funded in by NSF Climate and Large-Scale Dynamics

Causal Discovery Techniques for Studying Arctic-Midlatitude Connections

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Another tool for our toolbox

Lagged Regression/Correlations

- highly biased by autocorrelation
- does not provide direction of causality
- indirect connections via a 3rd actor can complicate things
- correlation ≠ causation

Targeted Model Experiments

- only quantify effects in isolation
- does not allow for feedbacks
- requires the model adequately simulates relevant processes
- results can differ across models

Forecasting Approach

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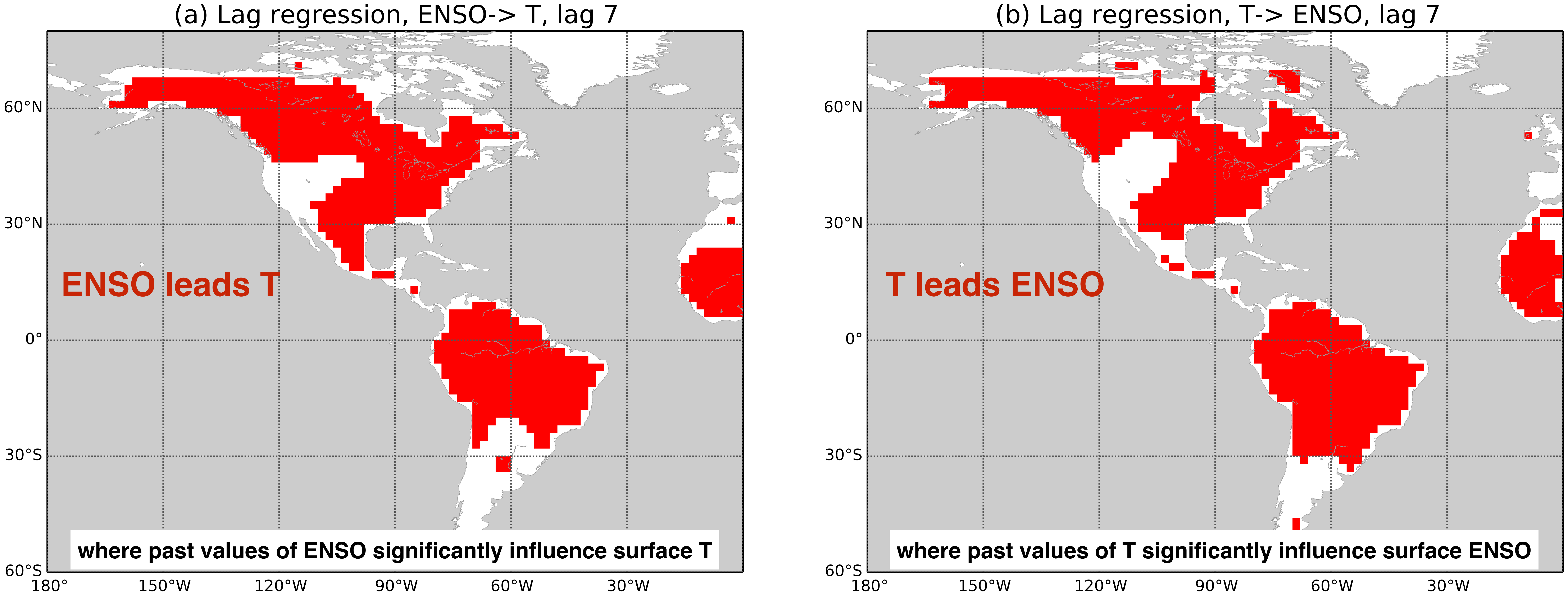
Causal Discovery Techniques

✓ uses rigorous definitions of causality (although there are different definitions)
✓ allows for feedbacks
✓ can compare connection strengths
✓ can analyze the observations and model simulations identically
✓ provides direction of connections
✓ ties to forecasting/prediction

Lagged regressions can get you in trouble



McGraw and Barnes (submitted)

Granger Causality

Clive Granger (1934-2009)
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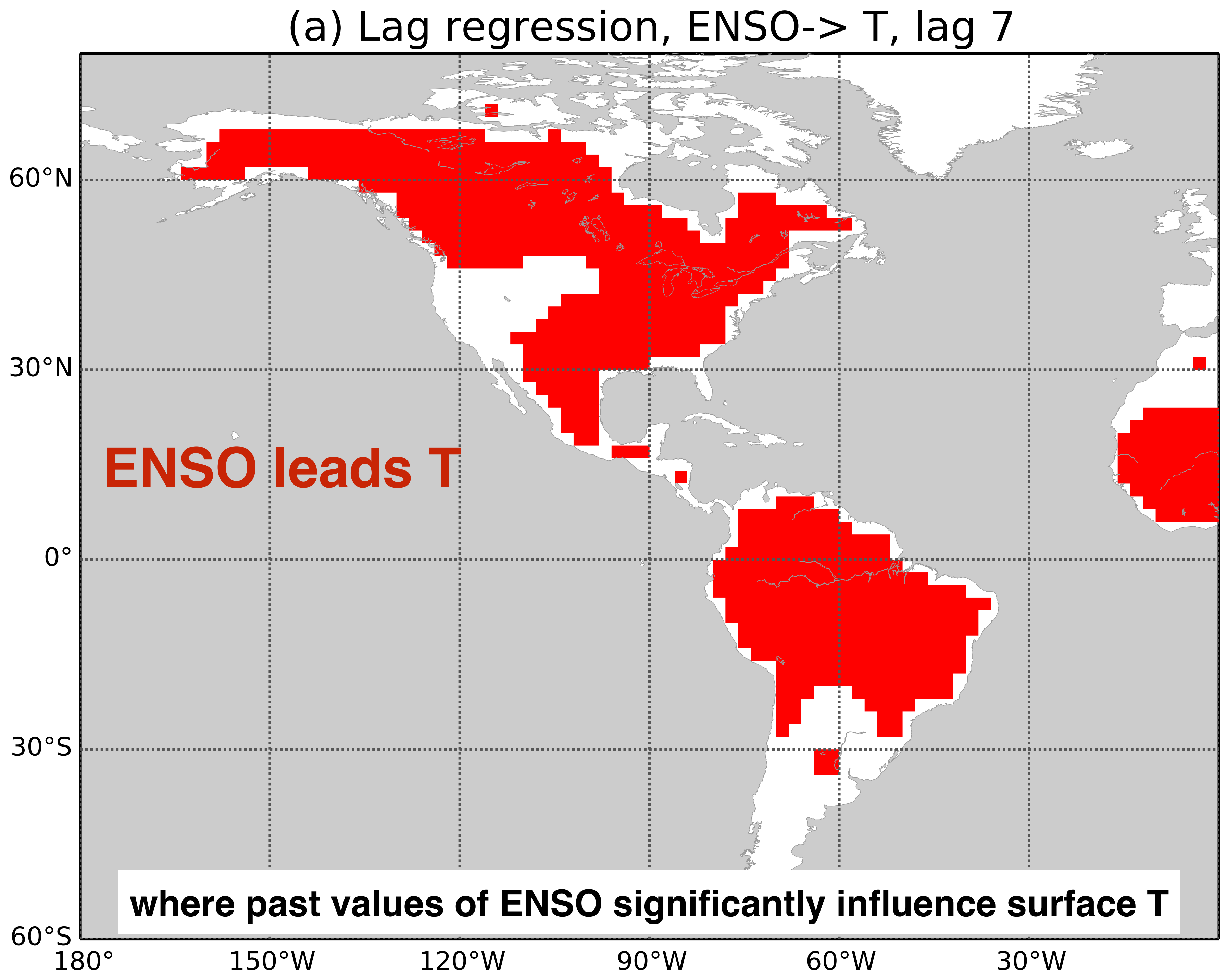
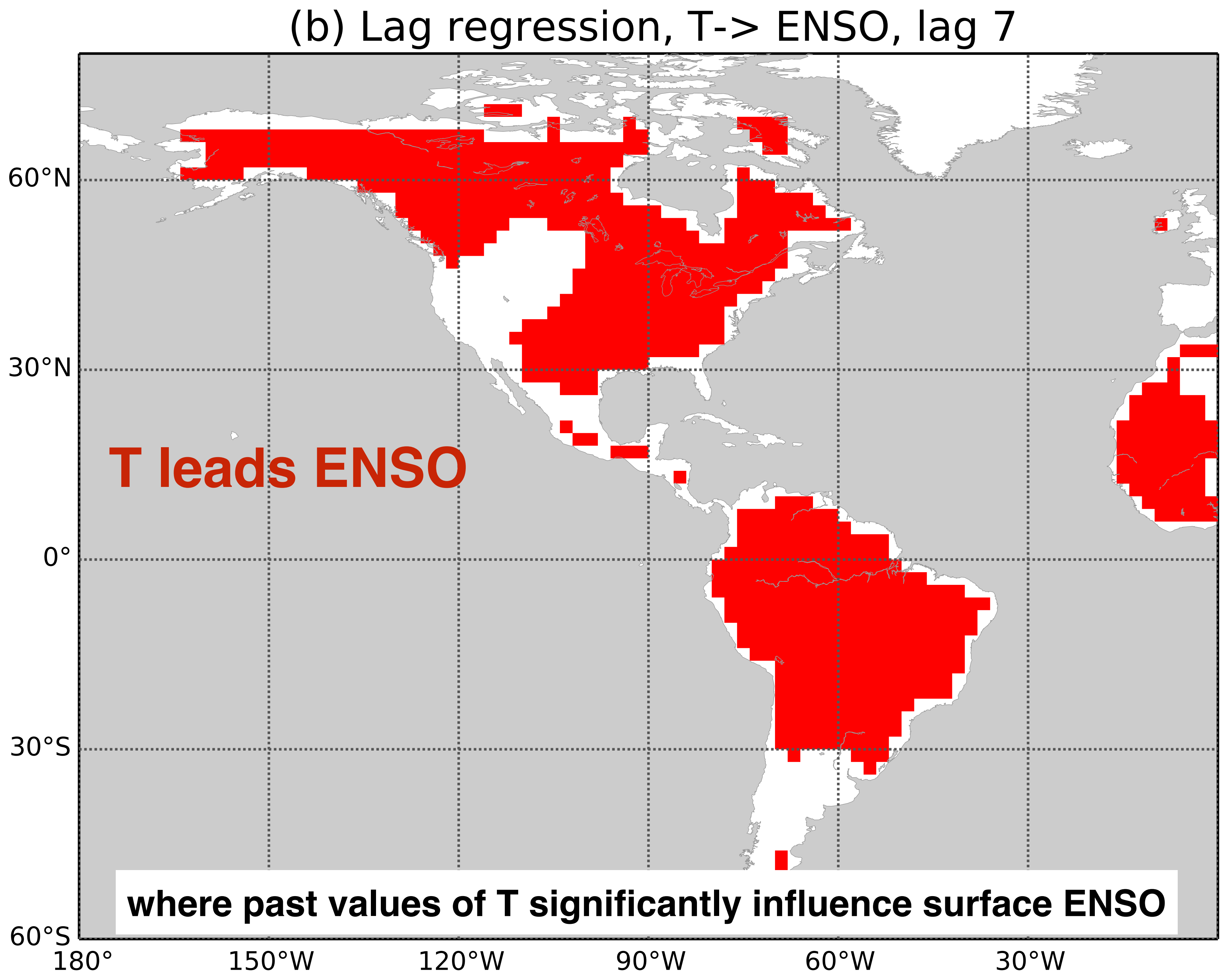
- there exists at least one significant **b** (t-test)
- all of the **b** terms collectively add power to the regression (F-test)

Lagged regression





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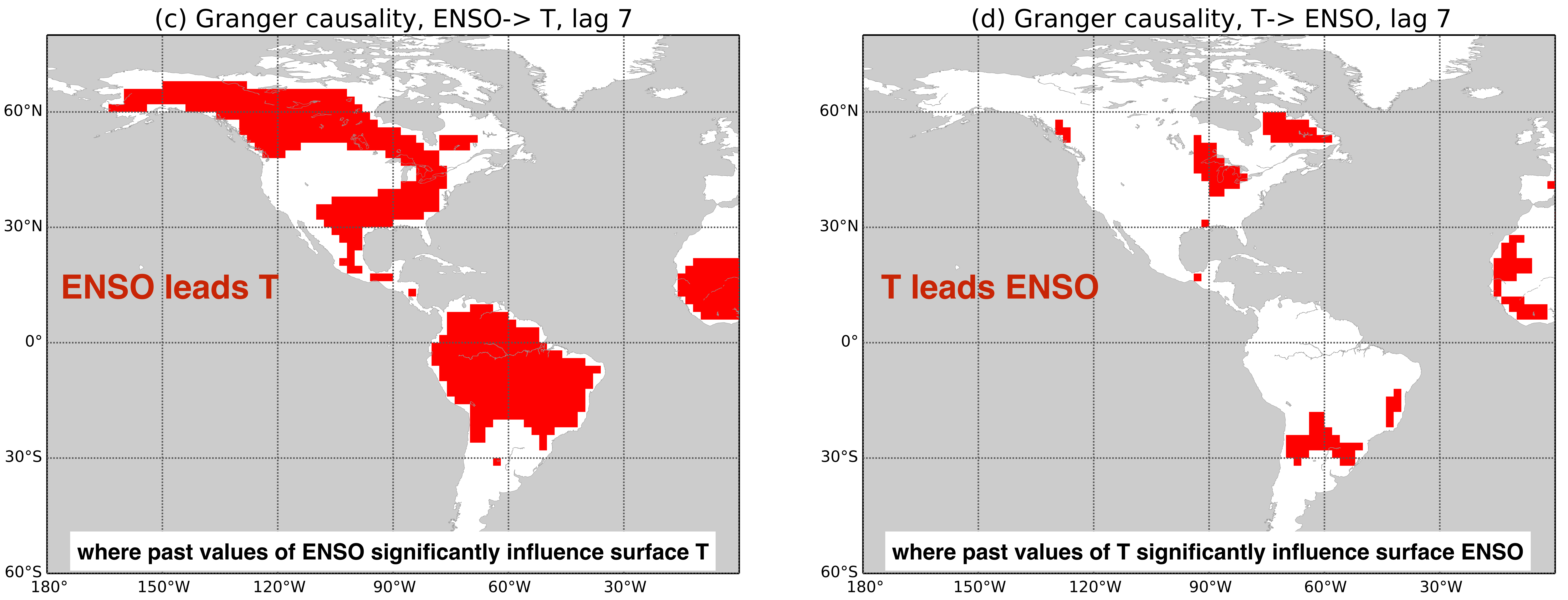

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Granger Causality

Observed Feedback between Winter Sea Ice and the North Atlantic Oscillation

COURTENAY STRONG* AND GUDRUN MAGNUSDOTTIR

Department of Earth System Science, University of California, Irvine, Irvine, California

