Identifying dominant atmospheric drivers of ocean variability using ECCO and the MITgcm adjoint: Implications for reducing model bias

Dan Amrhein, Dafydd Stephenson
National Center for Atmospheric Research

LuAnne Thompson, Noah Rosenberg
University of Washington

What are the **dominant patterns and pathways** by which the atmosphere drives **ocean variability**?

Outline

The ocean as an integrator (and source) of random variation

What dominates ocean variability? Views from the atmosphere and ocean

Reconciliation: A dynamics-weighted principal components analysis

Dominant atmospheric drivers of decadal AMOC variability

Impacts of dominant drivers over the observational period

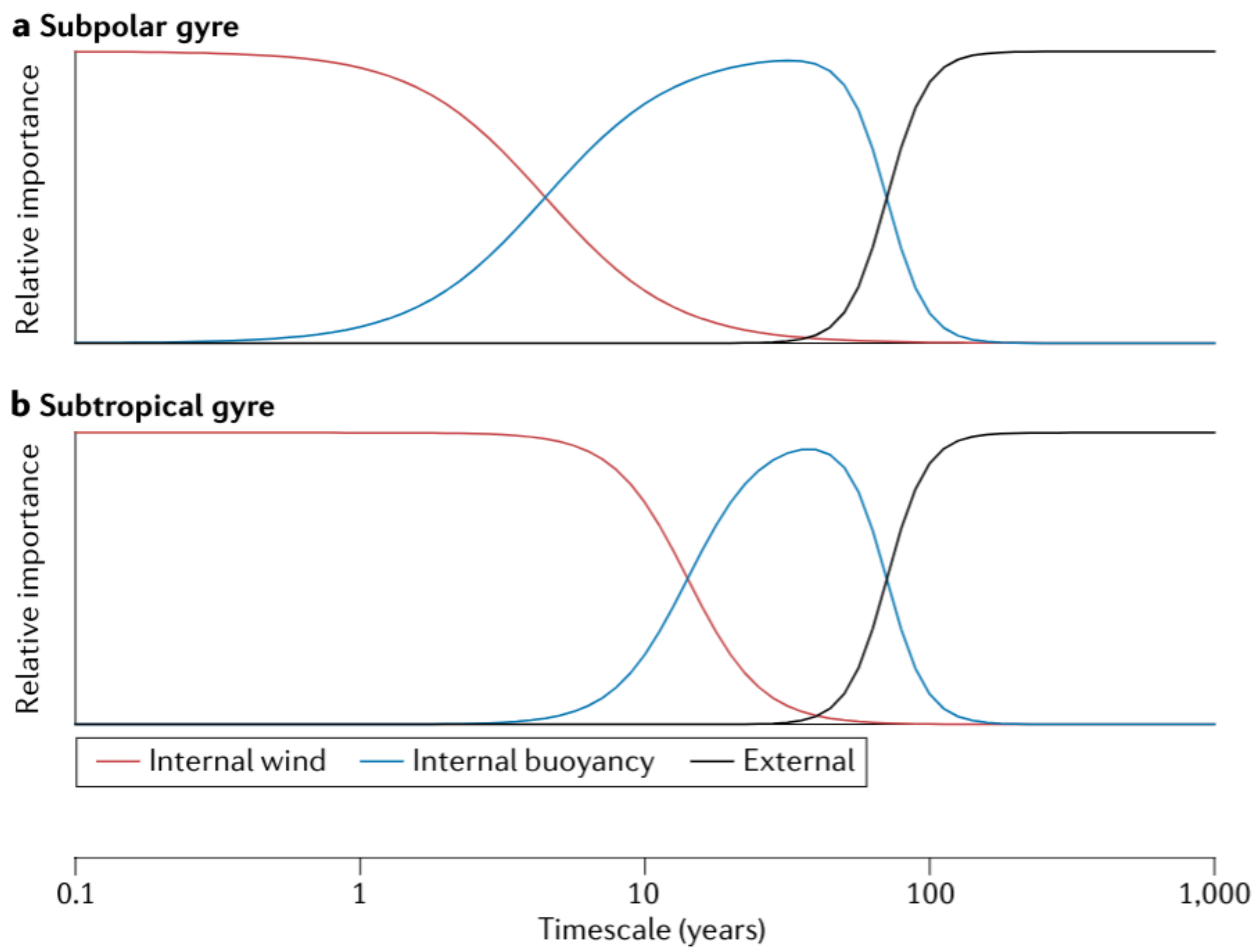
Tracing pathways of decadal AMOC change from atmosphere to ocean

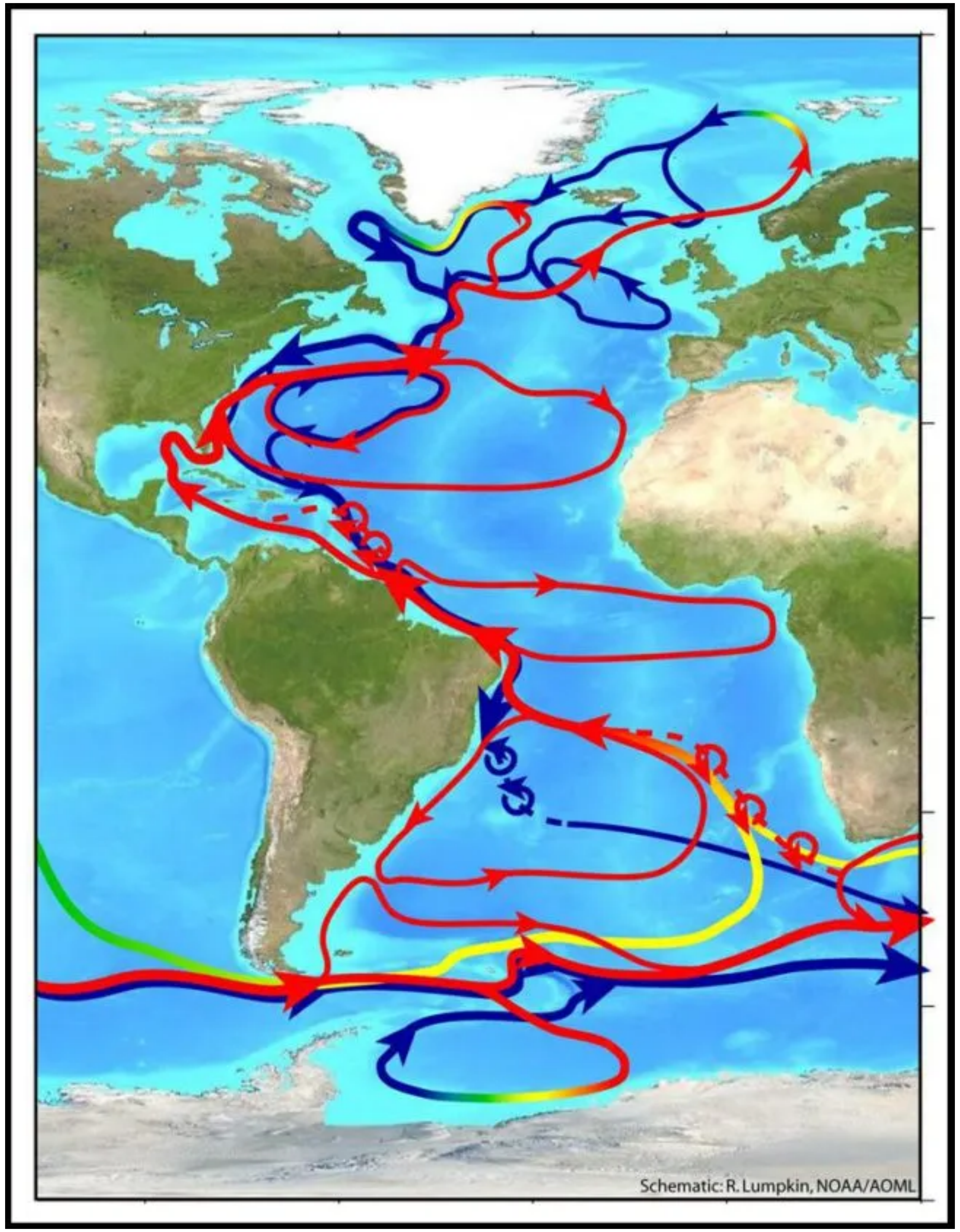
Case study: Variability in the Atlantic Meridional Overturning Circulation

Decadal variability in AMOC influences climate variability

Can mask anthropogenic warming signal

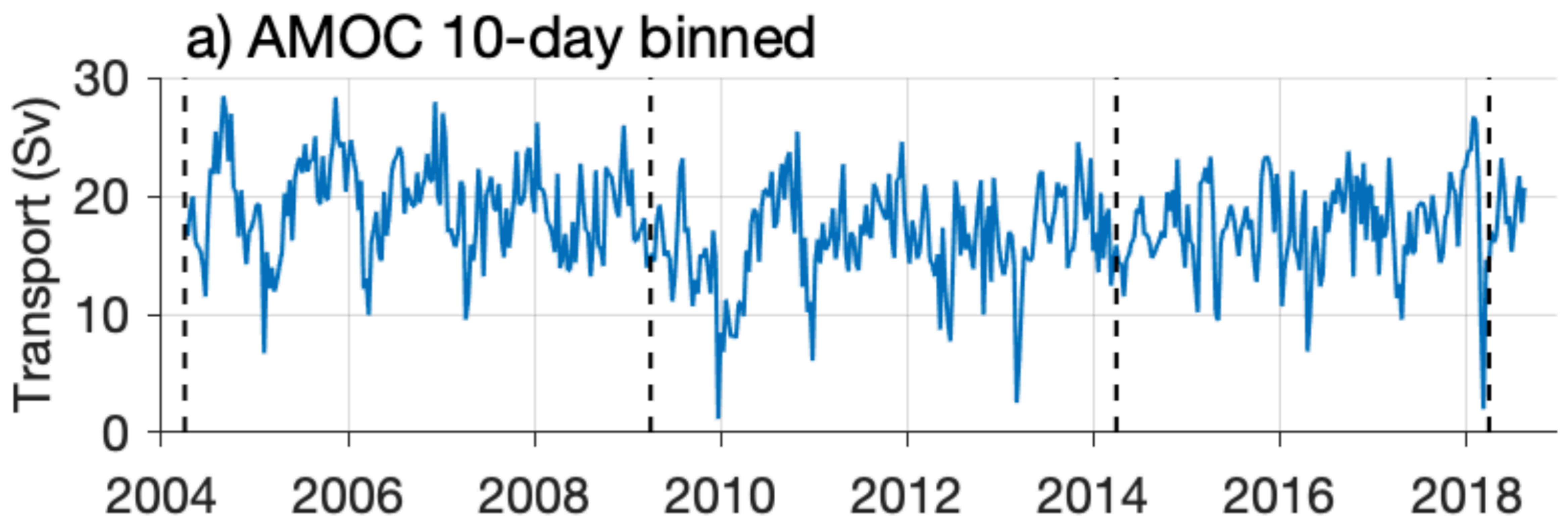
Junction between high-frequency (e.g. wind) and low-frequency (e.g. buoyancy) influences

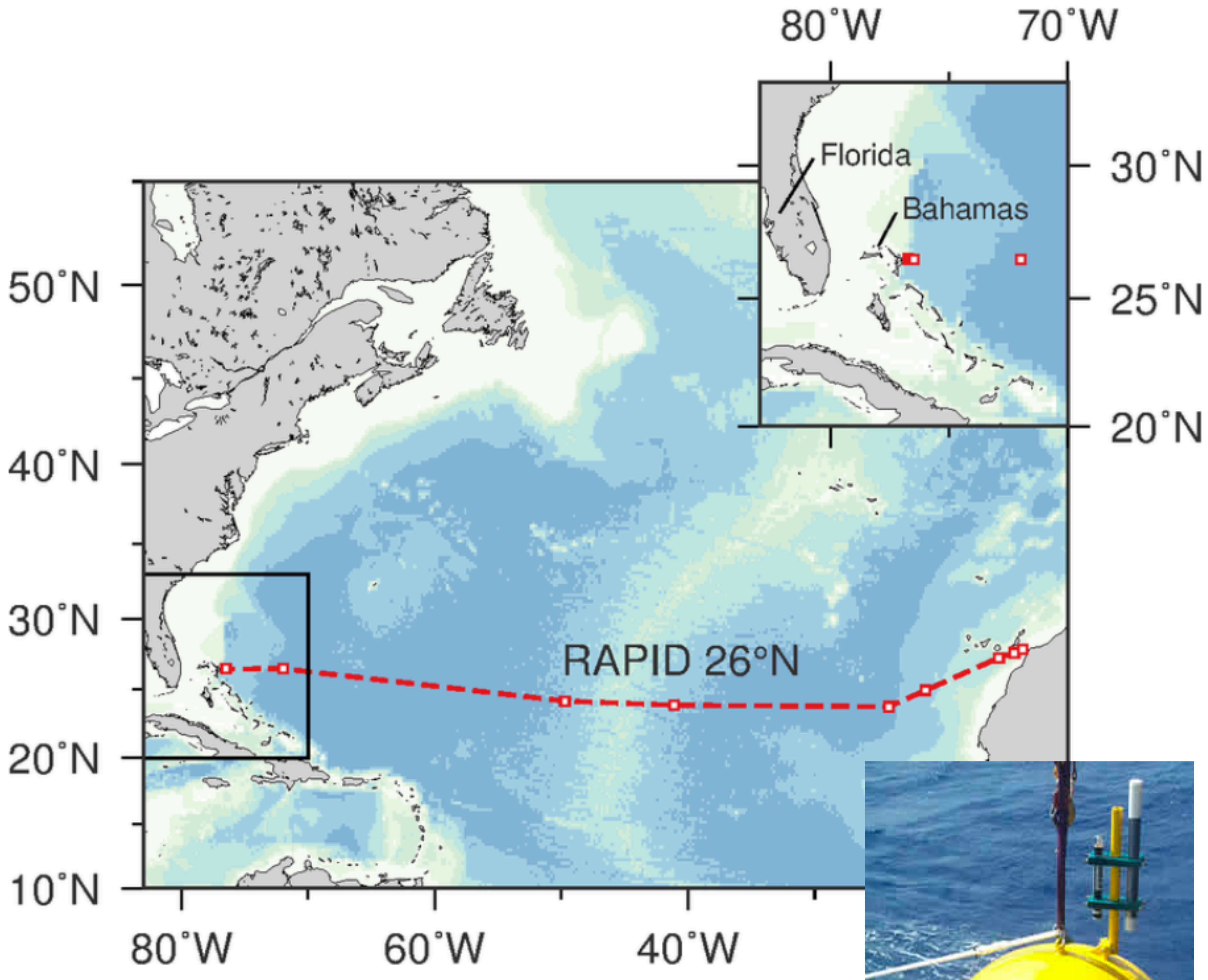




Jackson et al. 2022

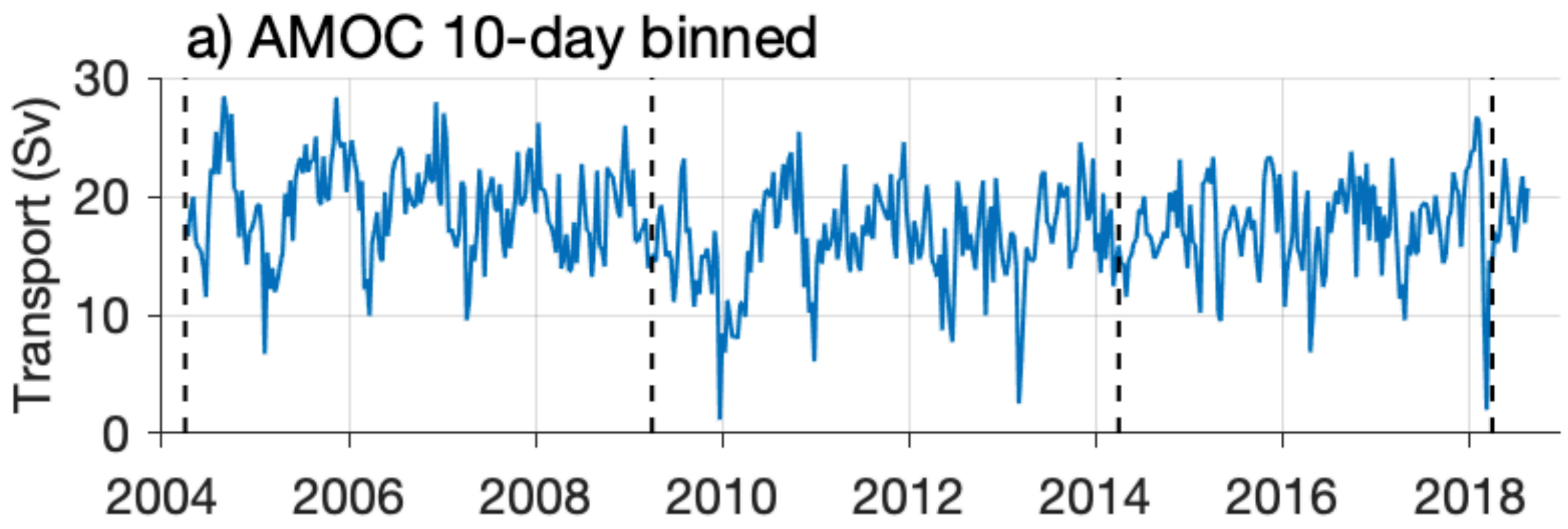
Observing AMOC variability





Frajka-Williams et al. 2016

Representing AMOC variability as a random process



$$X_{\mathbf{amoc}} = X_\tau + X_b + \dots$$

$$\textbf{var}\left(X_{\mathbf{amoc}}\right) = \textbf{var}\left(X_\tau\right) + \textbf{var}\left(X_b\right) + 2\textbf{cov}\left(X_b, X_\tau\right) + \dots$$

Moat et al. 2020

Representing AMOC variability as a random process

The zero-order result here is that a modern ocean–ice GCM, when least squares fit to the 2-decade-long global datasets available since 1992, produces a dynamically consistent estimate of the Atlantic MOC, one which is indistinguishable from a stationary Gaussian red-noise process. With the benefit of hindsight, the result is unsurprising: a system with long memory is subject to continuous small stochastic disturbances by external processes (winds, precipitation, etc.), which themselves

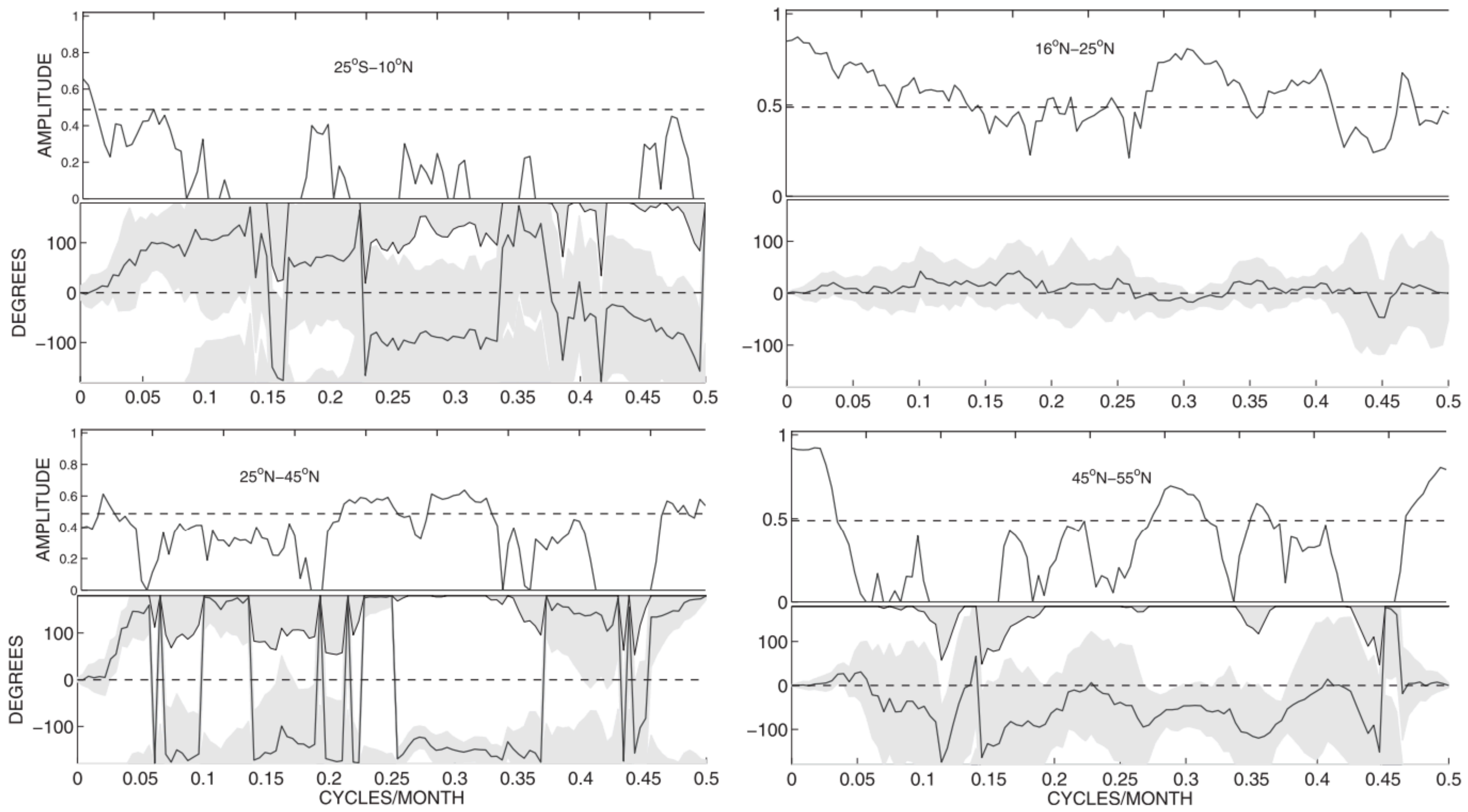


FIG. 9. Coherence magnitude and phase of the AMOC between four pairs of nearest-neighbor latitudes. The

Wunsch and Heimback 2013

Outline

The ocean as an integrator (and source) of random variation

What dominates ocean variability? Views from the atmosphere and ocean

Reconciliation: A dynamics-weighted principal components analysis

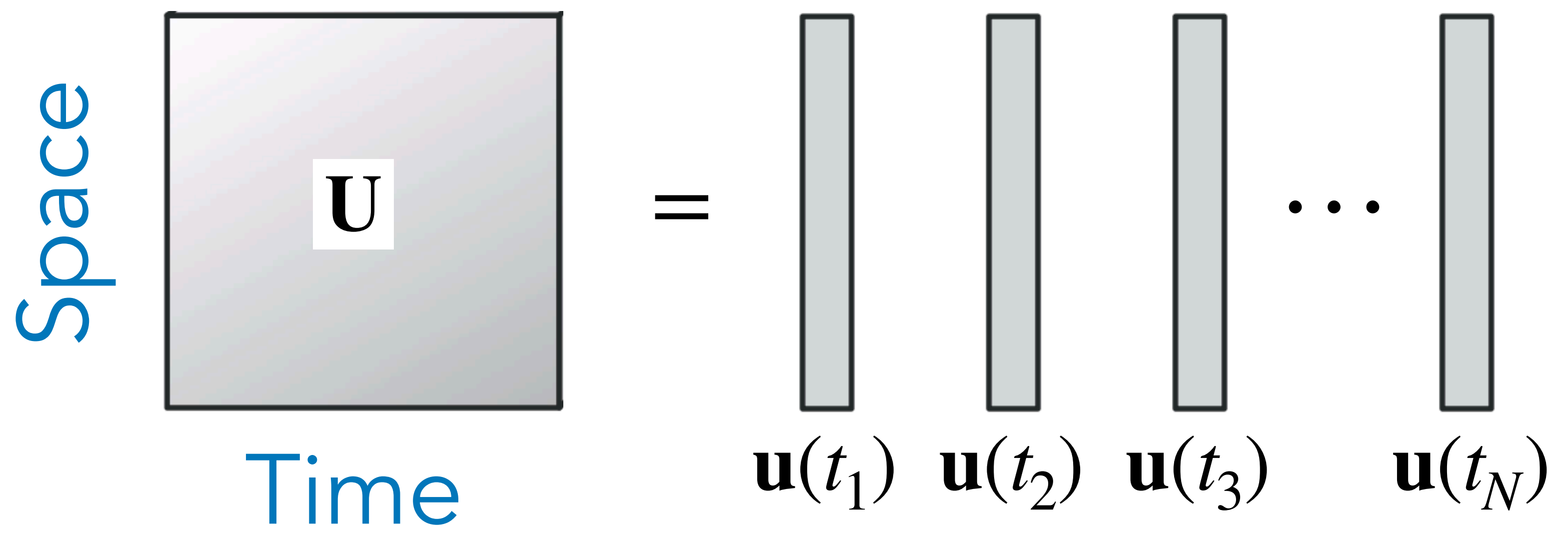
Dominant atmospheric drivers of decadal AMOC variability

Impacts of dominant drivers over the observational period

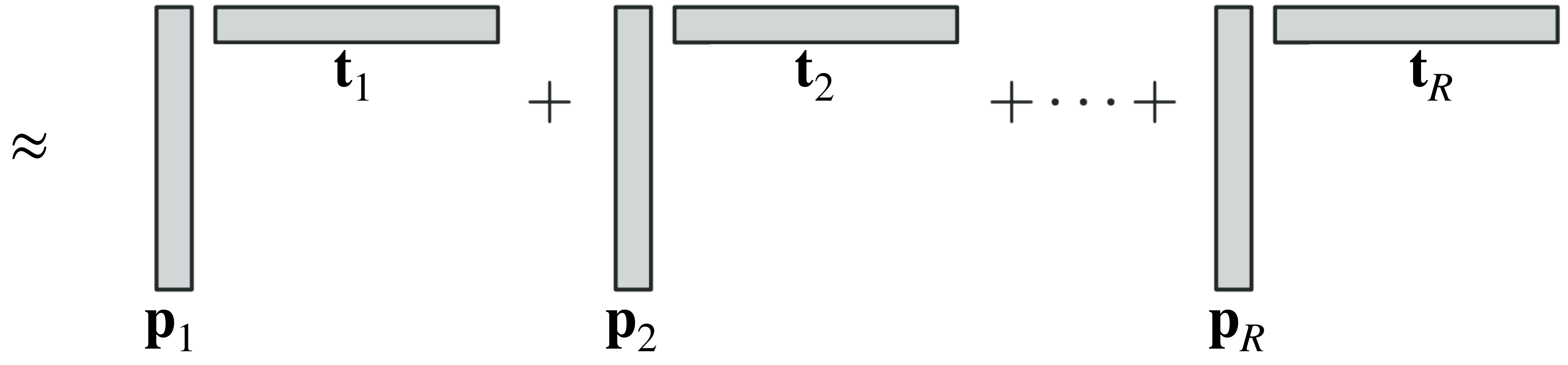
Tracing pathways of decadal AMOC change from atmosphere to ocean

The leading **EOF** answers the question:

What atmospheric pattern accounts for the greatest fraction of total atmospheric variance?

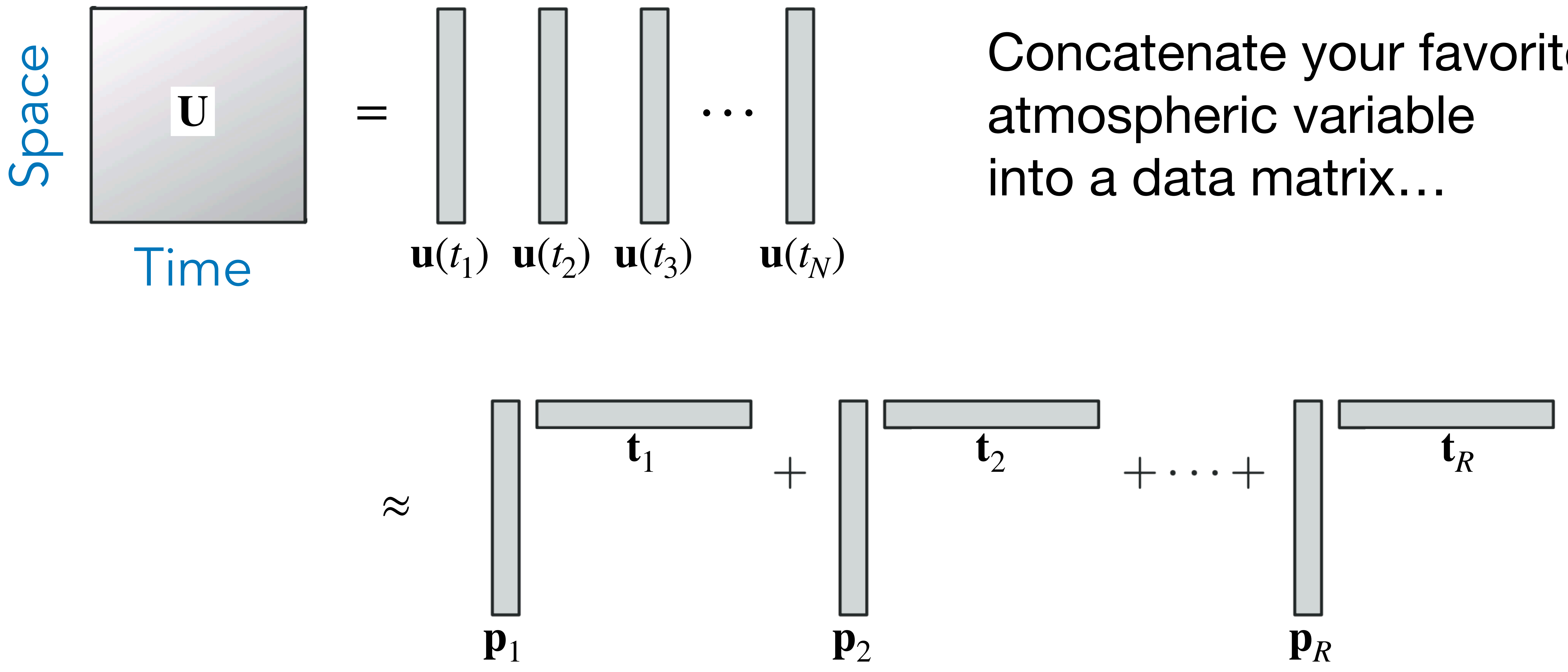


Concatenate your favorite atmospheric variable into a data matrix…

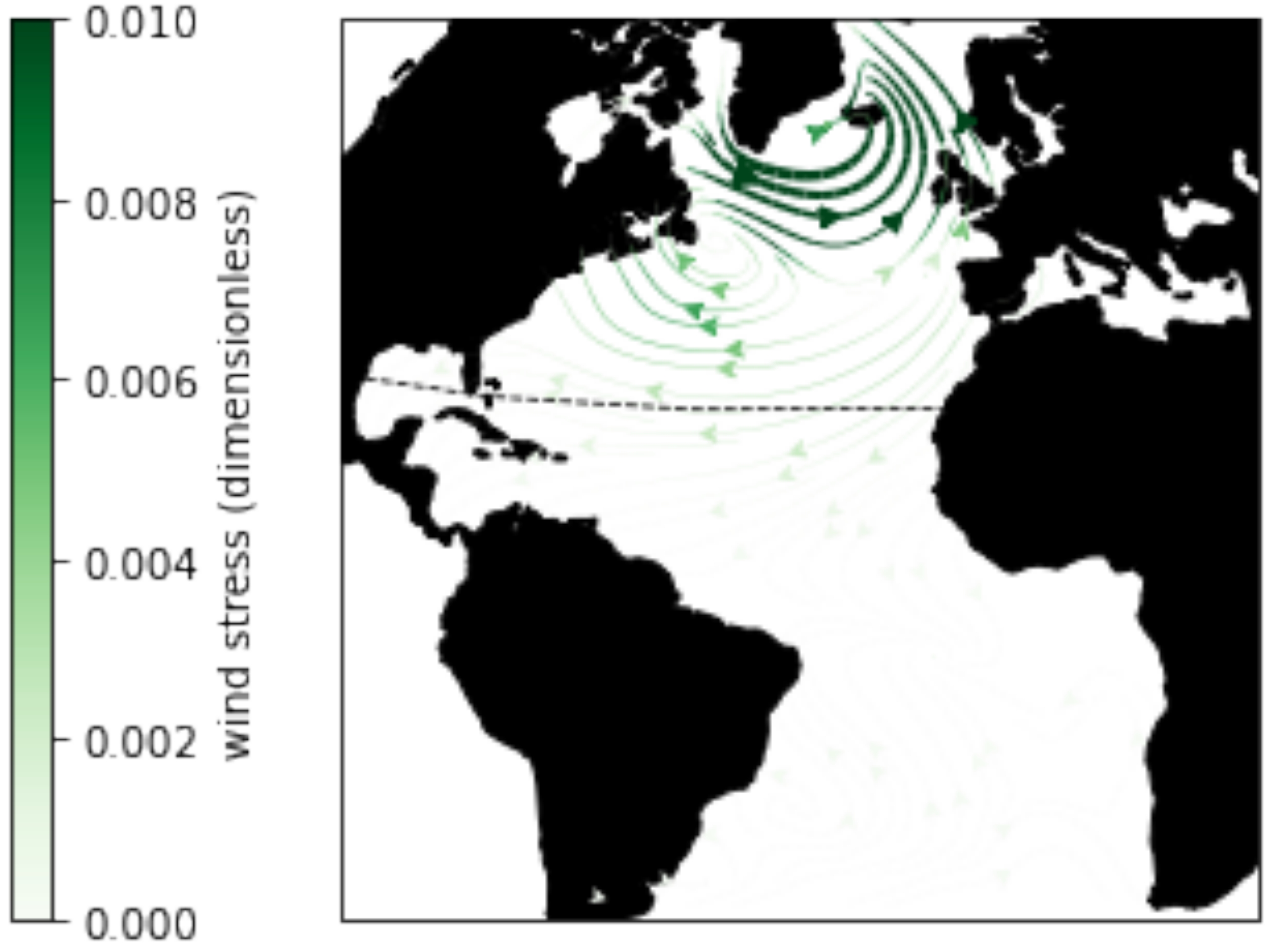


The leading **EOF** answers the question:

What atmospheric pattern accounts for the greatest fraction of total atmospheric variance?



