

Inferring the AMOC from Surface Observations

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To What Extent Can the AMOC be Inferred From Surface Information?

Past Work

[Latif et al., 2004](#); J. Climate: Reconstructing, Monitoring, and Predicting Multidecadal-Scale Changes in the NA Thermohaline Circulation with SST

[Hirschi and Marotzke 2007](#); JPO: Reconstructing the Meridional Overturning Circulation from Boundary Densities and the Zonal Wind Stress

[Zhang, 2008](#); GRL: Coherent surface-subsurface fingerprint of the AMOC

[Zhang, Rosati, Delworth, 2010](#); J. Climate: The Adequacy of Observing Systems in Monitoring the AMOC and North Atlantic Climate

[Mahajan et al. 2011](#); Deep-Sea Res. II: Predicting AMOC variations using subsurface and surface fingerprints

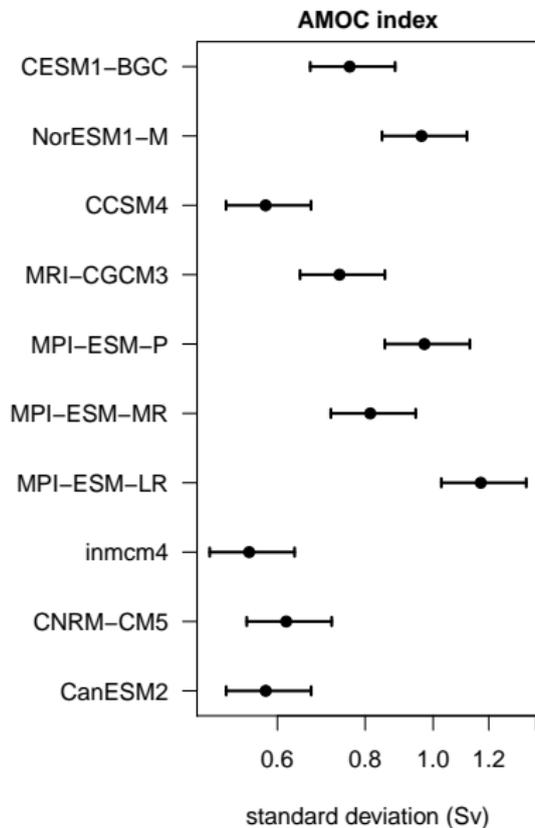
[Lopez et al., 2017](#); GRL: A reconstructed South Atlantic Meridional Overturning Circulation time series since 1870

No study has shown that a reconstruction method works in a suite of coupled atmosphere-ocean models.

New Analysis with CMIP5

- ▶ Analyze CMIP5 simulations
- ▶ Only piControl simulations at least 500 years long
- ▶ 5-year running mean SST North Atlantic basin (0-60N).
- ▶ AMOC index: maximum streamfunction at 40N
- ▶ AMOC index is 5-year running mean
- ▶ Only 11 models have 500-year control, AMOC index, and SST.
- ▶ MIROC5 has SST discontinuity, leaving 10 models.

Variance of AMOC



Linear Regression

Assume reconstruction model of the form

$$\text{reconstructed AMOC}(t) = w_1 X_1(t) + w_2 X_2(t) + \cdots + w_M X_M(t)$$

Least squares: select the weights \mathbf{w} to minimize

$$\left\| \begin{array}{c} \mathbf{y} \\ \text{AMOC} \end{array} - \begin{array}{c} \mathbf{X} \\ \text{SST} \end{array} \begin{array}{c} \mathbf{w} \\ \text{weights} \end{array} \right\|^2$$