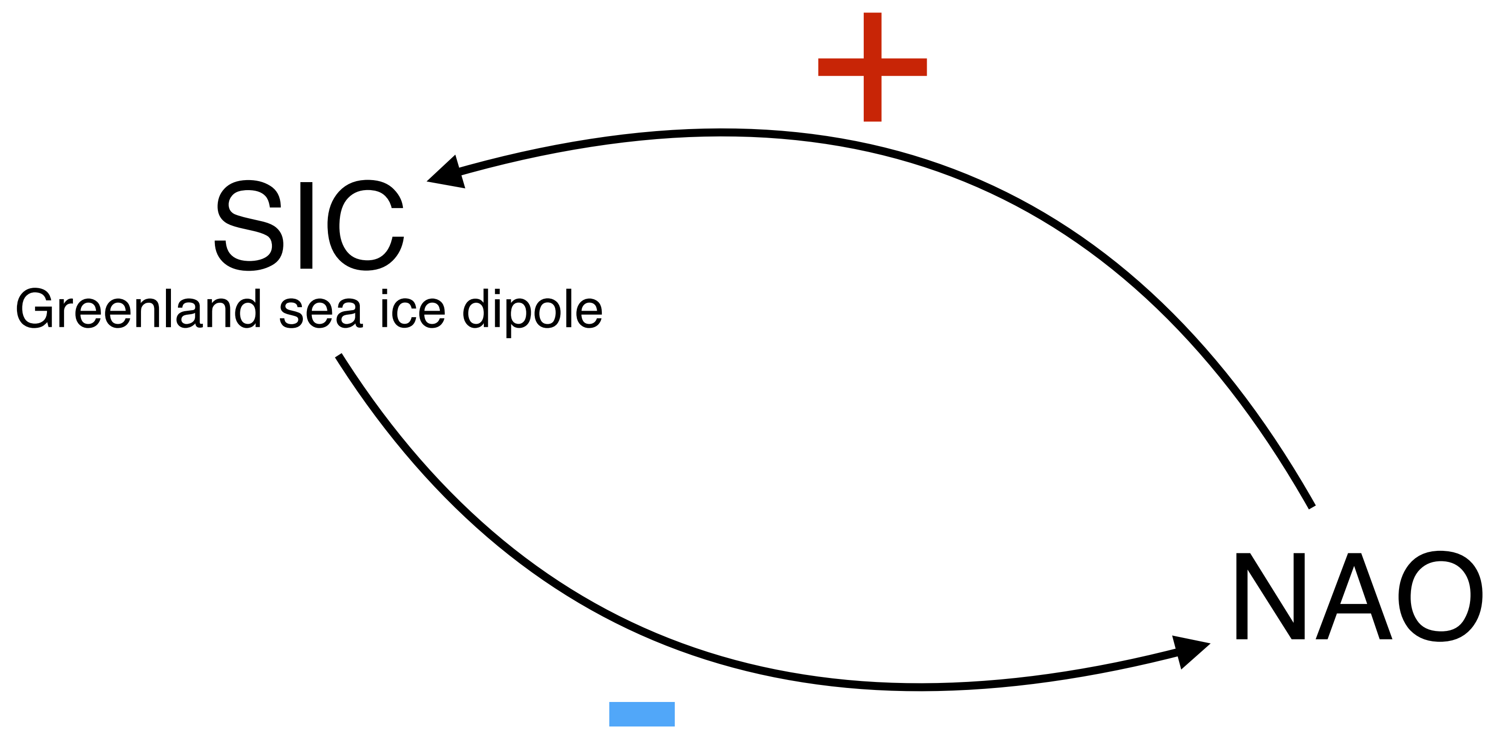
HAL STERN

Department of Statistics, University of California, Irvine, Irvine, California

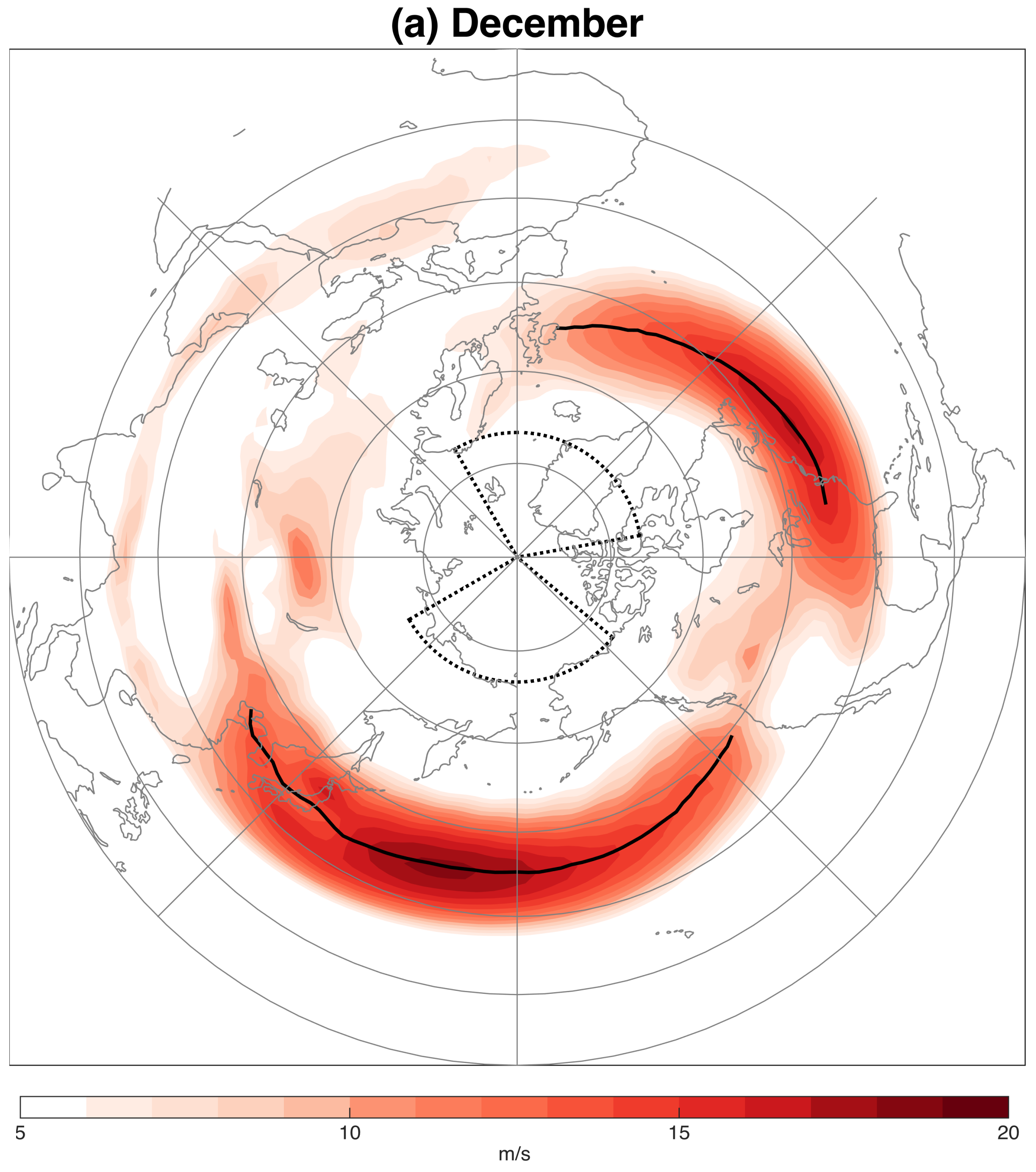
(Manuscript received 20 February 2009, in final form 17 June 2009)

ABSTRACT

Feedback between the North Atlantic Oscillation (NAO) and winter sea ice variability is detected and quantified using approximately 30 years of observations, a vector autoregressive model (VAR), and testable definitions of Granger causality and feedback. Sea ice variability is quantified based on the leading empirical orthogonal function of sea ice concentration over the North Atlantic [the Greenland Sea ice dipole (GSD)], which, in its positive polarity, has anomalously high sea ice concentrations in the Labrador Sea region to the southwest of Greenland and low sea ice concentrations in the Barents Sea region to the northeast of Greenland. In weekly data for December through April, the VAR indicates that NAO index (N) anomalies cause like-signed anomalies of the standardized GSD index (G), and that G anomalies in turn cause oppositely signed anomalies of N. This negative feedback process operates explicitly on lags of up to four weeks in the VAR but can generate more persistent effects because of the autocorrelation of G. Synthetic data are generated with the VAR to quantify the effects of feedback following realistic local maxima of N and G, and also for sustained high values of G. Feedback can change the expected value of evolving system variables by as much as a half a standard deviation, and the relevance of these results to intraseasonal and interannual NAO and sea ice variability is discussed.

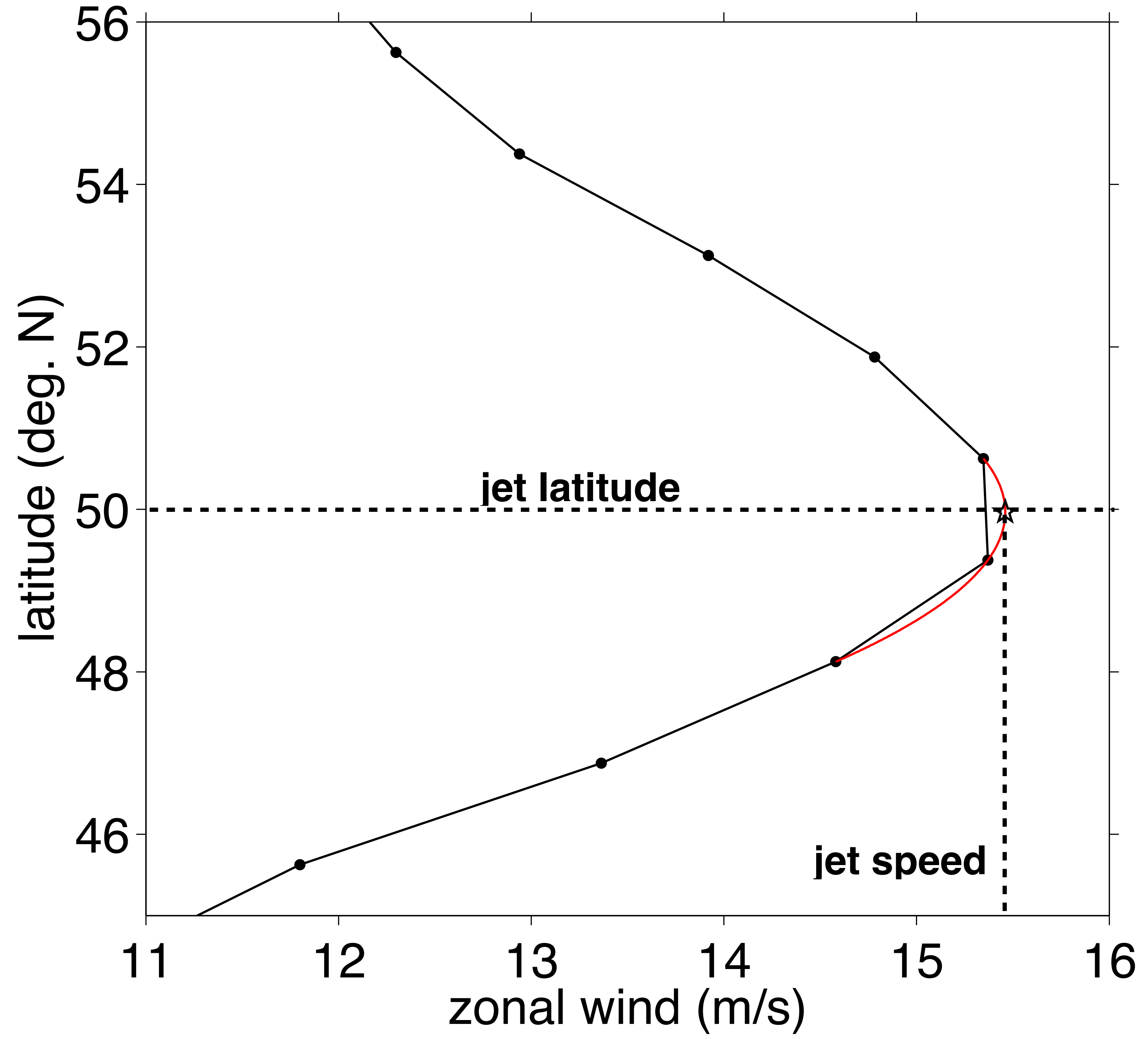


Setup: interested in importance of circulation seasonality



700 hPa zonal wind from the 20th Century Reanalysis (1851-2014)

- CMIP5 (historical + RCP8.5: *detrended*)
- daily data (averaged into 10-day chunks*)
- 700 hPa zonal wind
- 850 hPa air temperature



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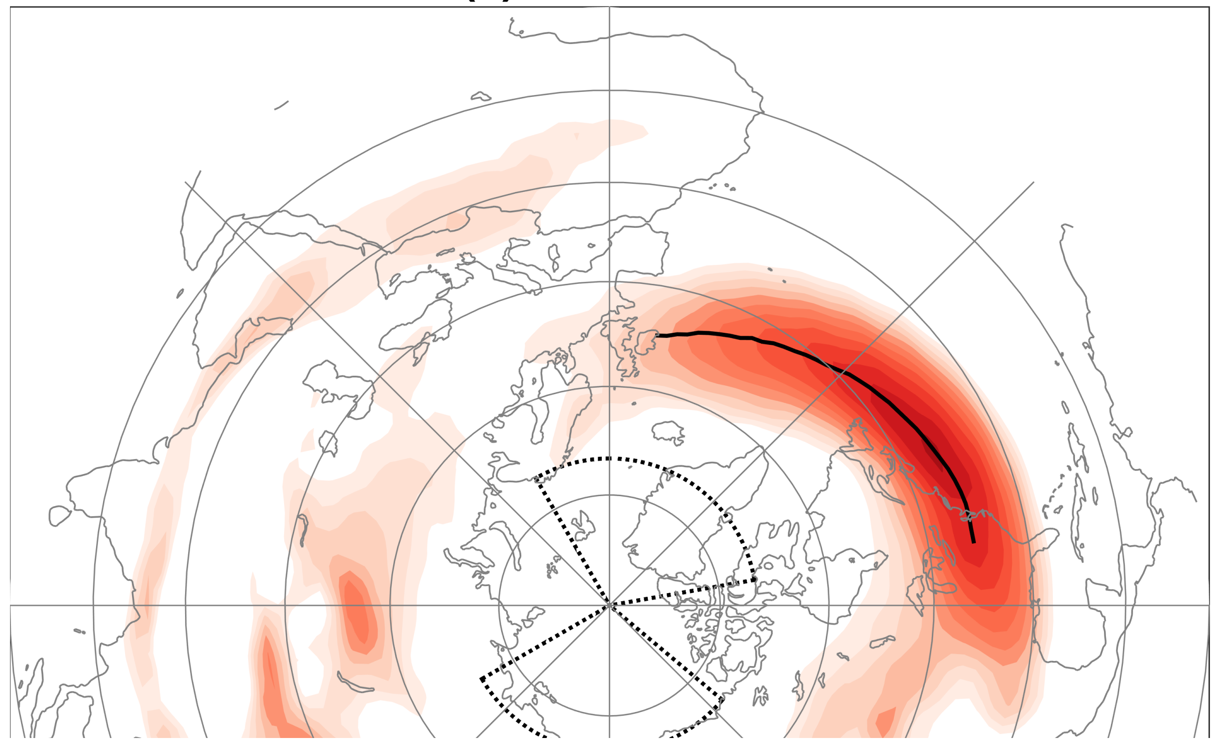

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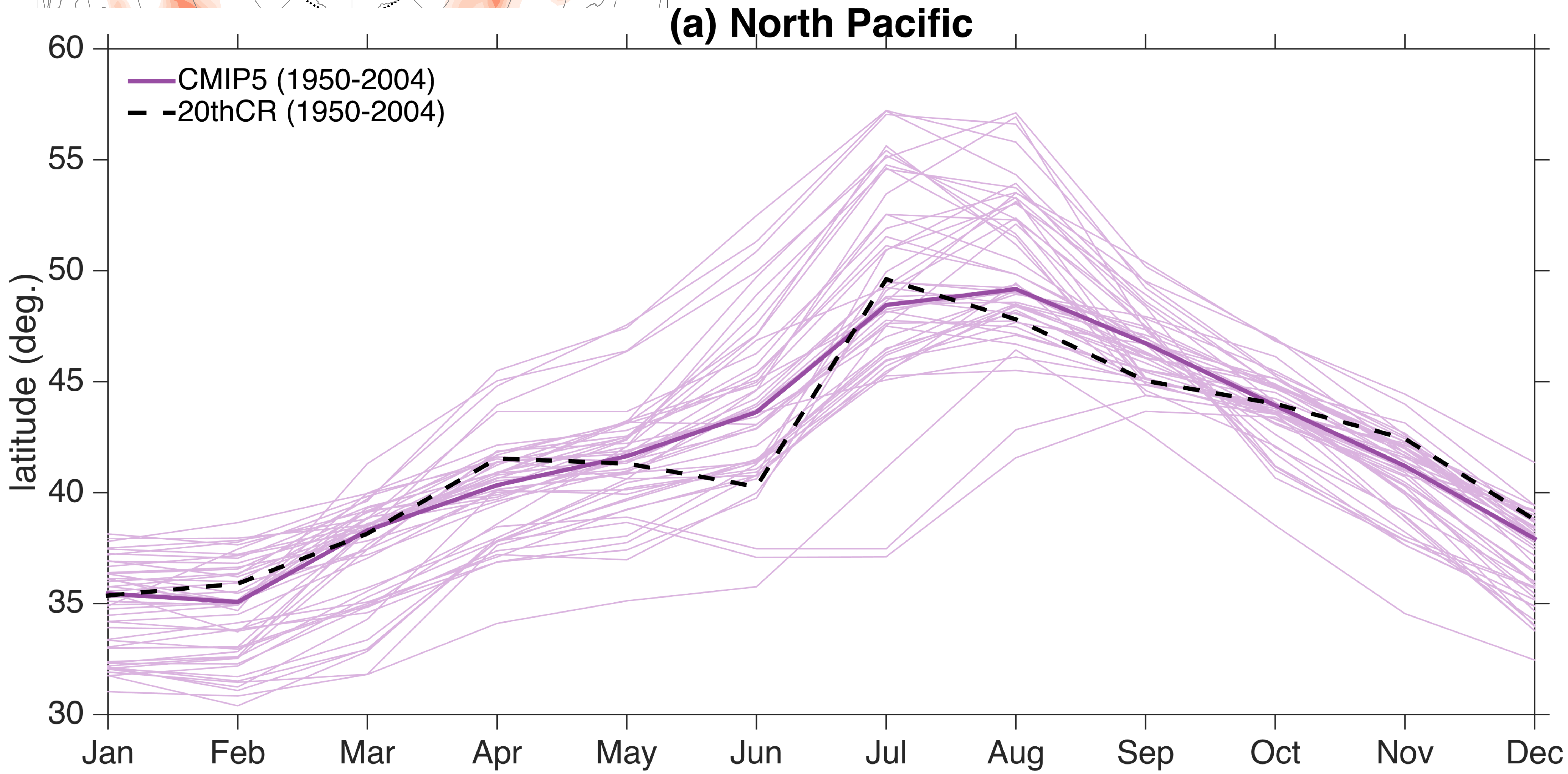