Concatenate your favorite atmospheric variable into a data matrix…



The leading EOF of wind stress in the ECCO v4r4 state estimate.

An ocean perspective:

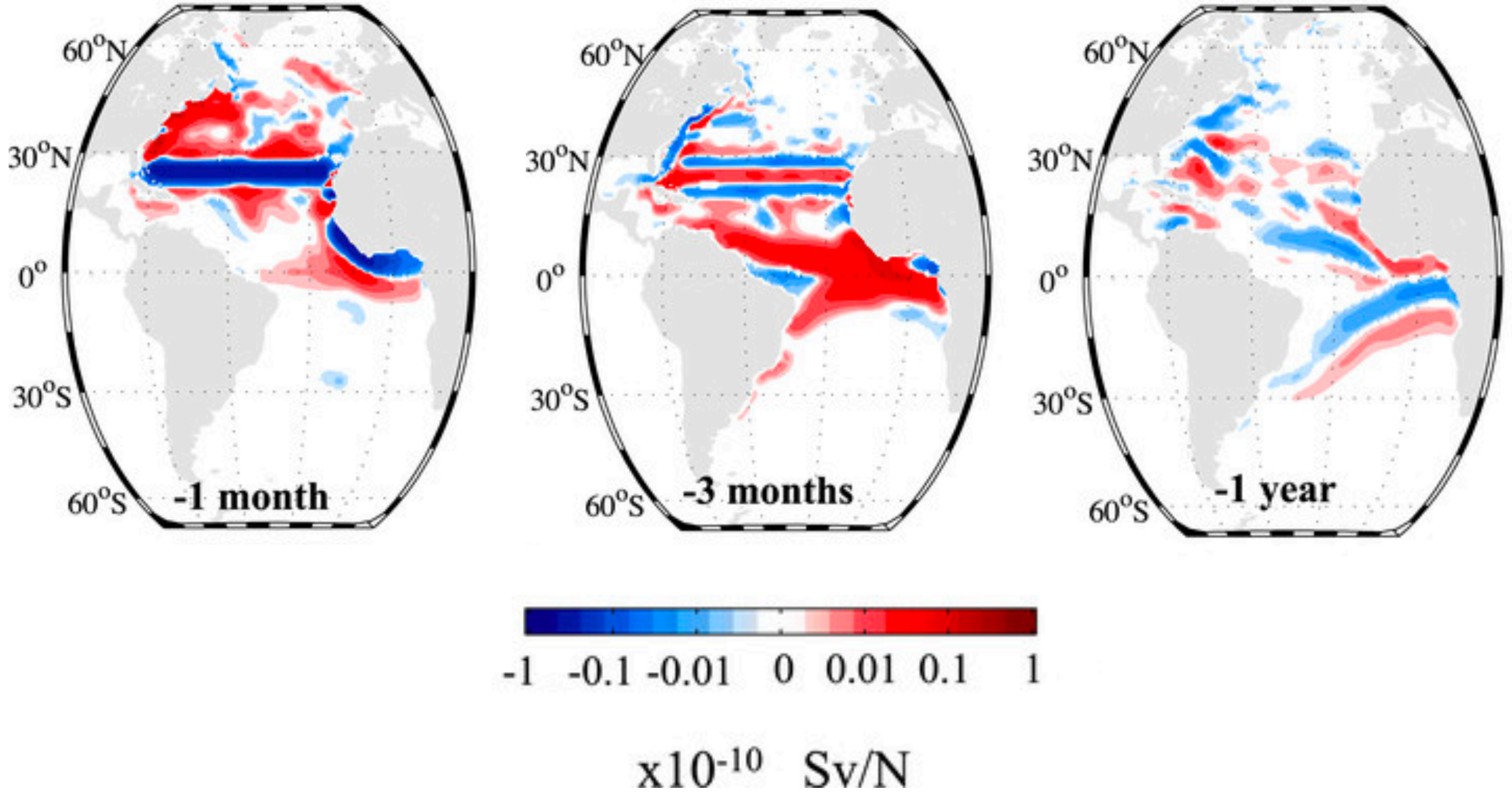
What atmospheric pattern would **most efficiently excite ocean variability?**

Ocean model adjoint sensitivities diagnose dominant drivers

$$\mathbf{s} = \frac{\partial x}{\partial \mathbf{u}}$$

AMOC strength
@ 26N in January

Zonal wind stress



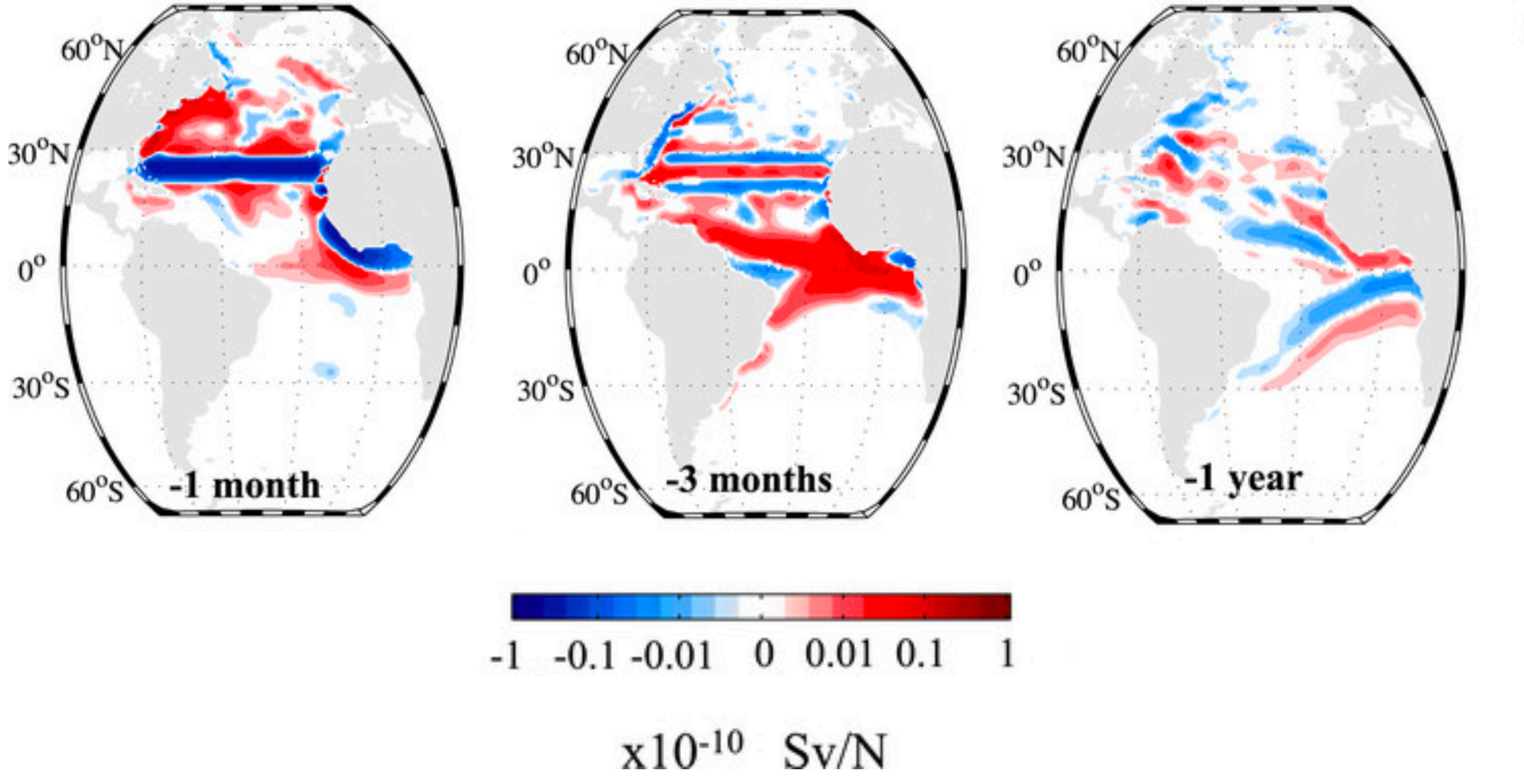
Pillar et al. 2016
Also Heimbach and Wunsch 2011; Jones et al. 2018; Kostov et al. 2019, 2021; Fukumori et al. 2021; Stephenson and Sevellec 2020, 2021

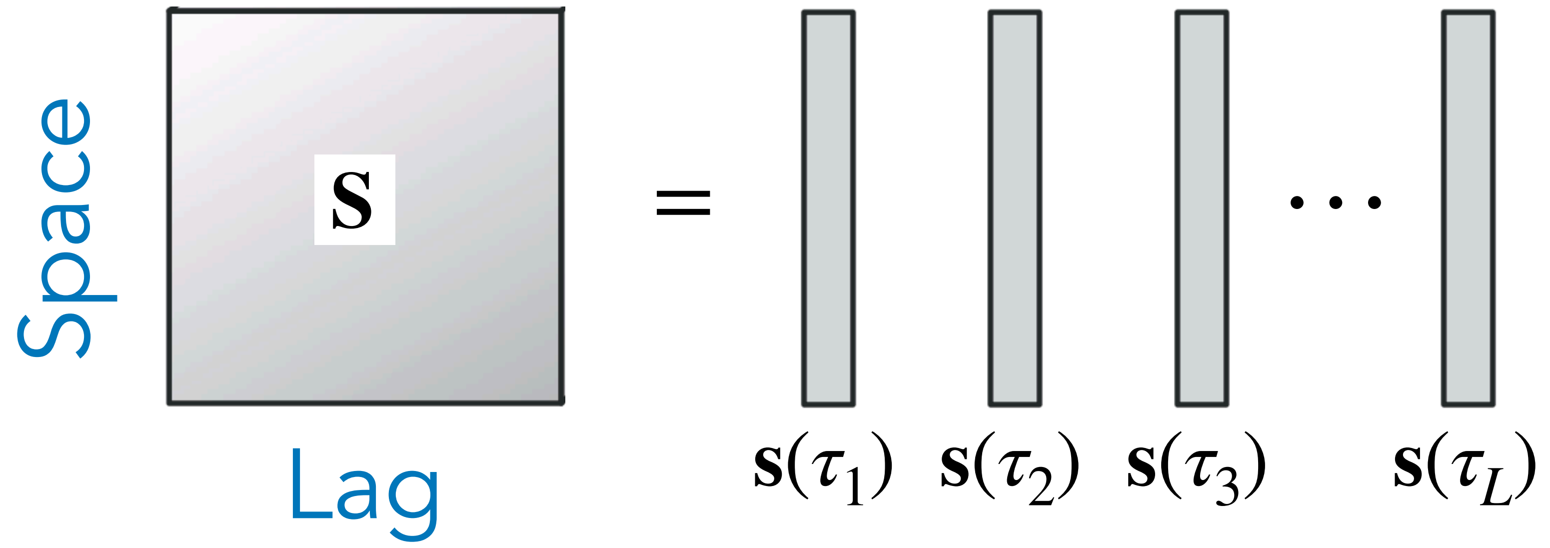
Ocean model adjoint sensitivities diagnose dominant drivers

$$\mathbf{s} = \frac{\partial x}{\partial \mathbf{u}}$$

AMOC strength @ 26N in January

Zonal wind stress



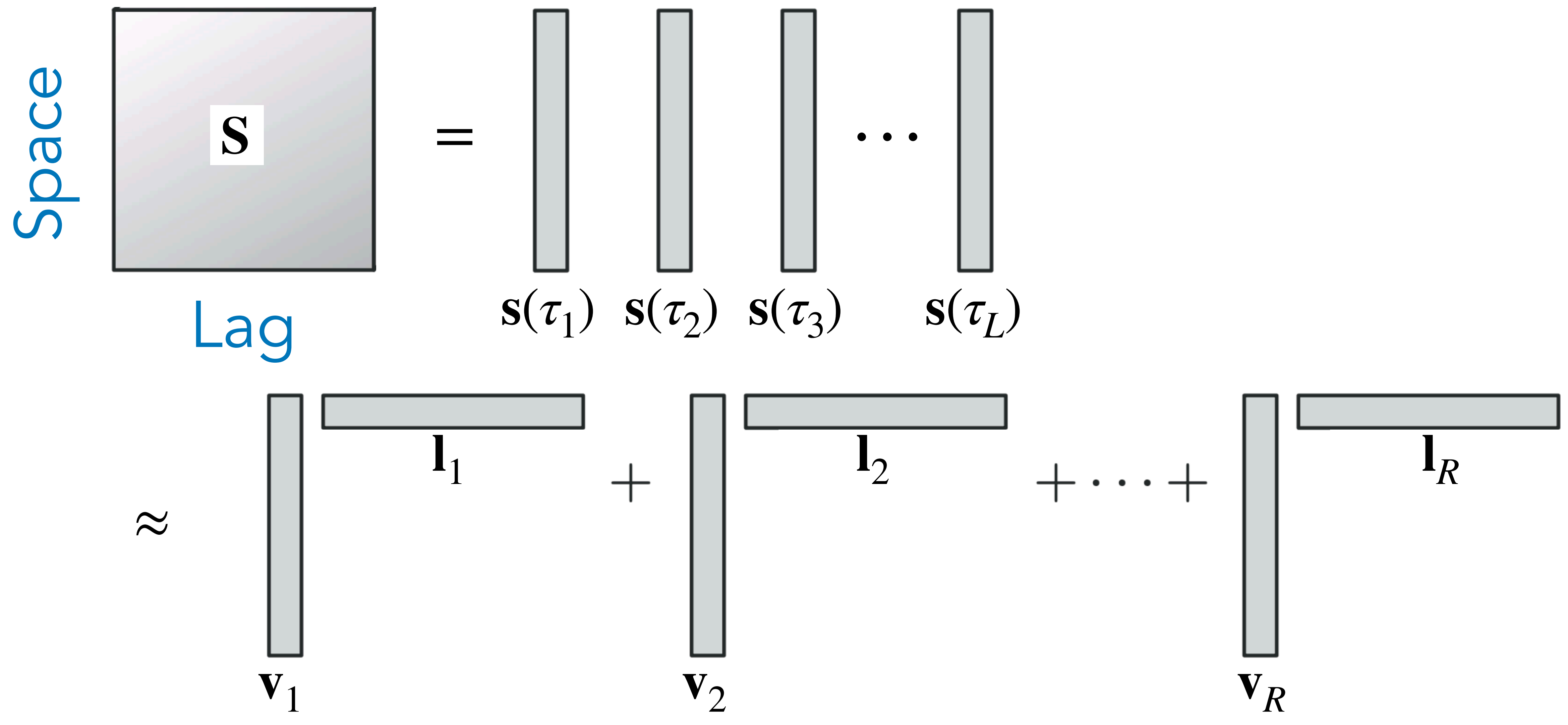


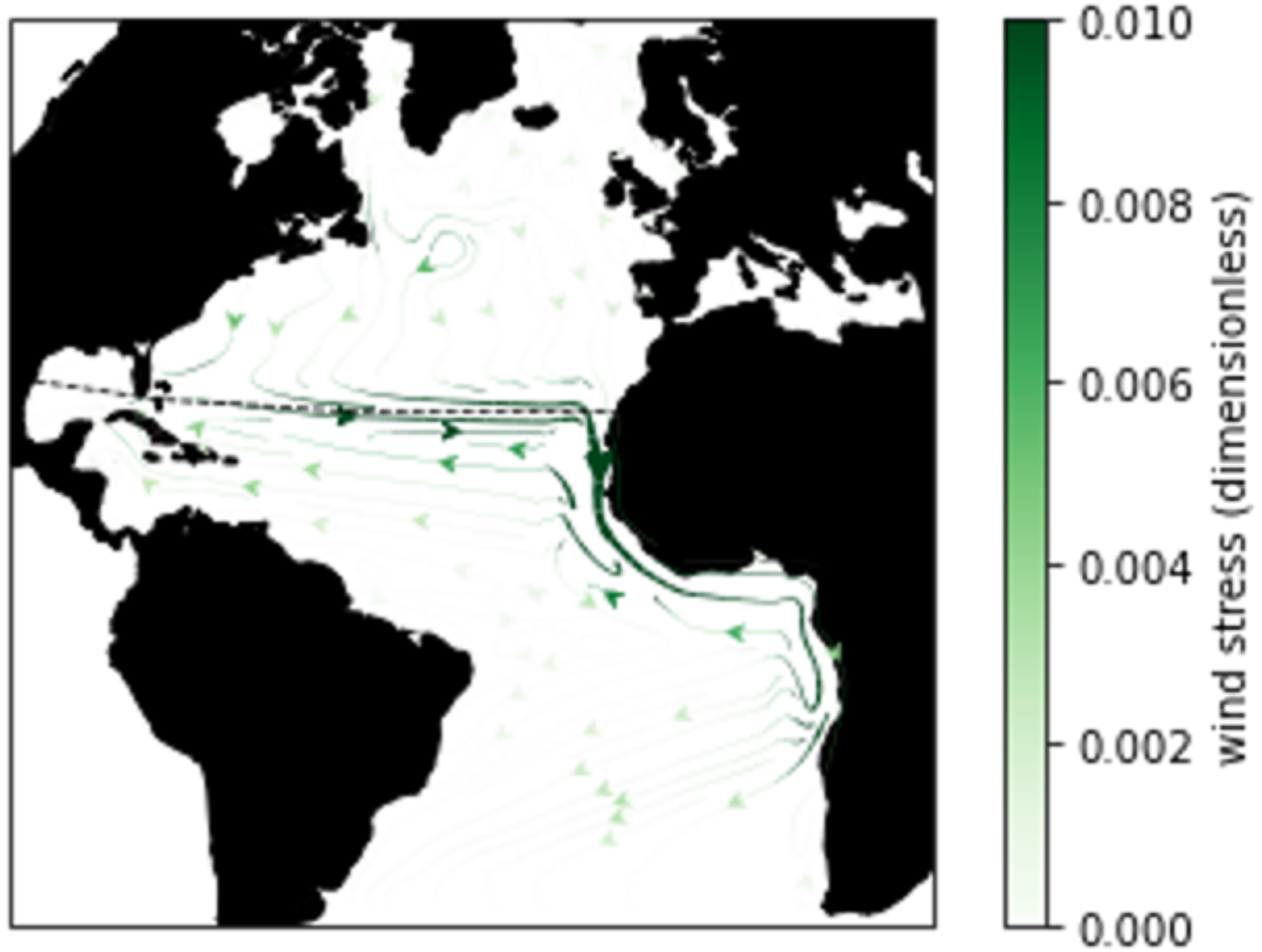
Pillar et al. 2016
Also Heimbach and Wunsch 2011; Jones et al. 2018; Kostov et al. 2019, 2021; Fukumori et al. 2021; Stephenson and Sevellec 2020, 2021

What atmospheric pattern would **most efficiently excite ocean variability?**

The leading **stochastic optimal.**

Farrell and Ioannou 1993, 1996; Kleeman and Moore, 1997

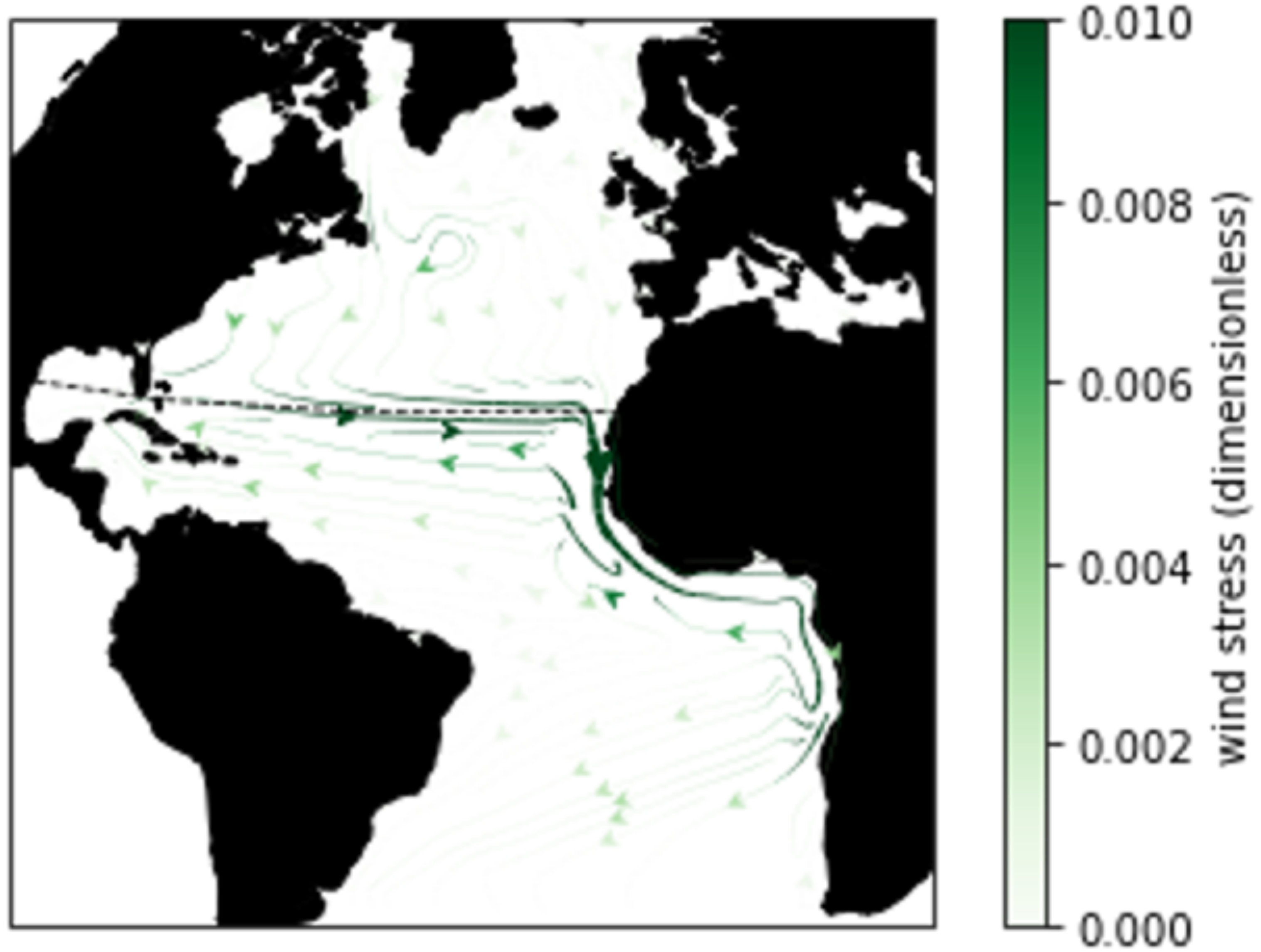




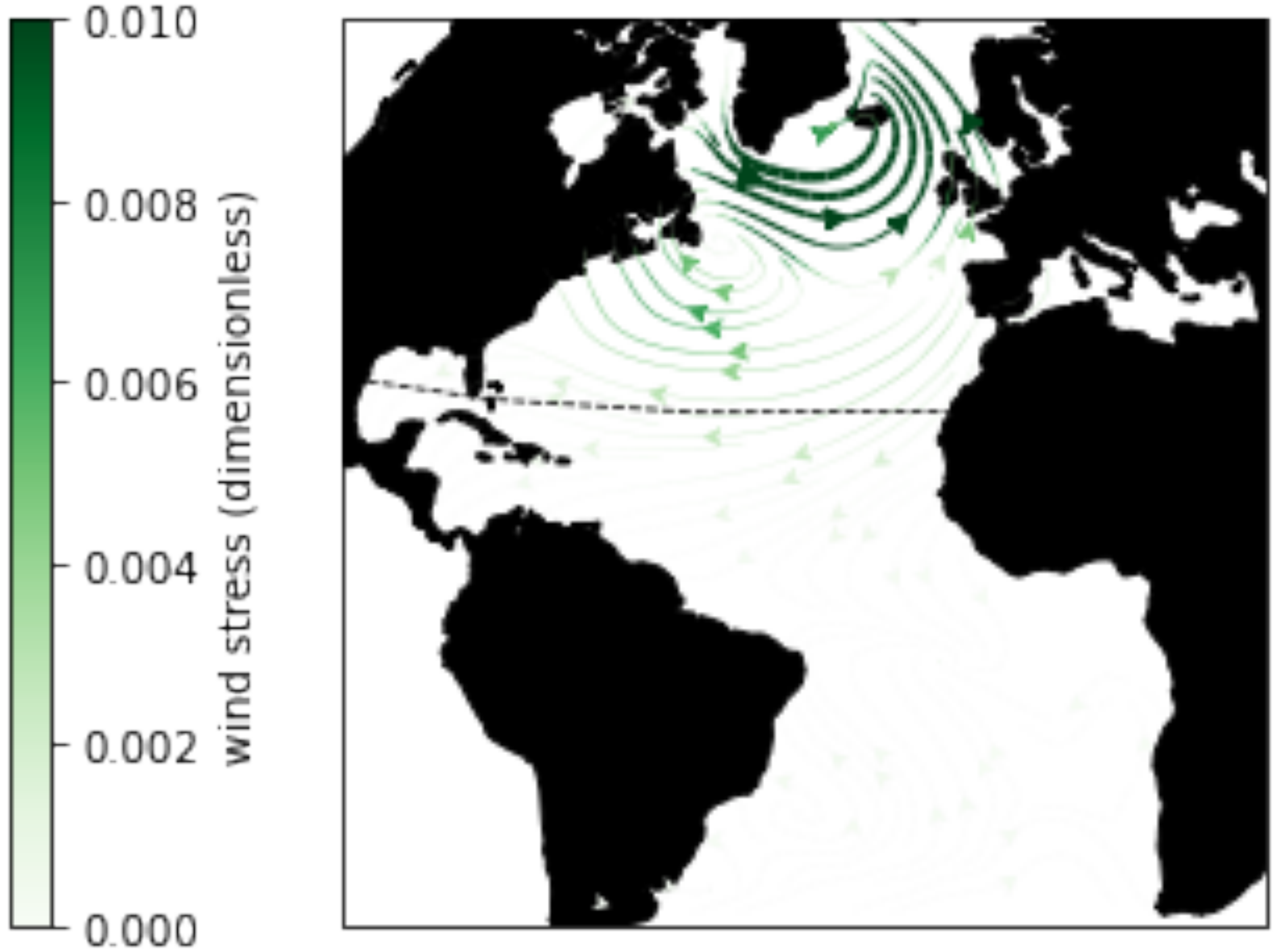
$\mathbf{v}_1$ for wind stress in ECCO v4r4

An interpretive quandary

What the ocean "wants"

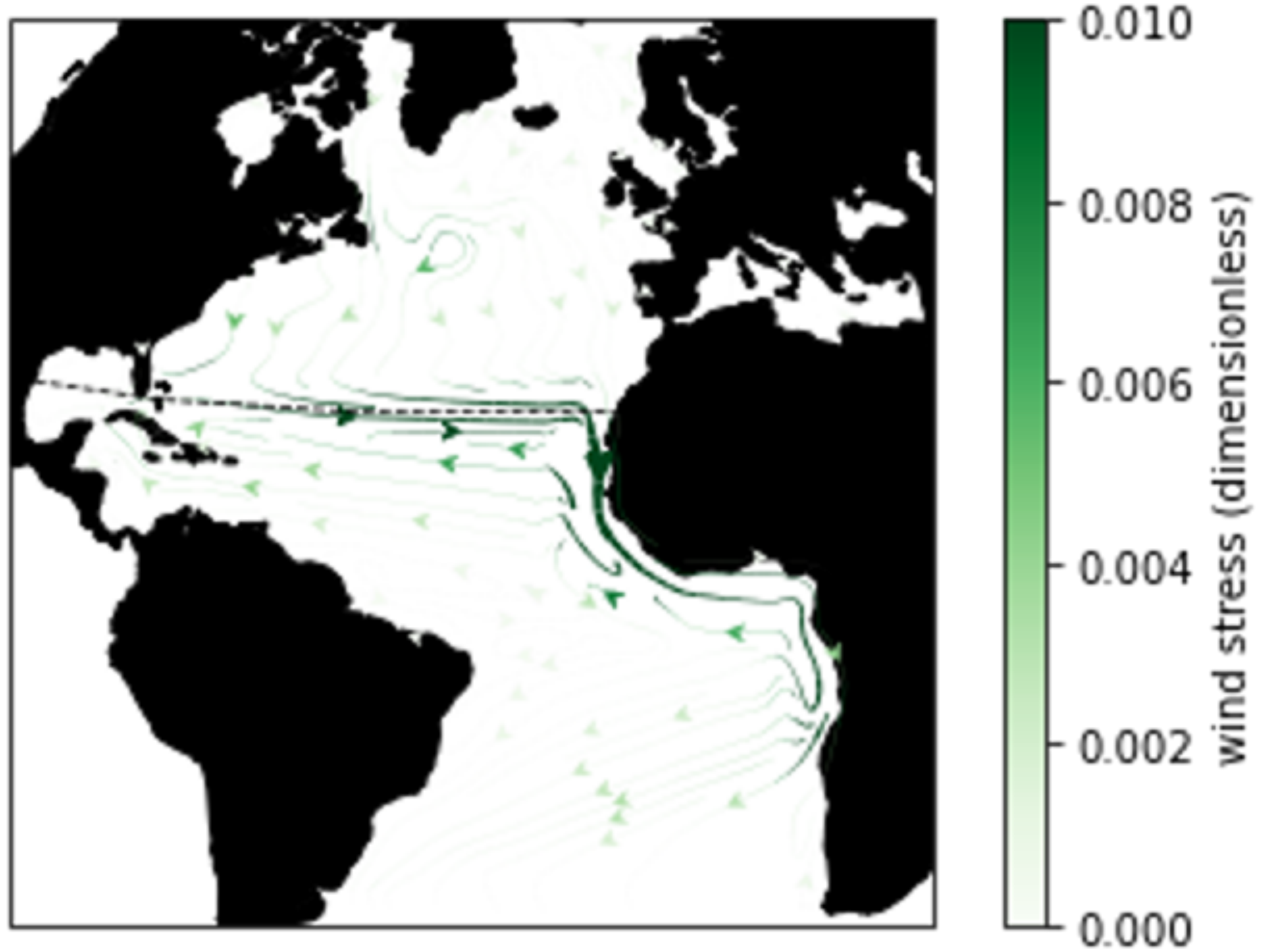


What the ocean "gets"