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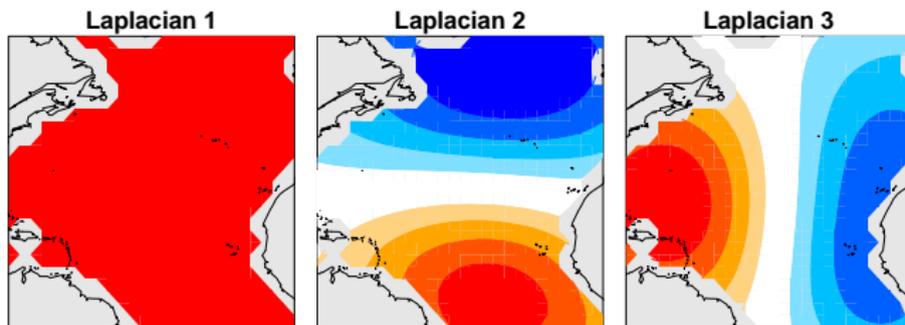
Problem: Not enough data.
There are more SST grid points than data.

Approach: impose constraints on the equation.

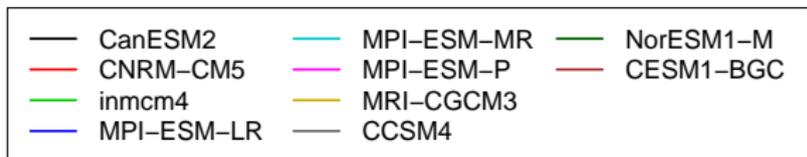
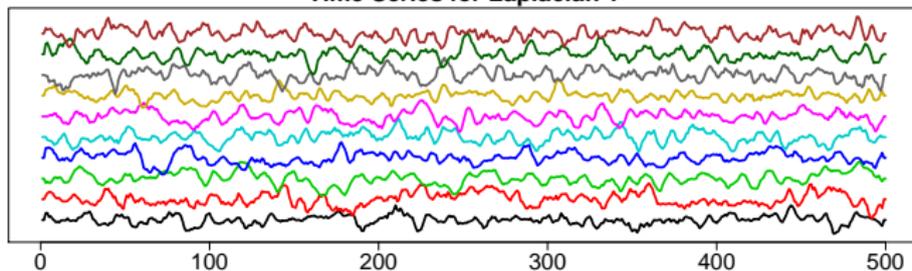
Approach: impose constraints on the equation.