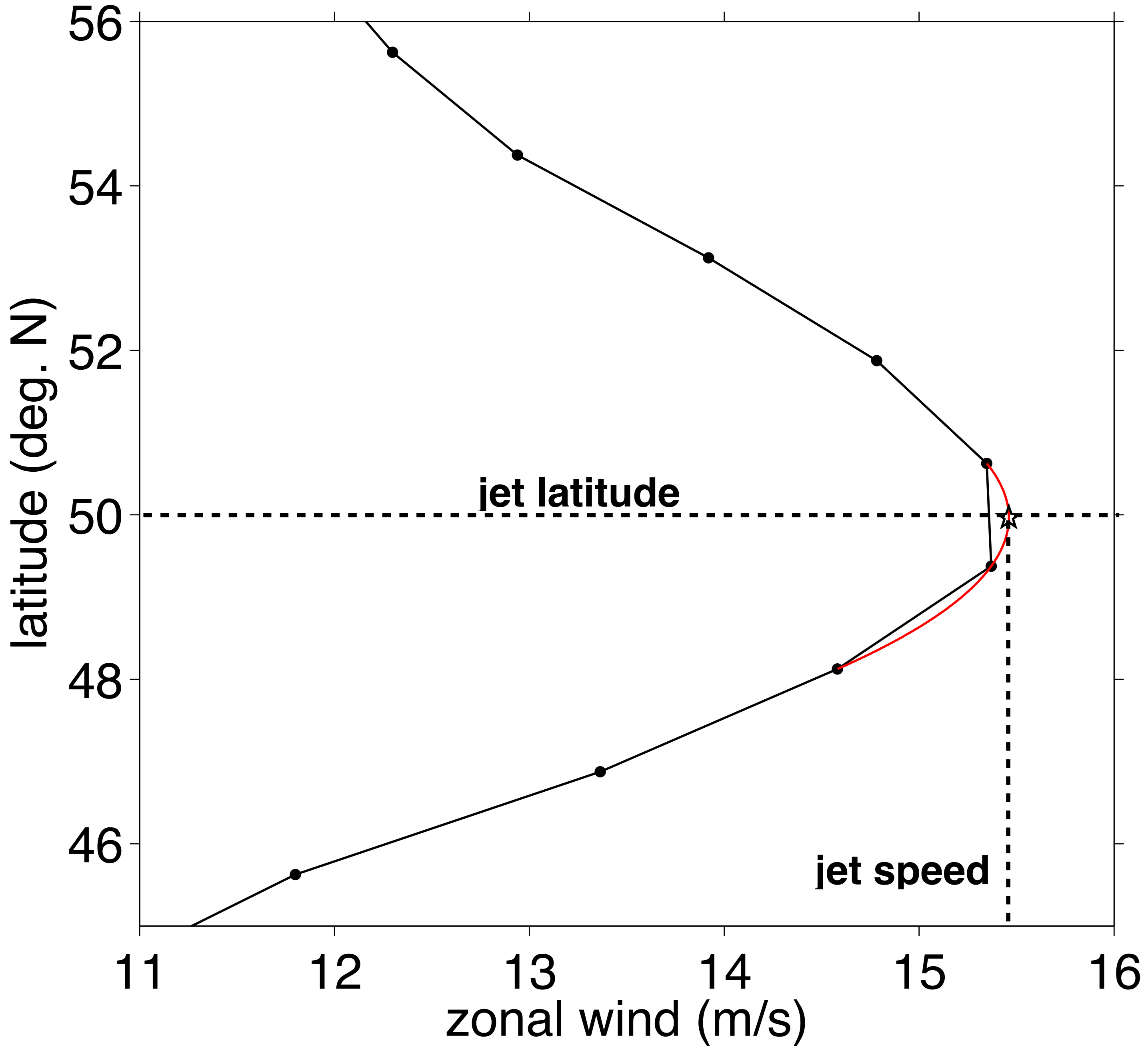

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how much?

Applying Granger Causality

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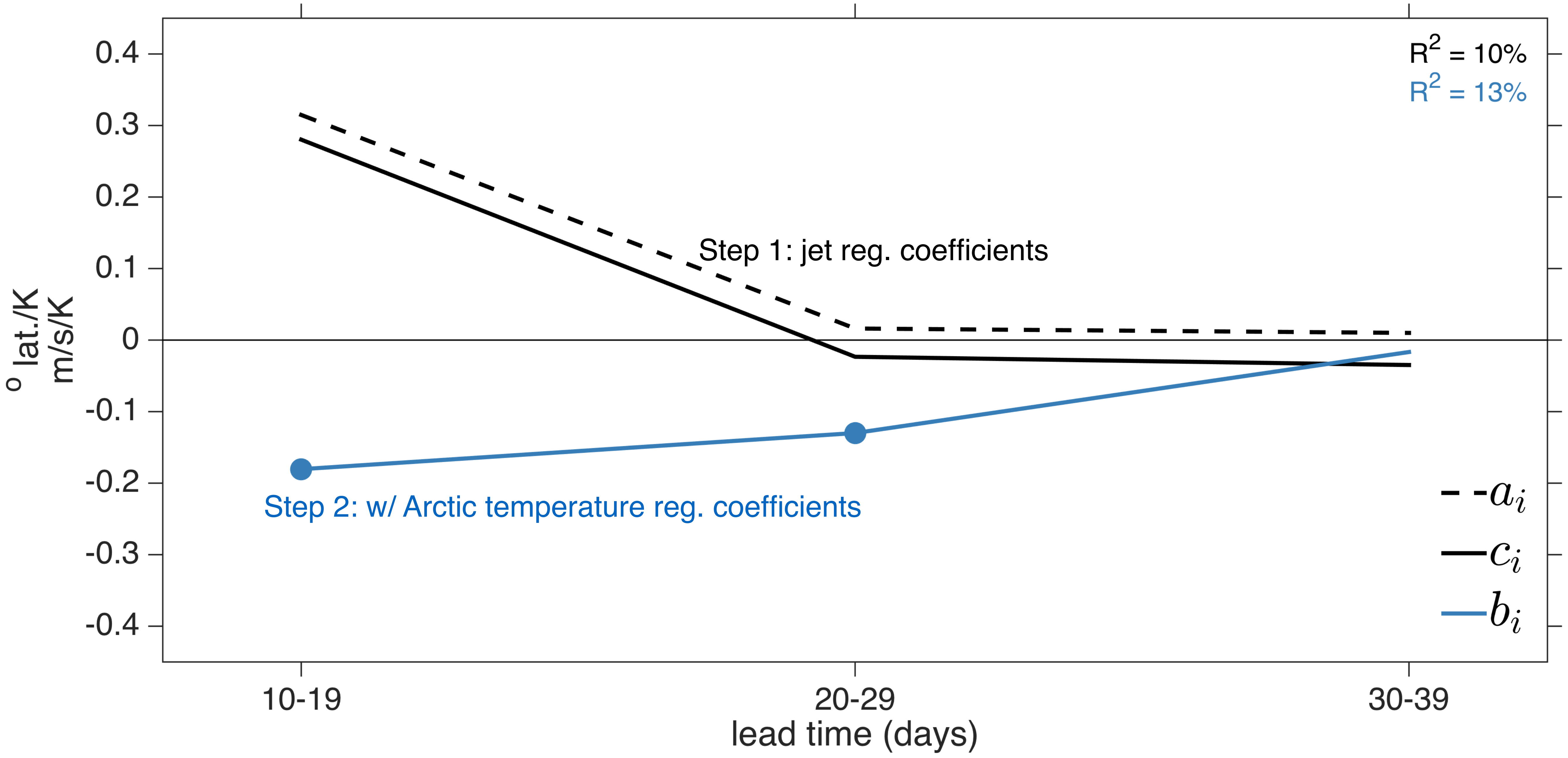
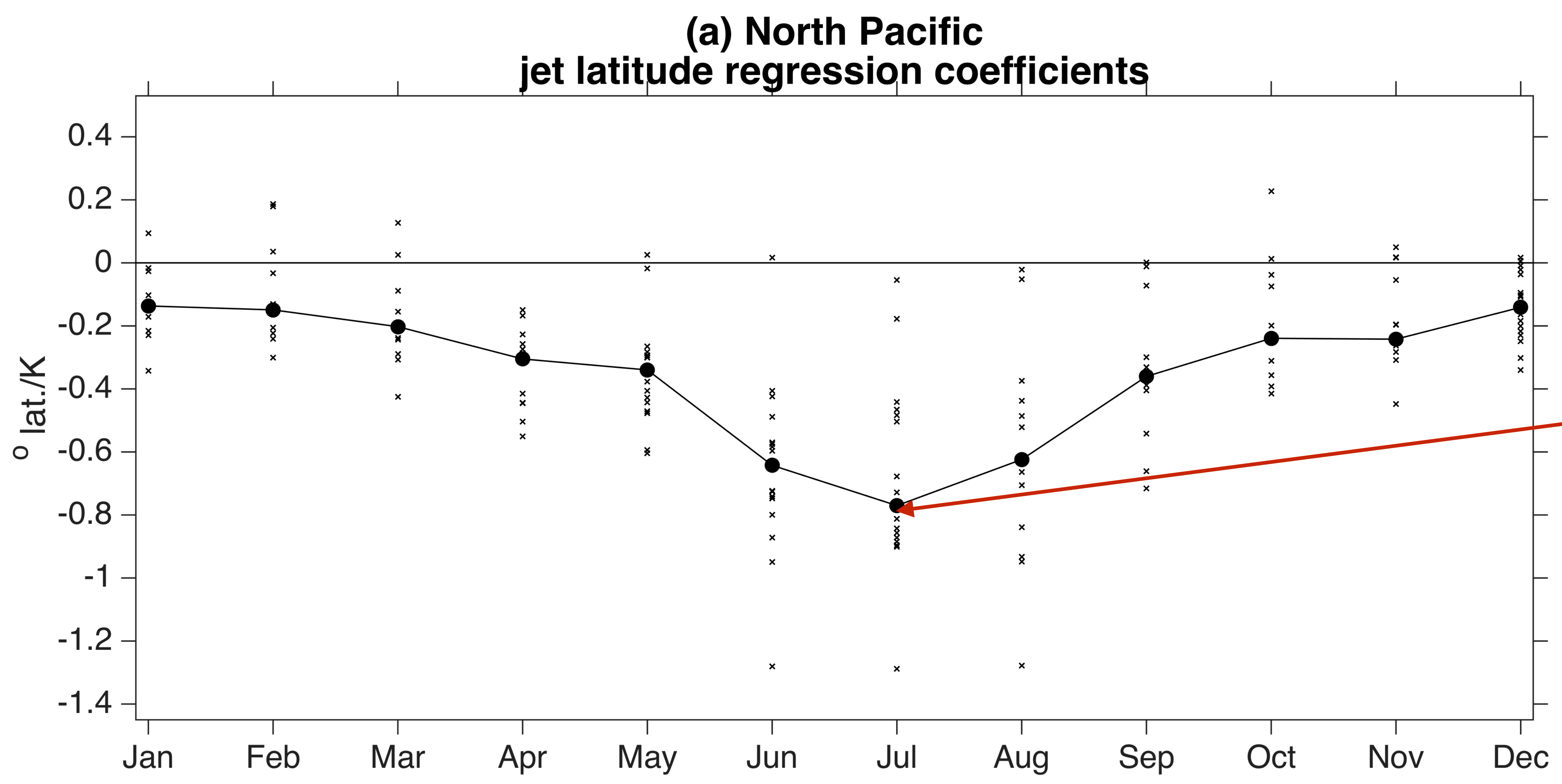


- jet shifts equatorward when Arctic was warm 10-30 days earlier
- first two coefficients are significant

An example Granger causality calculation for North Pacific jet latitude in March from the CanESM2 model. For this example, we use the combined Historical + RCP8.5 time series.

Barnes and Simpson (submitted)

How Much?: **jet position**



jet shifts **equatorward** more in warm months

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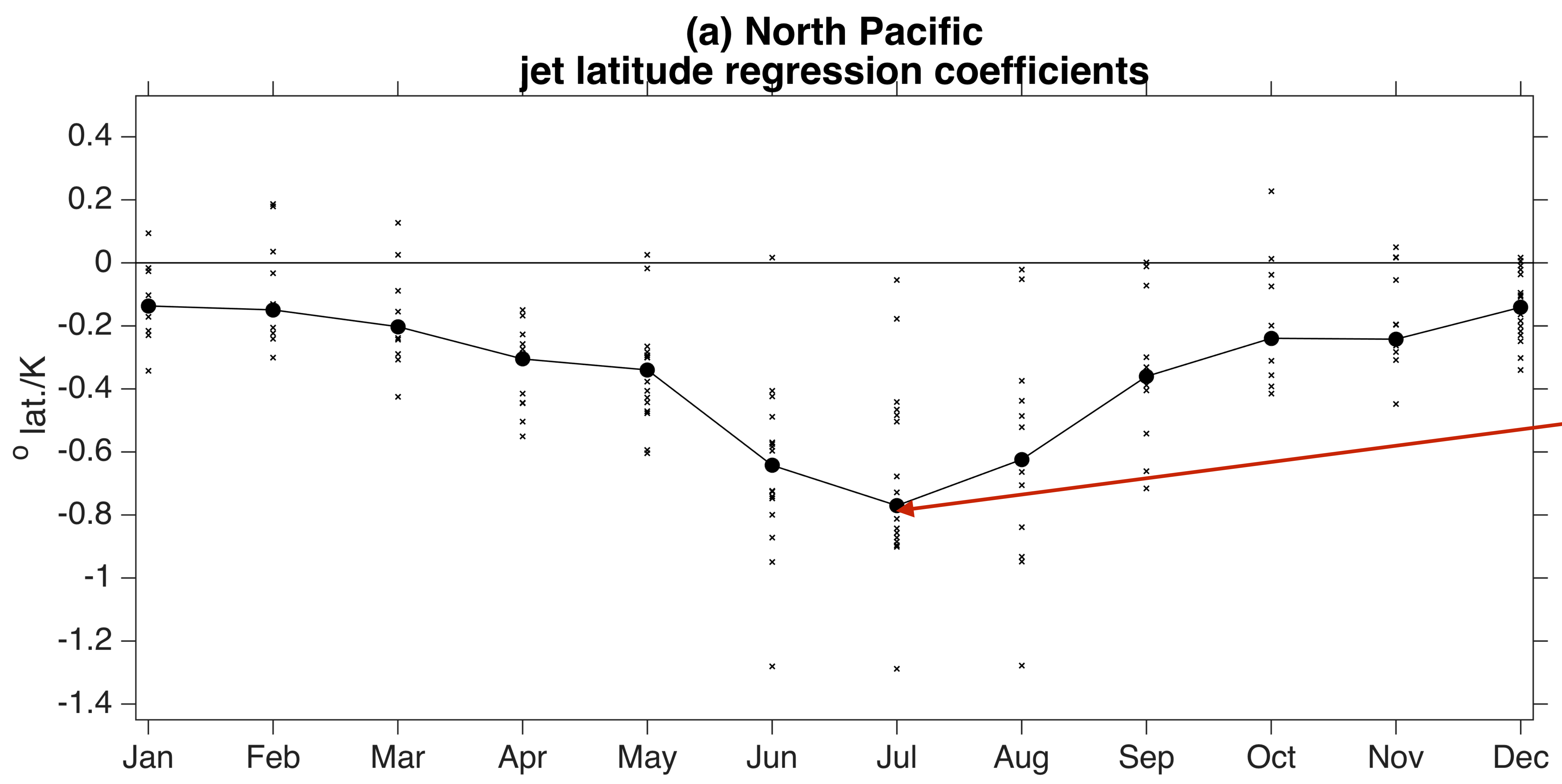