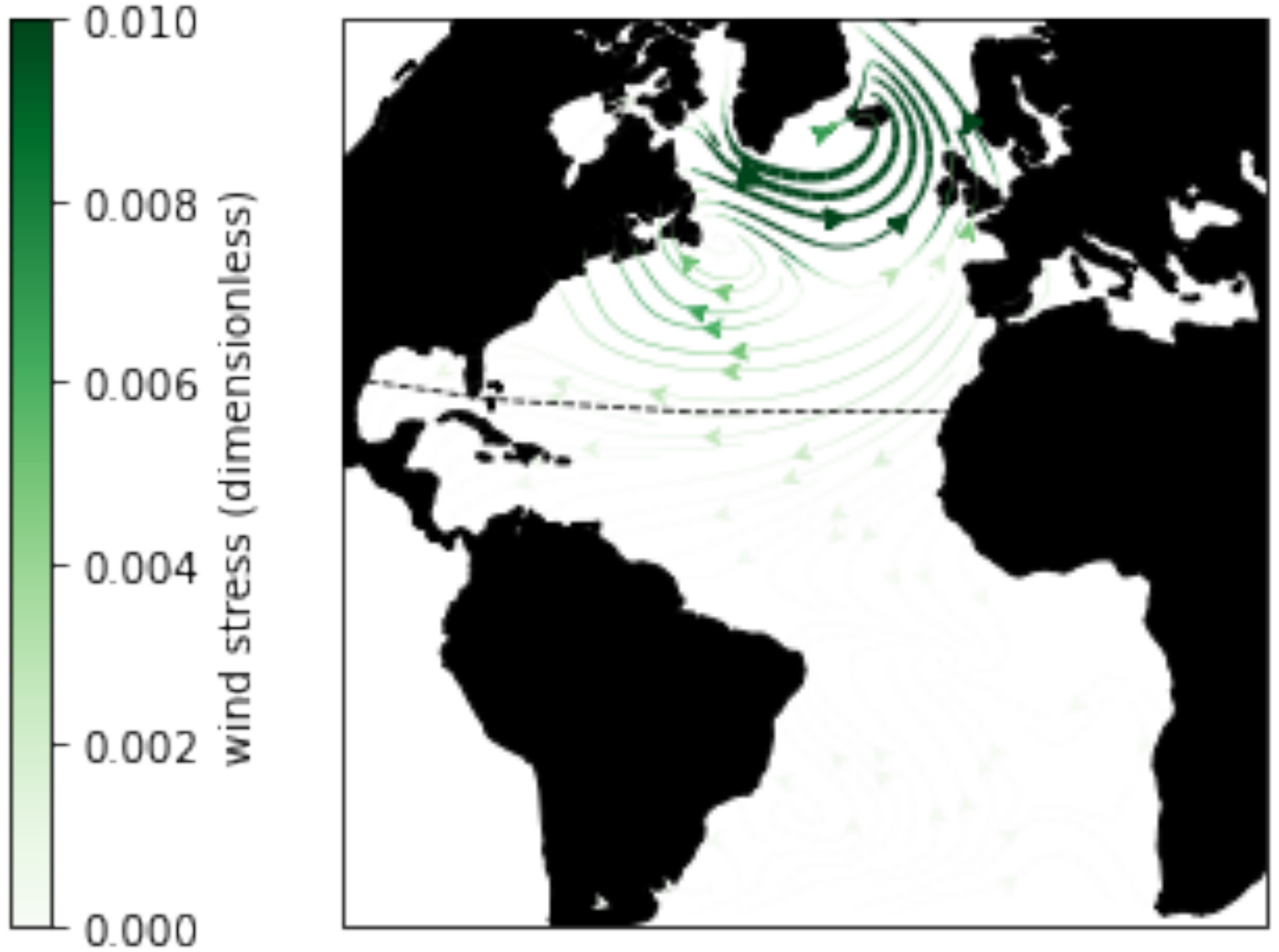


An interpretive quandary

What the ocean "wants"

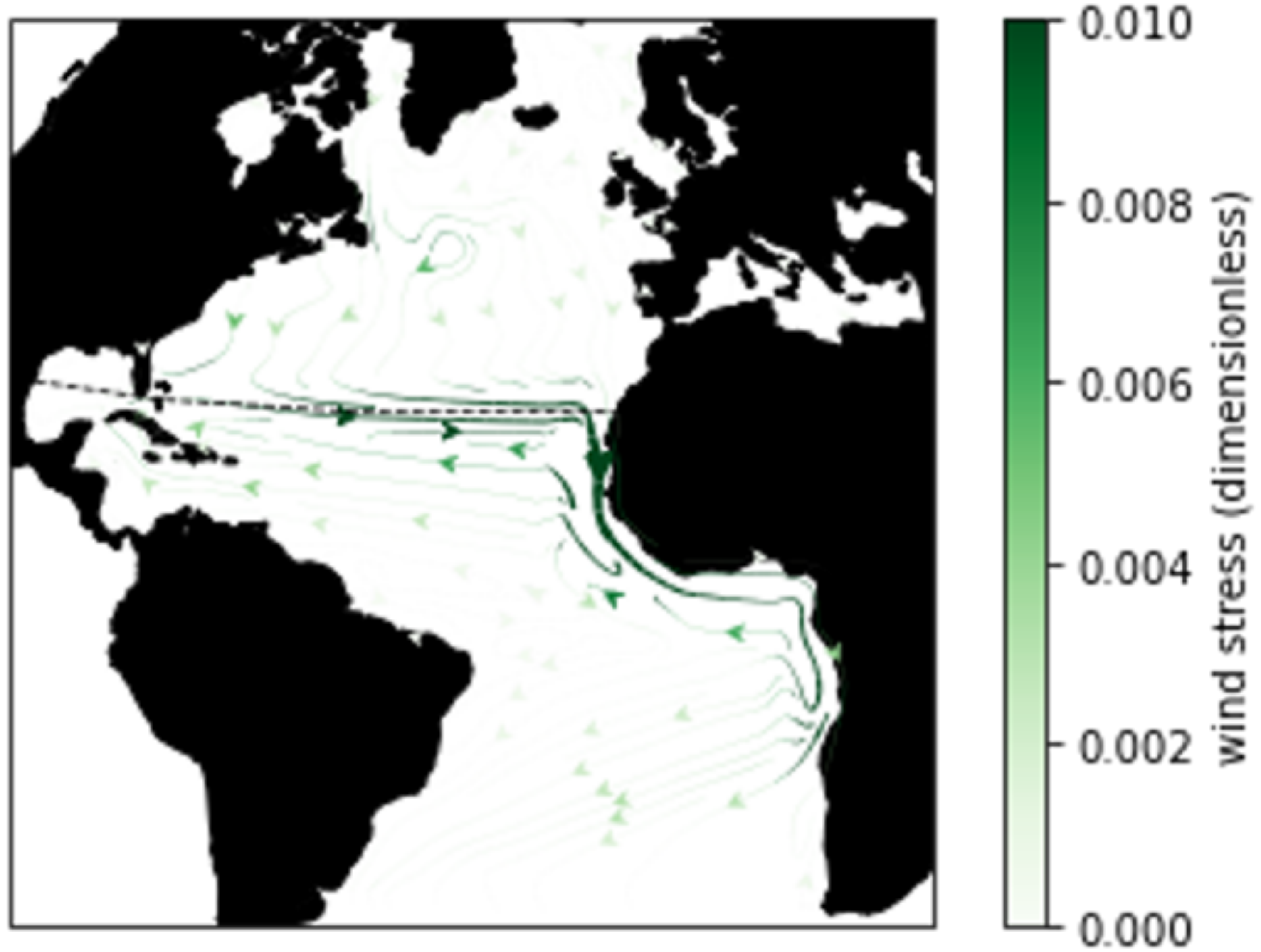


What the ocean "gets"

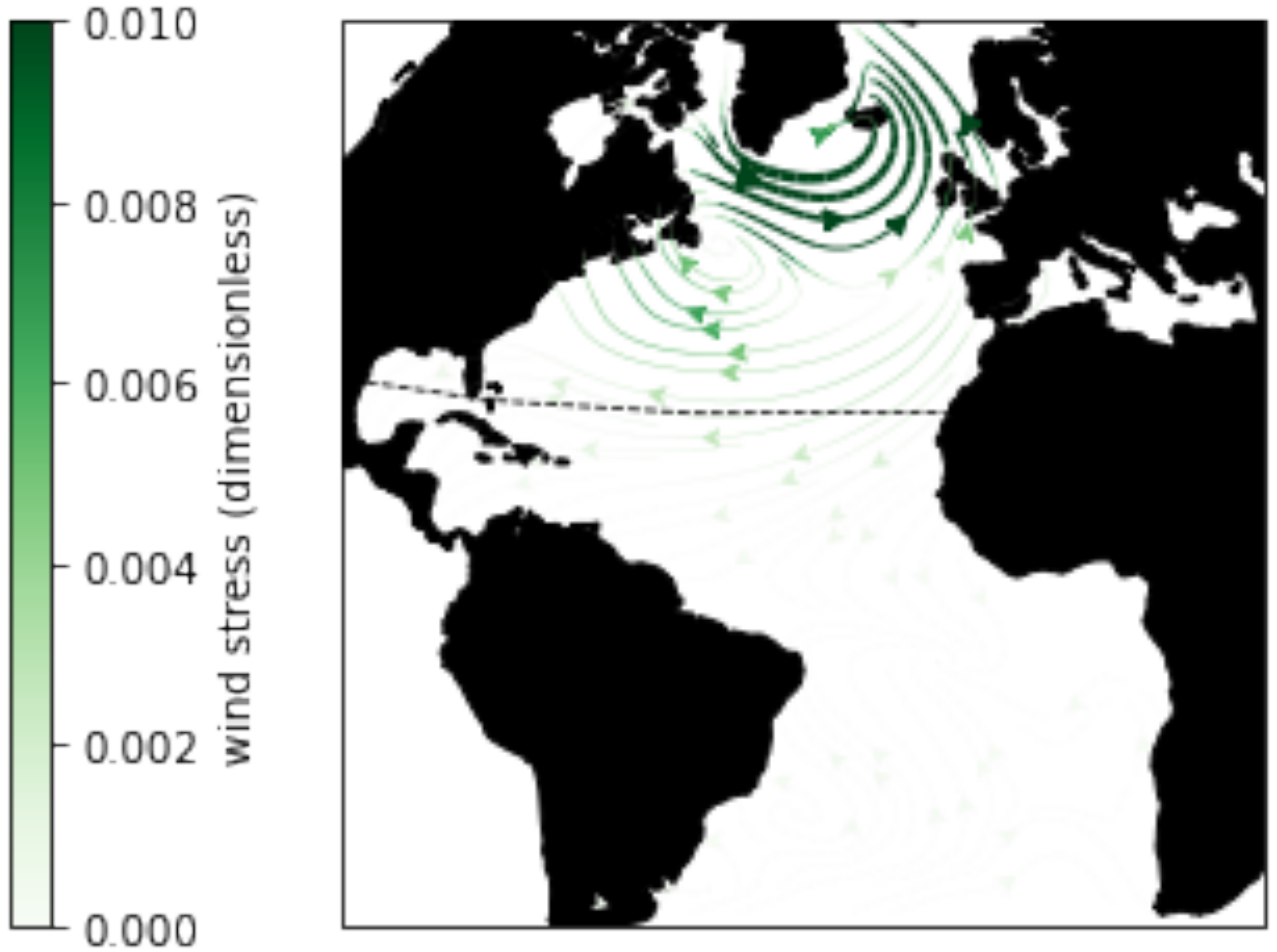


An interpretive quandary

What the ocean “wants”



What the ocean “gets”



Is the leading EOF the **leading driver** of variability in this ocean quantity?

Is the leading stochastic optimal really the most important **mechanism** for changing the ocean?

Outline

The ocean as an integrator (and source) of random variation

What dominates ocean variability? Views from the atmosphere and ocean

Reconciliation: A dynamics-weighted principal components analysis

Dominant atmospheric drivers of decadal AMOC variability

Impacts of dominant drivers over the observational period

Tracing pathways of decadal AMOC change from atmosphere to ocean

The math slide! Deriving dynamics-weighted principal components

$$\mathbf{s} = \frac{\partial x}{\partial \mathbf{u}}$$

Definition of adjoint sensitivity

The math slide! Deriving dynamics-weighted principal components

$$\mathbf{s} = \frac{\partial x}{\partial \mathbf{u}}$$

Definition of adjoint sensitivity

$$\delta x(t) \approx \sum_{i=1}^{N_\tau} \mathbf{s}(\tau_i)^\top \delta \mathbf{u}(t - \tau_i)$$

To change AMOC strength, we can make a control change $\delta \mathbf{u}$

The math slide! Deriving dynamics-weighted principal components

$$\mathbf{s} = \frac{\partial x}{\partial \mathbf{u}}$$

Definition of adjoint sensitivity

$$\delta x(t) \approx \sum_{i=1}^{N_\tau} \mathbf{s}(\tau_i)^\top \delta \mathbf{u}(t - \tau_i)$$

To change AMOC strength, we can make a control change $\delta \mathbf{u}$

$$\sigma_\Sigma^2 = \left\langle \left(\delta x(t) \right)^2 \right\rangle$$

The variance of the quantity of interest

The math slide! Deriving dynamics-weighted principal components

$$\mathbf{s} = \frac{\partial x}{\partial \mathbf{u}}$$

Definition of adjoint sensitivity

$$\delta x(t) \approx \sum_{i=1}^{N_\tau} \mathbf{s}(\tau_i)^\top \delta \mathbf{u}(t-\tau_i)$$

To change AMOC strength, we can make a control change $\delta\mathbf{u}$

$$\sigma_\Sigma^2 = \left\langle \left(\delta x(t)\right)^2 \right\rangle$$

The variance of the quantity of interest

$$= \sum_{i=1}^{N_\tau} \sum_{j=1}^{N_\tau} \mathbf{s}(\tau_i)^\top \left\langle \delta\mathbf{u}(t-\tau_i)\delta\mathbf{u}^\top(t-\tau_j) \right\rangle \mathbf{s}(\tau_j)$$

Substitution gets a bit sticky…

$$= \mathbf{tr}(\underline{\mathbf{C}}\,\underline{\mathbf{Z}})$$

Atmospheric spatial covariance

$$\mathbf{Z} = \mathbf{S}\mathbf{S}^\top$$

…but is simplified by two assumptions (see also Kleeman and Moore, 1997):

1. Flux covariances are separable in space and time
2. Sensitivities are stationary

The math slide! Deriving dynamics-weighted principal components

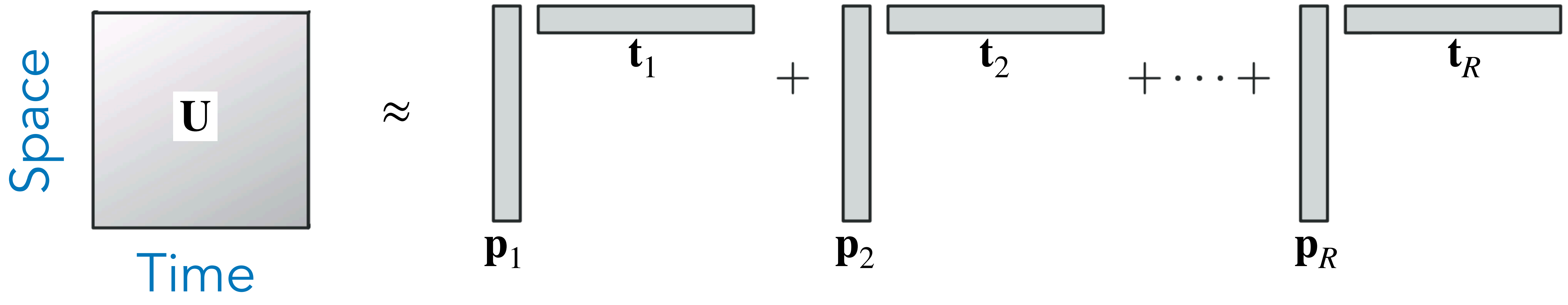
$$\sigma_\Sigma^2 = \mathbf{tr}(\mathbf{CZ})$$

$$\mathbf{U} = \sum \mathbf{p}_k \mathbf{t}_k^\top$$

$$\sigma_\Sigma^2 = \sum \sigma_k^2$$

Our requirements:

1. An EOF-like decomposition
2. Contributions to ocean variance that add (no cross terms)



The math slide! Deriving dynamics-weighted principal components

$$\sigma_{\Sigma}^2 = \mathbf{tr}(\mathbf{CZ})$$

$$\mathbf{U} = \sum \mathbf{p}_k \mathbf{t}_k^\top$$

$$\sigma_{\Sigma}^2 = \sum \sigma_k^2$$

Contributions to QoI variance

$$\mathbf{S}^\top \mathbf{U} = \mathbf{L} \boldsymbol{\Gamma} \mathbf{T}^\top$$

$$\mathbf{P} = \mathbf{UT}$$

Spatial patterns ranked by their contribution to ocean QoI variance

Our requirements:

1. An EOF-like decomposition
2. Contributions to ocean variance that add (no cross terms)

…yields an SVD optimization problem!

Amounts to computing principal components weighted by adjoint sensitivities.

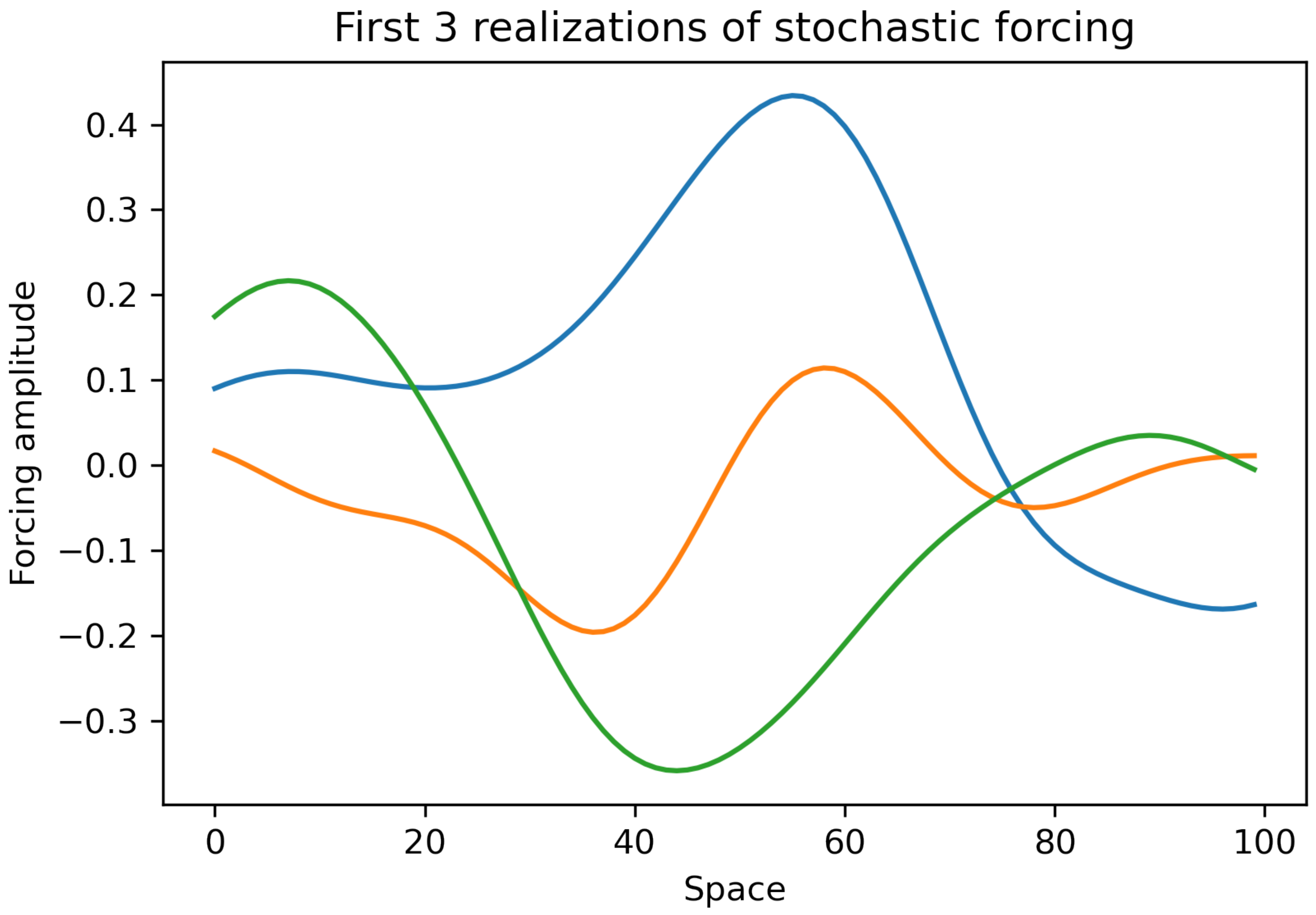
EOF-like, but singular values are ocean QoI variance rather than atmospheric variance.

Patterns are orthogonal in time, but not space.

Recovers EOFs and SOs for limit cases.

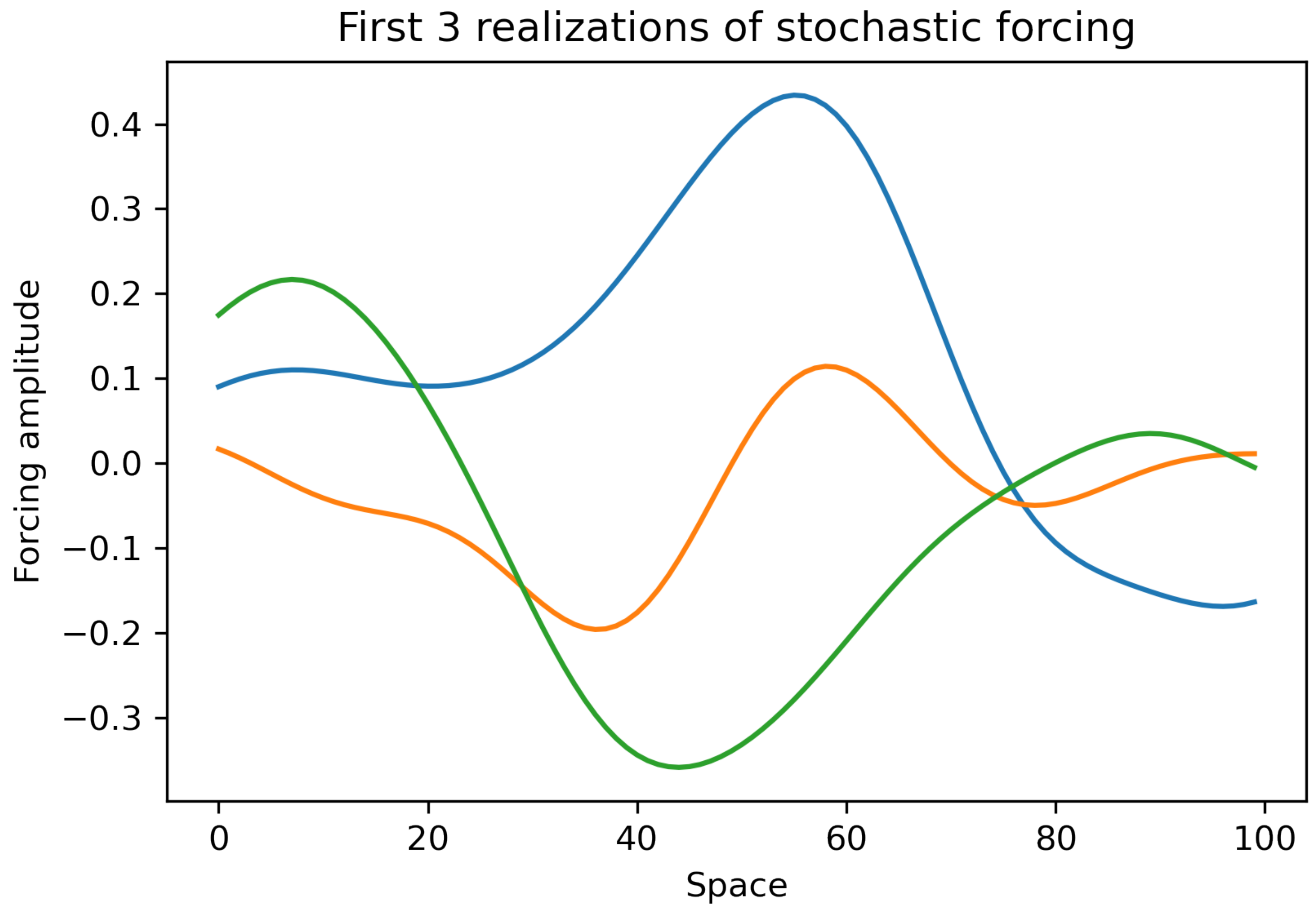
AKA "balanced truncation": Moore (1981); Farrell and Ioannou (2001); Moore et al. (2022)

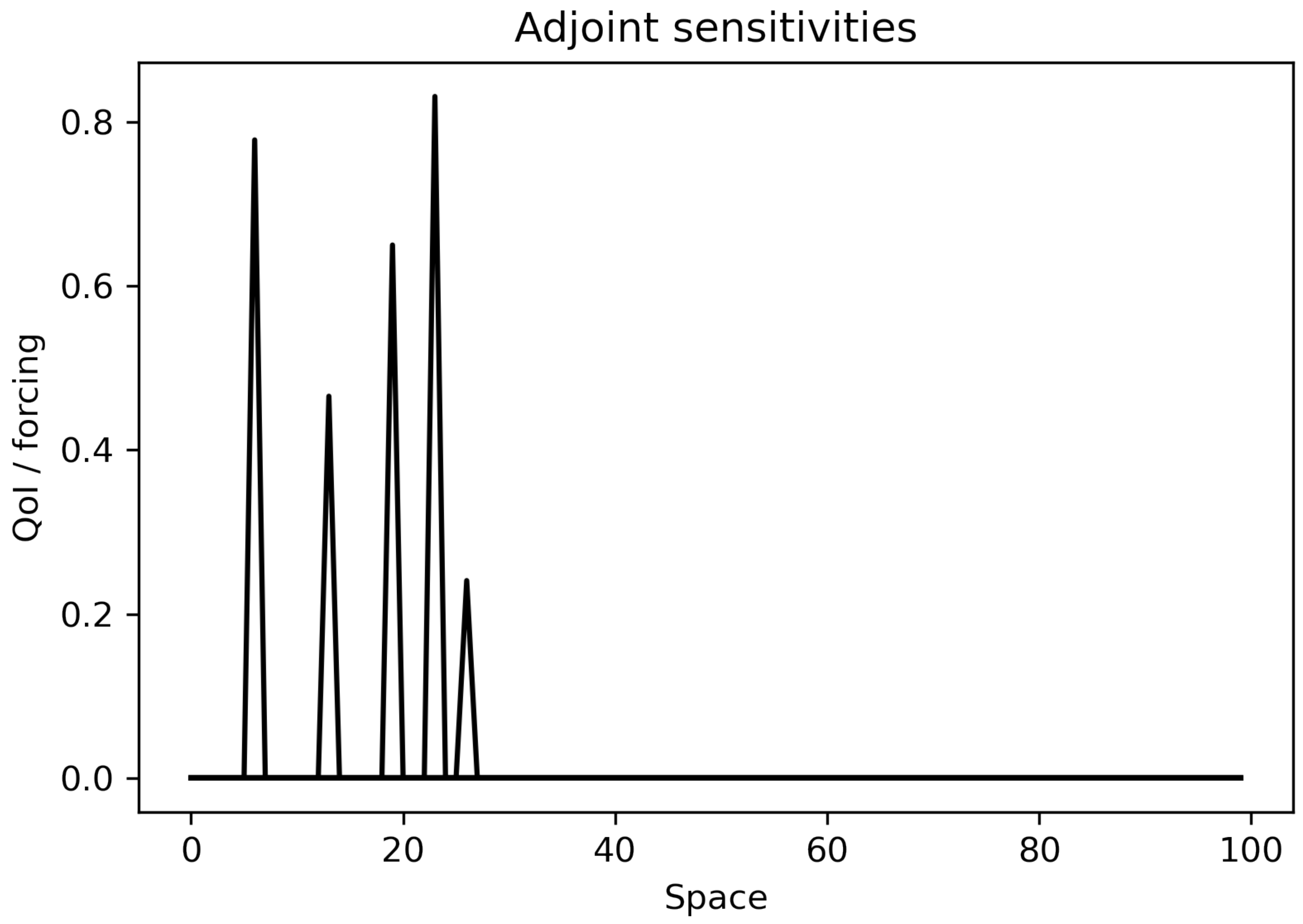
Demonstration in a (very) simple system



Consider a 1-dimensional system with stochastic forcing that is **smooth in space** and Gaussian **white noise in time**.