**A priori assumption:
AMOC affects the **large-scale SST**.**

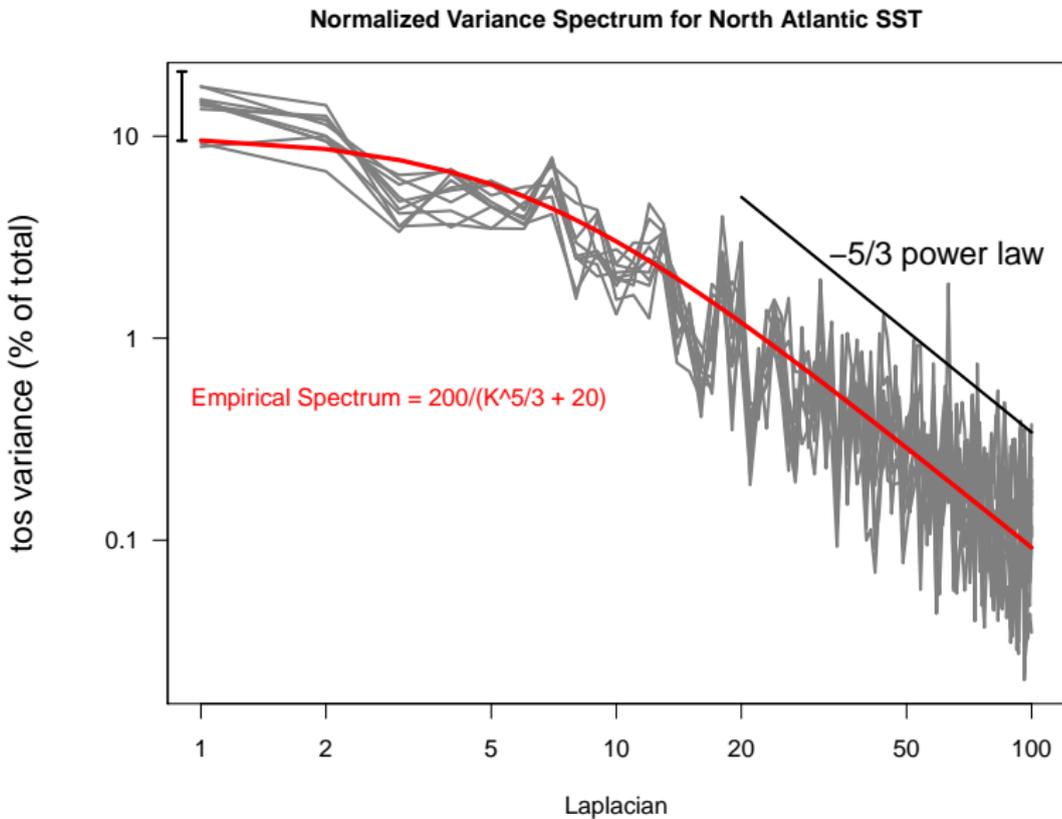
Laplacians



Time Series for Laplacian 1



Normalized Variance Spectrum for N. Atlantic SST



Constrained Least Squares

Constrained least squares is equivalent to minimizing the function

$$\left\| \begin{array}{c} \mathbf{y} \\ \text{AMOC} \end{array} - \begin{array}{c} \mathbf{L} \\ \text{SST} \end{array} \begin{array}{c} \mathbf{w} \\ \text{weights} \end{array} \right\|^2 + \lambda R(\mathbf{w}),$$

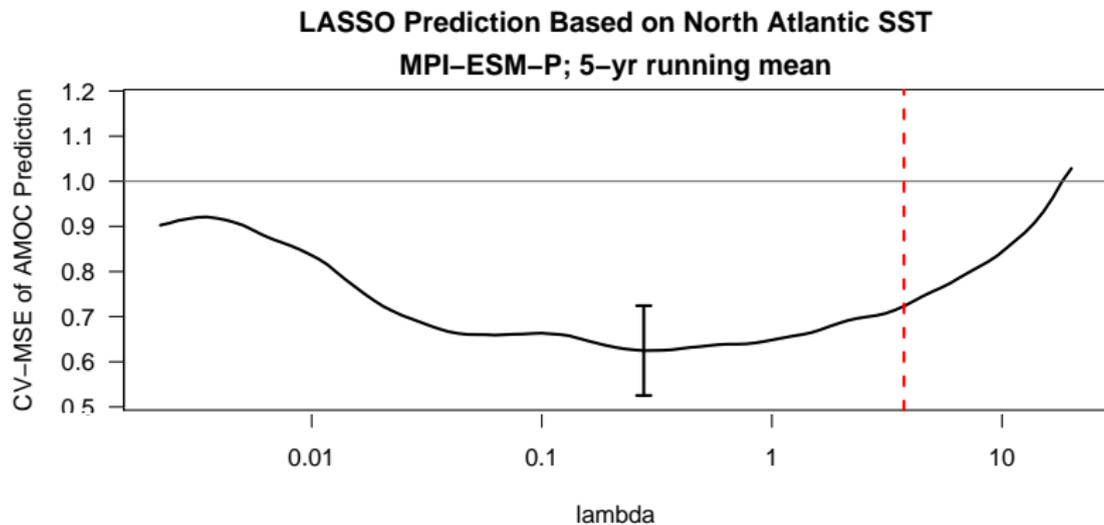
where $R(\mathbf{w})$ is a non-negative “penalty” function of the weights.

LASSO corresponds to $R(\mathbf{w}) = \sum_i |w_i|$. It tends to sign zero weight to high-wavenumbers because they have small variance.