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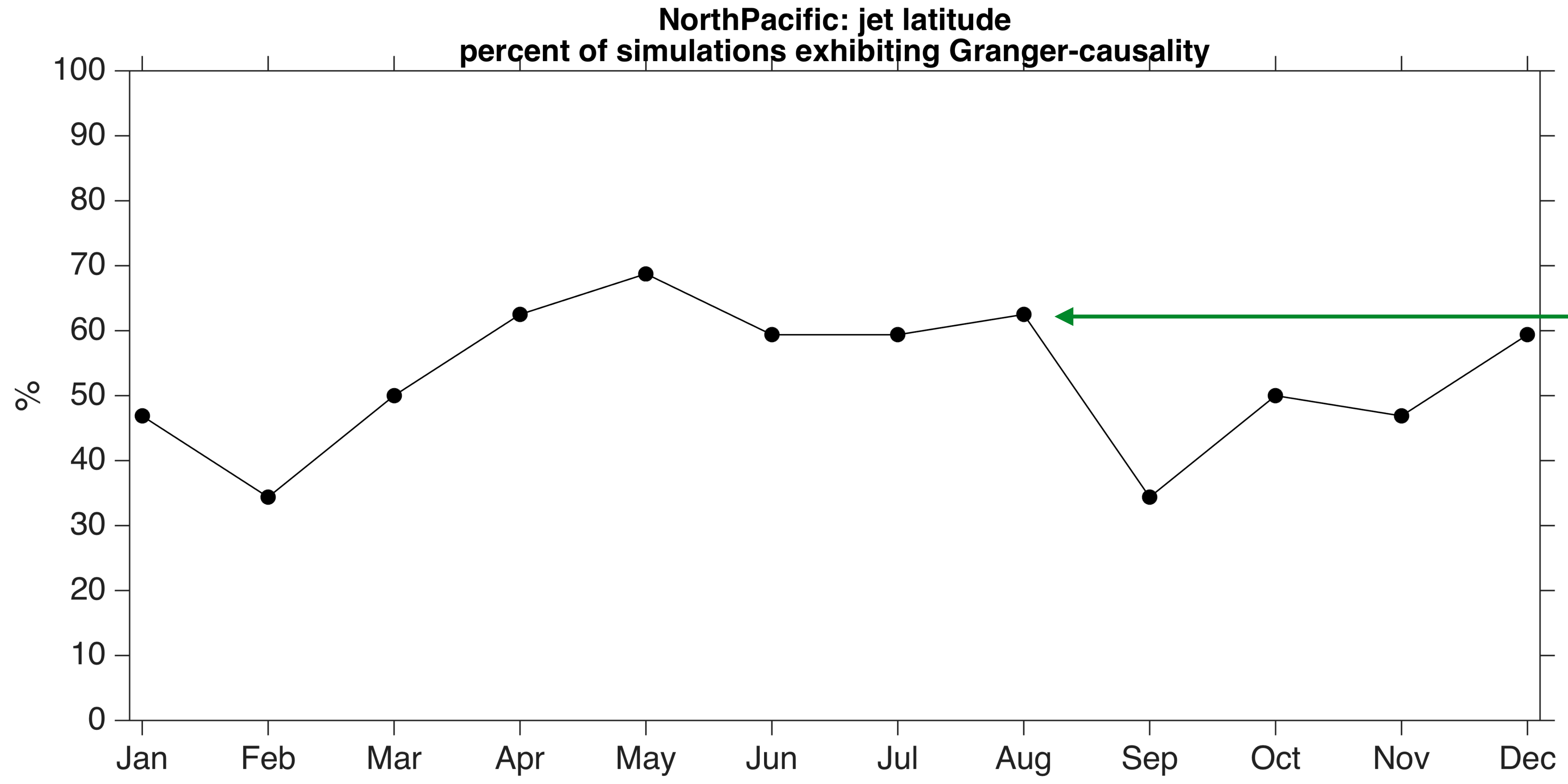

40-60% of simulations exhibit Granger-causality

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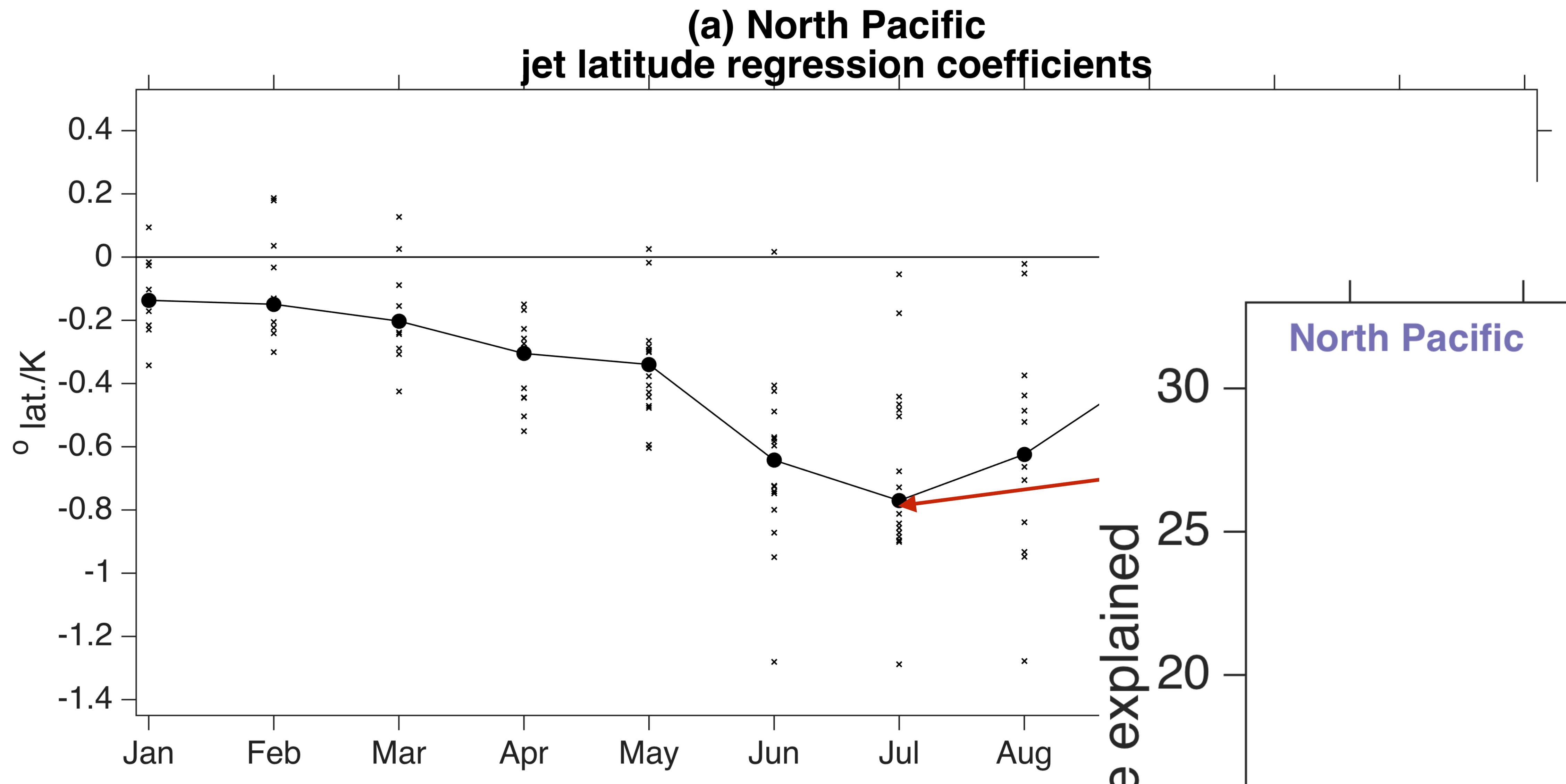

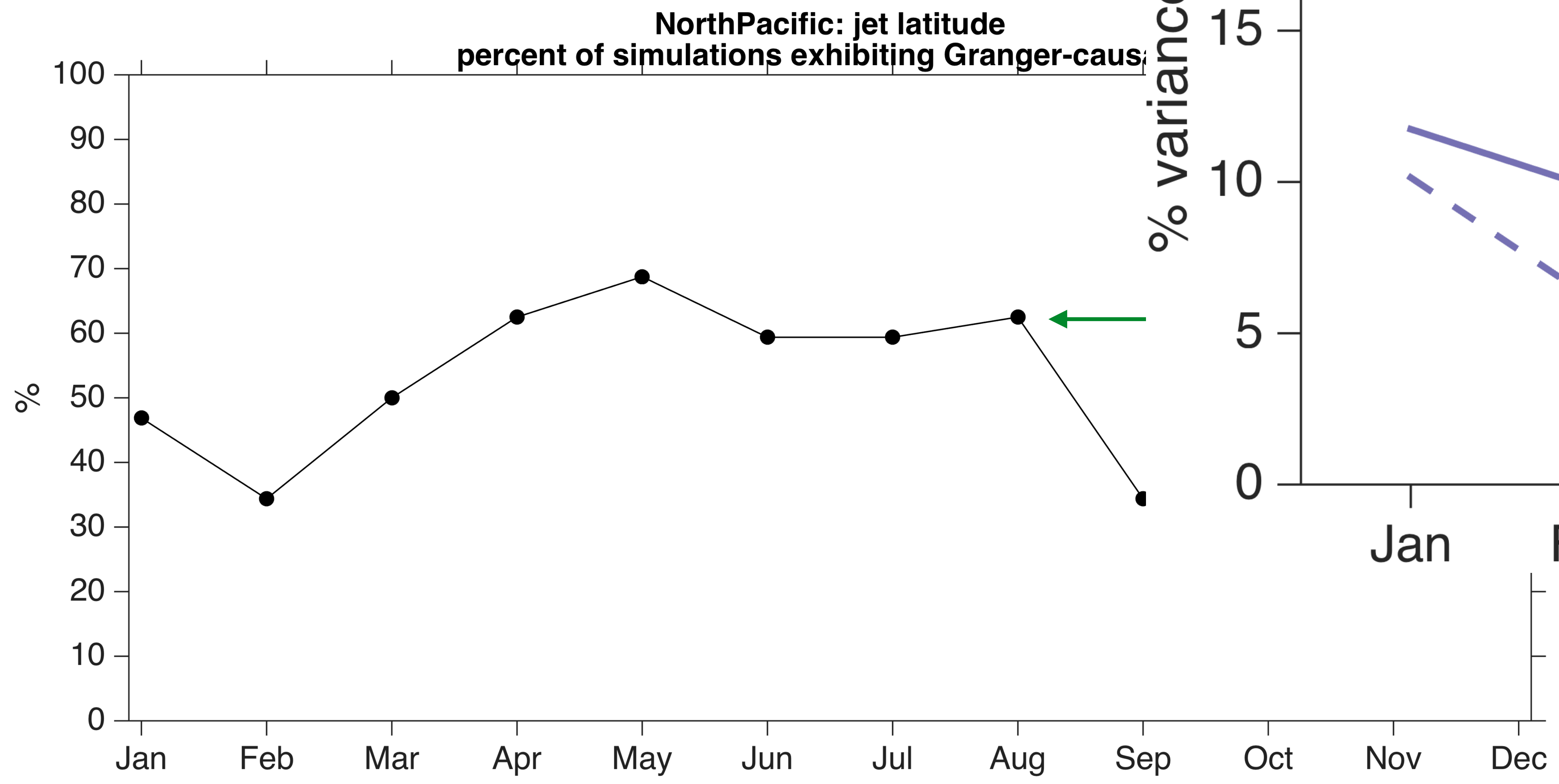

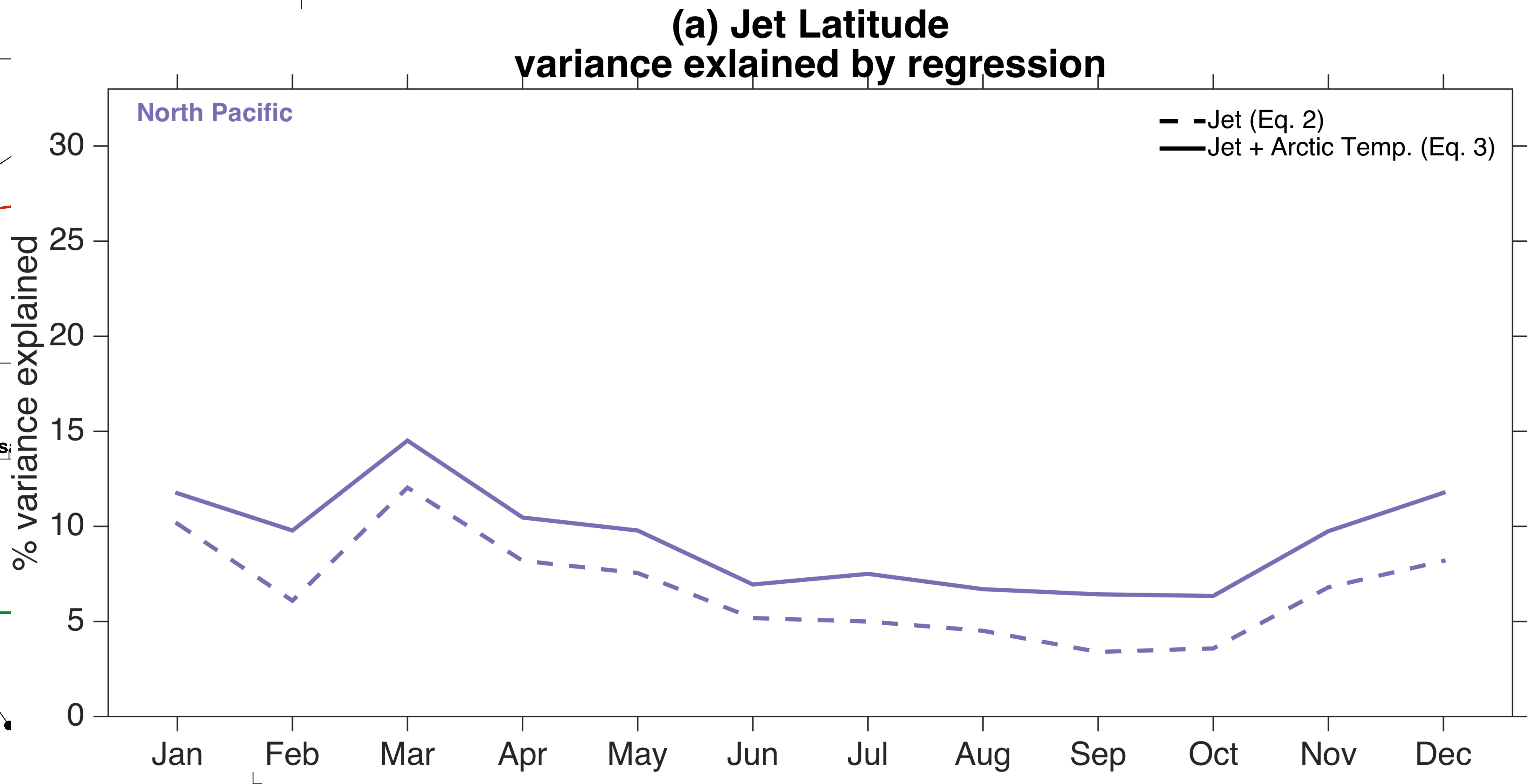

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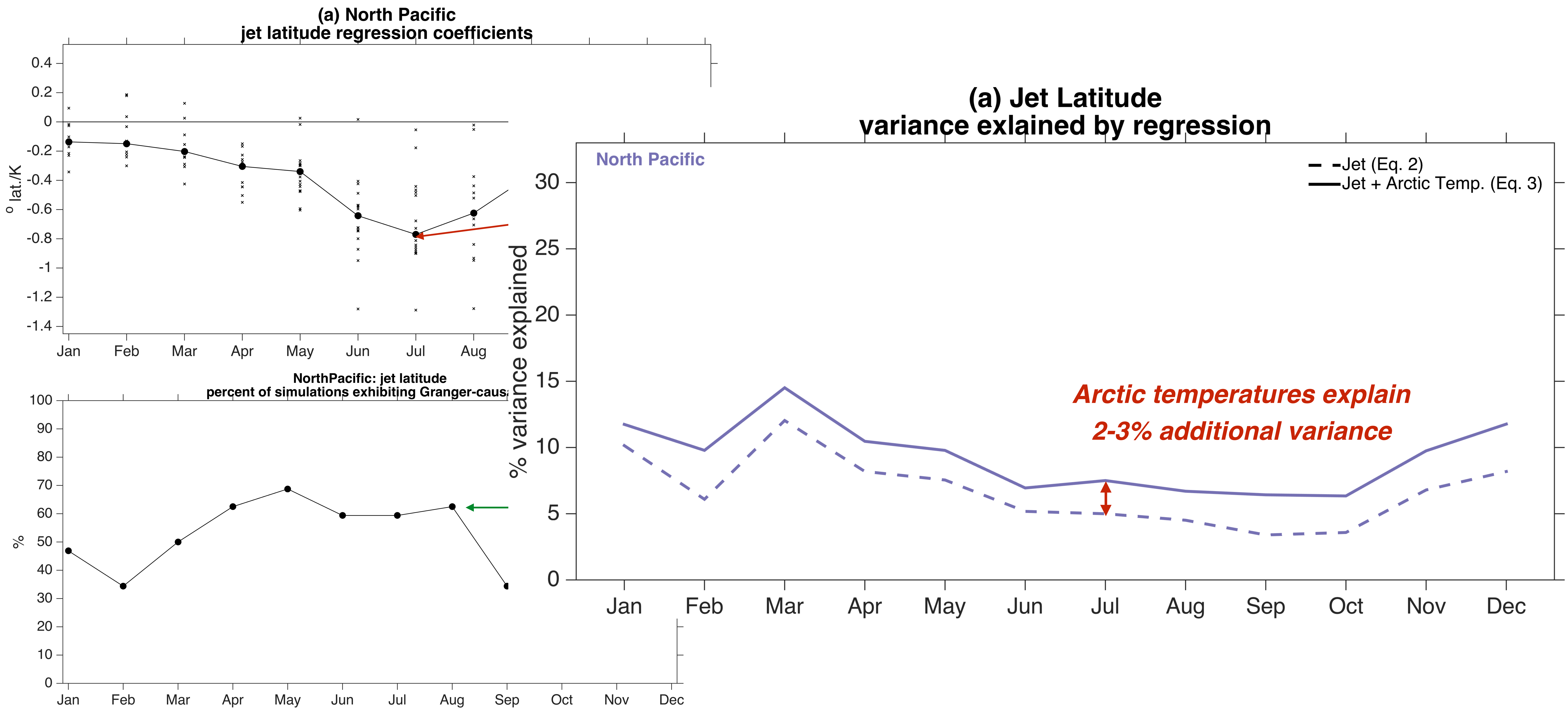