Demonstration in a (very) simple system

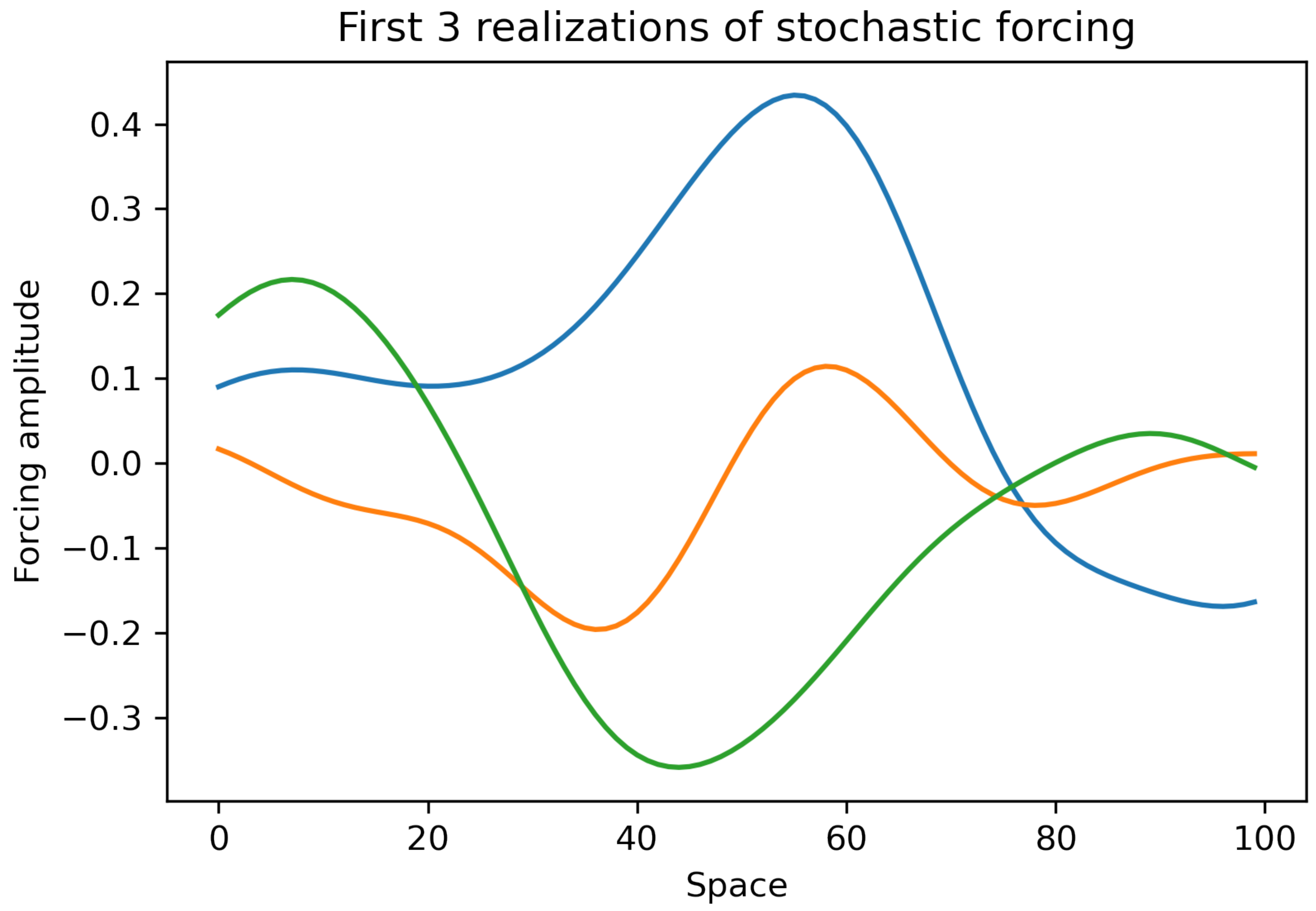




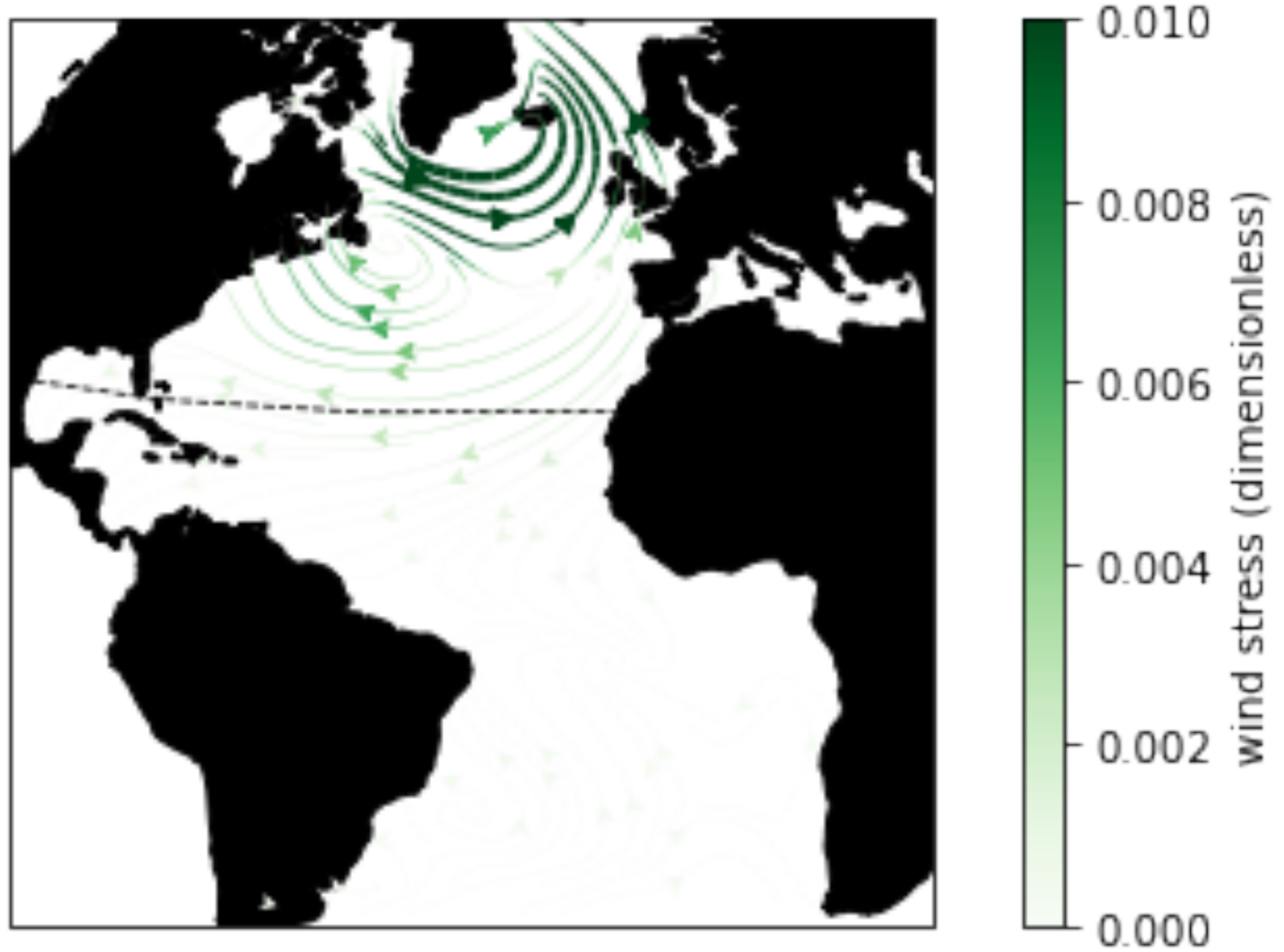
Consider a 1-dimensional system with stochastic forcing that is **smooth in space** and Gaussian **white noise in time**.

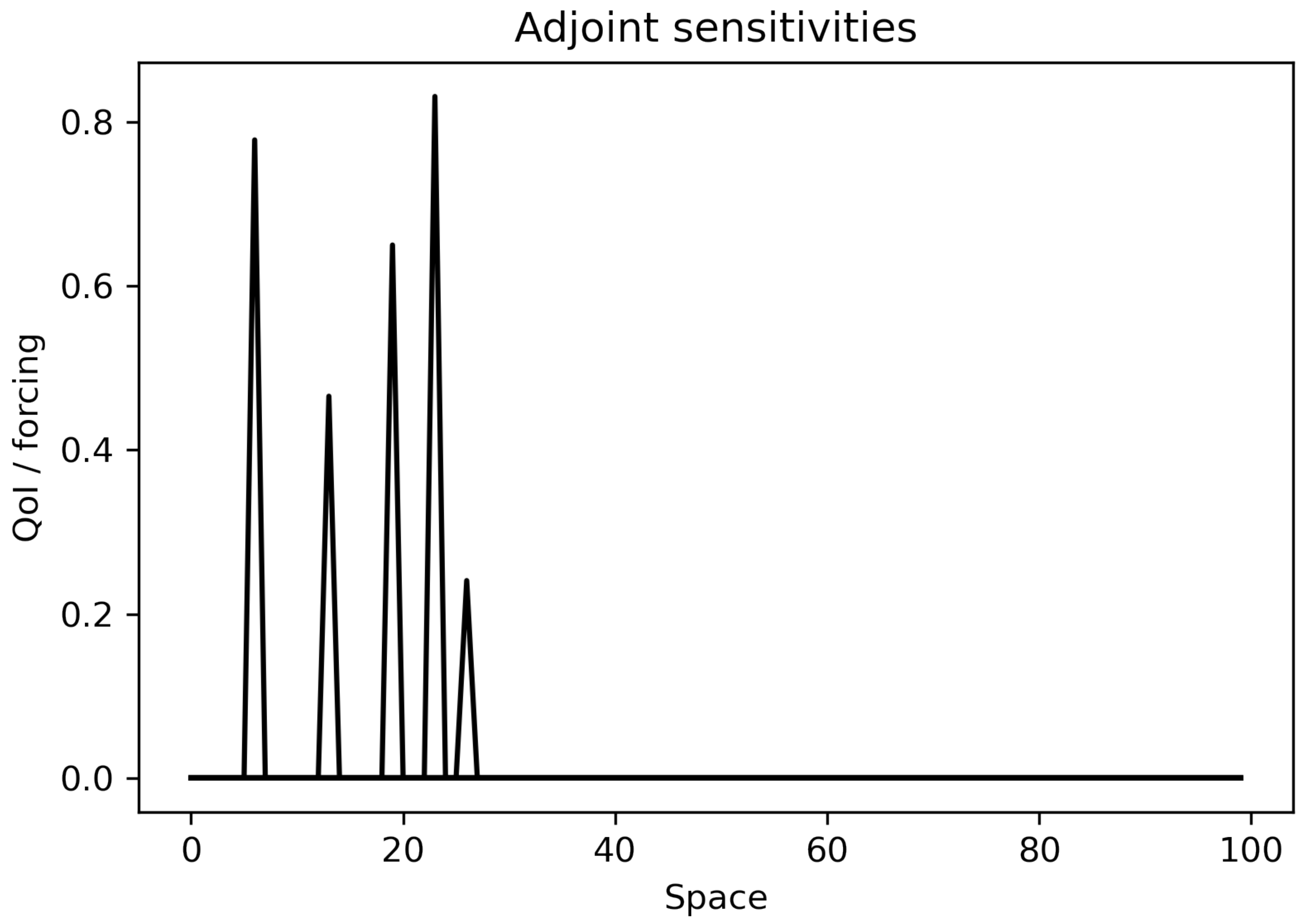
..and adjoint sensitivities of a hypothetical ocean QoI that have **shorter length scales** and are **localized in space**.