λ controls the strength of the penalty:

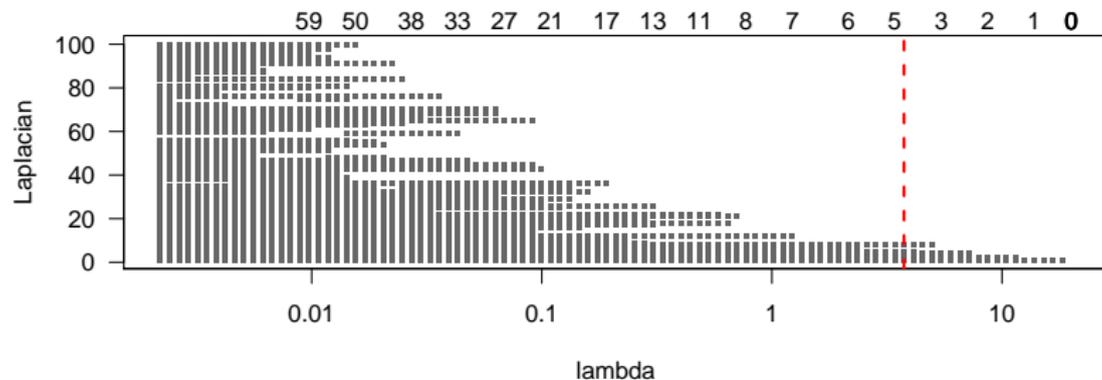
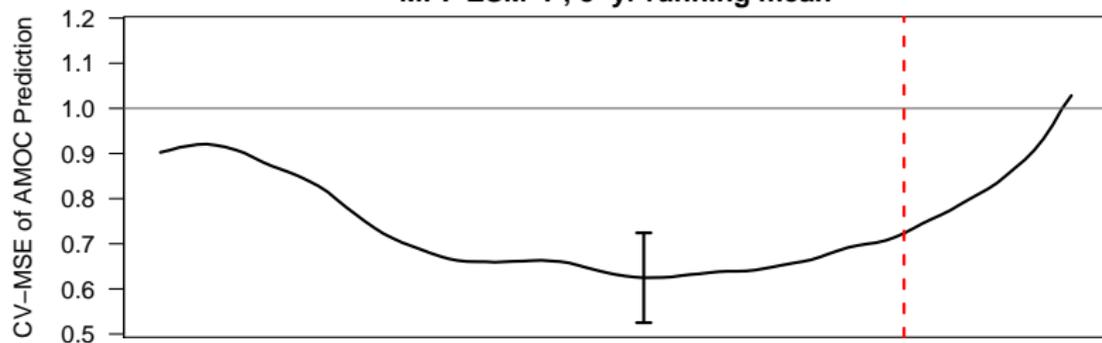
- ▶ large λ means most w 's are zero: field is smooth
- ▶ small λ means more w 's are non-zero: field can be noisy.