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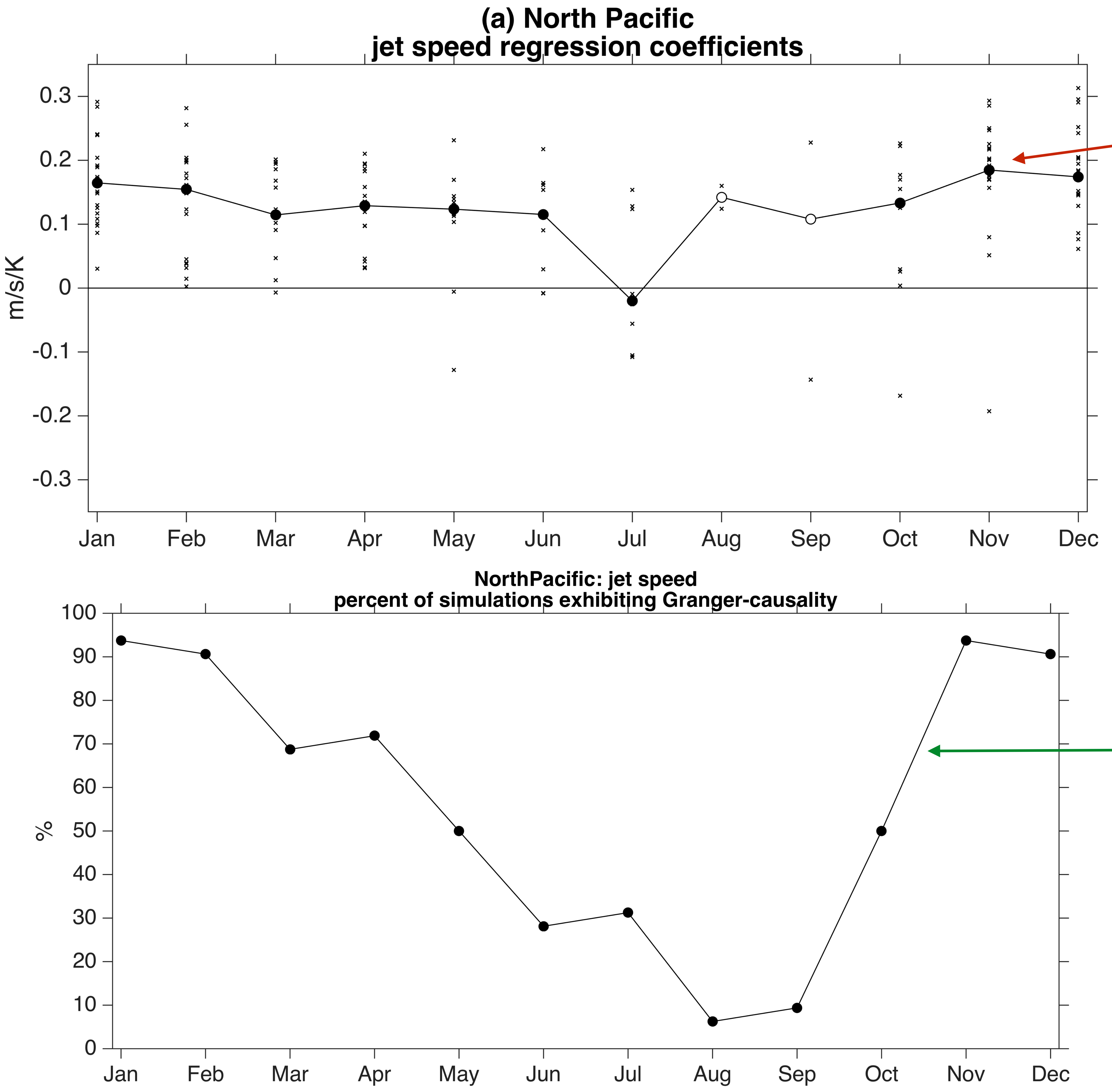
How Much?: **jet speed**



jet **strengthens** in most months

large seasonality in number of models exhibiting Granger-causality

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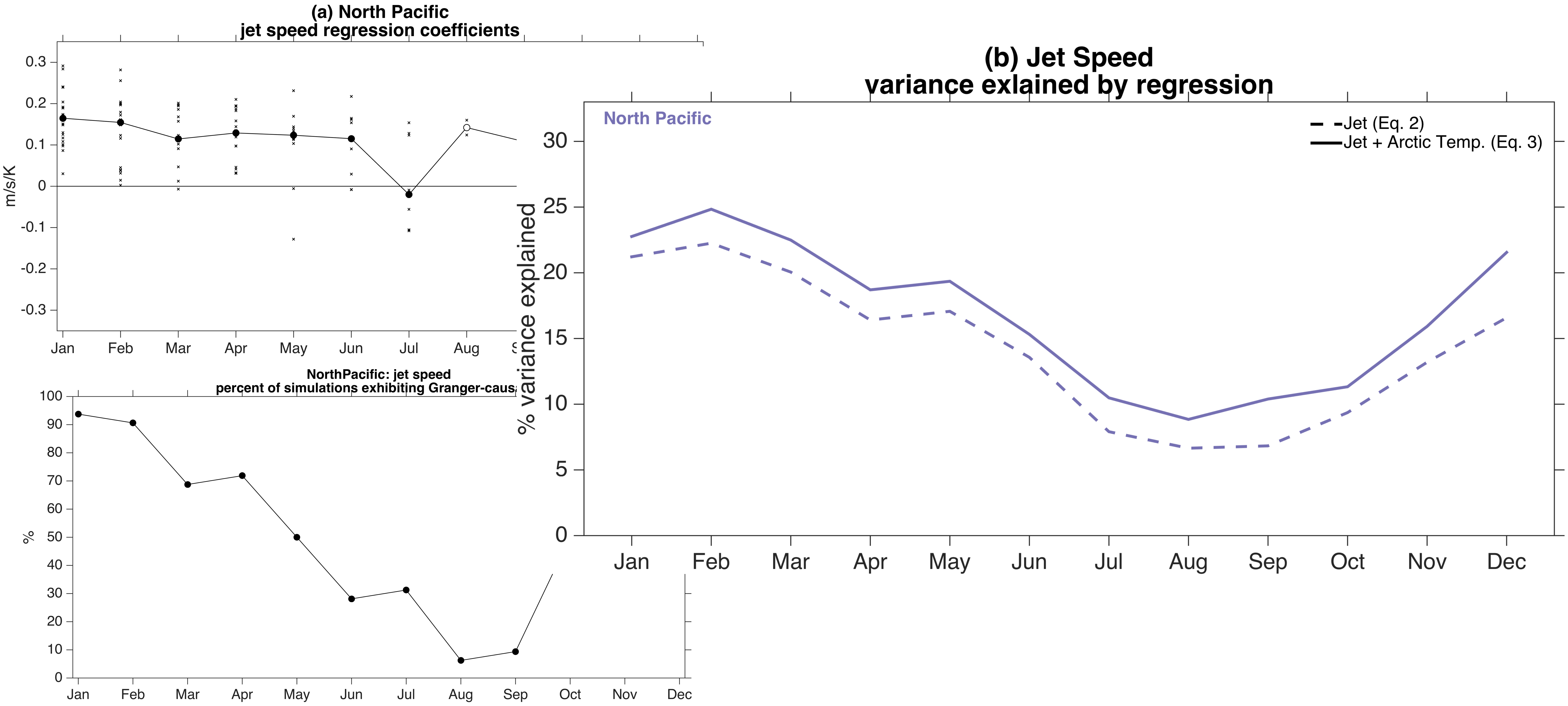

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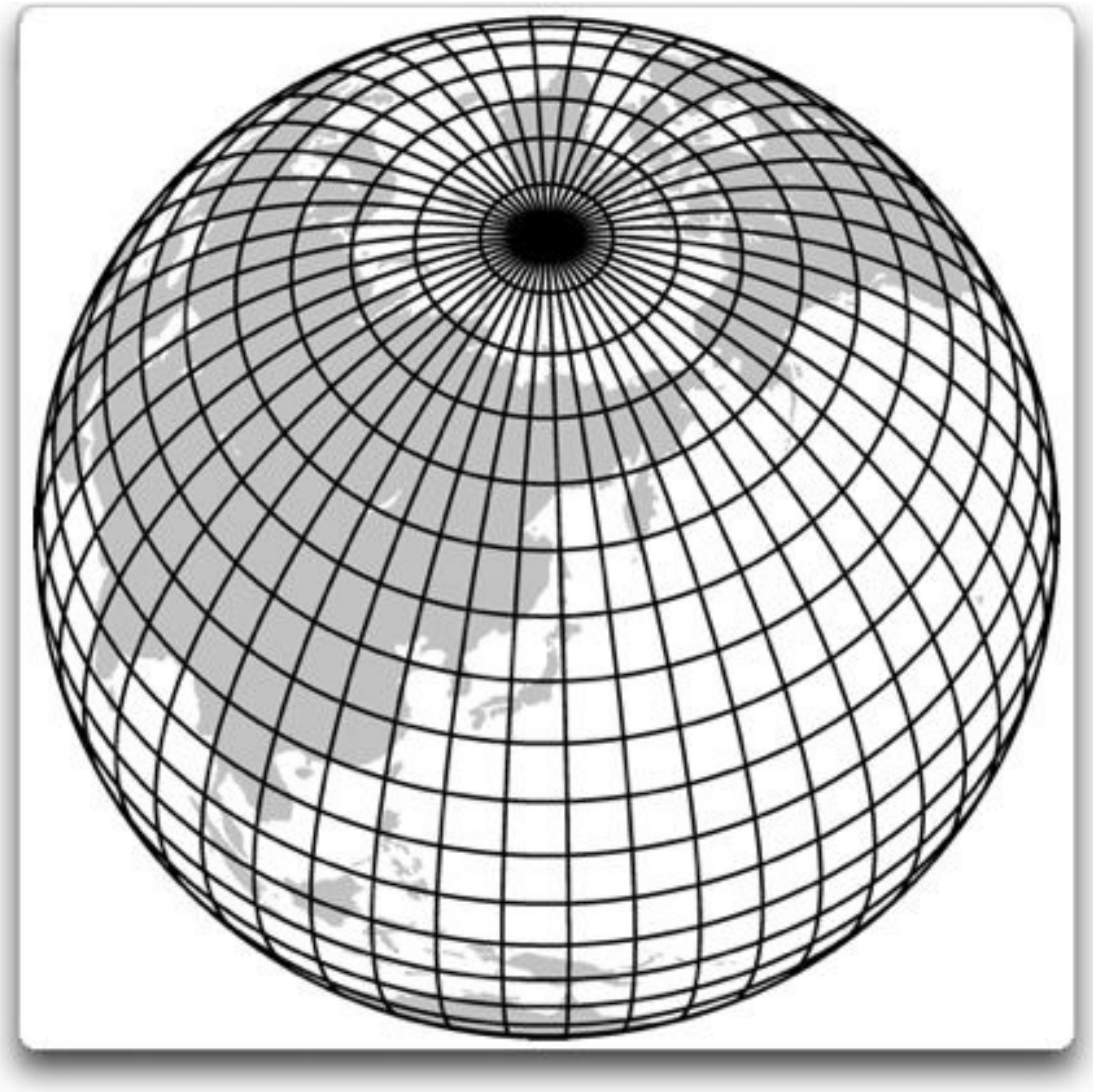

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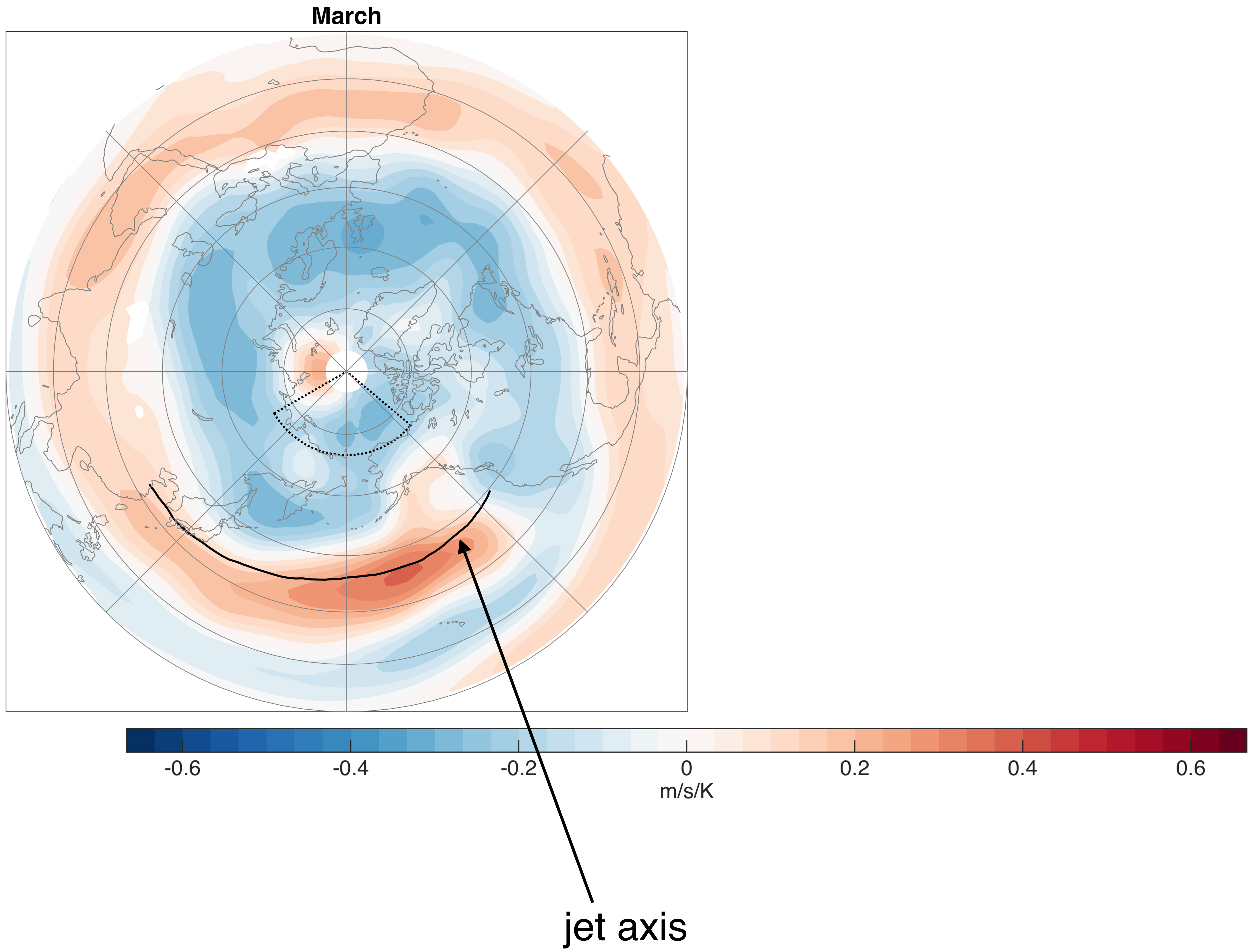
Looking closer at the seasonality



colors = CMIP5 model mean regression coefficients (via Granger-causality)

Barnes and Simpson (submitted)

