### What are the dominant atmospheric drivers of interannual AMOC variability?

### Dan Amrhein, Dafydd Stephenson National Center for Atmospheric Research

### LuAnne Thompson, Noah Rosenberg University of Washington

Also thanks to Ichiro Fukumori, Yavor Kostov









NATIONAL CENTER FOR ATMOSPHERIC RESEARCH



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### "Variance budgets" describe contributions to ocean variability



### $X_{\text{amoc}} = X_{\tau} + X_b + \dots$

### $\operatorname{var}\left(X_{\operatorname{amoc}}\right) = \operatorname{var}\left(X_{\tau}\right) + \operatorname{var}\left(X_{b}\right) + 2\operatorname{cov}\left(X_{b}, X_{\tau}\right) + \dots$



### "Variance budgets" describe contributions to ocean variability



Stephenson and Sevellec 2021a: The Active and Passive Roles of the Ocean in Generating Basin-Scale Heat Content Variability, GRL 2021b: Dynamical Attribution of N. Atlantic Interdecadal Predictability to Oceanic and Atmospheric Turbulence under Diagnosed and Optimal Stochastic Forcing, J Clim Close et al. 2020, Jamet et al. 2020...



### Ocean model adjoint sensitivities diagnose dominant drivers

#### "Quantity of interest"

Any function of the model state (e.g., AMOC strength)

# $\mathbf{S} = \frac{\partial x}{\partial \mathbf{q}}$

#### "Controls"

Vector in time and space of ocean model inputs that can change *x* (e.g., surface heat fluxes)

### **Adjoint sensitivity**

How much will changing **q** change *x*? (A *locally linear* estimate)

### Ocean model adjoint sensitivities diagnose dominant drivers



Pillar et al. 2016 Also Heimbach and Wunsch 2011; Jones et al. 2018; Kostov et al. 2019, 2021; Fukumori et al. 2021



x10-10 Sv/W

### Ocean model adjoint sensitivities diagnose dominant drivers



Sensitivities reveal **"optimal"** drivers of *x* that reflect **ocean** length and time scales.

In the spirit of variance budgets, can we derive sensitivities to derive atmospheric patterns that contribute most to *ocean* variance?

Pillar et al. 2016 Also Heimbach and Wunsch 2011; Jones et al. 2018; Kostov et al. 2019, 2021; Fukumori et al. 2021





 $x = \mathbf{s}^{\mathsf{T}} \mathbf{q}$  $\operatorname{var}(x) = \mathbf{s}^{\mathsf{T}} \mathbf{C} \mathbf{s}$  $= \operatorname{tr}(\mathbf{S}^{\mathsf{T}} \mathbf{C}_{s} \mathbf{S})$ 

Sensitivities allow us to write x (AMOC) as a linear function of fluxes q...

... and the variance of x in terms of the (*space-time*!) covariance of q.

Assuming q is white noise simplifies to a function of purely *spatial* covariances

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$$x = \mathbf{s}^{\mathsf{T}} \mathbf{q}$$
  
var (x) =  $\mathbf{s}^{\mathsf{T}} \mathbf{C} \mathbf{s}$   
= tr ( $\mathbf{S}^{\mathsf{T}} \mathbf{C}_{s} \mathbf{S}$ )  
= tr ( $\mathbf{C}^{1/2} \mathbf{S}_{s}^{\mathsf{T}} \mathbf{S} \mathbf{C}^{\mathsf{T}/2}$ )

Sensitivities allow us to write x (AMOC) as a linear function of fluxes q...

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 $\mathbf{P} \mathbf{\Lambda} \mathbf{P}^{\mathsf{T}} =$ 

$$= \mathbf{C}^{1/2} \mathbf{S}_s^{\mathsf{T}} \mathbf{S}_s \mathbf{C}^{\mathsf{T}/2}$$

Eigenvectors  $(\mathbf{p}_j)$  are atmospheric patterns whose variability maximizes var  $(x^2)$ .



 $\mathbf{P} \mathbf{\Lambda} \mathbf{P}^{\top} =$ 

If  $\mathbf{C} = \mathbf{I}$  (**q** is white noise in space),  $\mathbf{p}_j$  are **optimal patterns** for stochastic excitation (e.g., Farrell and Iaonnou 1996)

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> If  $\mathbf{S}_{s}^{\mathsf{T}}\mathbf{S}_{s} = \mathbf{I}$  (e.g. adjoint sensitivities are orthonormal in time),  $\mathbf{p}_i$ are atmospheric EOFs



Voila, an eigenvector problem!  $\mathbf{P} \mathbf{\Lambda} \mathbf{P}^{\top} =$ Eigenvectors  $(\mathbf{p}_j)$  are atmospheric patterns whose variability maximizes var  $(x^2)$ .