AMOC Prediction

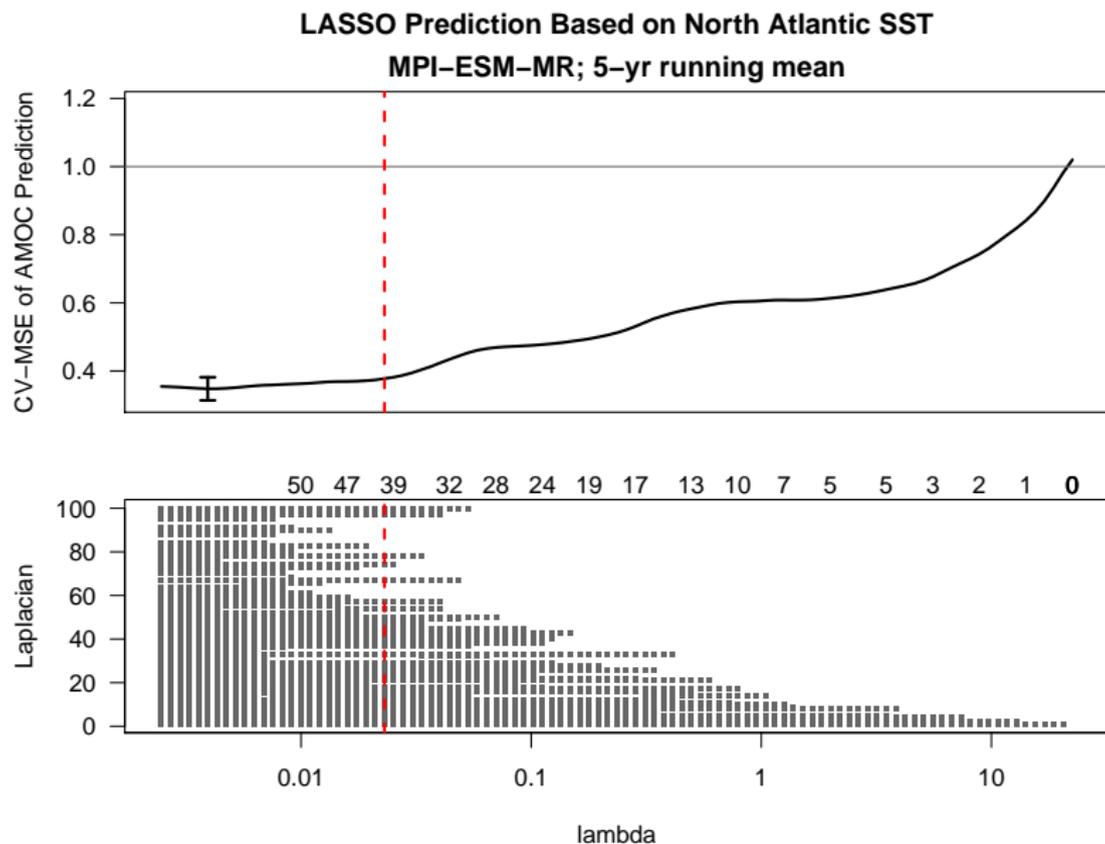


AMOC Prediction

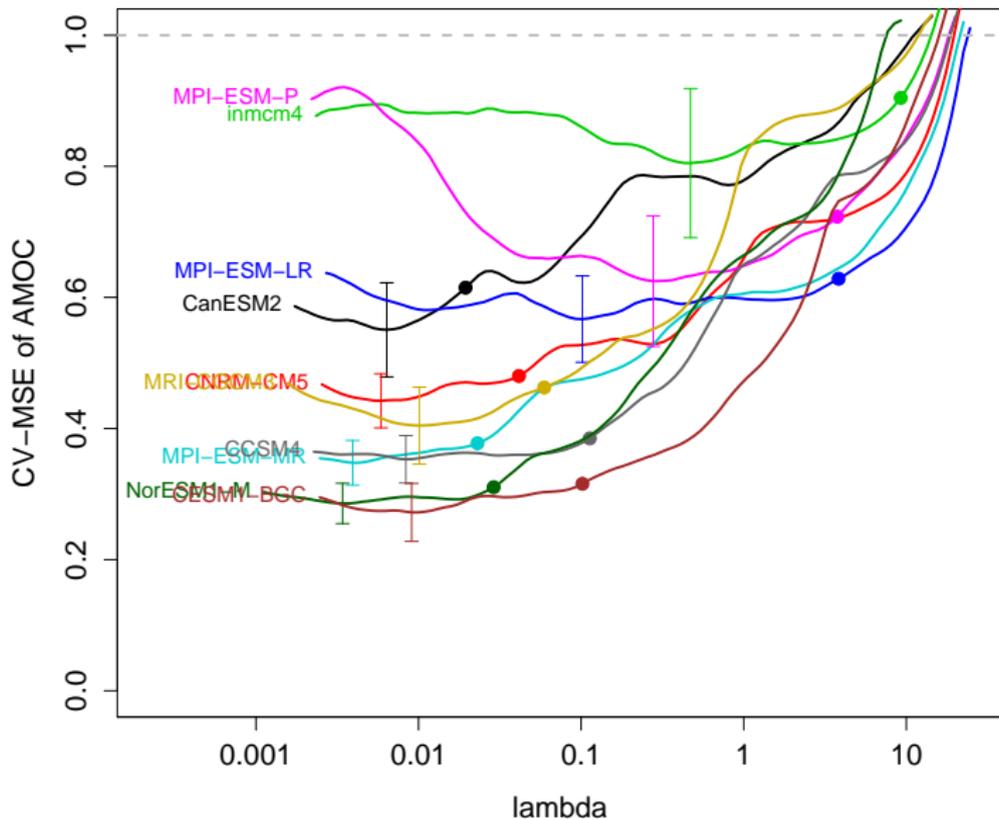
LASSO Prediction Based on North Atlantic SST
MPI-ESM-P; 5-yr running mean