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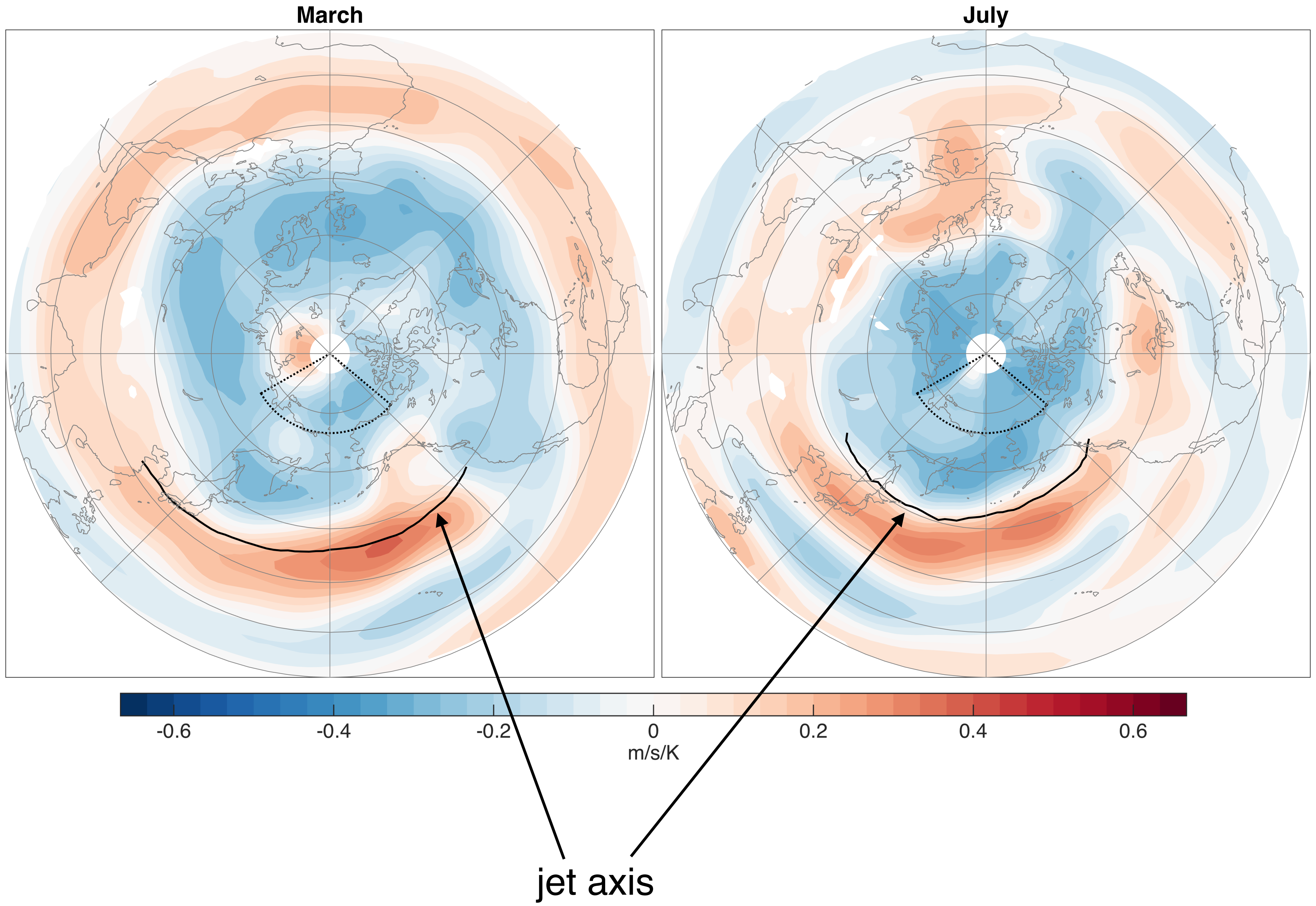

- jet shifts with the seasonal cycle
- wind anomalies remain relatively fixed in latitude
- this has implications for GCM biases (and can be quantified)

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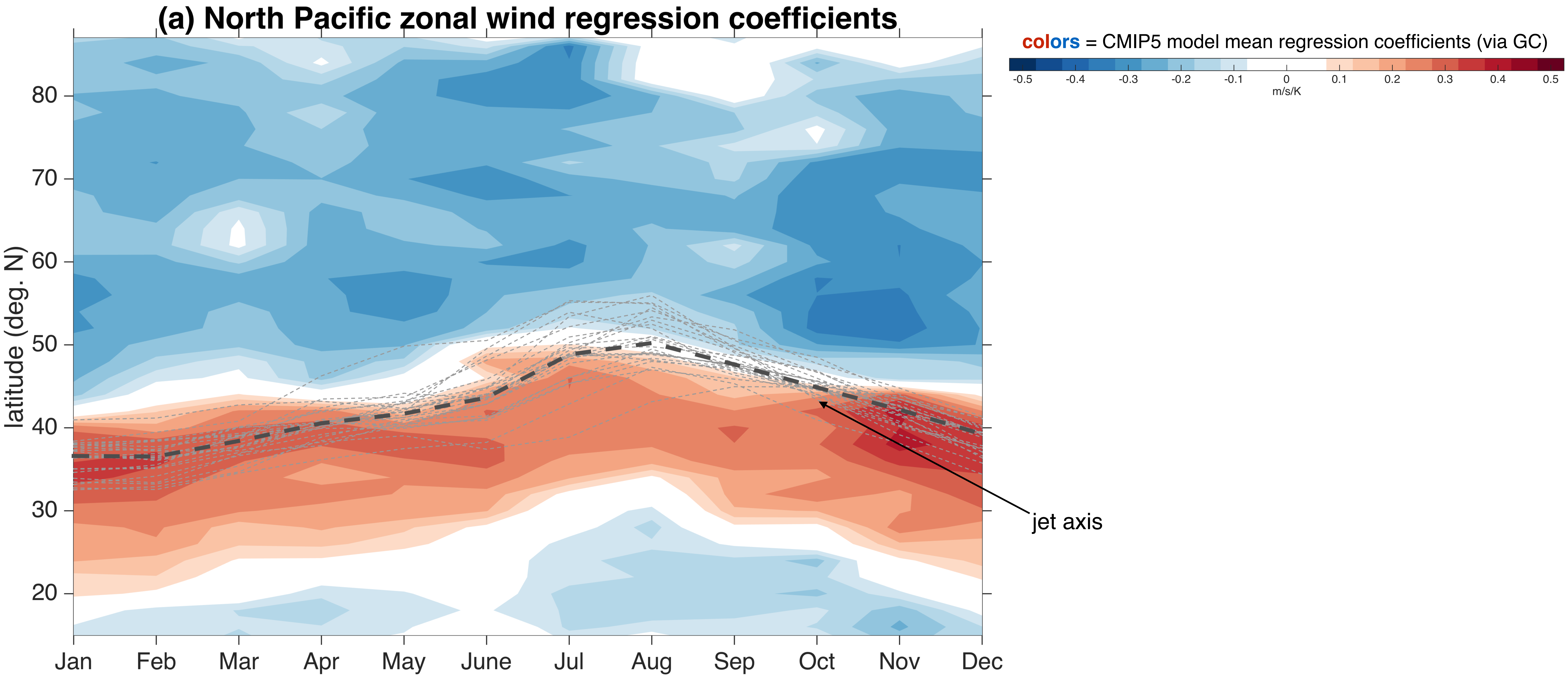

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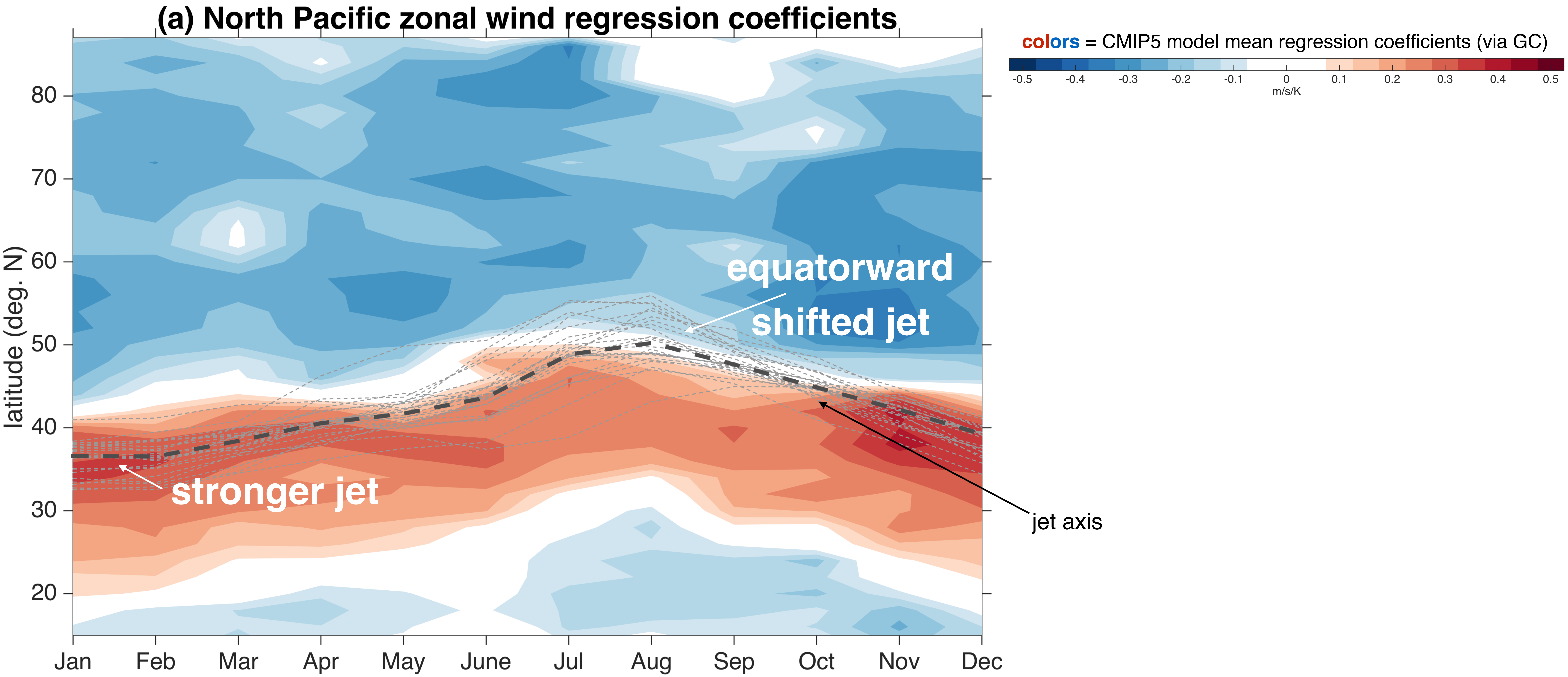

Barnes and Simpson (submitted)

Models with higher latitude jets shift further

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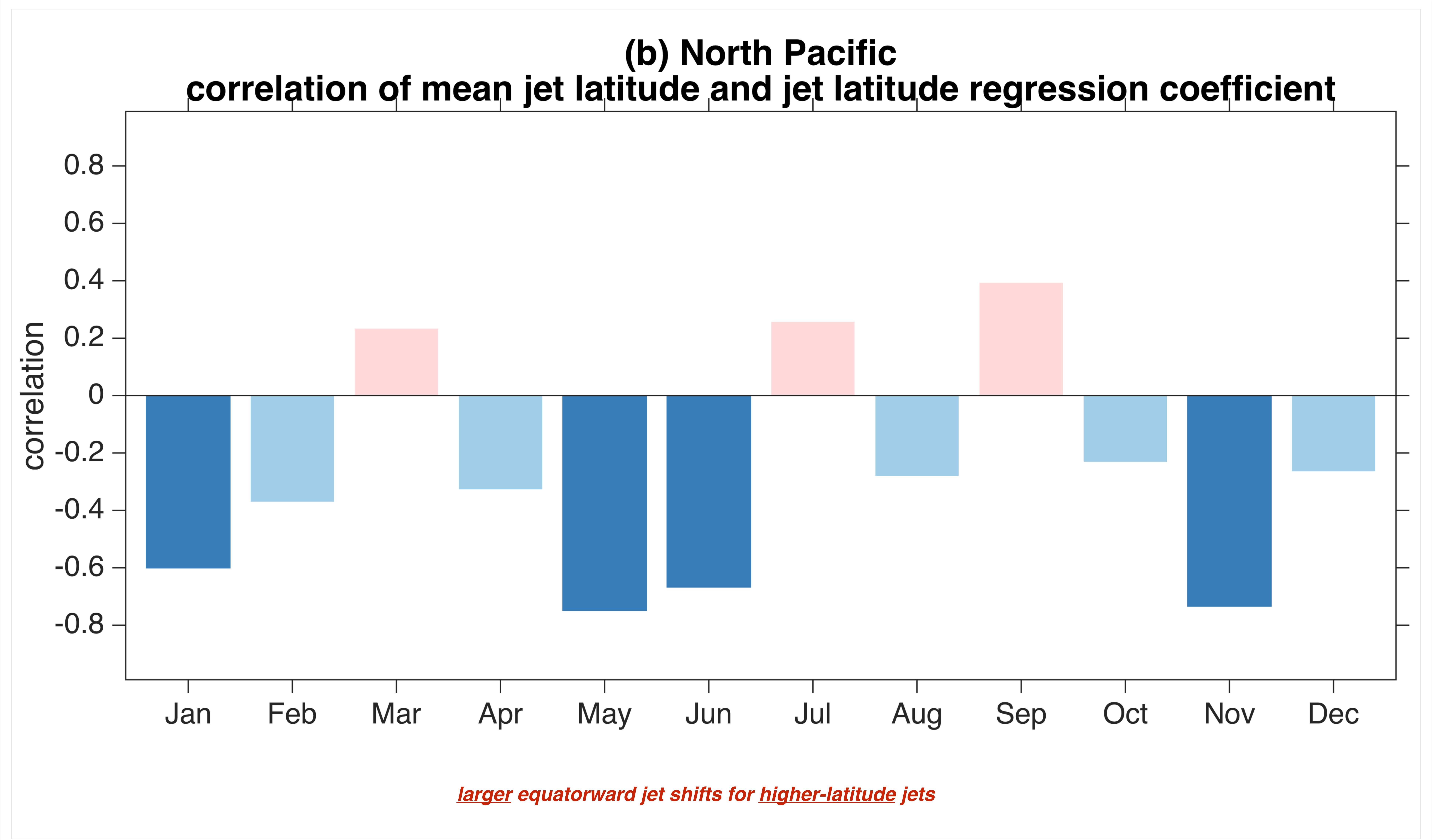
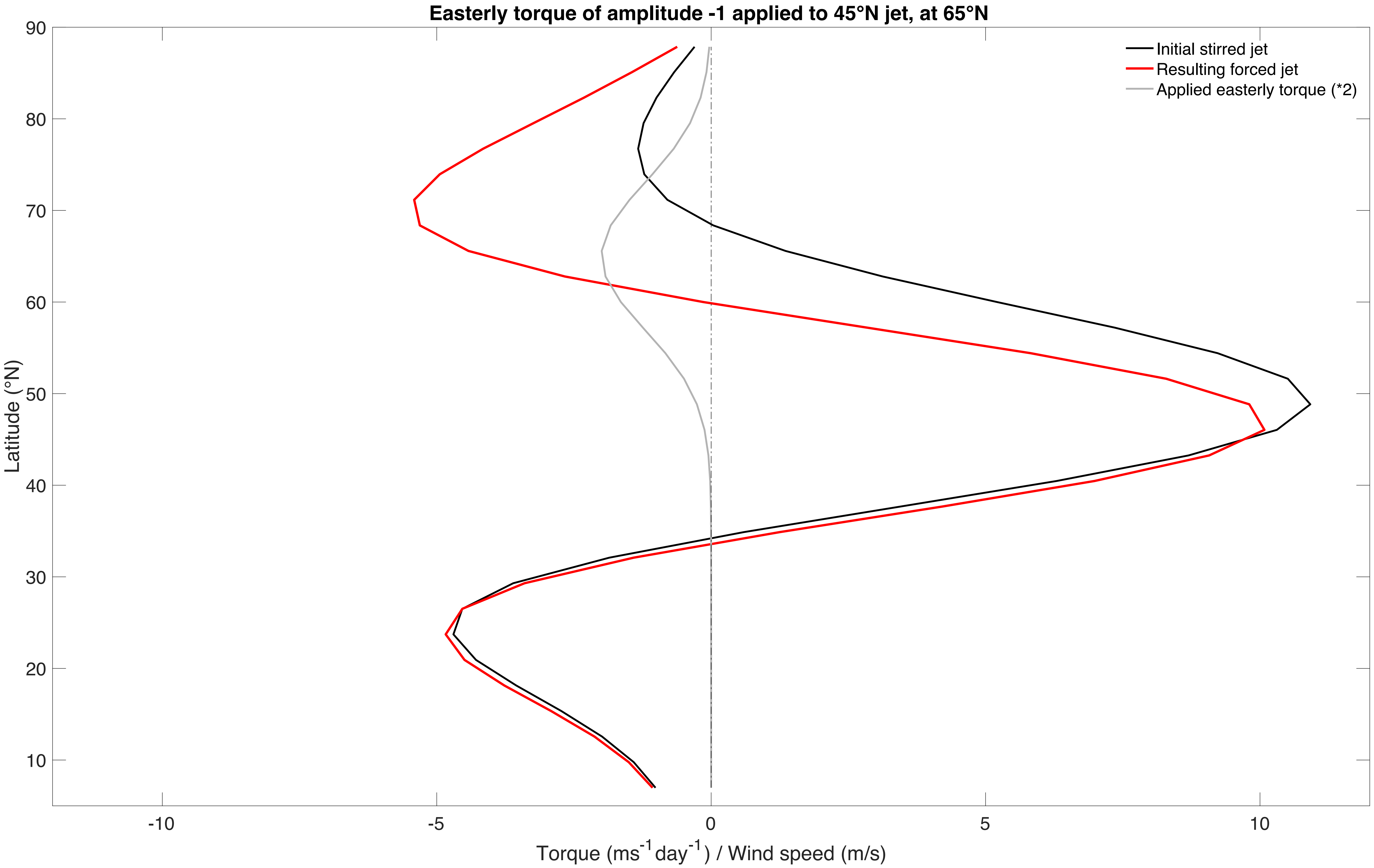
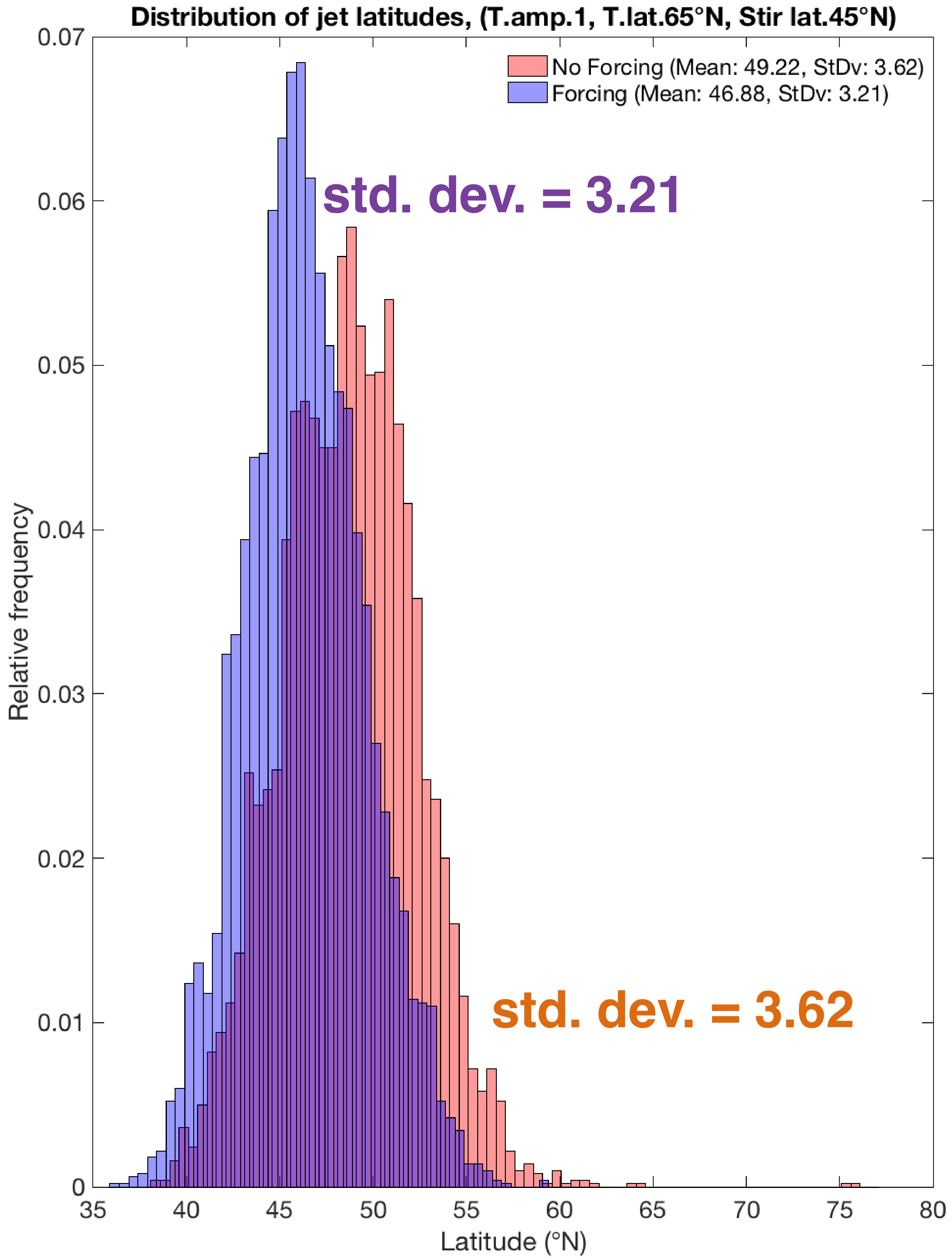


