: reconstructed global mean temperature

Hakim, G. J., J. Emile-Geay, E. J. Steig, D. Noone, D. M. Anderson, R. Tardif, N. Steiger, and W. A. Perkins (2016), The last millennium climate reanalysis project: Framework and first results, J. Geophys. Res. Atmos.

Takeaways ...

- **Q1:** Cross-media covariances, how to reliably estimate?
 - A: Use time-averaging over appropriate scale
 - Averaging over "noise" in fast atmosphere = > enhances covariability w/ slow ocean
- **Q2**: Benefits from multiple timescale DA approach?

A: Yes!

- More accurate analyses of **fast & slow**
- Reduced errors at intermediate (~annual) scales from DA of monthly & decadal.avg. obs.
- **Q3**: What role atmospheric obs. in initializing ocean's fast & slow components ?

A: Can be significant:

- Frequent DA for fast ocean component: Fast response to winds, surface fluxes etc.
- Less significant role for constraining slow, if ocean *sufficiently* well-observed
- Fully coupled DA of time-averaged obs. important when poorly observed ocean (w/ appropriate choice of assimilated obs.)