AMOC Prediction

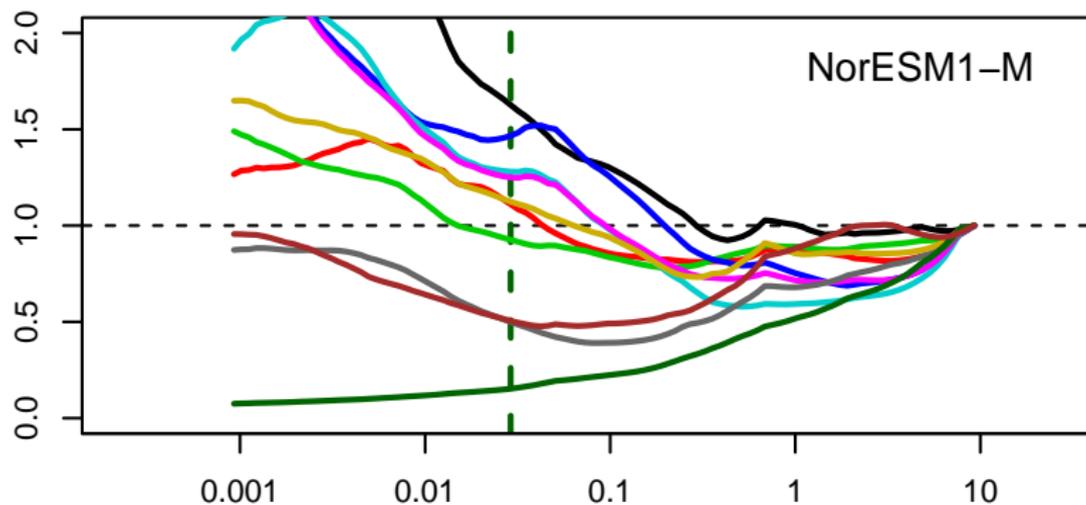


AMOC Prediction

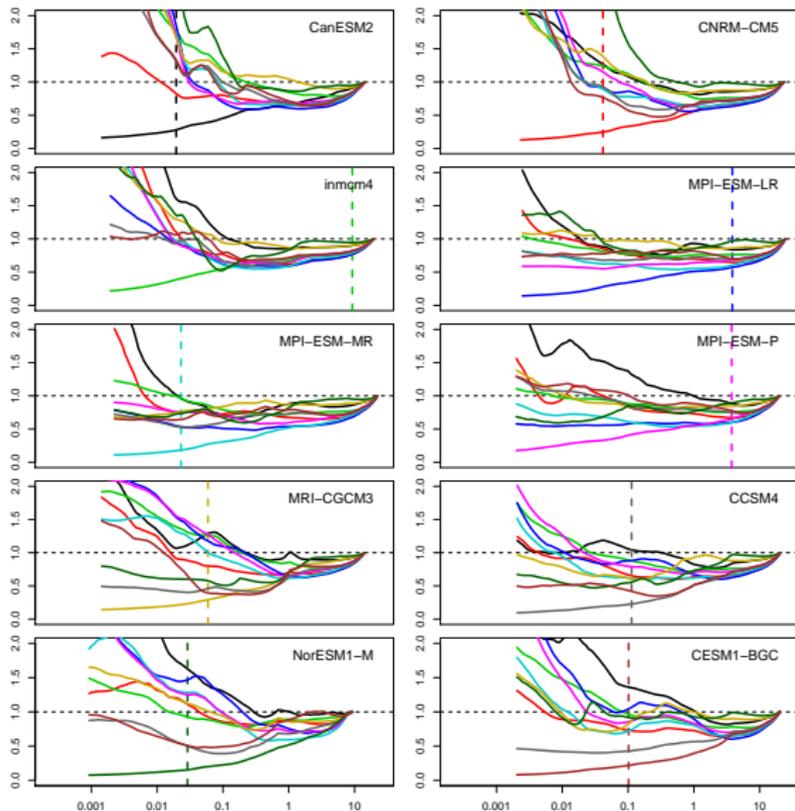


Cross-Model Predictions

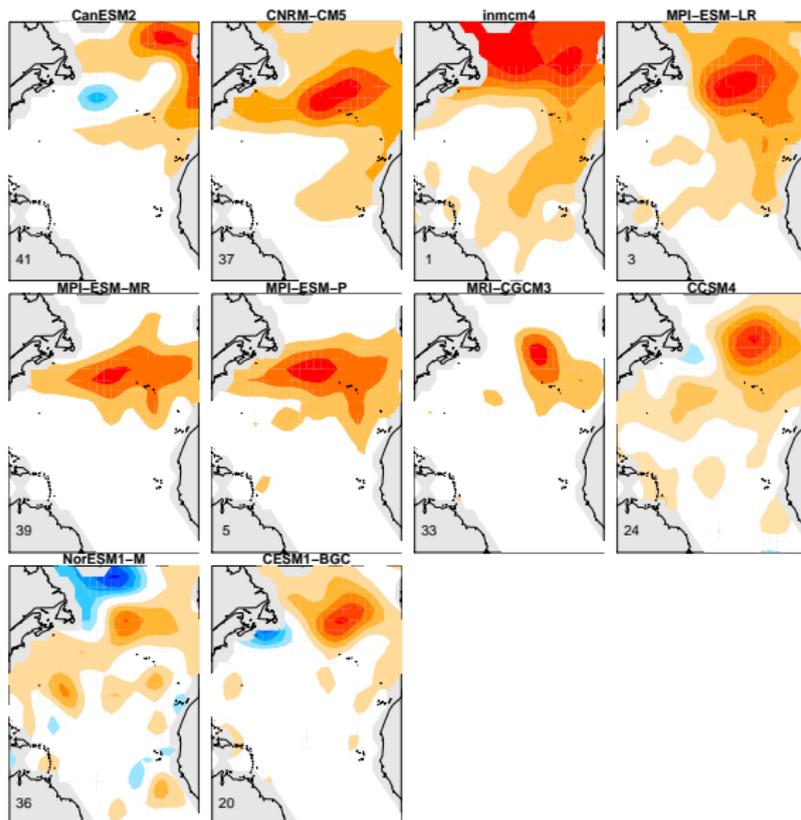
Train on one model, test in another model.



AMOC Prediction



SST that Co-Varies with AMOC ($\lambda = \text{optimal}$)



Conclusions

1. We reconstruct the AMOC based on surface observations using a combination of regularized regression and Laplacian basis functions.
2. Fraction of AMOC that is predictable from Atlantic SST: 10-70%.
3. A reconstruction equation that works well in one climate model can perform poorly in other climate models.
4. Reconstructions at $\lambda = 1$ tend to have skill in all models.
5. Reconstructions at $\lambda = 0.1$ suggest model clusters:
 - ▶ CCSM4, CESM1-BGC, NorESM1-M
 - ▶ MPI models
 - ▶ CanESM2, CNRM-CM5
 - ▶ INMCM4
 - ▶ MRI-CGCM3

Next step: include time lags and other variables (e.g., SSS).
Optimal Fingerprinting.