Barnes and Simpson (submitted)

Barotropic Model





Ronalds and Barnes (in prep)

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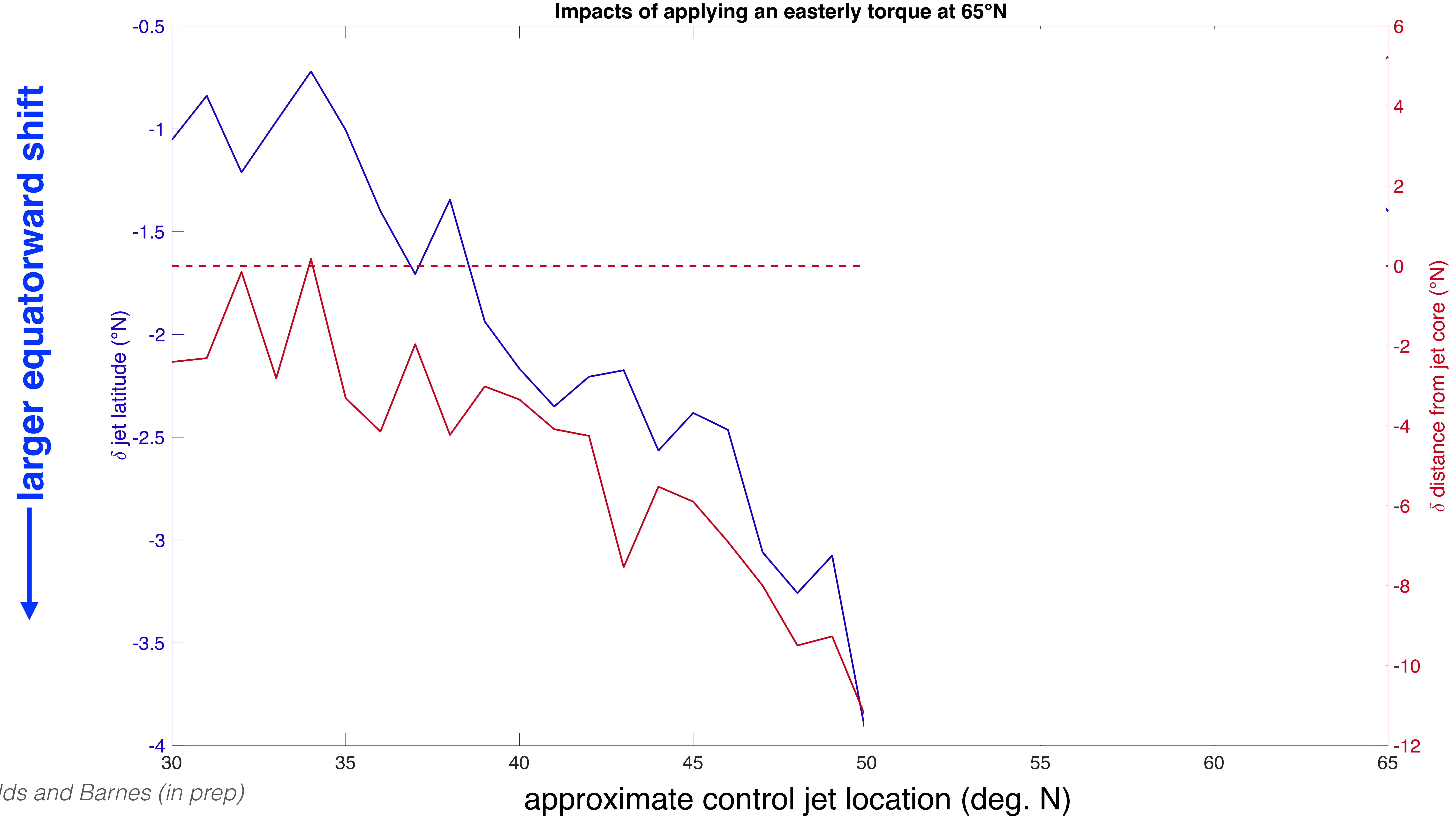

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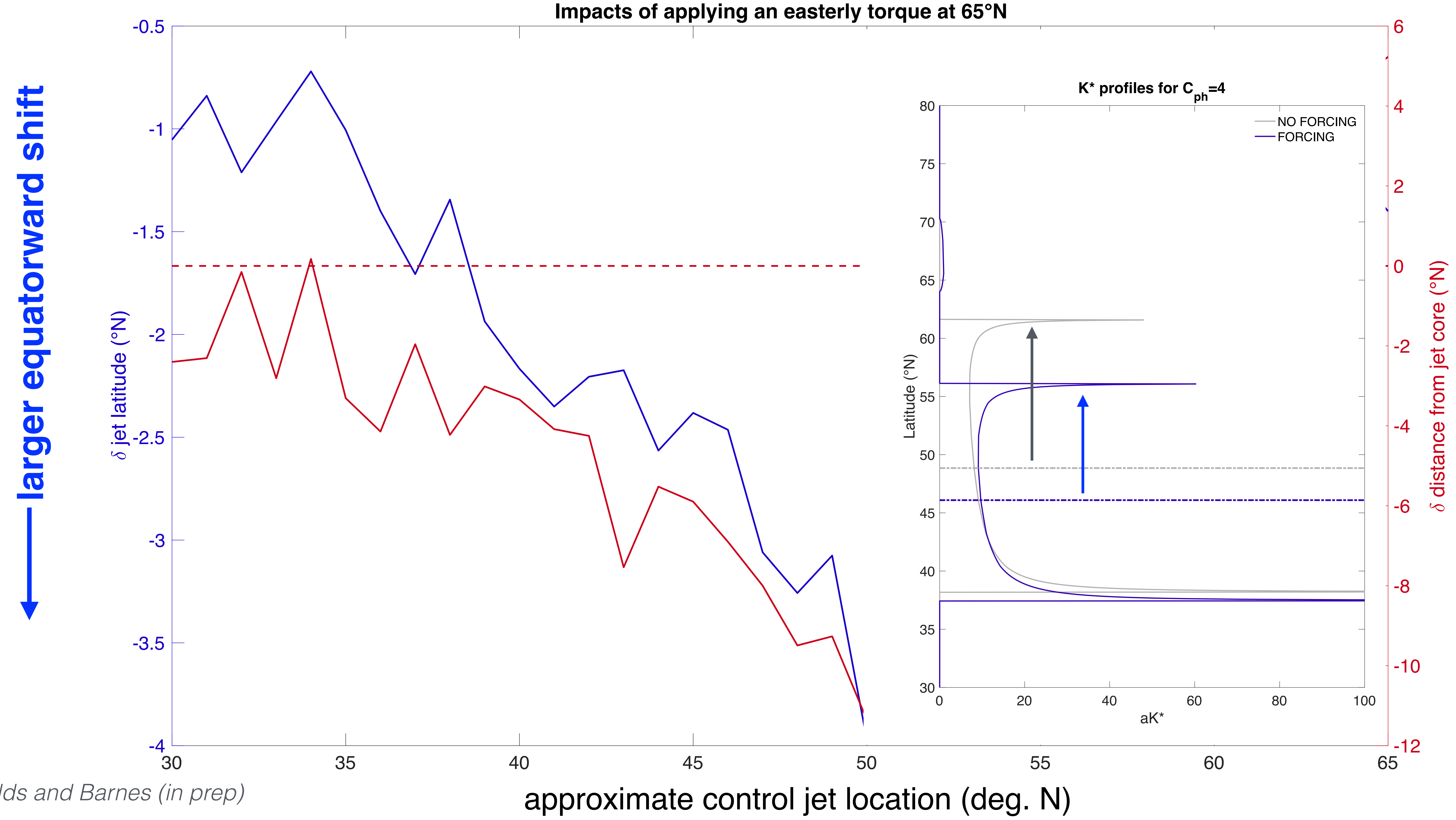


Ronalds and Barnes (in prep)

Conditional Independence of X & Y

$$\mathbf{Pr}(X = x | Y = y, Z = z) = \mathbf{Pr}(X = x | Z = z)$$

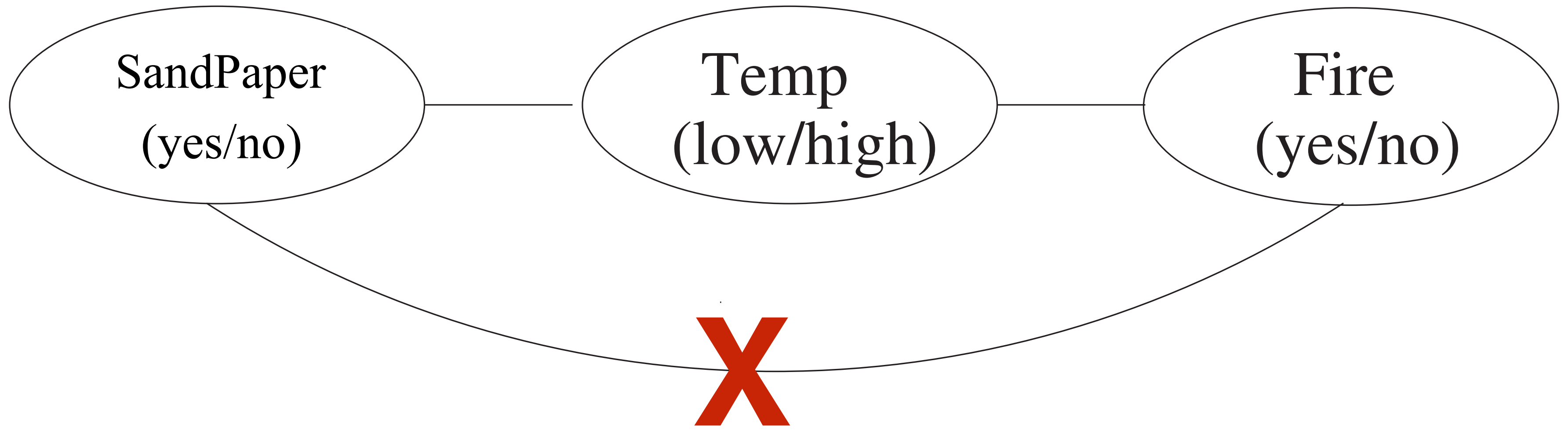
$$Y \longrightarrow Z \longrightarrow X$$

high correlation between X and Y only occurs because of the indirect link via Z

Ebert-Uphoff and Deng (2012; JCLI)
Kretschmer et al. (2016; JCLI)

Causal Effect Networks/Bayesian Networks

Correlation Graph



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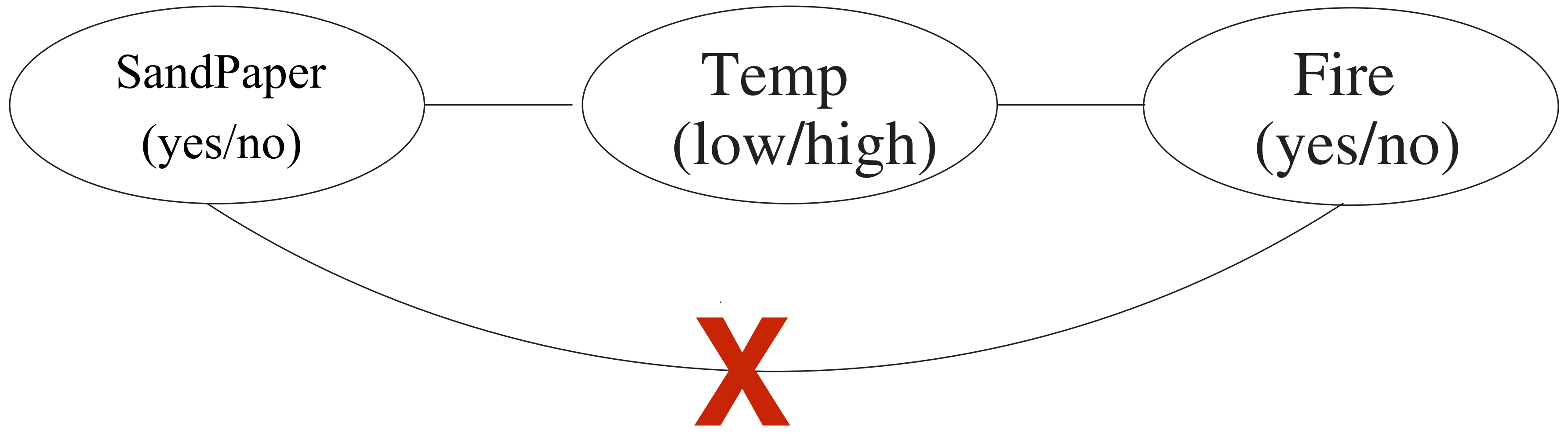
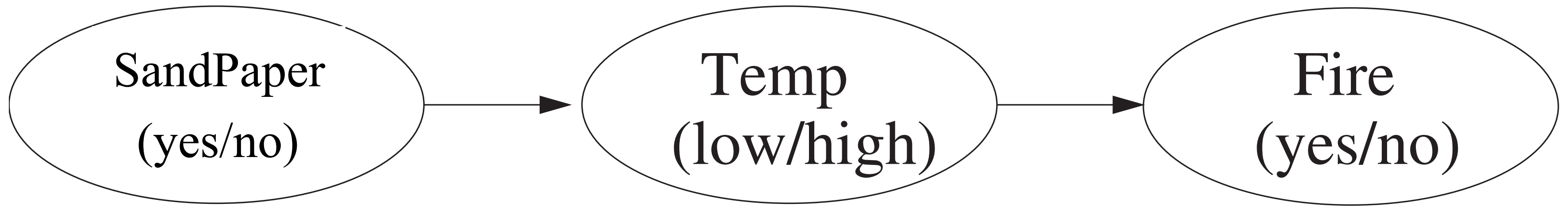