If  $\mathbf{C} = \mathbf{I}$  (**q** is white noise in space),  $\mathbf{p}_i$  are **optimal patterns** for stochastic excitation (e.g., Farrell and Iaonnou 1996)

$$= \mathbf{C}^{1/2} \mathbf{S}_s^{\mathsf{T}} \mathbf{S}_s \mathbf{C}^{\mathsf{T}/2}$$

"COFs" = combined orthogonal functions

If  $\mathbf{S}_s^{\top} \mathbf{S}_s = \mathbf{I}$  (e.g. adjoint sensitivities are orthonormal in time),  $\mathbf{p}_i$ are atmospheric EOFs



### ~1° resolution MITgcm ECCO v4 configuration

Ocean and sea ice components spun up under 4800 years following *Wolfe et al. 2017*).

Adjointed and run to compute sensitivities of AMOC transport at climatological maximum depth at annual and decadal averages across several latitudes.

Fluxes are 6-hourly from ECCO v4r4.



#### ECCO: Forget et al. 2015; CNYF: Large and Yeager 2009





Leading stochastic optimal for AMOC variance at 55N by heat fluxes







### Leading stochastic optimal for AMOC variance at 55N by heat fluxes

Leading EOF of ECCO v4r4 heat fluxes







- 0.04

- 0.02

- 0.00

-0.02

-0.04

### Leading stochastic optimal for AMOC variance at 55N by heat fluxes

Leading EOF of ECCO v4r4 heat fluxes



Leading heat flux COF contributing to decadal-mean AMOC variability







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### Leading stochastic optimal for AMOC variance at 55N by heat fluxes

Leading EOF of ECCO v4r4 heat fluxes

A region of "latent" AMOC variance production?



Leading heat flux COF contributing to decadal-mean AMOC variability







- 0.04

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-0.04

### Leading stochastic optimal for AMOC variance at 55N by heat fluxes

Leading EOF of ECCO v4r4 heat fluxes



Leading heat flux COF contributing to decadal-mean AMOC variability

Very similar leading patterns (r~.99) were found across latitudes and when targeting annual and decadal AMOC variability.





### Looking familiar?

SLP EOF1





### Leading heat flux COF contributing to decadal-mean AMOC variability







#### Regression of SLP PC1 onto HF





### Leading heat flux COF contributing to decadal-mean AMOC variability



## In "perturbed ECCO" simulations, removing the leading COF from ECCO forcing drives more AMOC variance than the leading EOF across time scales



"Perturbed ECCO" simulations run in a **"flux-only" configuration** to isolate contributions from different fluxes (*Fukumori et al. 2021*).

### In "perturbed ECCO" simulations removing heat flux patterns, the leading COF drives more AMOC variance than the leading EOF across time scales



"Perturbed ECCO" simulations run in a "flux-only" configuration to isolate contributions from different fluxes (Fukumori et al. 2021).



Longer time scales of AMOC variability are reduced most and have greatest meridional extent





L\_100

### Longer time scales of AMOC variability are reduced most and have greatest meridional extent



Jackson et al. 2022





-100

### Might non-NAO, decadal-scale wind be important for *meridional* asynchrony?



55N

Jackson et al. 2022 see e.g. Häkkinen et al. 2011; Barrier et al. 2014; Kim et al. 2016...

### Wind stress: leading stochastic optimals

#### Zonal component



Meridional component



### Leading COFs

Zonal component



Meridional component

































### **Conclusions and future work**

Adjoints tell us what the **ocean wants from the atmosphere**. Atmospheric EOFs describe **dominant atmospheric patterns**. By combining adjoints and atmospheric statistics, we identify causal atmospheric structures that dominate ocean variability.

When applied to AMOC on annual- and decadal-average time scales, a common NAO-like heat flux pattern dominates variance change across time scales and latitudes by reducing density anomaly amplitudes in the SPG.

A related procedure permits smoothing adjoint sensitivities to reflect prior atmospheric covariances and additional observations of the atmosphere. These procedures are useful in state estimation (especially paleo!).

Caveats: Linear sensitivities. Covariances assume stationary fluxes. Using a 1° ocean-only model.



From Dafydd: Please reach out if you're interested in setting up or running an ocean adjoint model! <u>dafydd@ucar.edu</u>