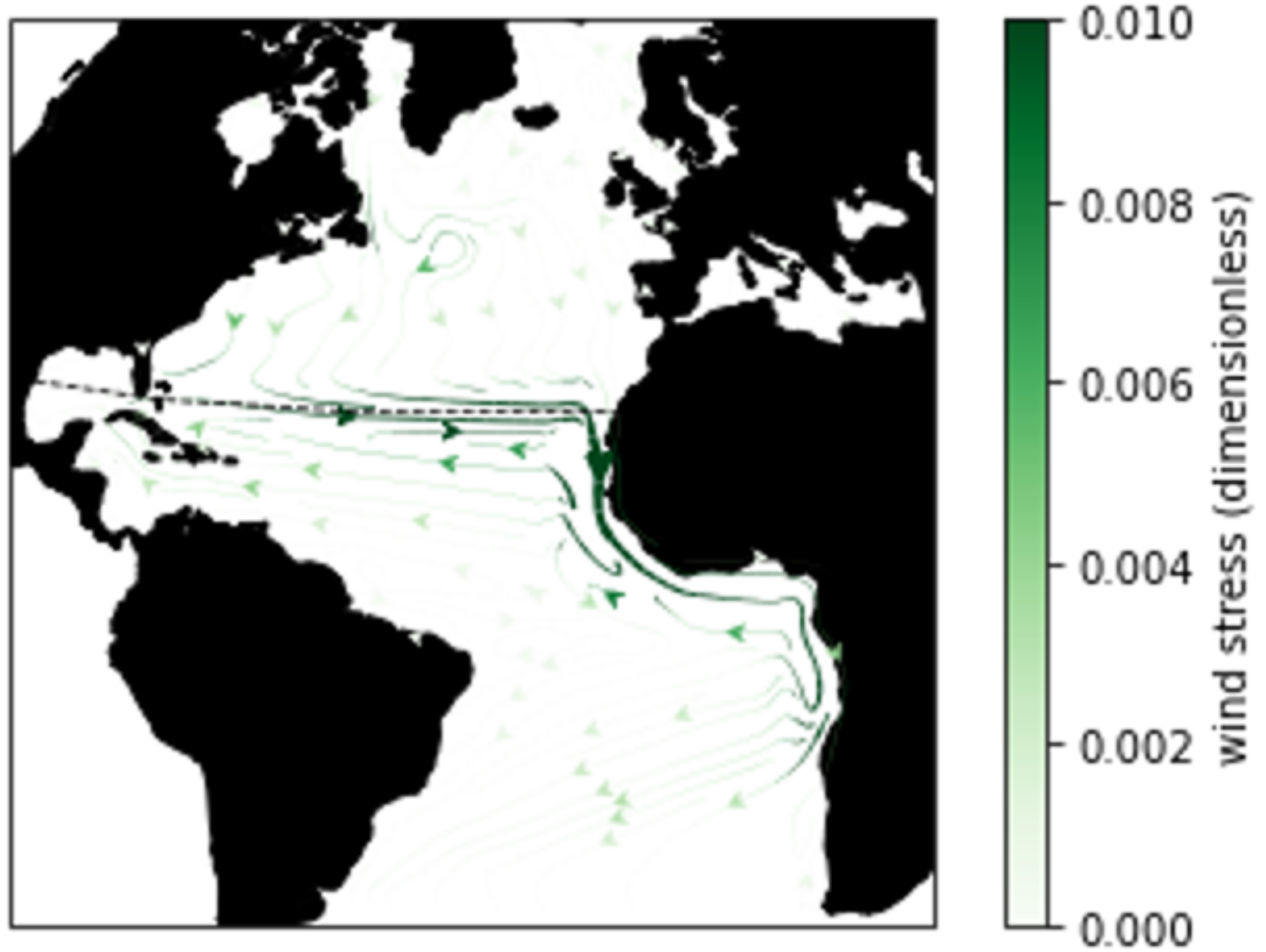
Demonstration in a (very) simple system



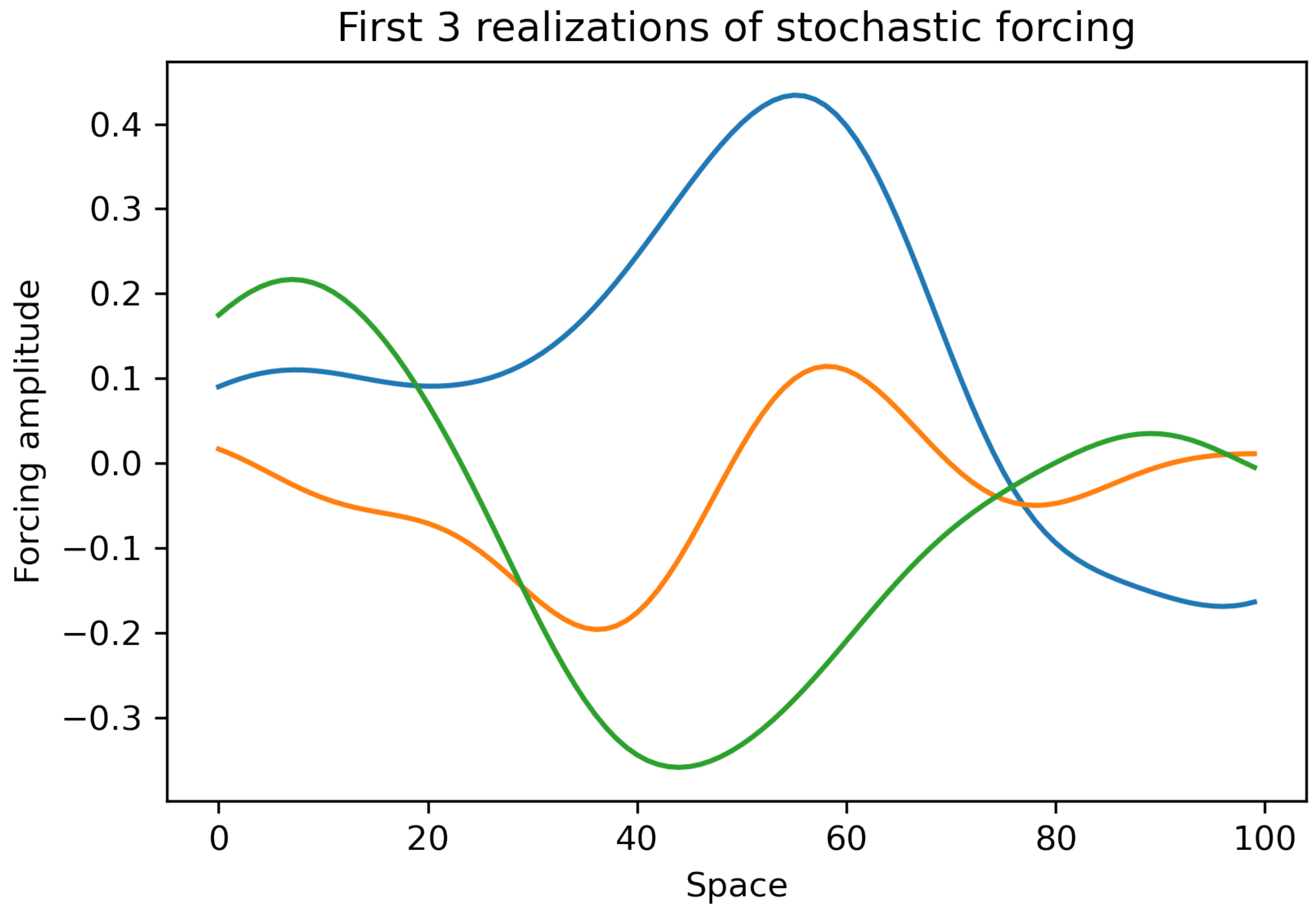
~

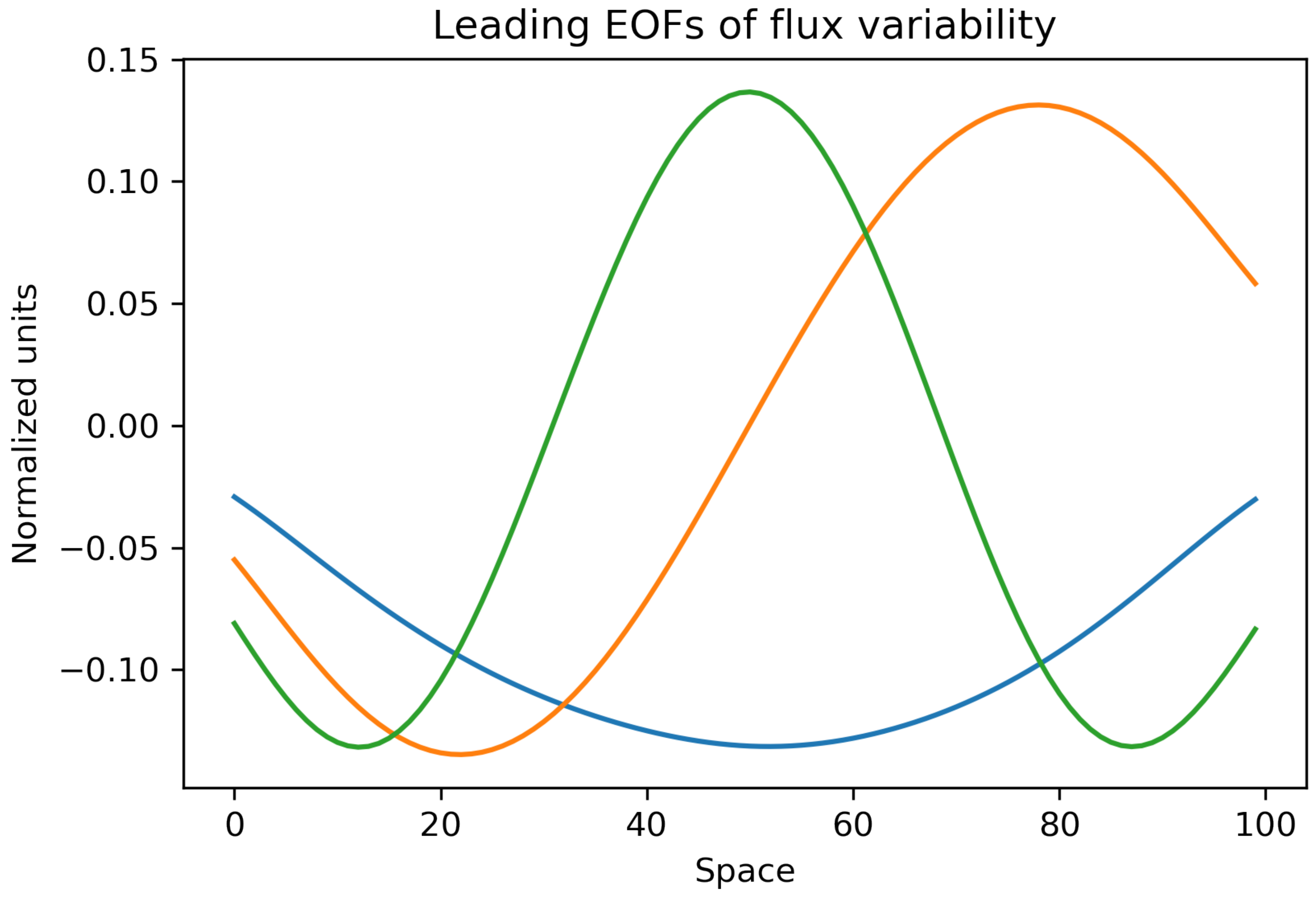


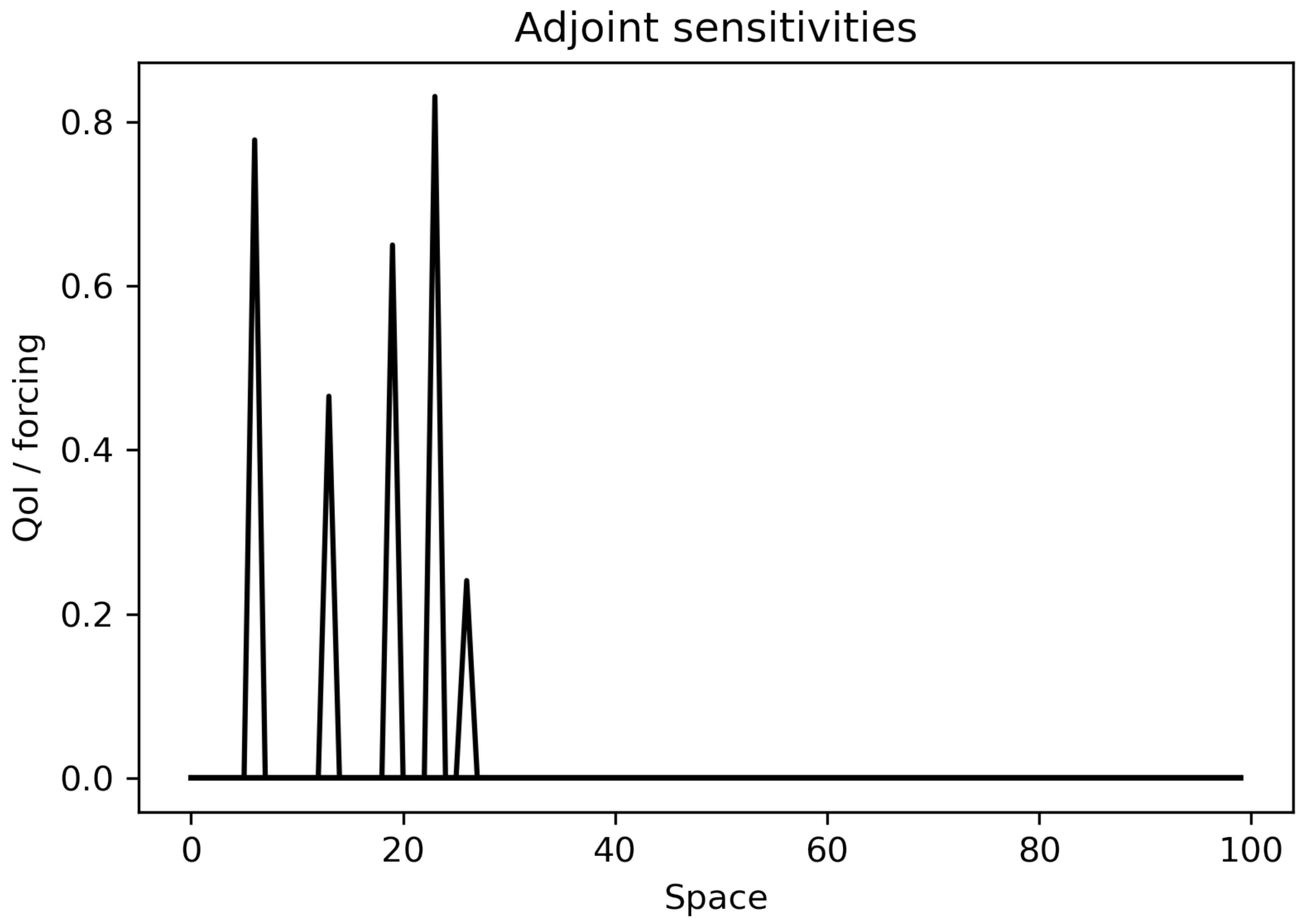




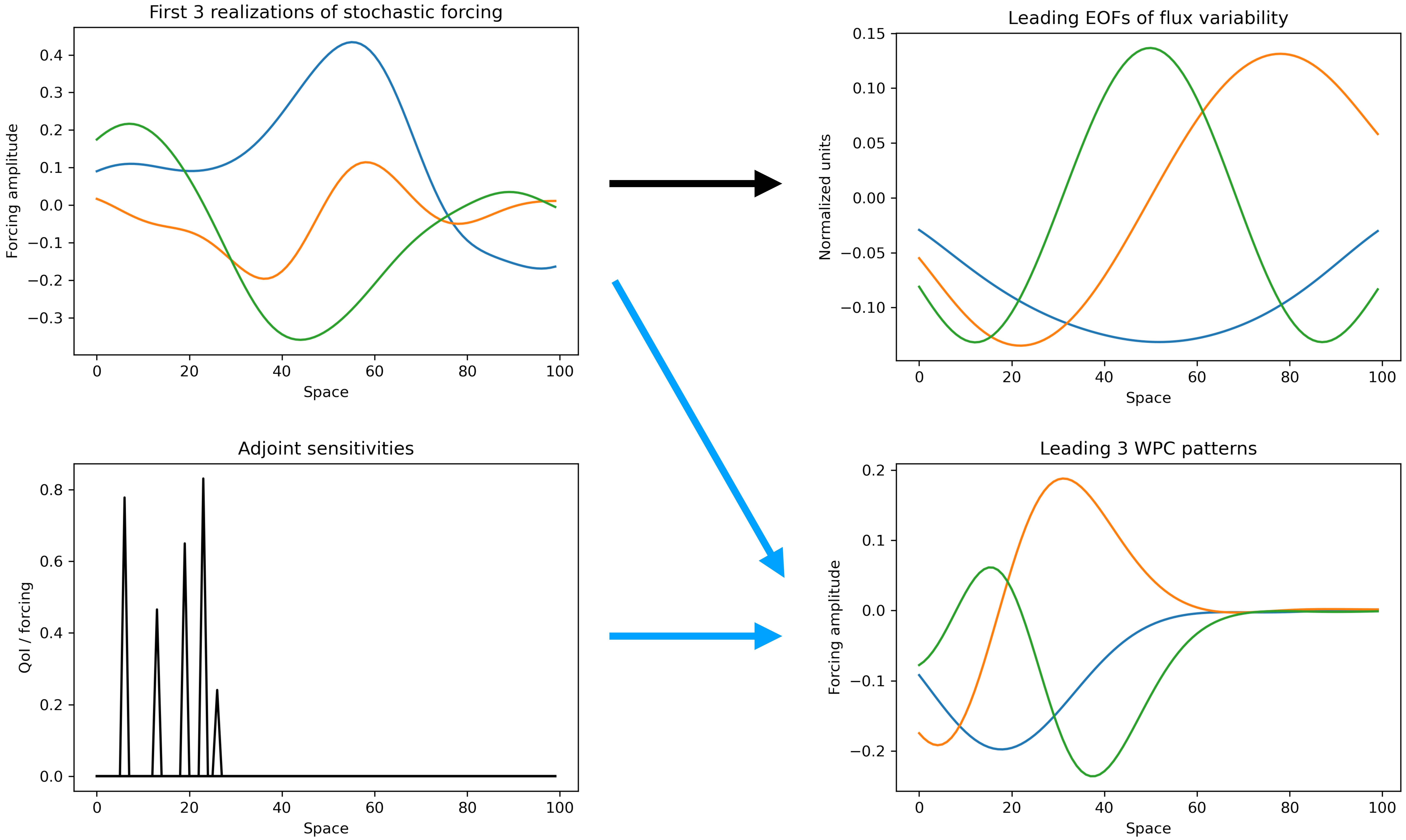
Demonstration in a (very) simple system



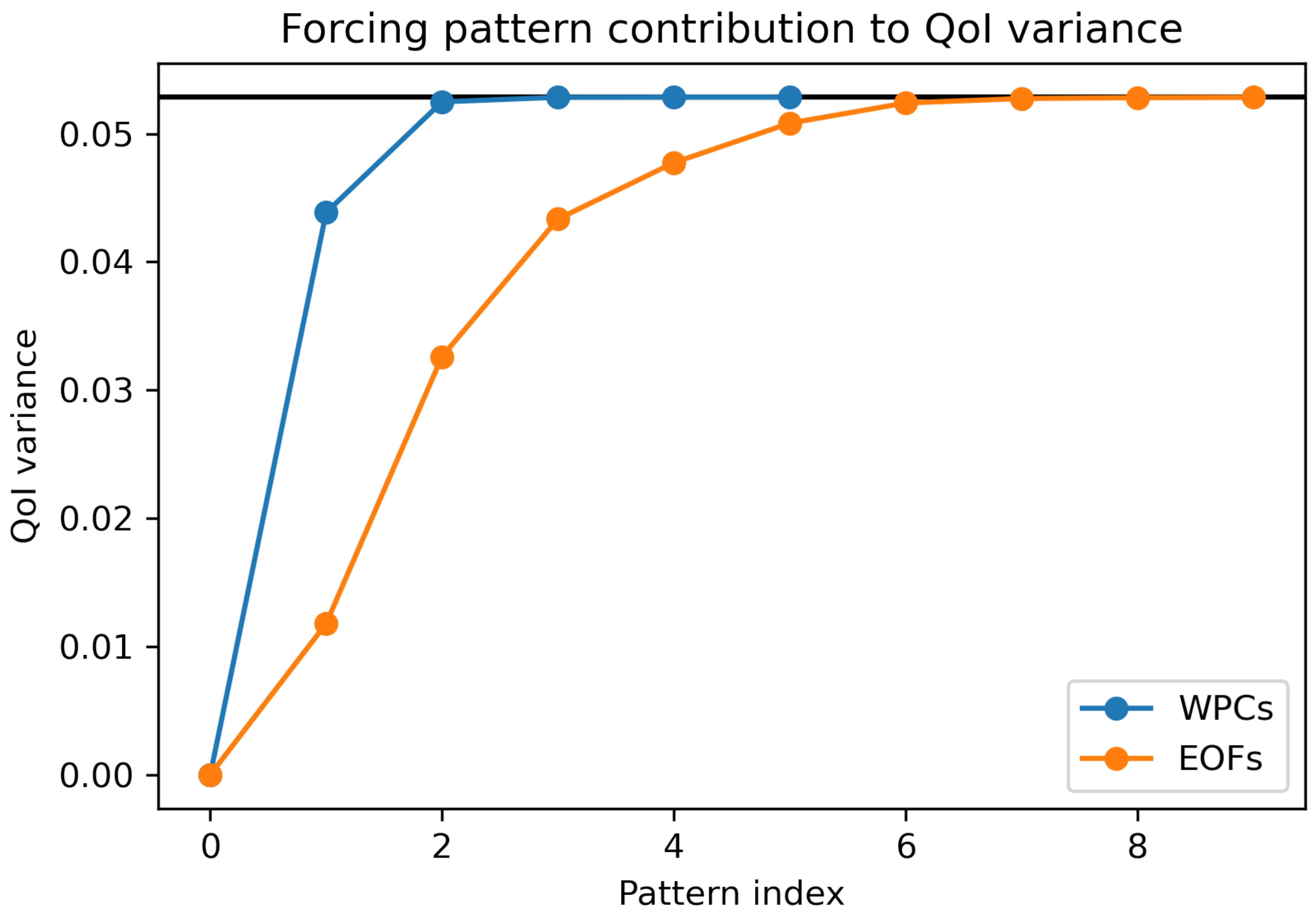


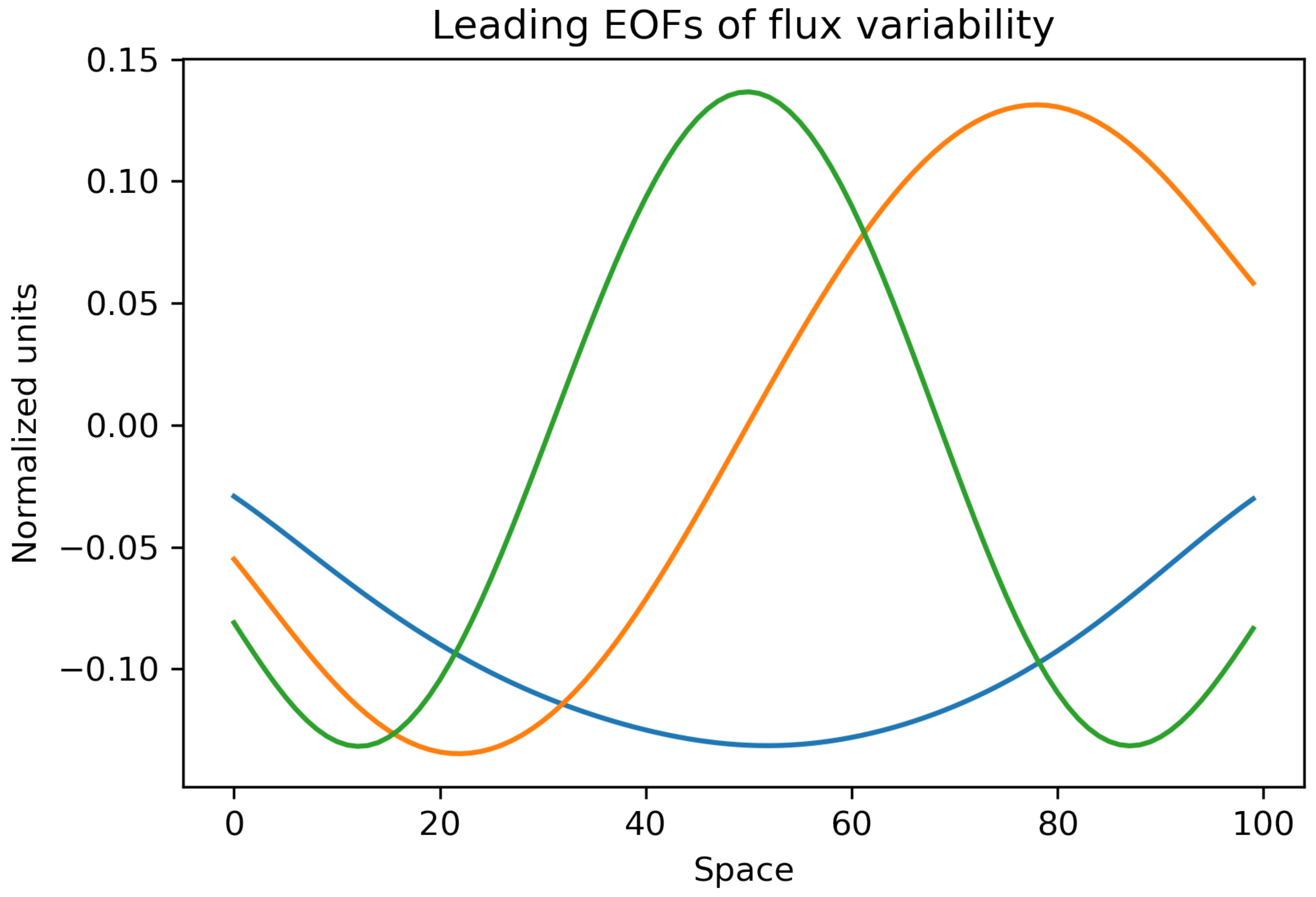


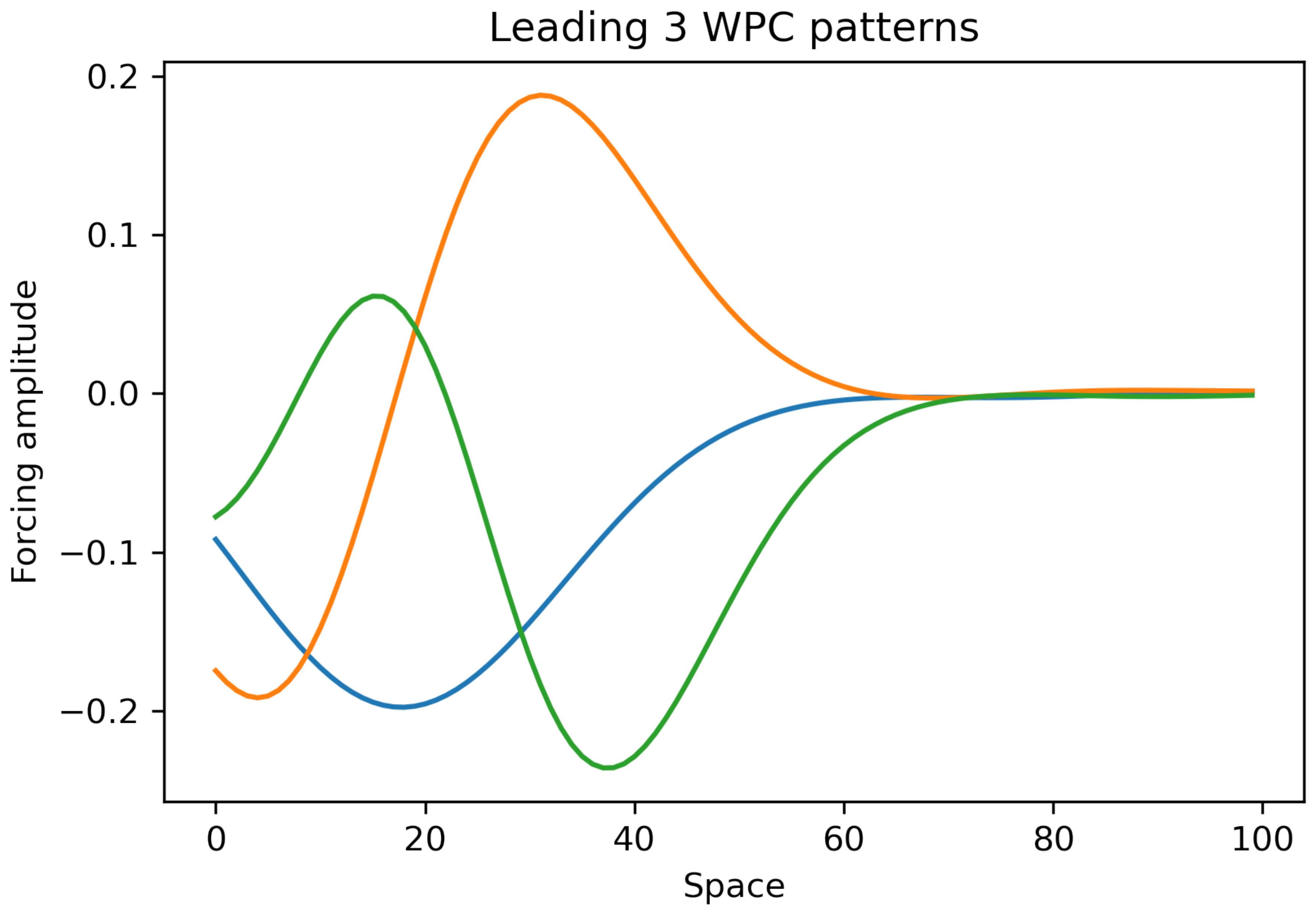
Demonstration in a (very) simple system



Demonstration in a (very) simple system







WPC patterns outperform EOFs at driving QoI variance.

Outline

The ocean as an integrator (and source) of random variation

What dominates ocean variability? Views from the atmosphere and ocean

Reconciliation: A dynamics-weighted principal components analysis

Dominant atmospheric drivers of decadal AMOC variability

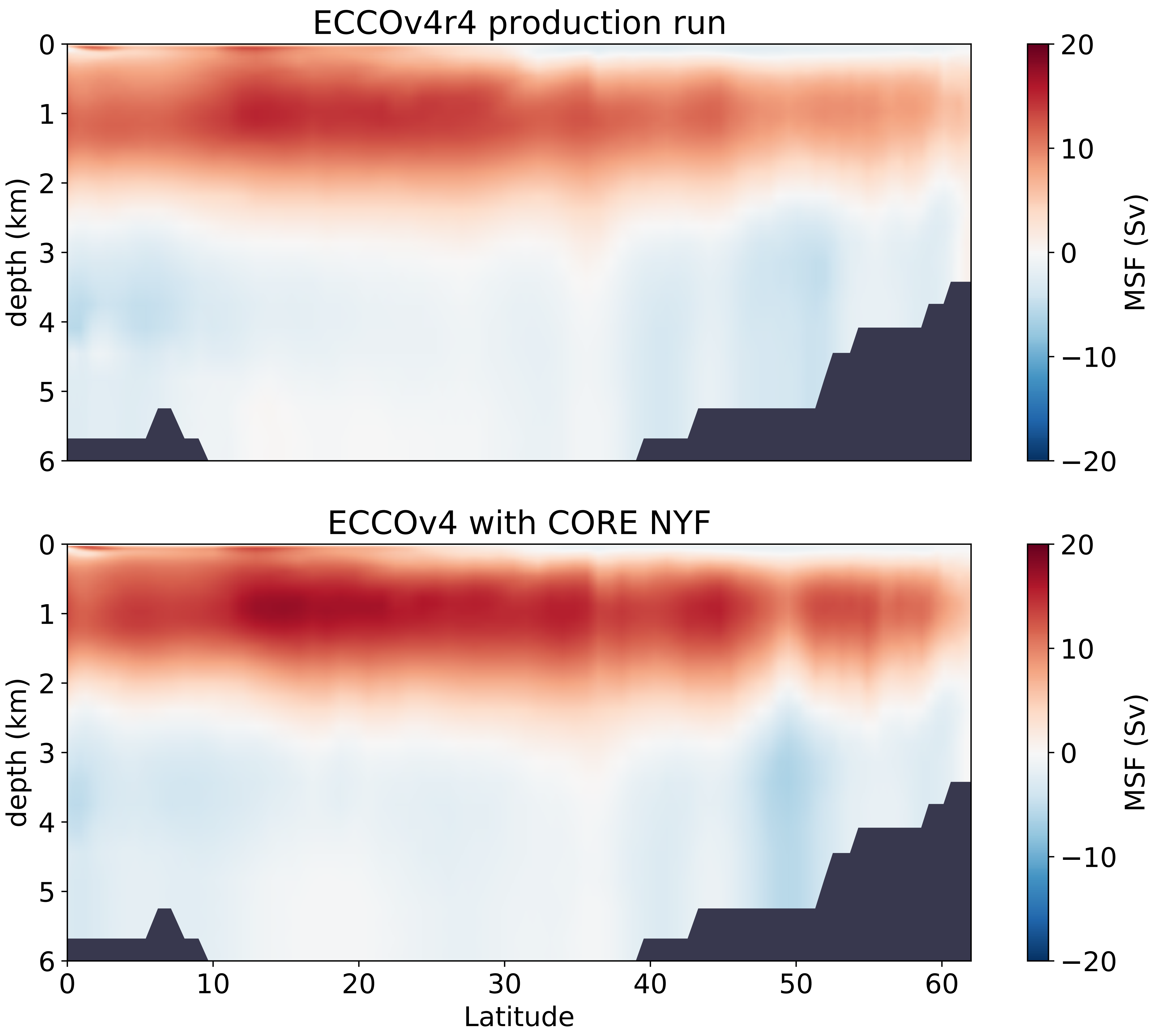
Impacts of dominant drivers over the observational period

Tracing pathways of decadal AMOC change from atmosphere to ocean

~1° resolution, flux-forced 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 **decadal averages** across several latitudes.

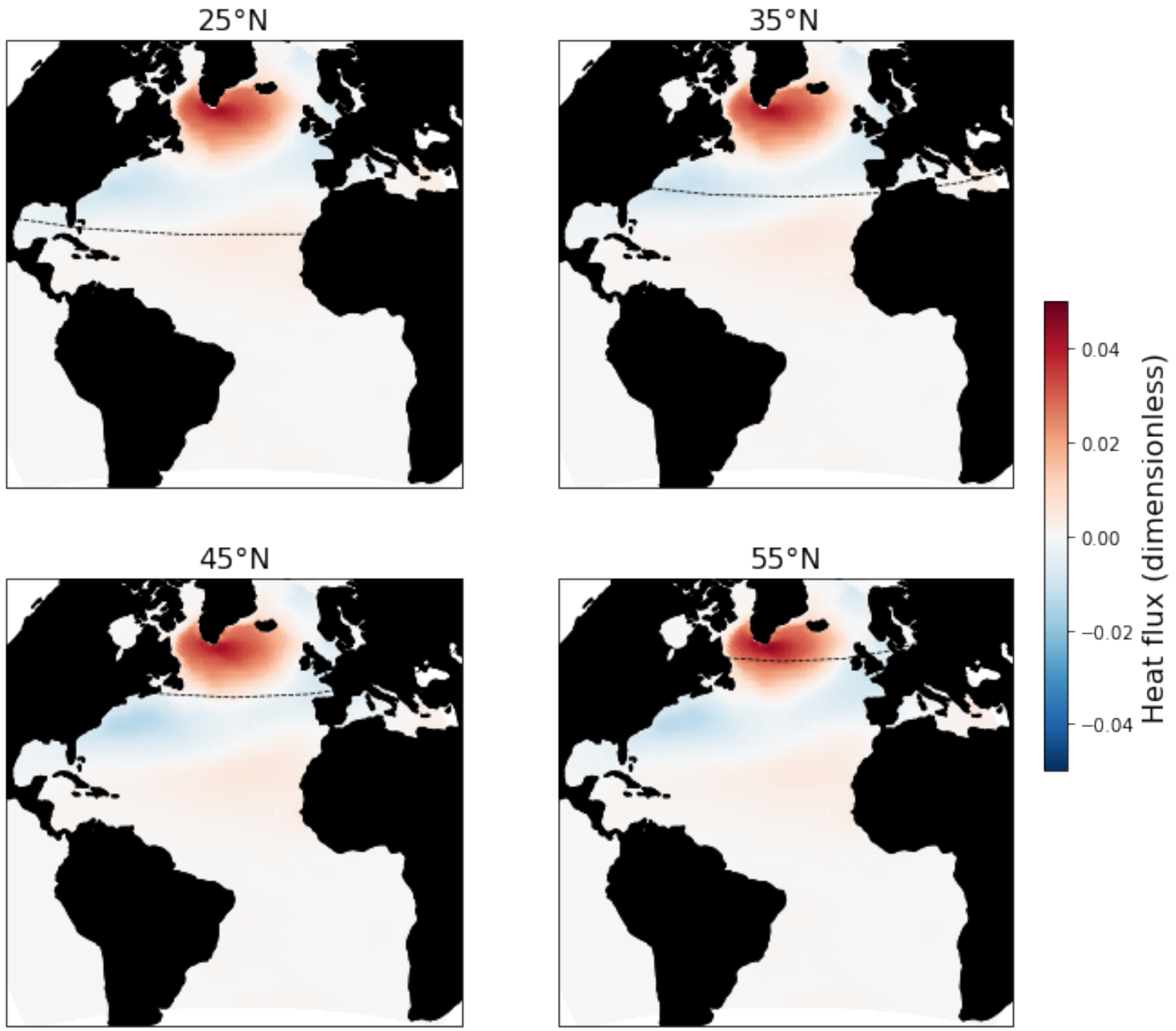
Fluxes are 6 hourly from ECCO v4r4.



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

What are the dominant atmospheric patterns responsible for surface-forced decadal AMOC variability?

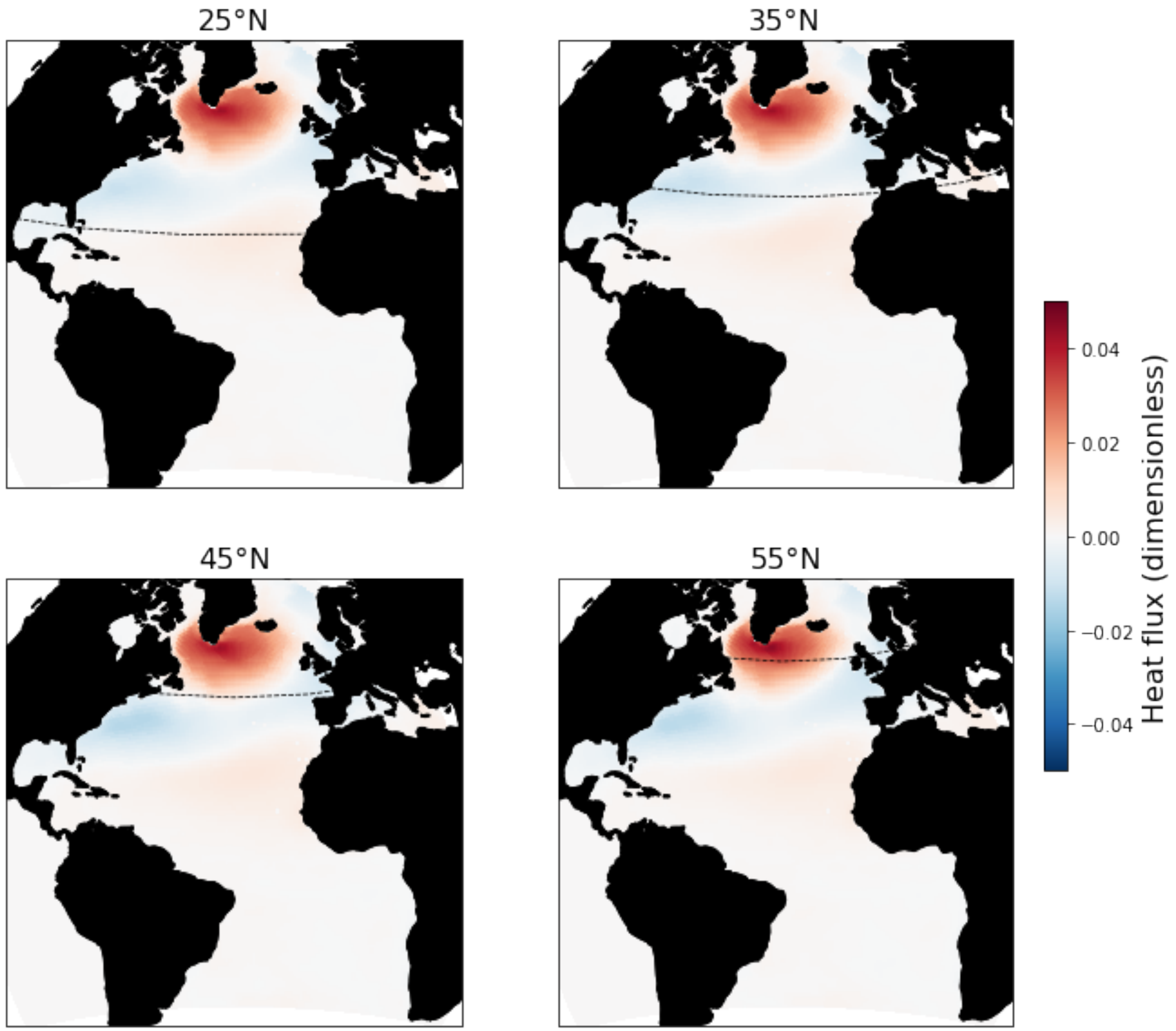
Heat flux patterns (four latitudes):



Leading pattern is almost identical at all four latitudes (>99% agreement)

What are the dominant atmospheric patterns responsible for surface-forced decadal AMOC variability?

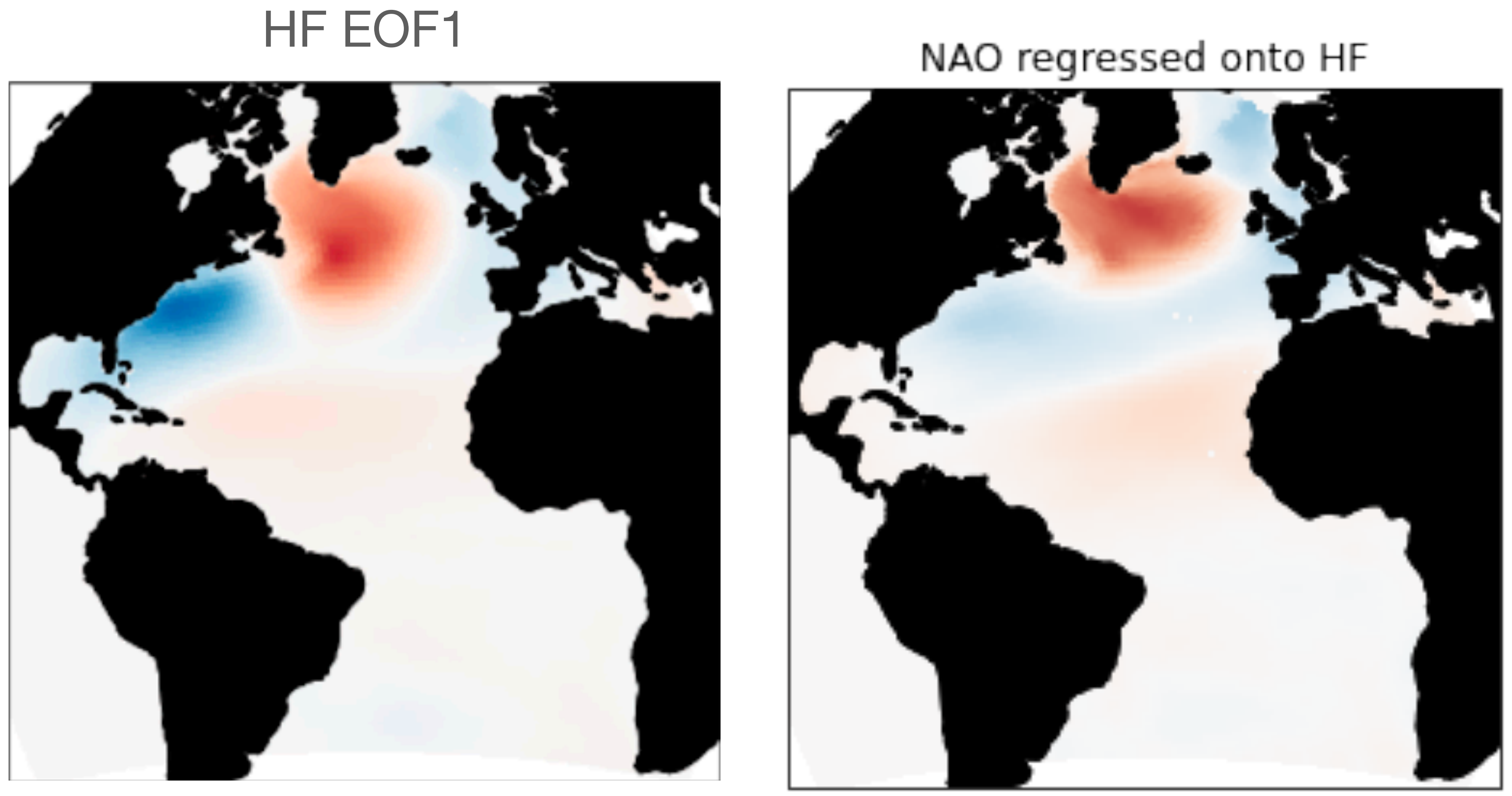
Heat flux patterns (four latitudes):



Leading pattern is almost identical at all four latitudes (>99% agreement)

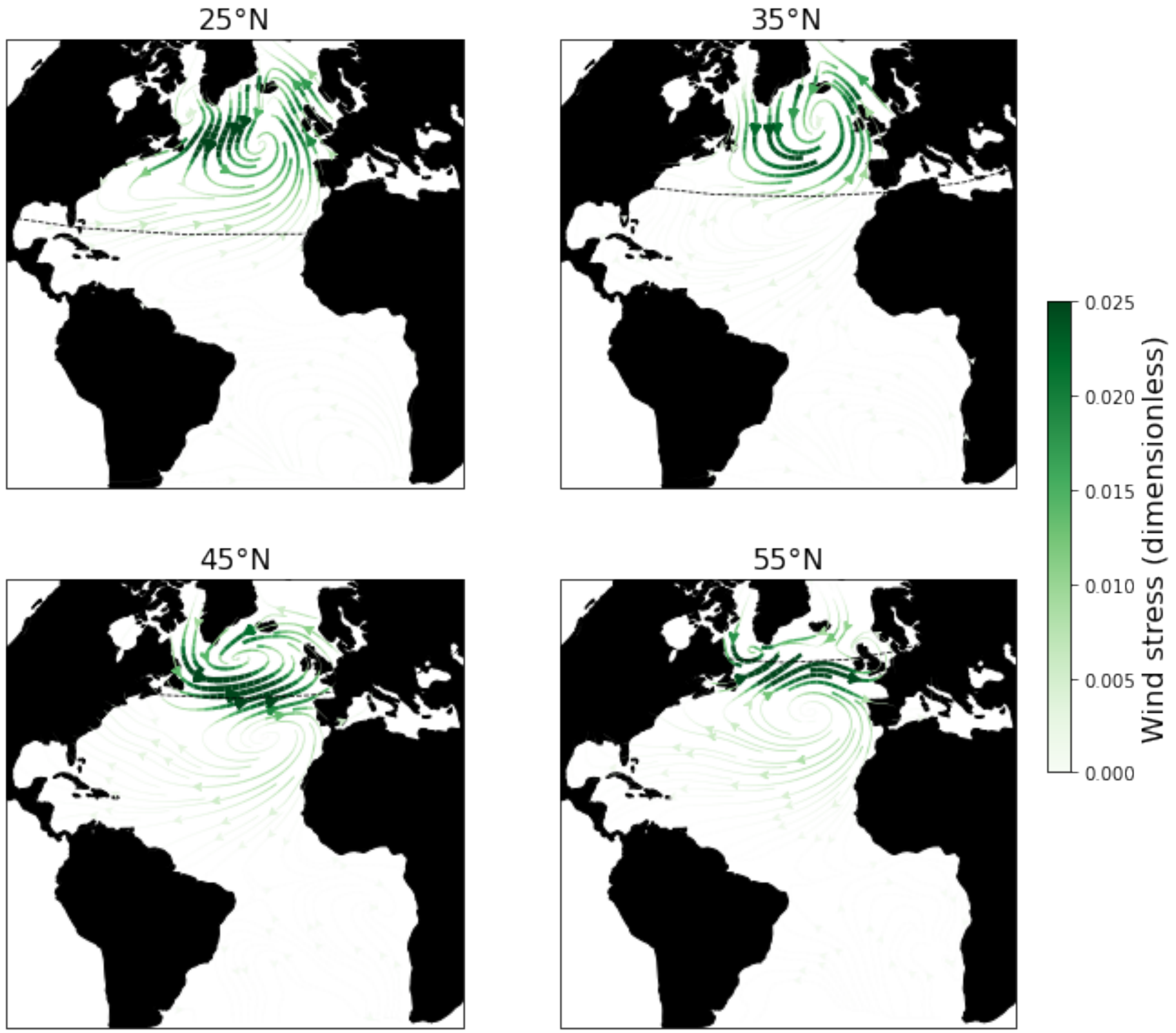
Structurally different from leading EOF pattern

… but highly similar to the heat flux signature of NAO (>90% agreement)



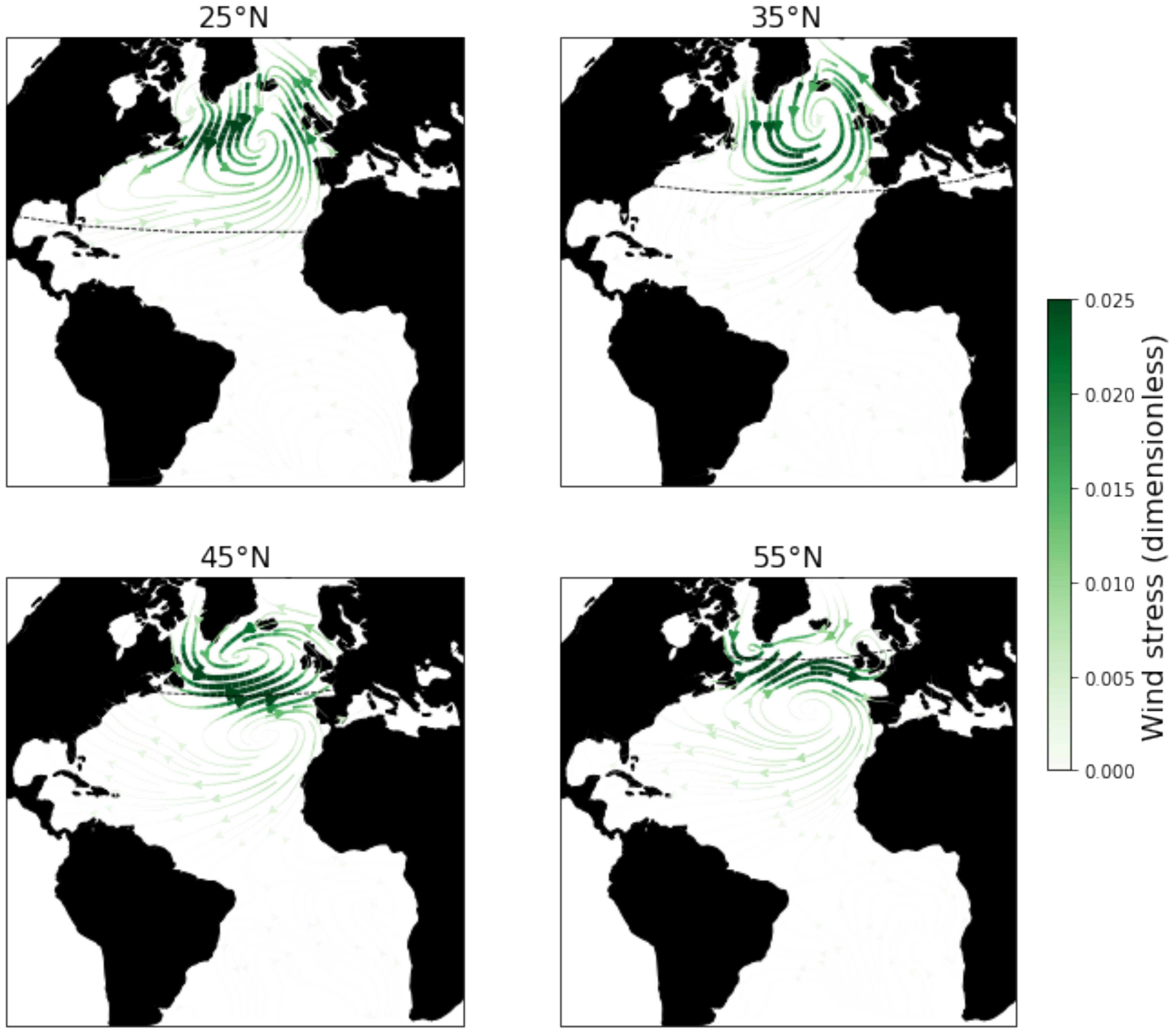
What are the dominant atmospheric patterns responsible for surface-forced decadal AMOC variability?

Leading WPC patterns (four latitudes):

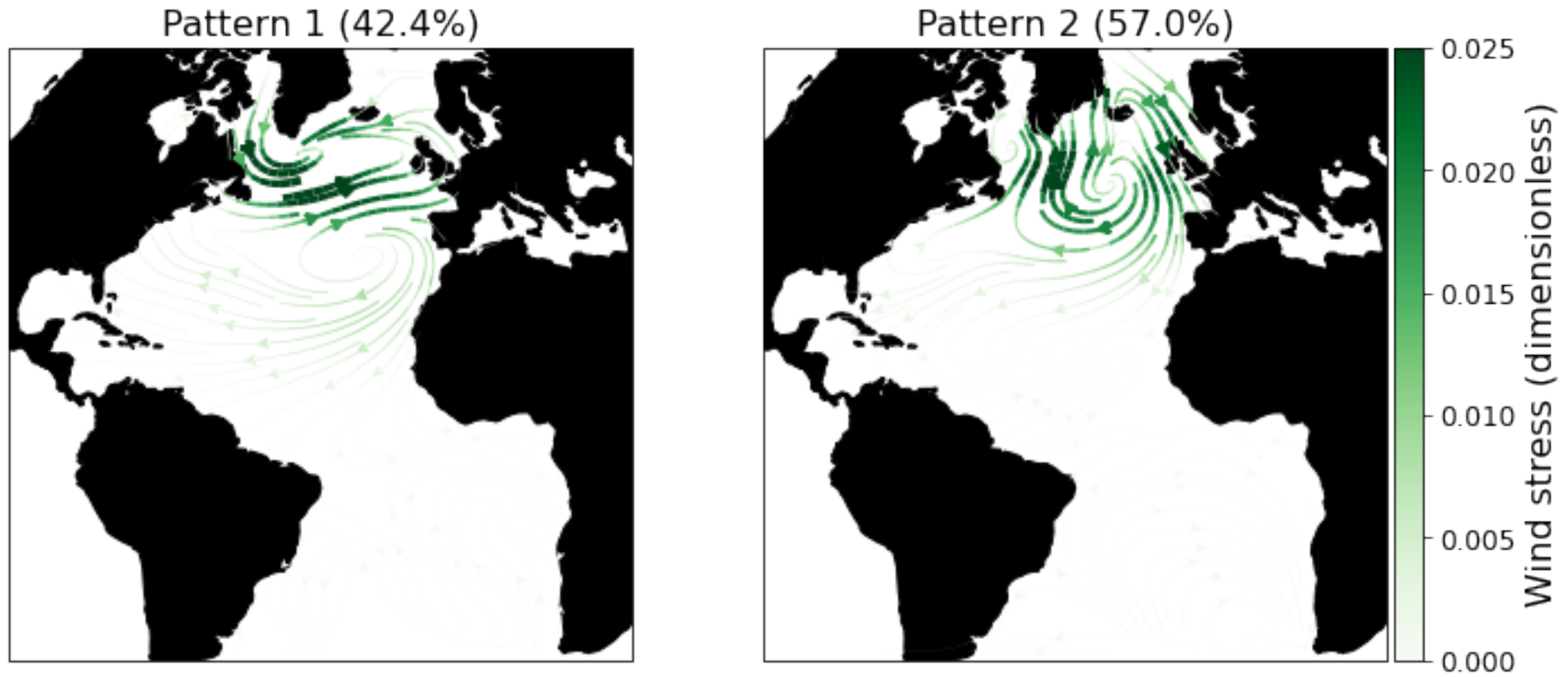


What are the dominant atmospheric patterns responsible for surface-forced decadal AMOC variability?

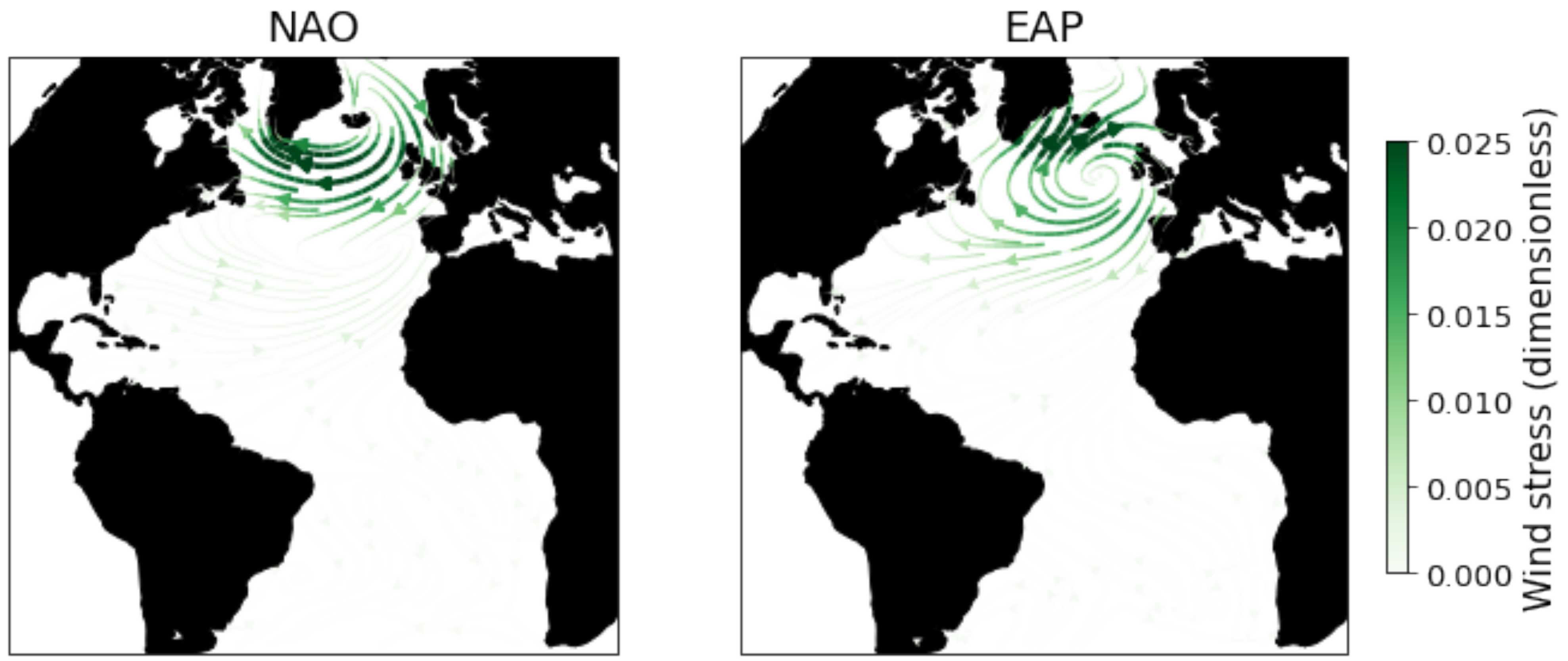
Leading WPC patterns (four latitudes):



Substantially different between AMOC latitudes **but** can be >99% explained by a subpolar pattern (1) and a subtropical pattern (2)



Qualitative similarities to the NAO and EAP:



Outline

The ocean as an integrator (and source) of random variation

What dominates ocean variability? Views from the atmosphere and ocean

Reconciliation: A dynamics-weighted principal components analysis

Dominant atmospheric drivers of decadal AMOC variability

Impacts of dominant drivers over the observational period

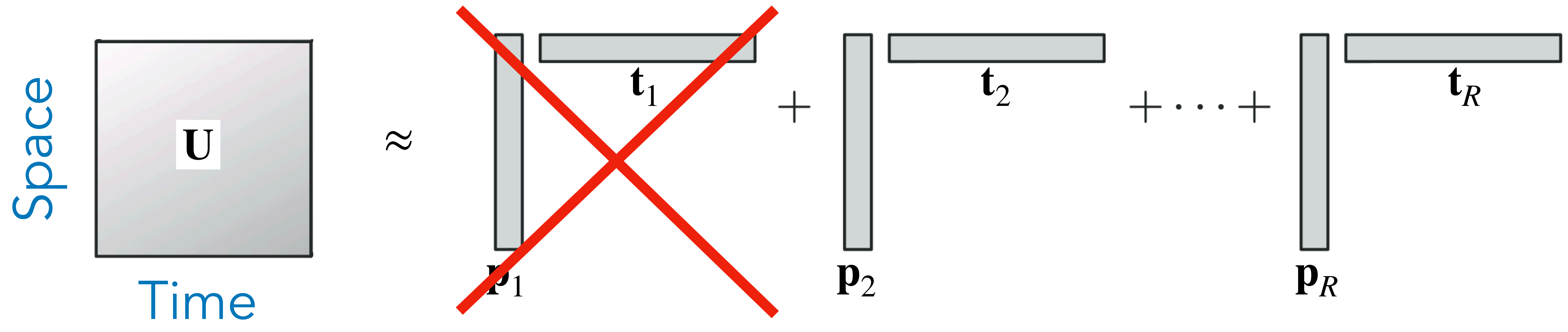
Tracing pathways of decadal AMOC change from atmosphere to ocean

Using ECCO as a climate sandbox

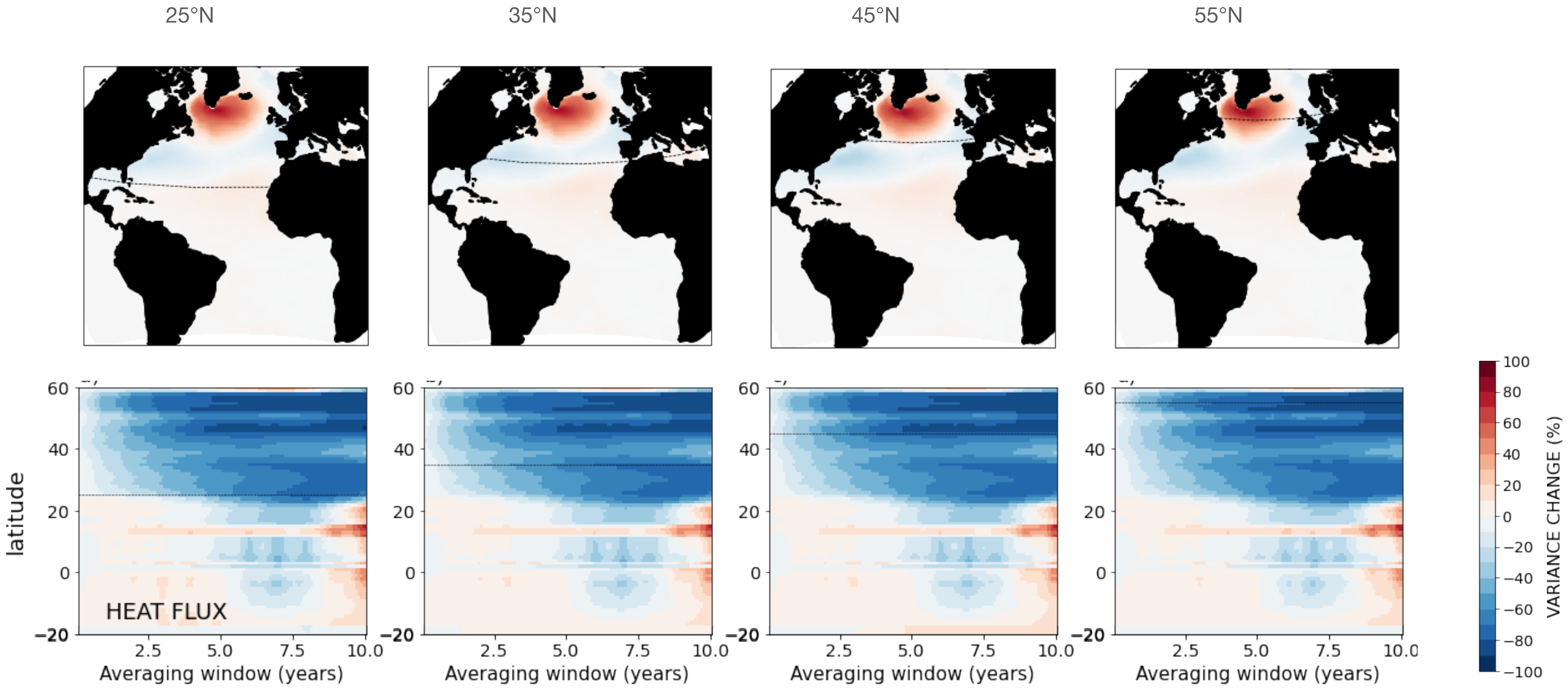
ECCO is a **forward run of the MITgcm** that conserves ocean properties.

…so we can make **changes** to the forcing and rerun the MITgcm to evaluate **impacts** and **mechanisms** of atmospheric forcings.

1. **Omit a leading WPC pattern**

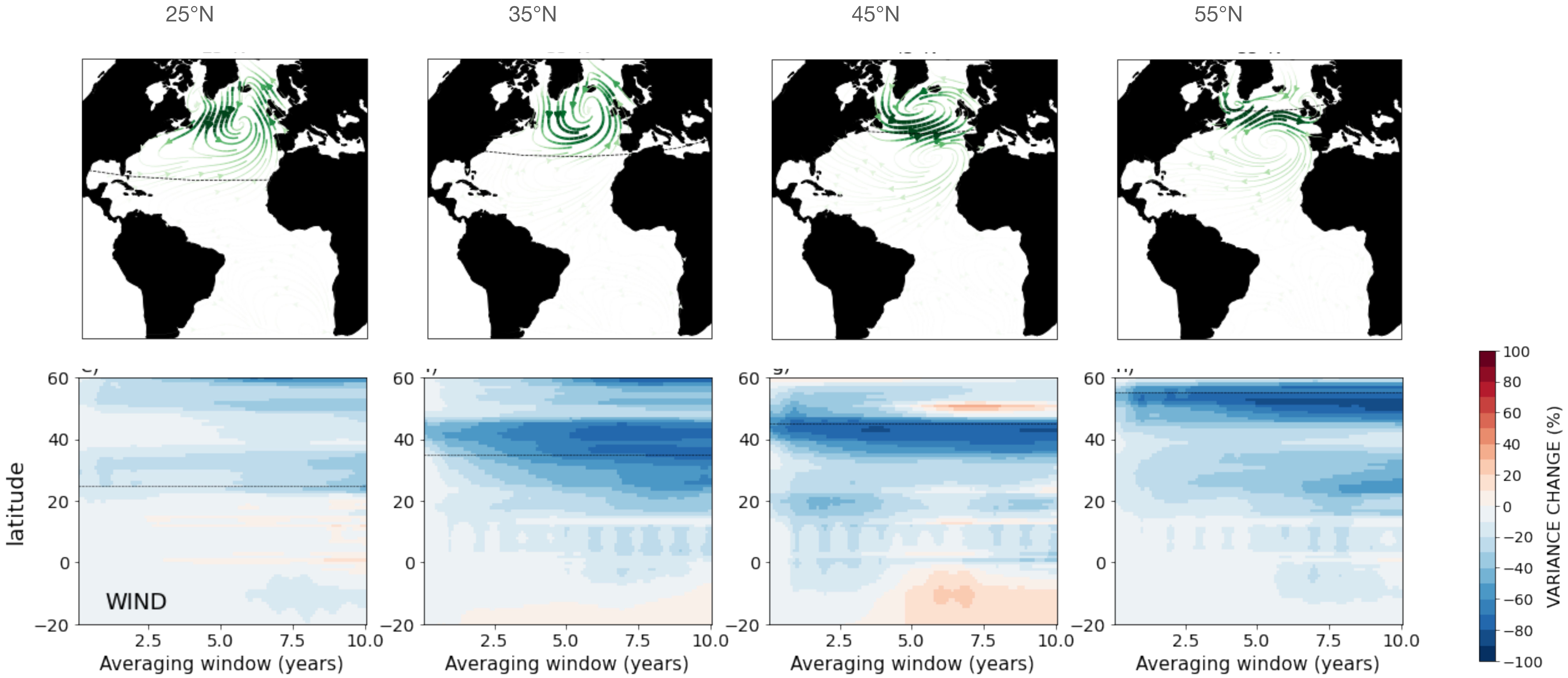


How much AMOC variability do these patterns explain?



Up to **90% change** in variance at the decadal time scale (vs. <30% with the first EOF)
NB: this is in the full nonlinear model (not tangent linear)

How much AMOC variability do these patterns explain?



Outline

The ocean as an integrator (and source) of random variation

What dominates ocean variability? Views from the atmosphere and ocean

Reconciliation: A dynamics-weighted principal components analysis

Dominant atmospheric drivers of decadal AMOC variability

Impacts of dominant drivers over the observational period

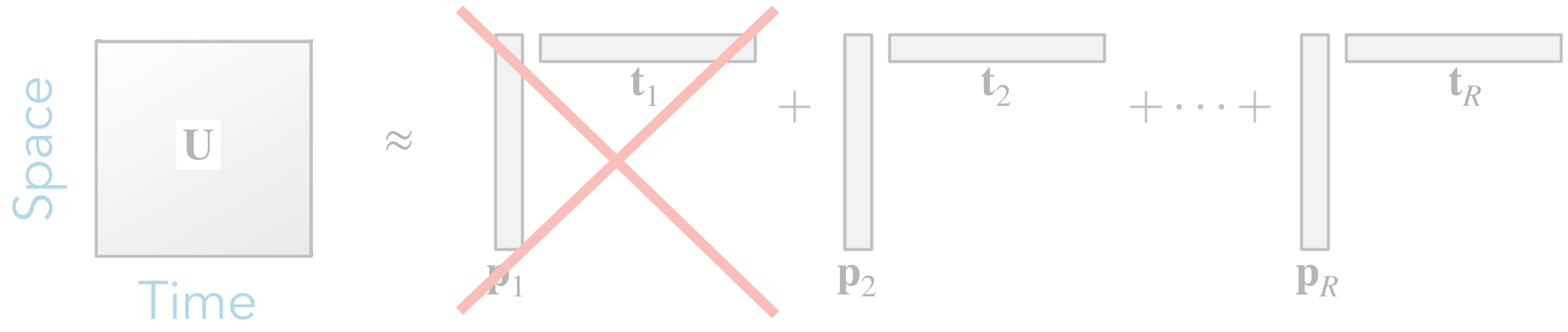
Tracing pathways of decadal AMOC change from atmosphere to ocean

Using ECCO as a climate sandbox

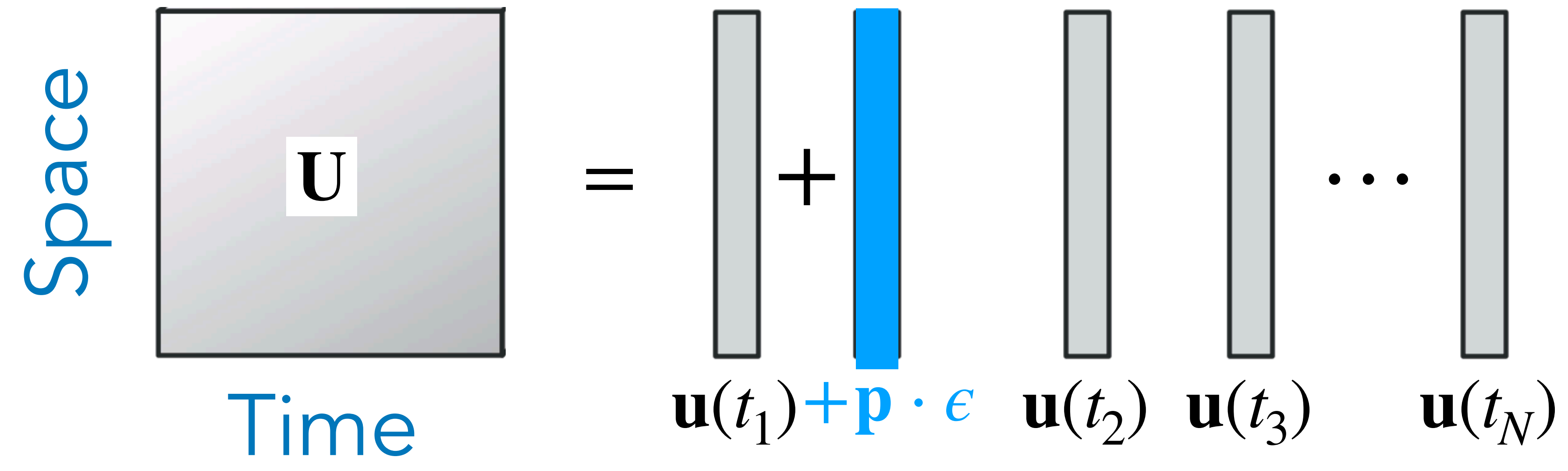
The final product is a **forward run of the MITgcm** that conserves ocean properties.

…so we can make **changes** to the forcing and rerun the MITgcm to evaluate **impacts** and **mechanisms** of atmospheric forcings.

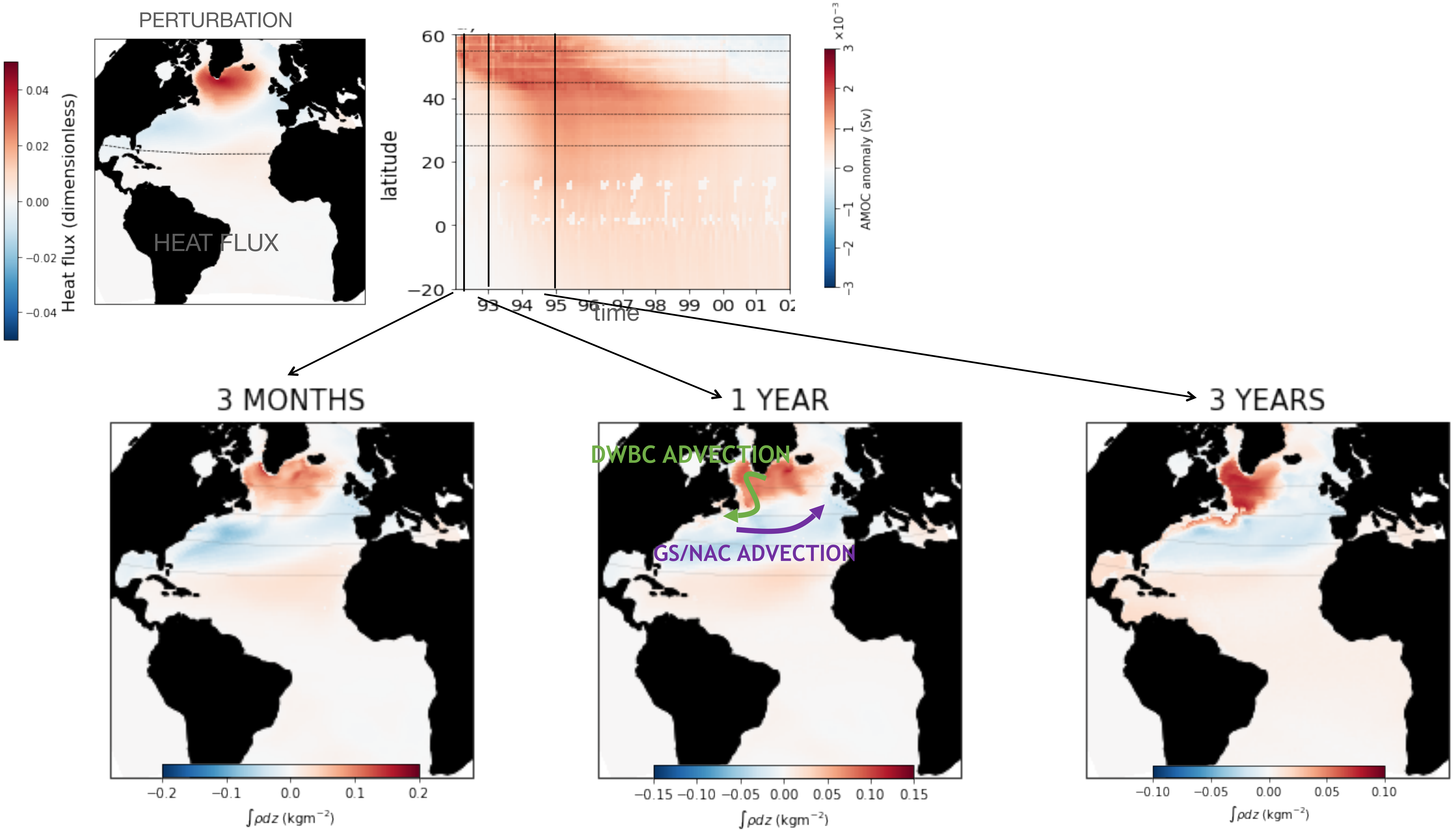
1. Omit a leading WPC pattern



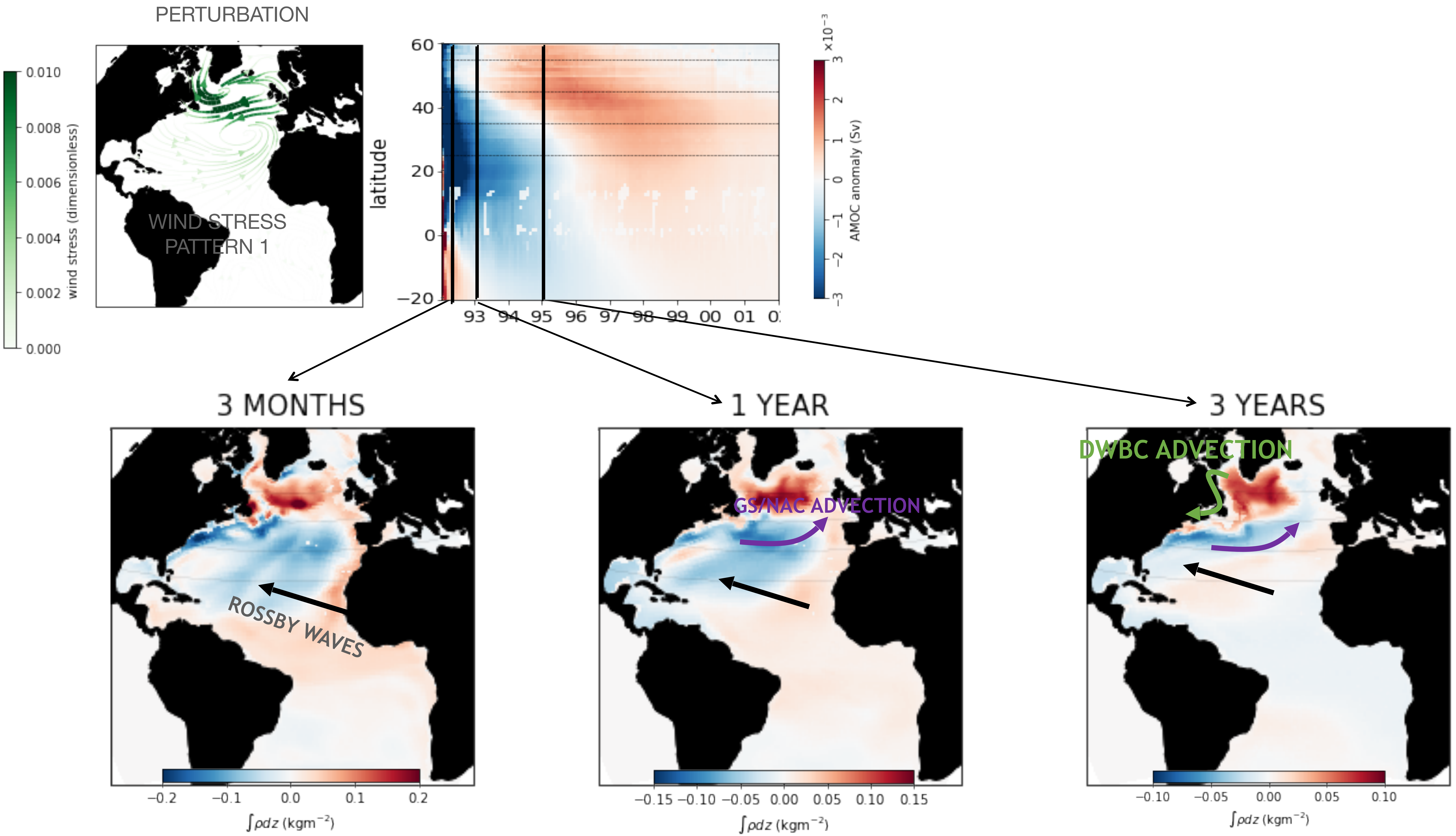
2. **Perturb model forcings with the WPC pattern**



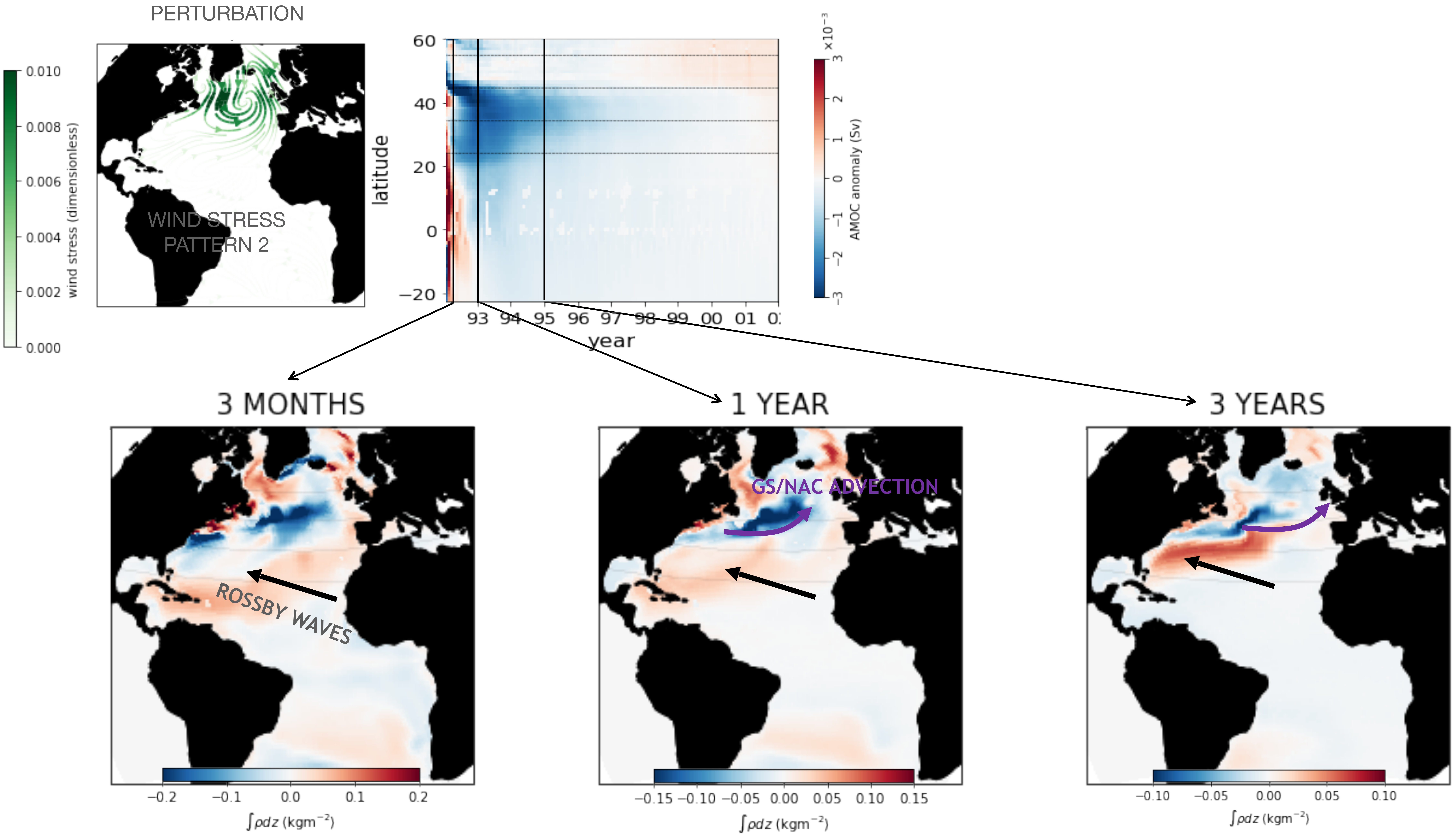
How are low-frequency AMOC anomalies established?



How are low-frequency AMOC anomalies established?



How are low-frequency AMOC anomalies established?



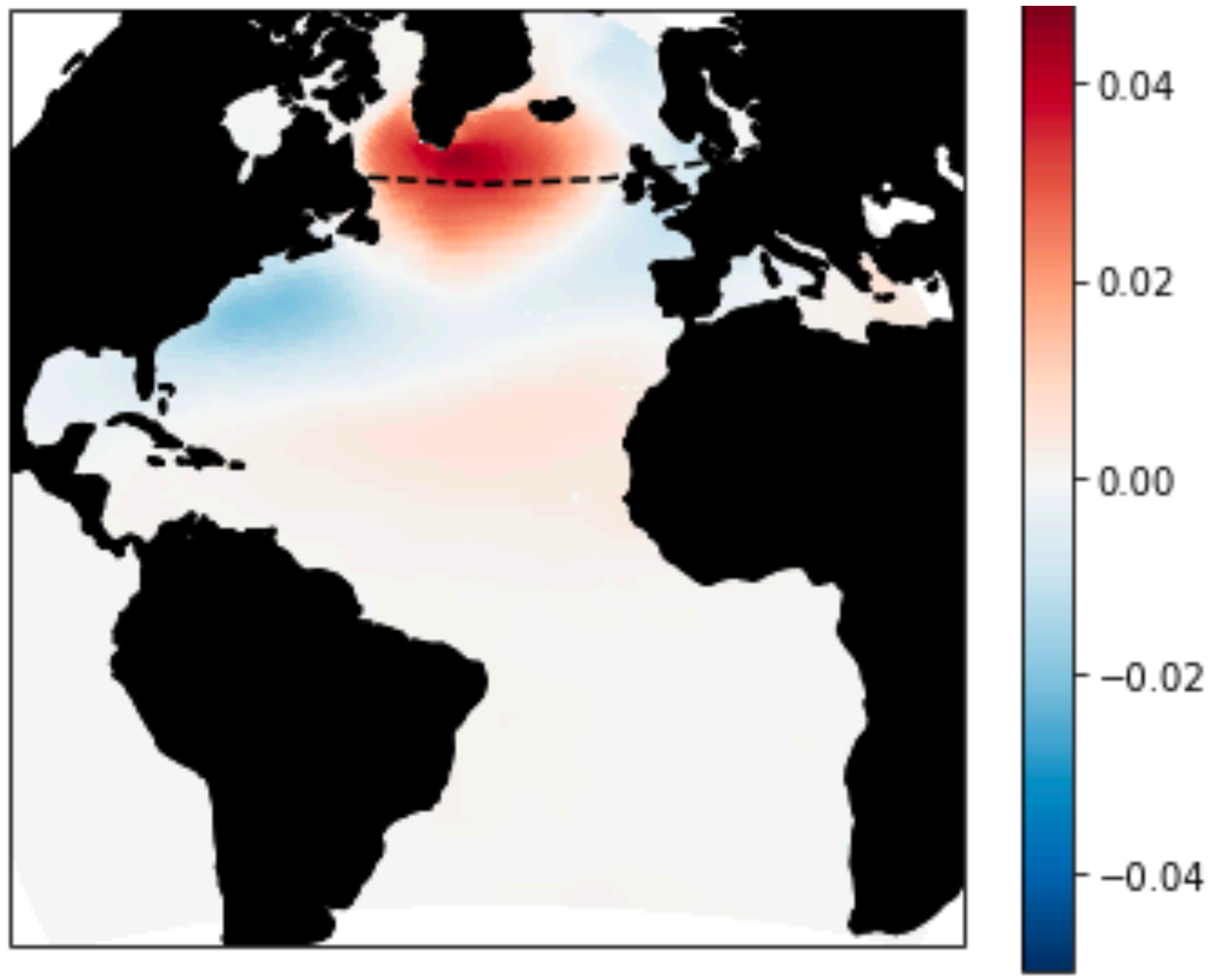
Conclusions and future work

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

Corresponding wind patterns vary between latitudes, but have EAP-like (subtropics) and NAO-like (subpolar) components. Removing these patterns reduces AMOC variability at decadal time-scales by up to 90% through a **combination of slow responses**.

Caveats: It's a model(!) Using a **1°**, **ocean-only, flux-forced** model. No guarantee of **significance** of atmospheric modes. We ignore **nonstationarities** in fluxes and adjoint sensitivities (for now).

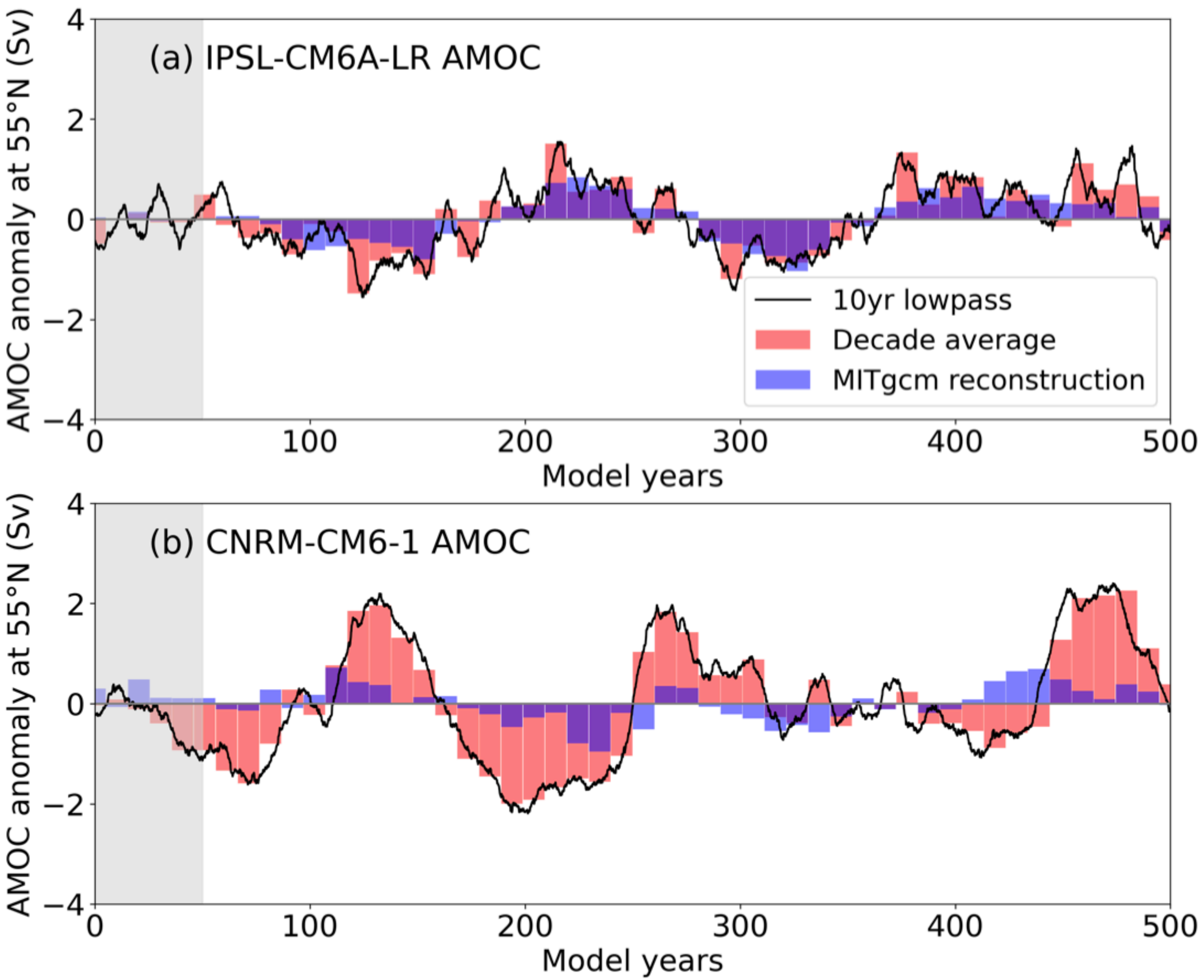


Papers:
Amrhein et al. (methods), subm. J Clim

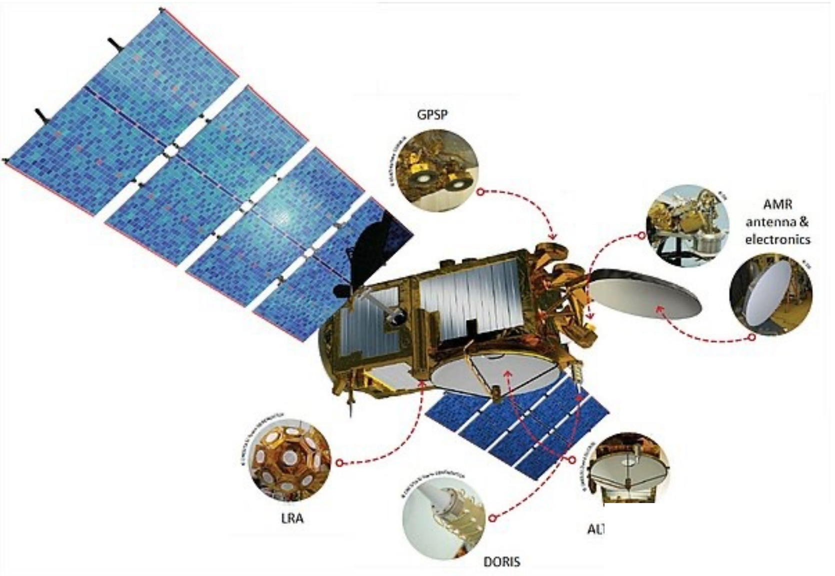
Stephenson et al. (AMOC results), in prep

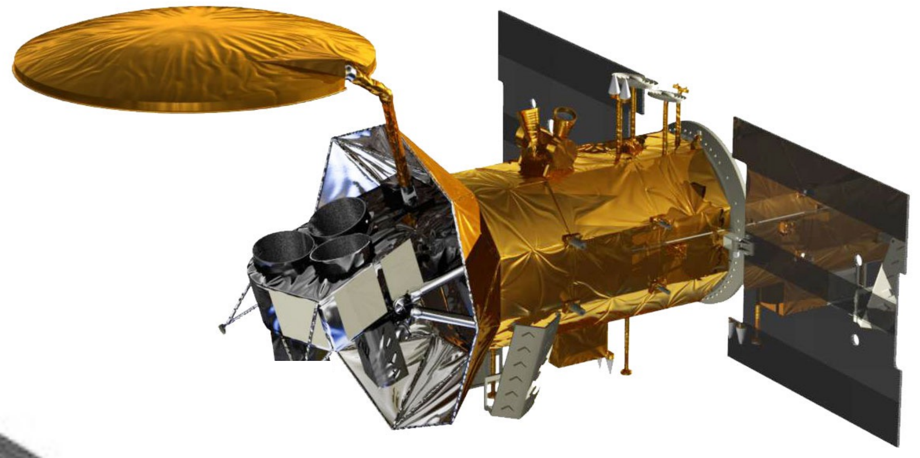
Conclusions and future work

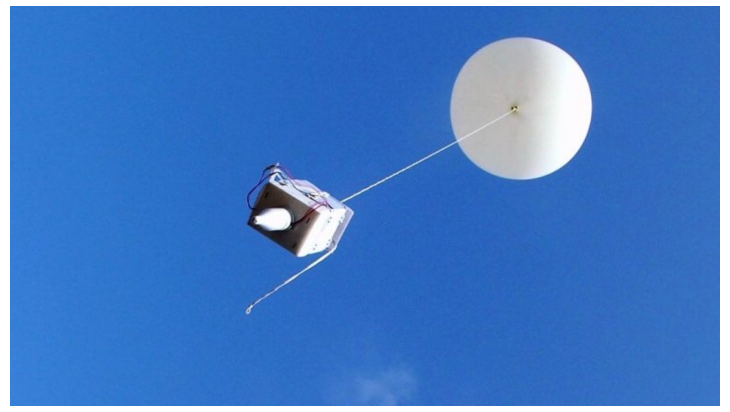
Investigating MITgcm adjoint sensitivities in CMIP6 coupled models — a path for quantifying structural uncertainties?



Integration of CESM and the Data Assimilation Research Testbed







CAM6 reanalysis | Global 1°, 80 ensemble members, 2011-2020. Publicly available for forcing CESM.

High-resolution ocean DA | 80-member ocean reanalyses spanning 2011-2017 at 1° and 0.1°

DA and parameter estimation in CLM to improve carbon cycle, hydrologic, and atmospheric forecasting

DA tailored to "bounded" climate quantities (sea ice concentration, tracer concentrations, parameters…)

DA and parameter estimation in MOM6/MARBL

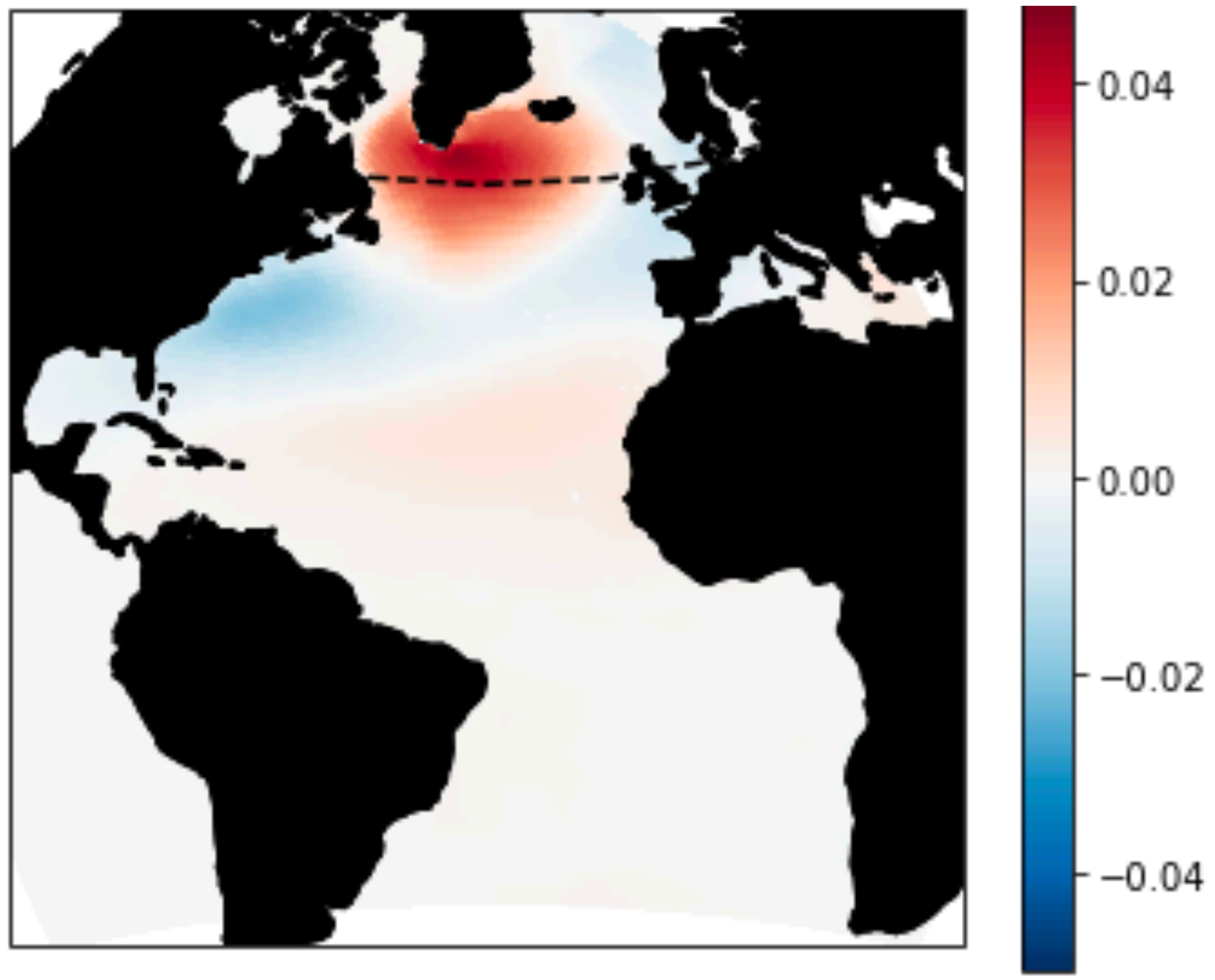
A workhorse DA compset for coupled climate data assimilation in CESM3 with DART
Dan Amrhein, Alper Altuntas, Helen Kershaw, Kevin Raeder, Jim Edwards

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 ***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.

Corresponding wind patterns vary between latitudes, but have EAP-like (subtropics) and NAO-like (subpolar) components.
Removing these patterns reduces AMOC variability at decadal time-scales by up to 90% through a **combination of slow responses**.



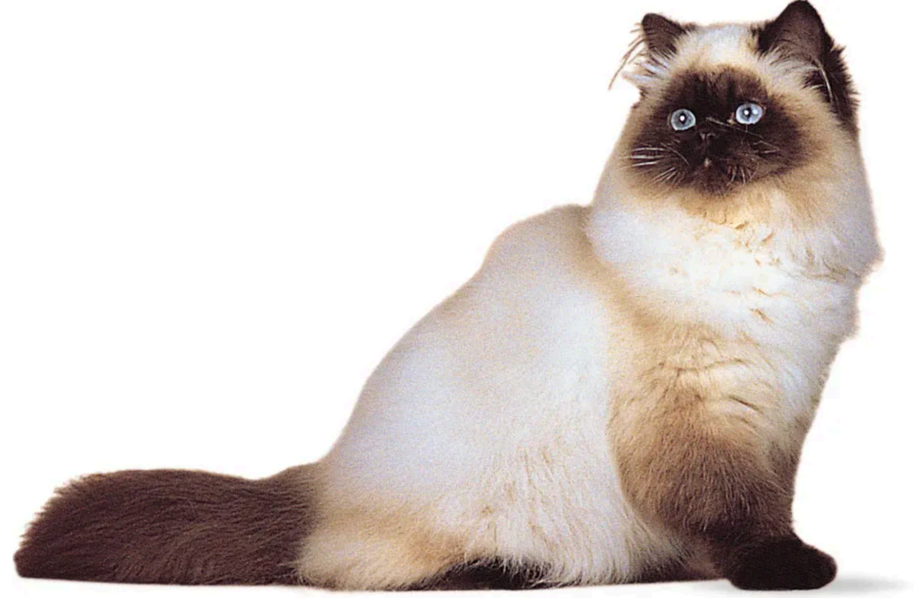
Caveats: It's a model(!) Using a **1°**, **ocean-only, flux-forced** model. No guarantee of **significance** of atmospheric modes. We ignore **nonstationarities** in fluxes and adjoint sensitivities (for now).

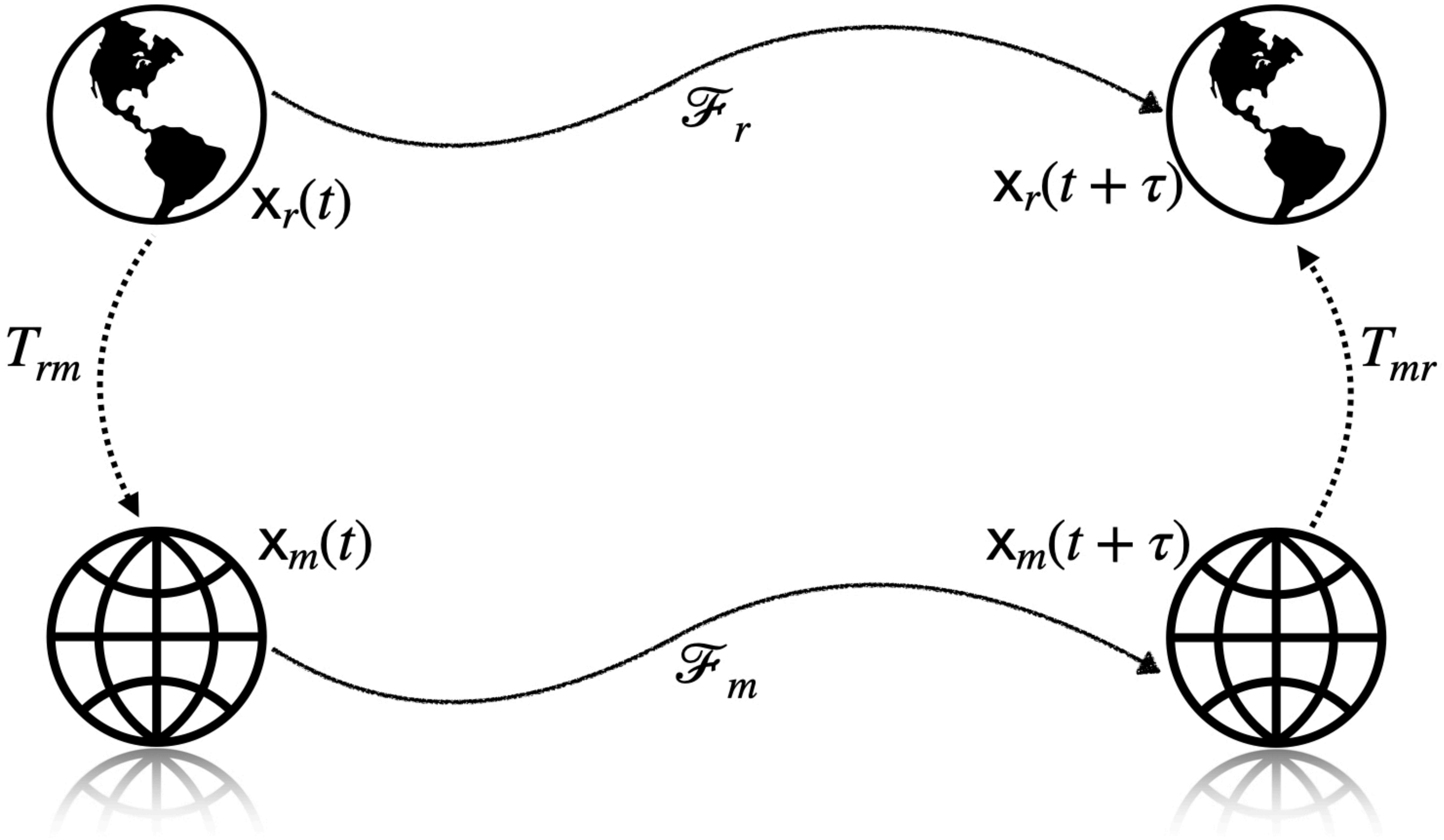
Papers:
Amrhein et al. (methods), subm. J Clim

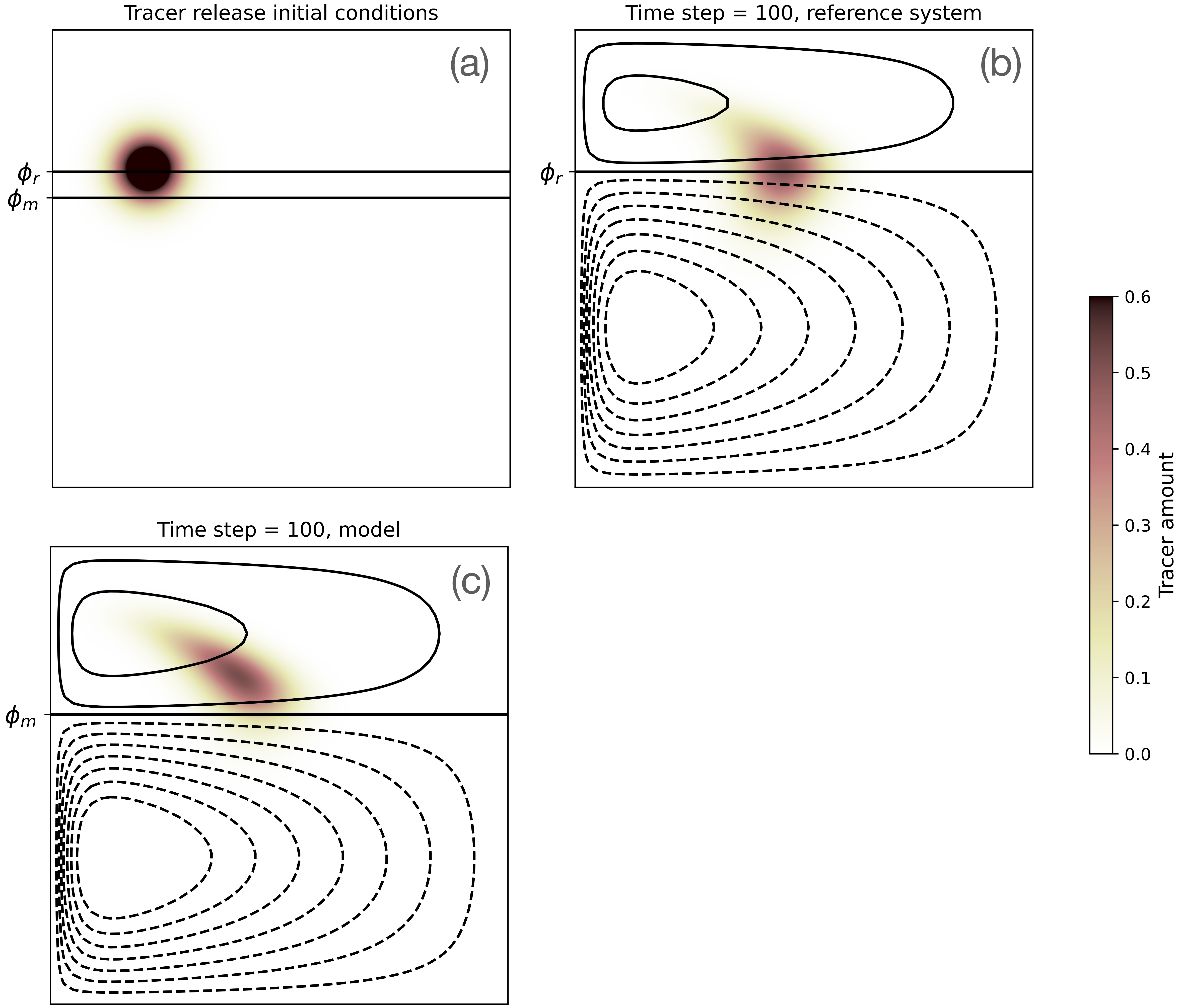
Stephenson et al. (AMOC results), in prep

Other things / what's next: Cross-attractor transforms (CATs)

with Ian Grooms and Niraj Agarwal (CU)

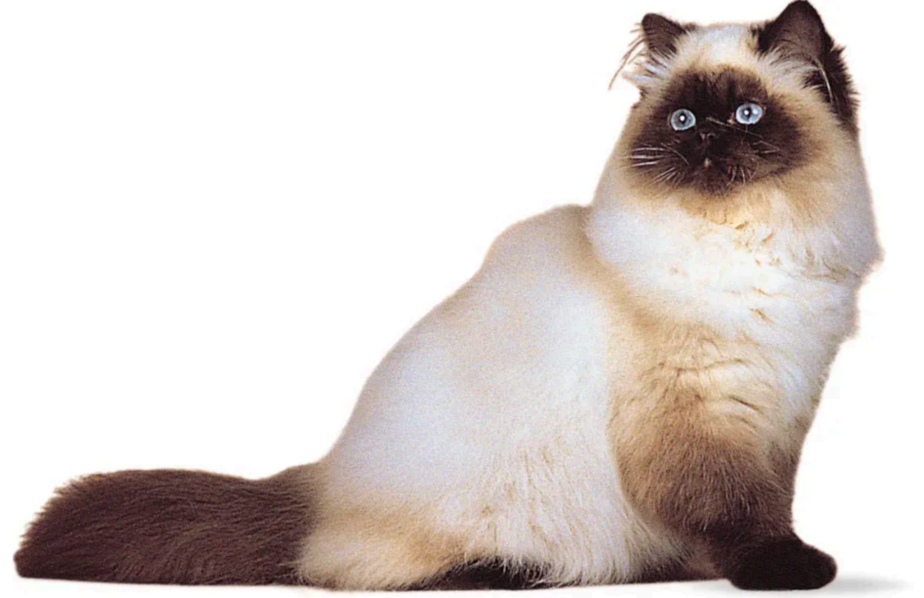


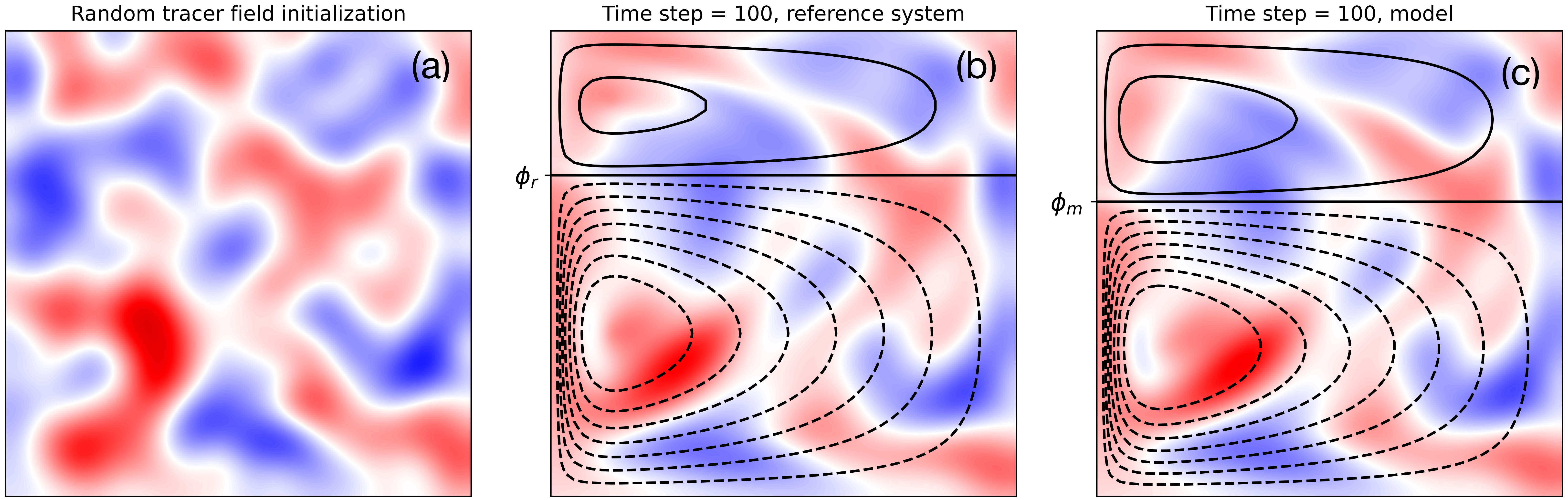




Other things / what's next:
Cross-attractor transforms (CATs)

with Ian Grooms and Niraj Agarwal (CU)

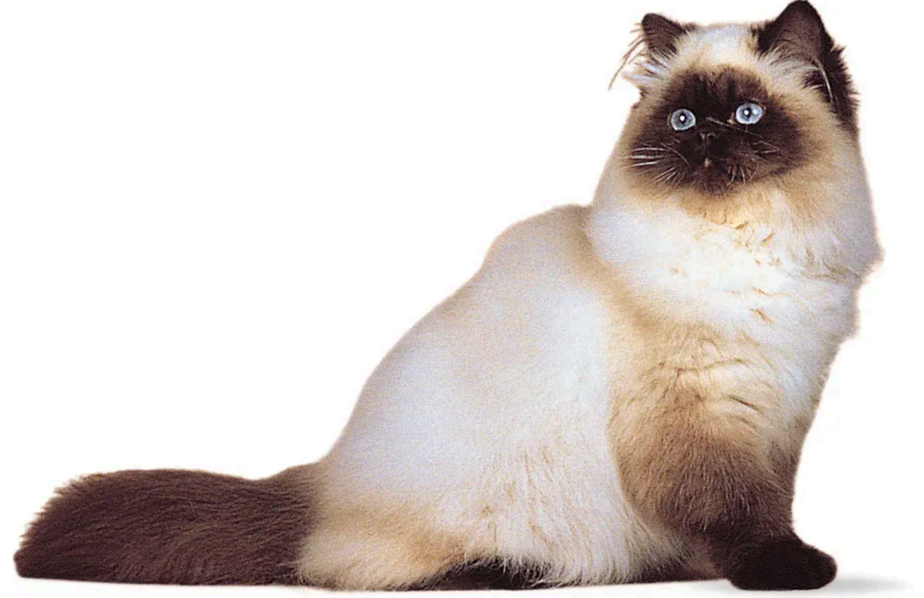


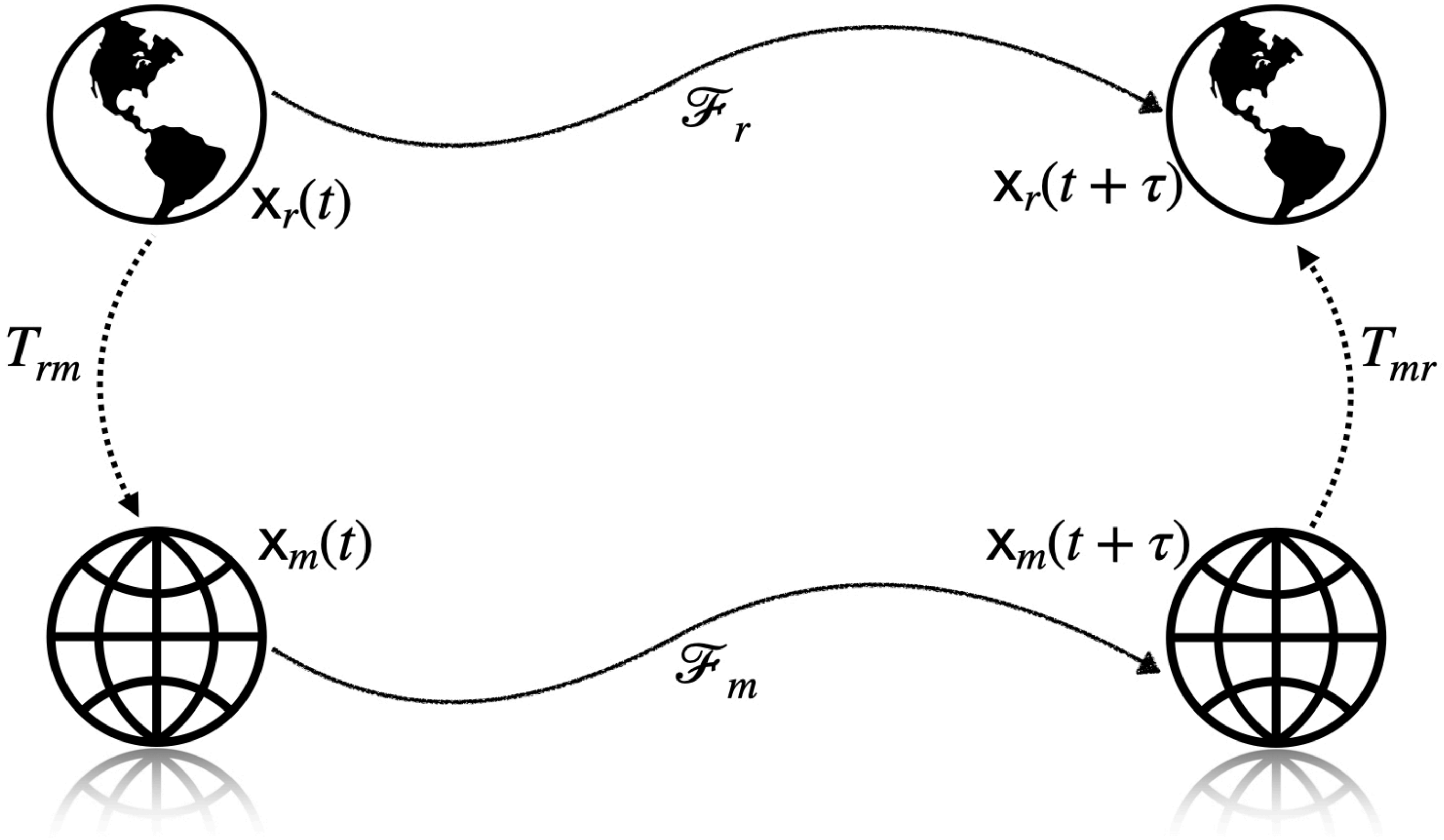


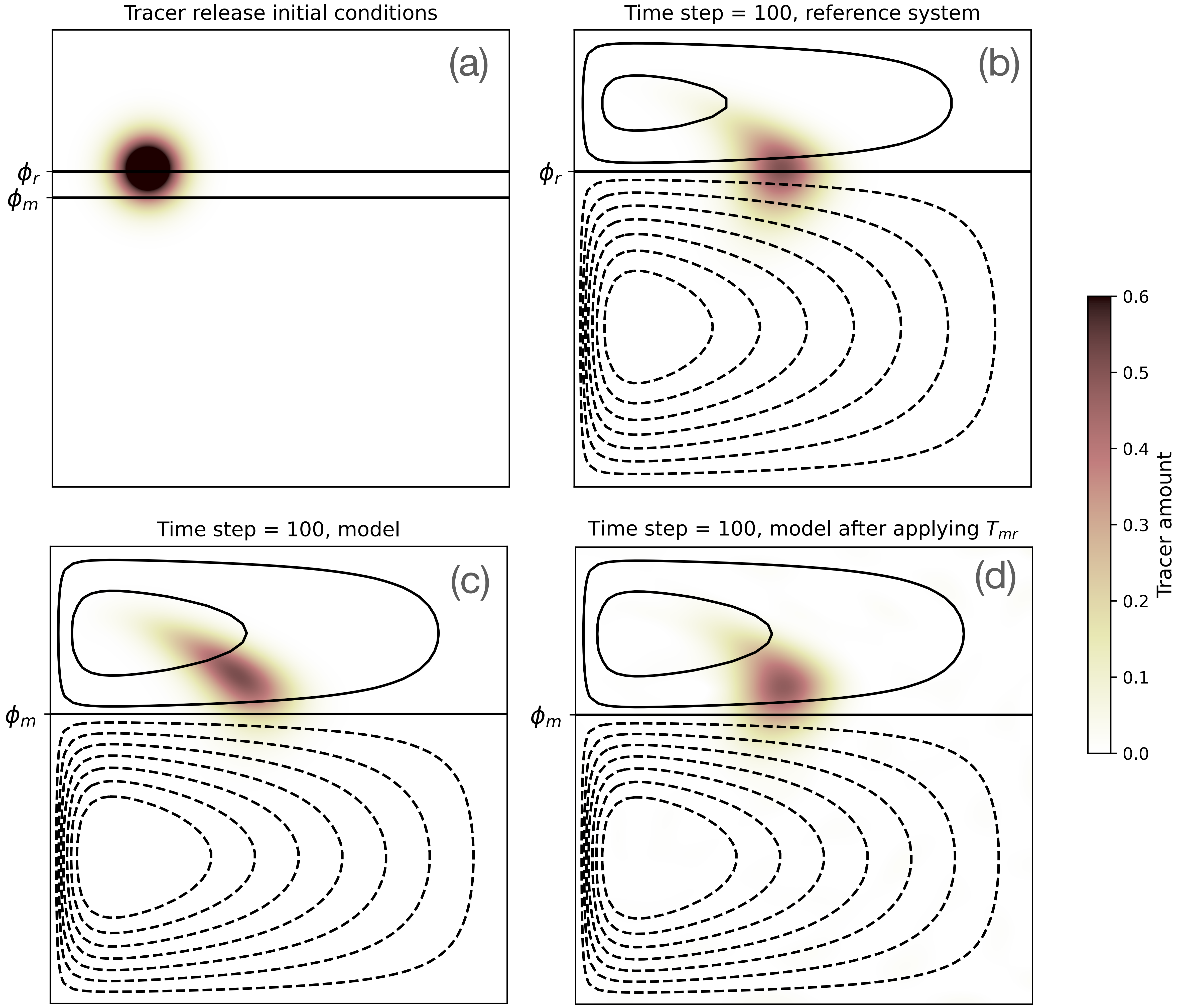
$$\tilde{\mathbf{T}}_{mr} = \mathbf{x}_m^{+}\mathbf{x}_r^{+\top}\left(\mathbf{x}_m^{+}\mathbf{x}_m^{+\top}\right)^{-1}$$

Other things / what's next:
Cross-attractor transforms (CATs)

with Ian Grooms and Niraj Agarwal (CU)

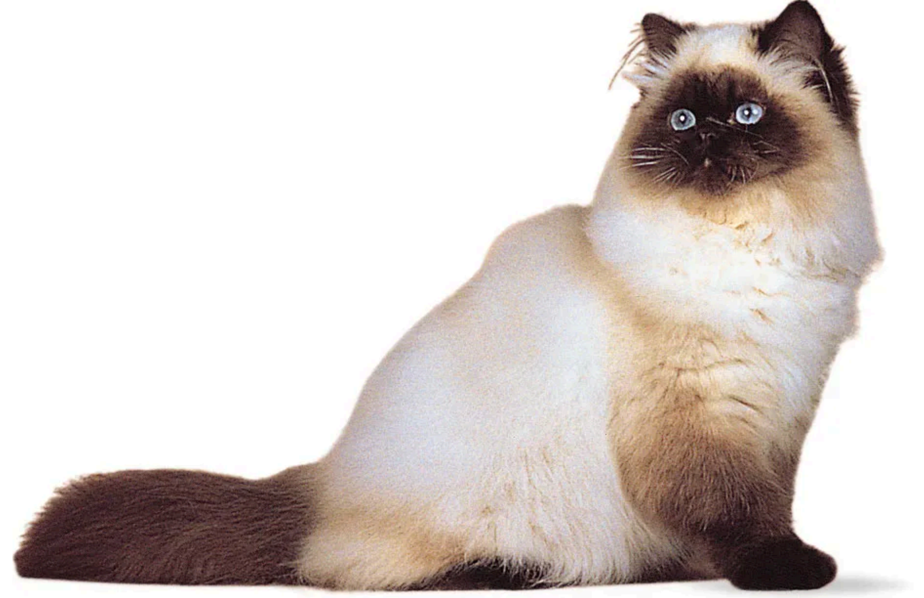


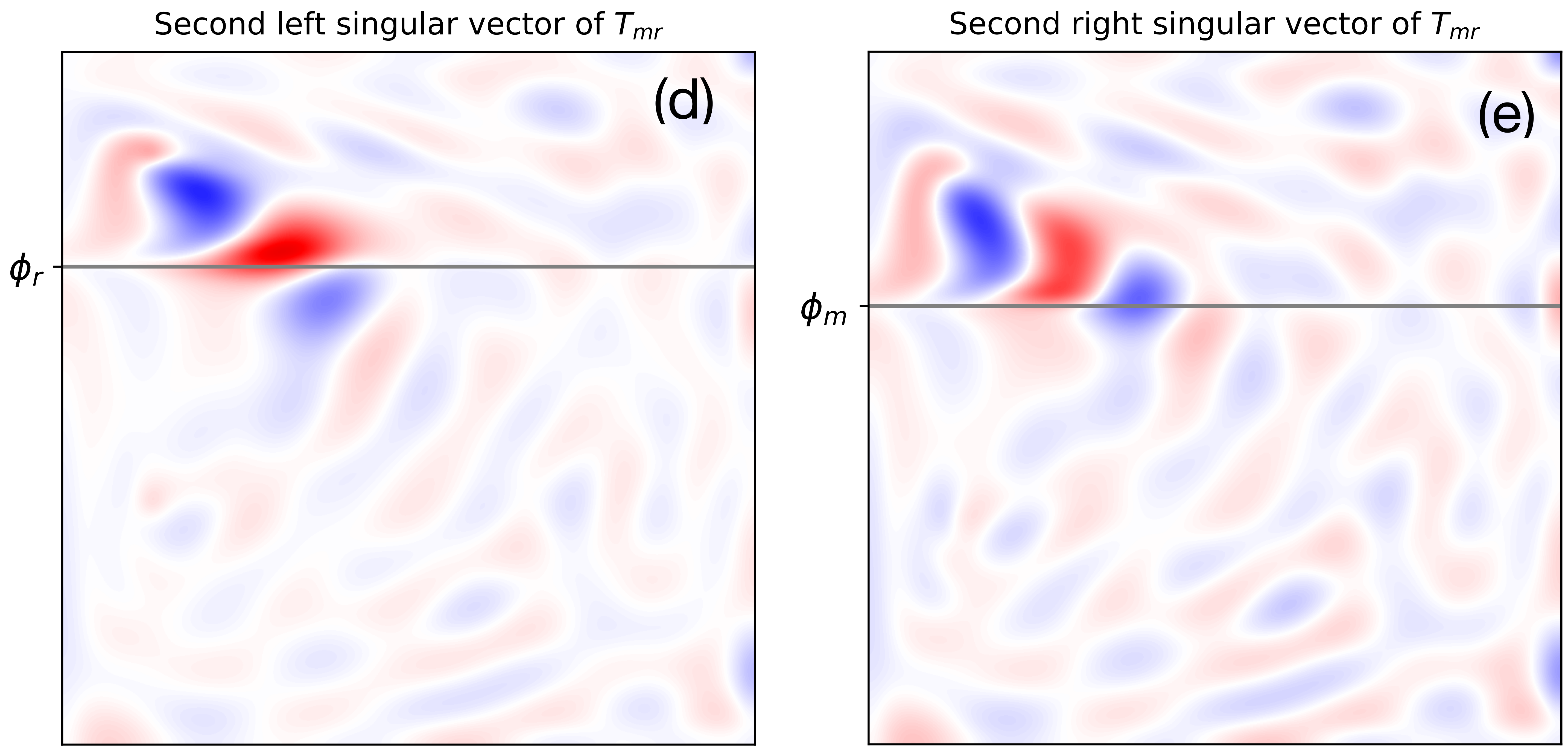




Other things / what's next:
Cross-attractor transforms (CATs)

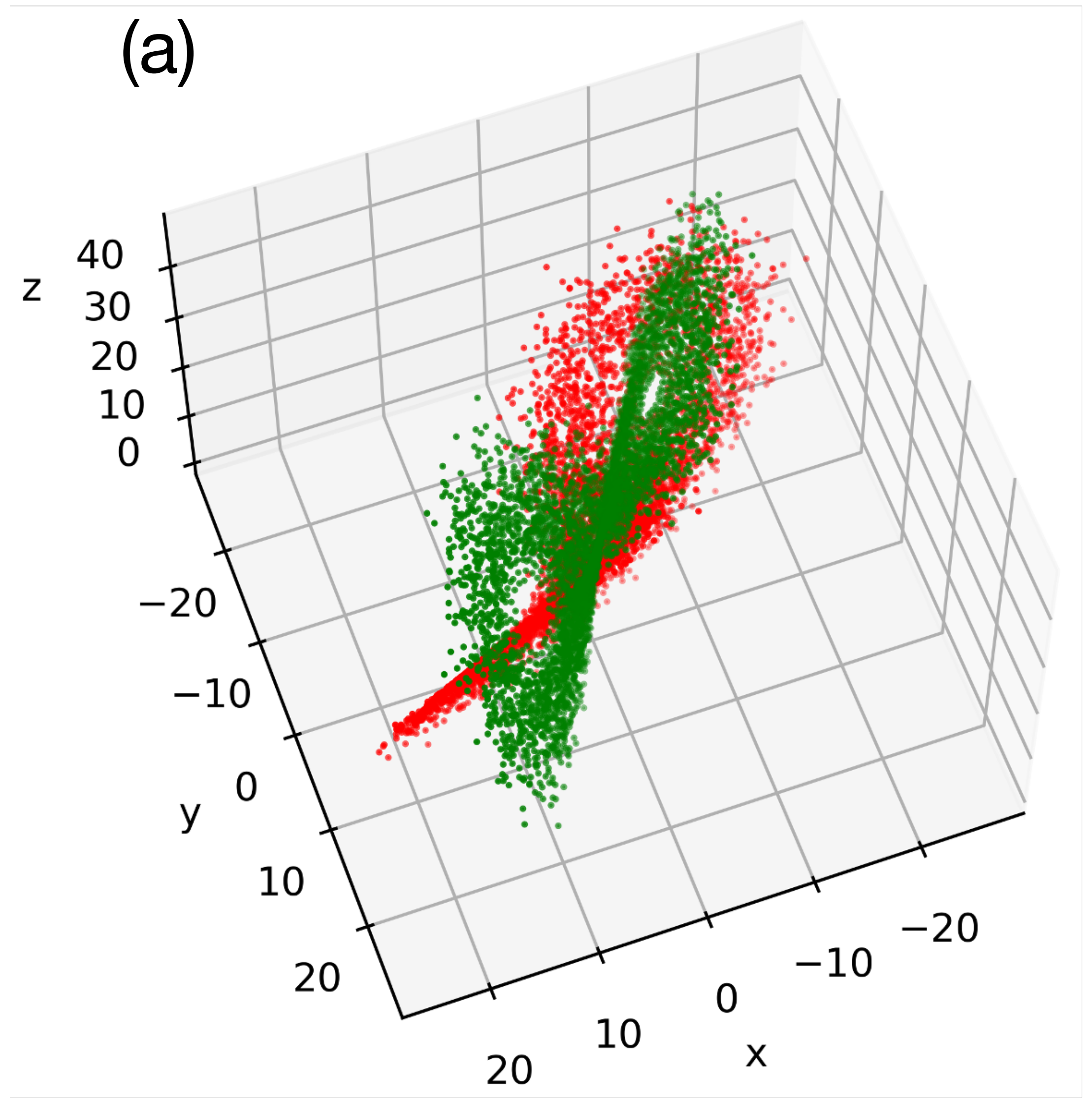
with Ian Grooms and Niraj Agarwal (CU)





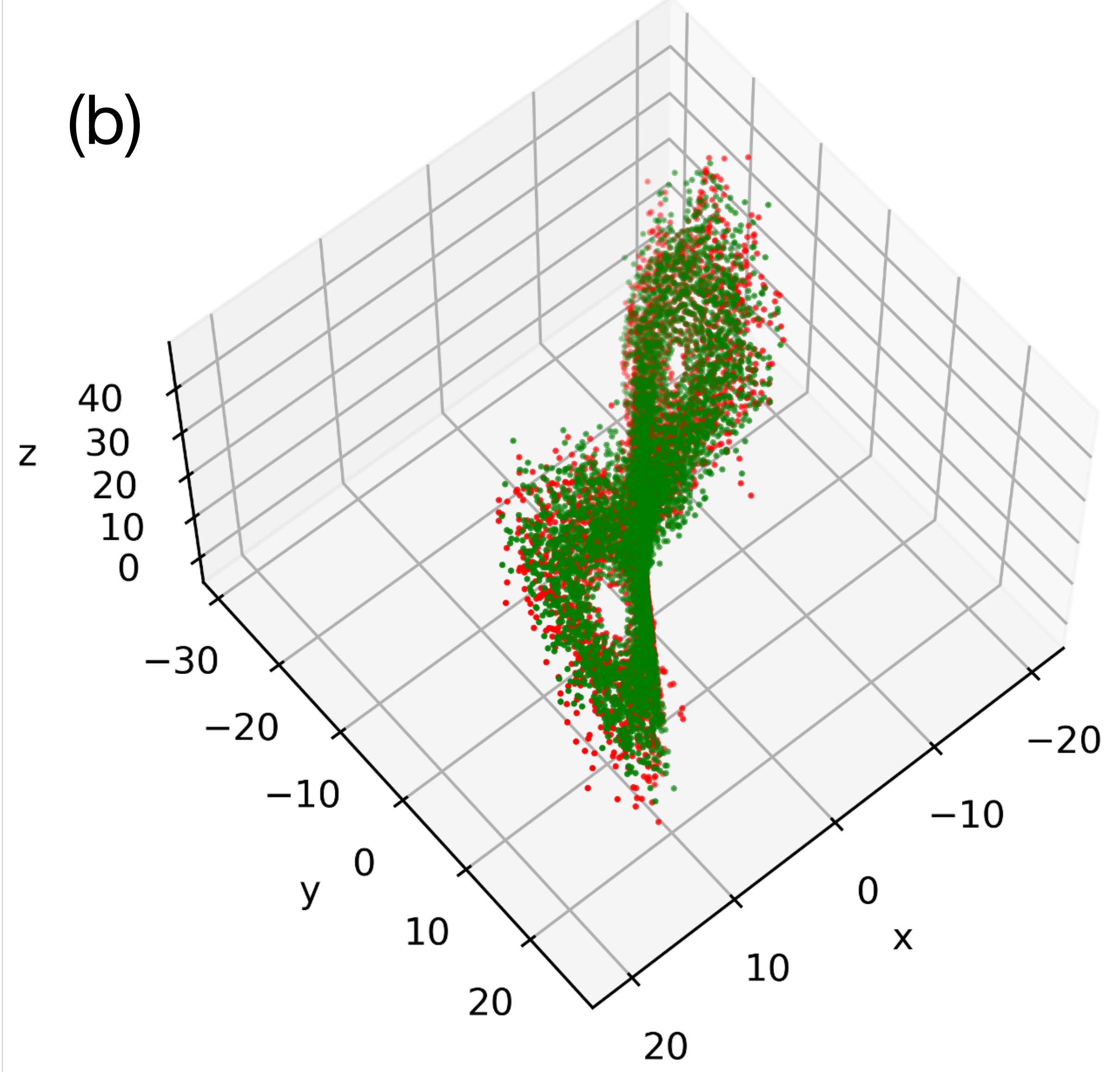
Other things / what's next:
Cross-attractor transforms (CATs)

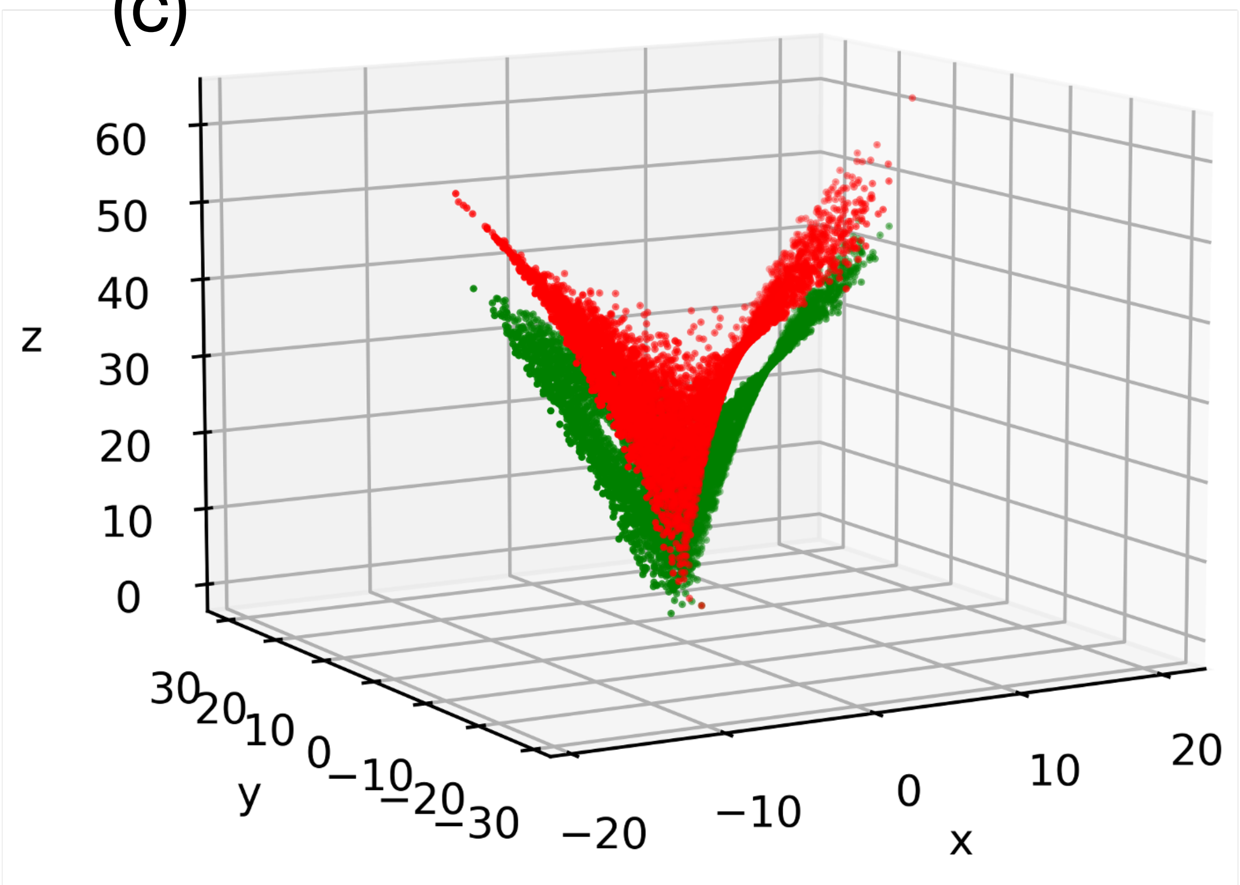
with Ian Grooms and Niraj Agarwal (CU)



CATs

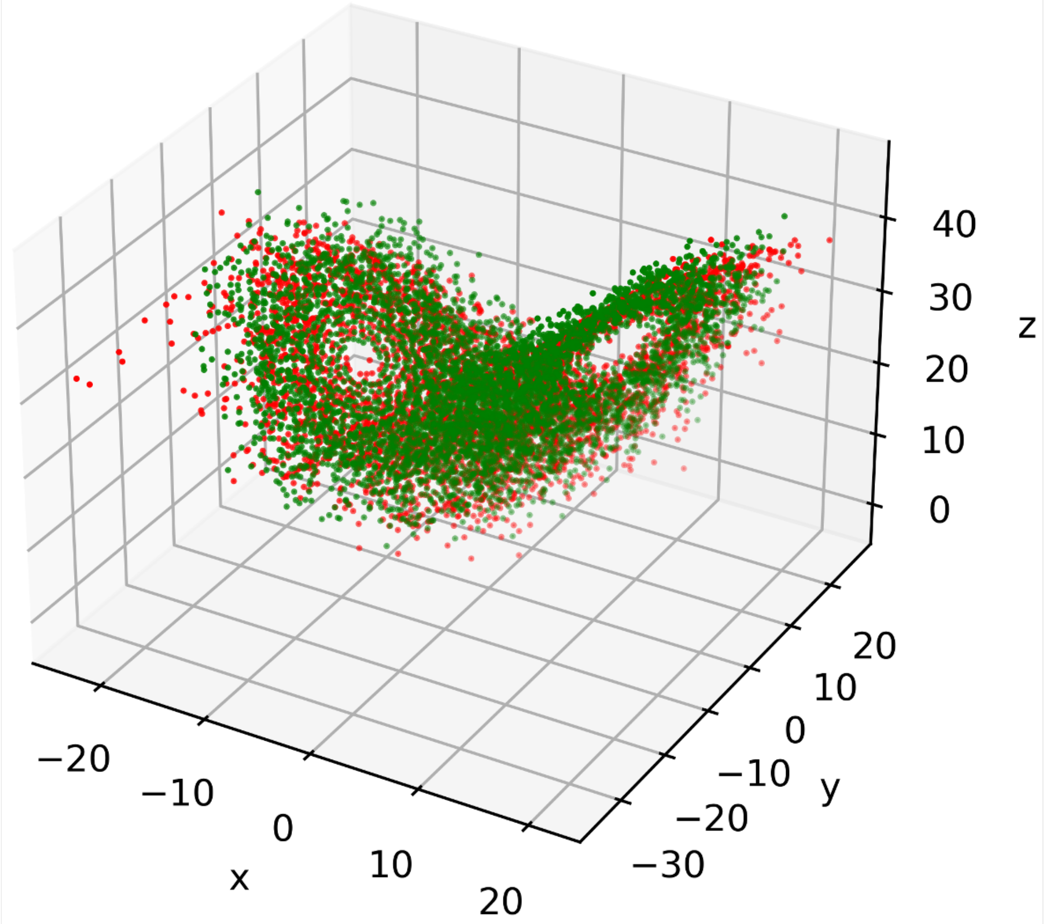
1 hidden layer with 3 neurons;
Linear activation;
MAE loss; Adam optimizer;
Standardized inputs; 50 Epochs; 32 batch size





CATs

NN configuration same as in case 1



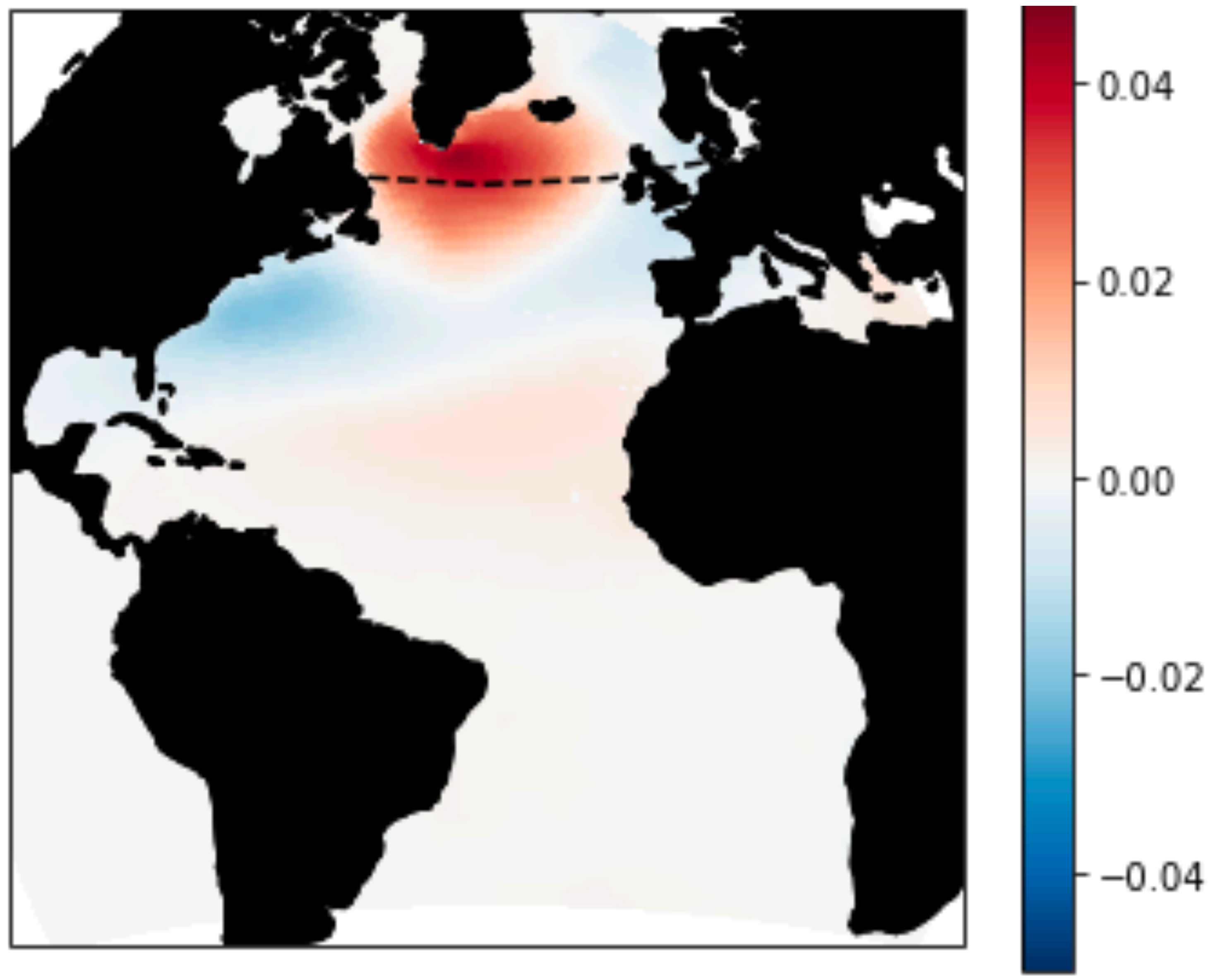
Conclusions and future work

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

Corresponding wind patterns vary between latitudes, but have EAP-like (subtropics) and NAO-like (subpolar) components.
Removing these patterns reduces AMOC variability at decadal time-scales by up to 90% through a **combination of slow responses**.

Caveats: It's a model(!) Using a **1°**, **ocean-only, flux-forced** model. No guarantee of **significance** of atmospheric modes. We ignore **nonstationarities** in fluxes and adjoint sensitivities (for now).



Papers:
Amrhein et al. (methods), subm. J Clim

Stephenson et al. (AMOC results), in prep

Ocean surface temperature variability: Large model–data differences at decadal and longer periods

Thomas Laepple[a,1] and Peter Huybers[b]