Directed independence graph



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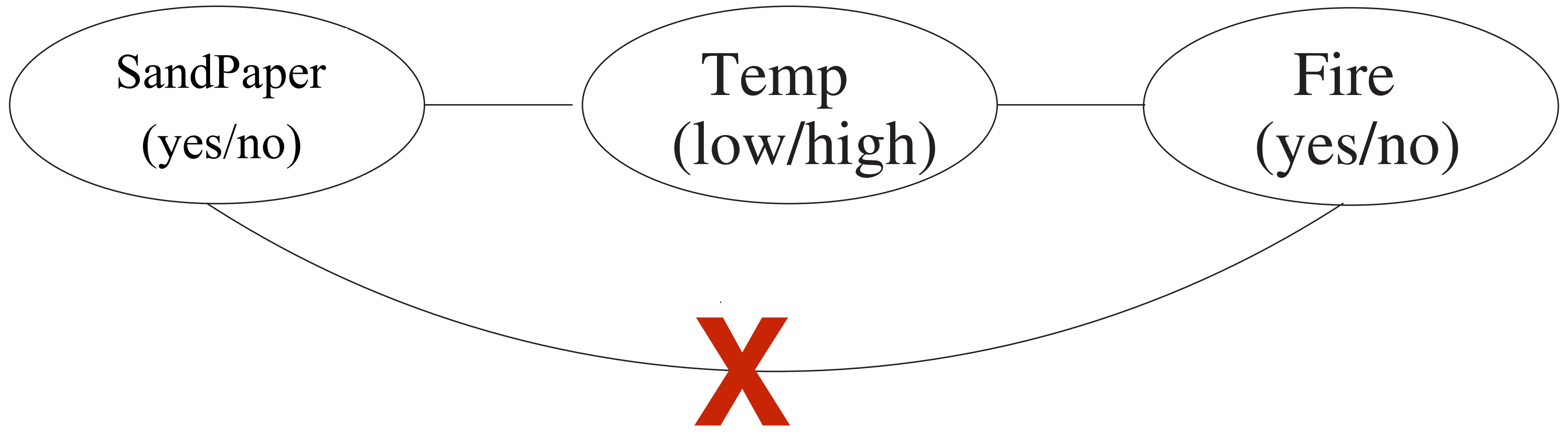

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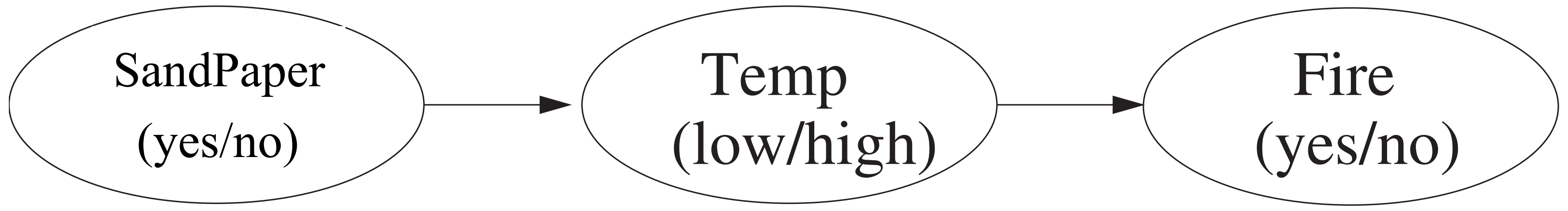


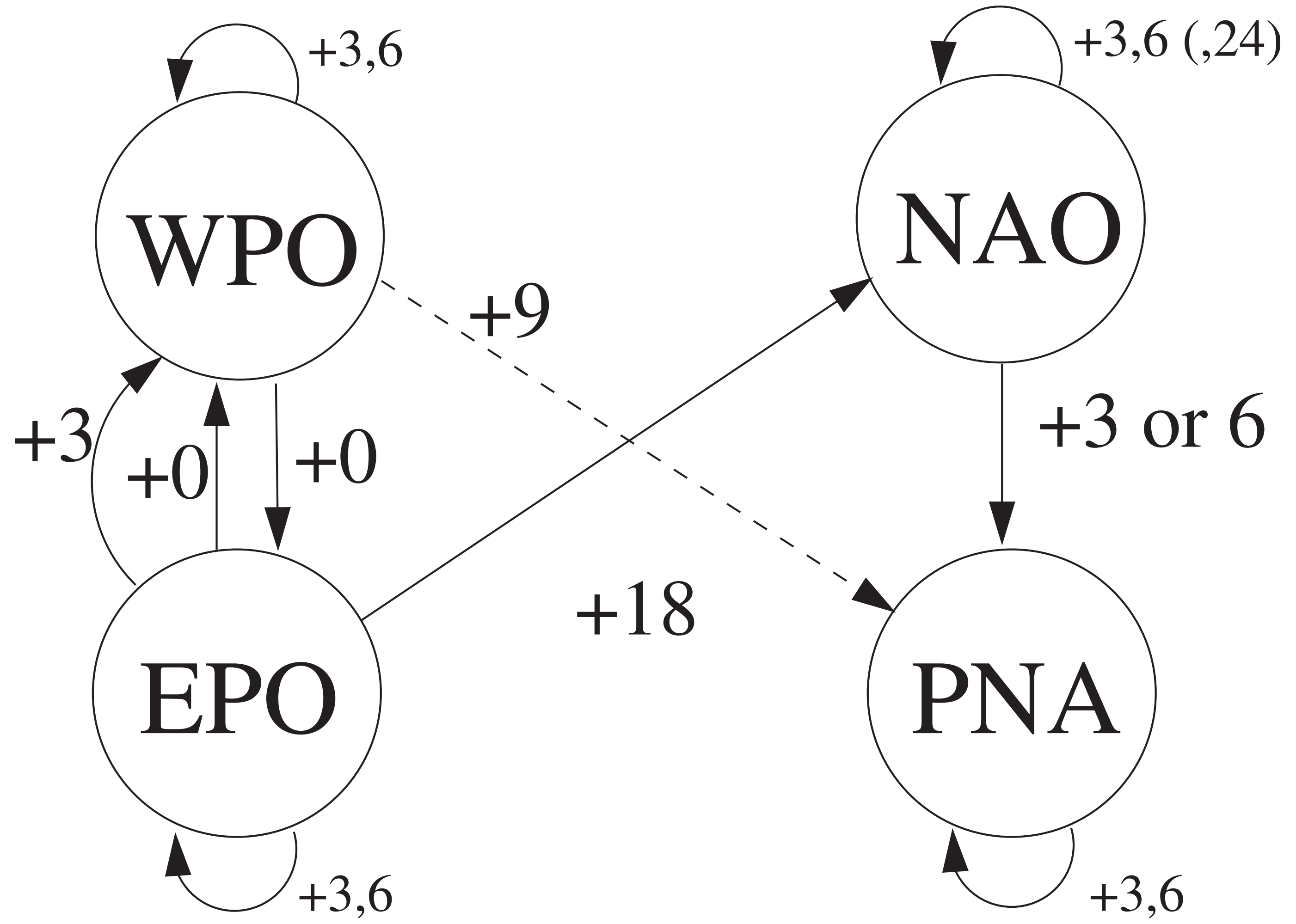
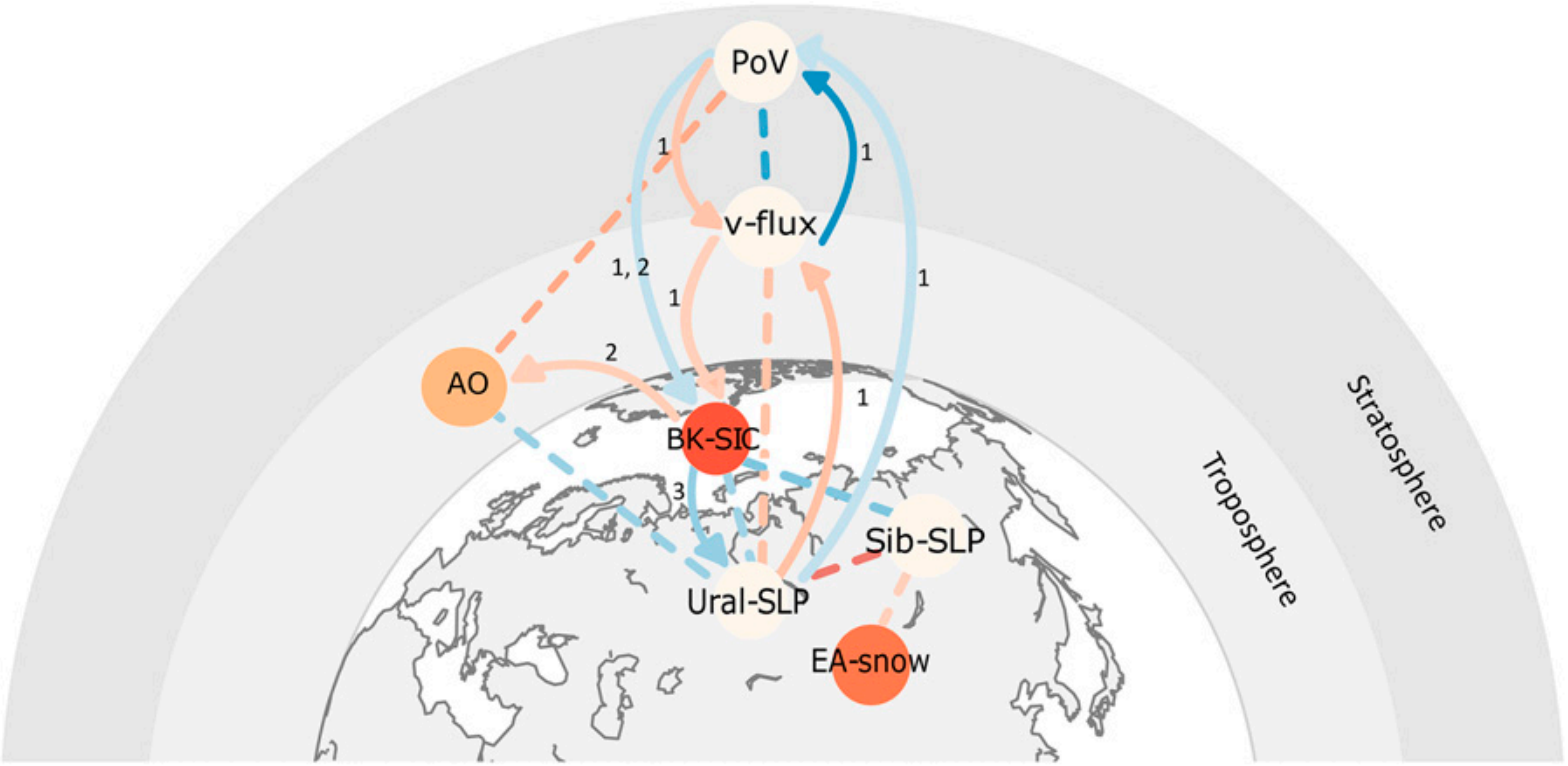


FIG. 7. Summary graph for $D = 3$ and $\alpha = 0.01$. Strong (medium) strength connections are shown as solid (dashed) arrows with corresponding time delays.

Ebert-Uphoff and Deng (2012; JCLI)

Causal Effect Networks



Kretschmer et al. (2016; JCLI)

Using Causal Effect Networks to Analyze Different Arctic Drivers of Midlatitude Winter Circulation

Marlene Kretschmer

Potsdam Institute for Climate Impact Research, and Department of Mathematics, University of Potsdam, Potsdam, Germany

Dim Coumou

Potsdam Institute for Climate Impact Research, Potsdam, Germany

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ABSTRACT

In recent years, the Northern Hemisphere midlatitudes have suffered from severe winters like the extreme 2012/13 winter in the eastern United States. These cold spells were linked to a meandering upper-tropospheric jet stream pattern and a negative Arctic Oscillation index (AO). However, the nature of the drivers behind these circulation patterns remains controversial. Various studies have proposed different mechanisms related to changes in the Arctic, most of them related to a reduction in sea ice concentrations or increasing Eurasian snow cover.

Here, a novel type of time series analysis, called causal effect networks (CEN), based on graphical models is introduced to assess causal relationships and their time delays between different processes. The effect of different Arctic actors on winter circulation on weekly to monthly time scales is studied, and robust network patterns are found. Barents and Kara sea ice concentrations are detected to be important external drivers of the midlatitude circulation, influencing winter AO via tropospheric mechanisms and through processes involving the stratosphere. Eurasia snow cover is also detected to have a causal effect on sea level pressure in Asia, but its exact role on AO remains unclear. The CEN approach presented in this study overcomes some difficulties in interpreting correlation analyses, complements model experiments for testing hypotheses involving teleconnections, and can be used to assess their validity. The findings confirm that sea ice concentrations in autumn in the Barents and Kara Seas are an important driver of winter circulation in the midlatitudes.

1. Introduction

The recent cold winters in North America and Eurasia were characterized by a meandering jet stream pattern that allowed cold Arctic air to reach lower latitudes (Cohen et al. 2014b). Moreover, these winters were dominated by a negative phase of the Arctic Oscillation index (AO), which is usually associated with pronounced meridional wind patterns, whereas in a positive AO phase strong zonal flow dominates the wind field. Although a negative AO and meandering flow patterns have been linked to surface extremes (Thompson 2001; Coumou et al. 2014; Screen and Simmonds 2014), it is intensively discussed what the mechanisms behind AO variability are.

Classical atmosphere dynamic theories relate a meandering jet stream structure to above-normal sea

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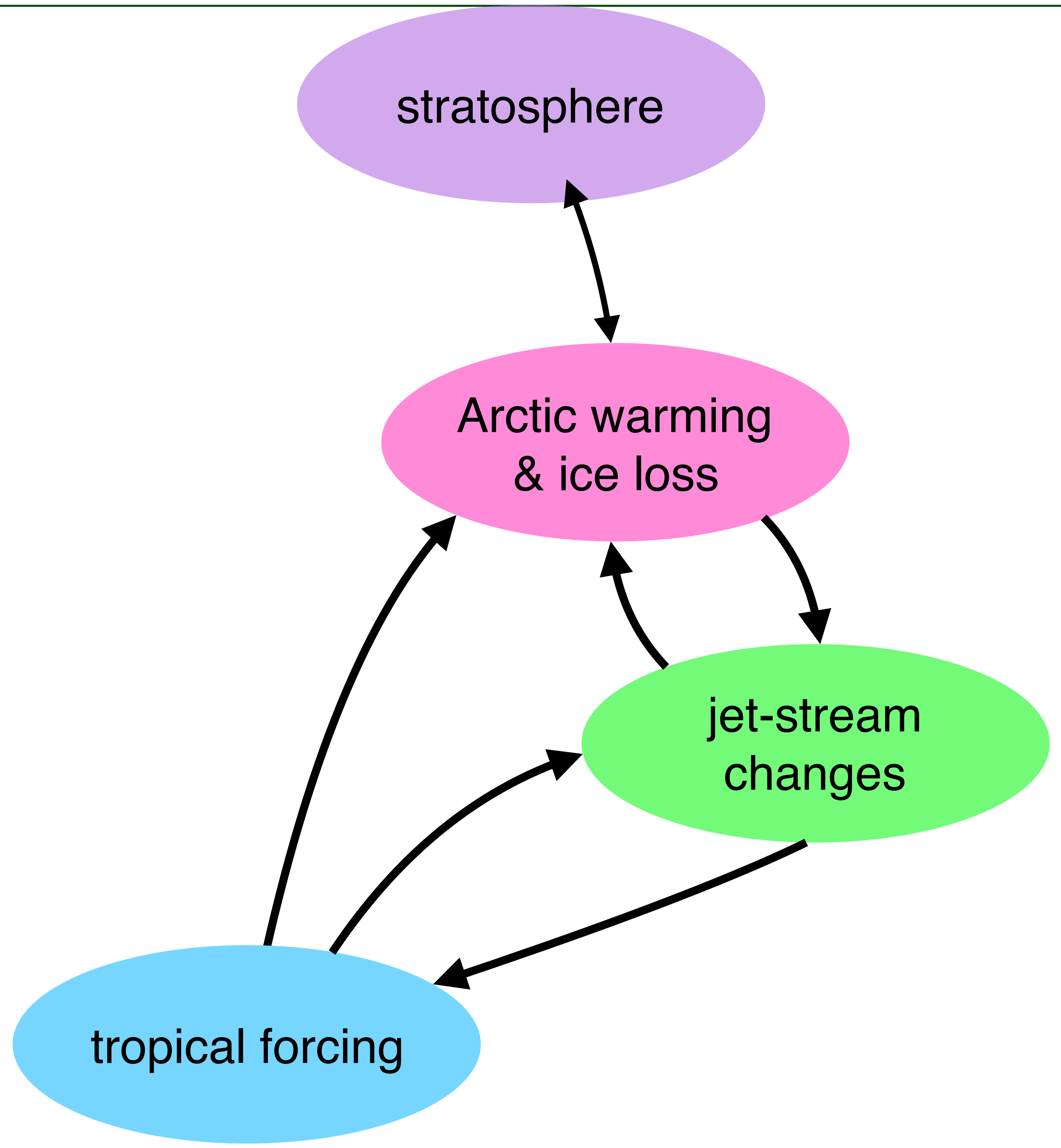
Another tool for our toolbox

Lagged Regression/Correlations

Targeted Model Experiments

Forecasting Approach



Another tool for our toolbox

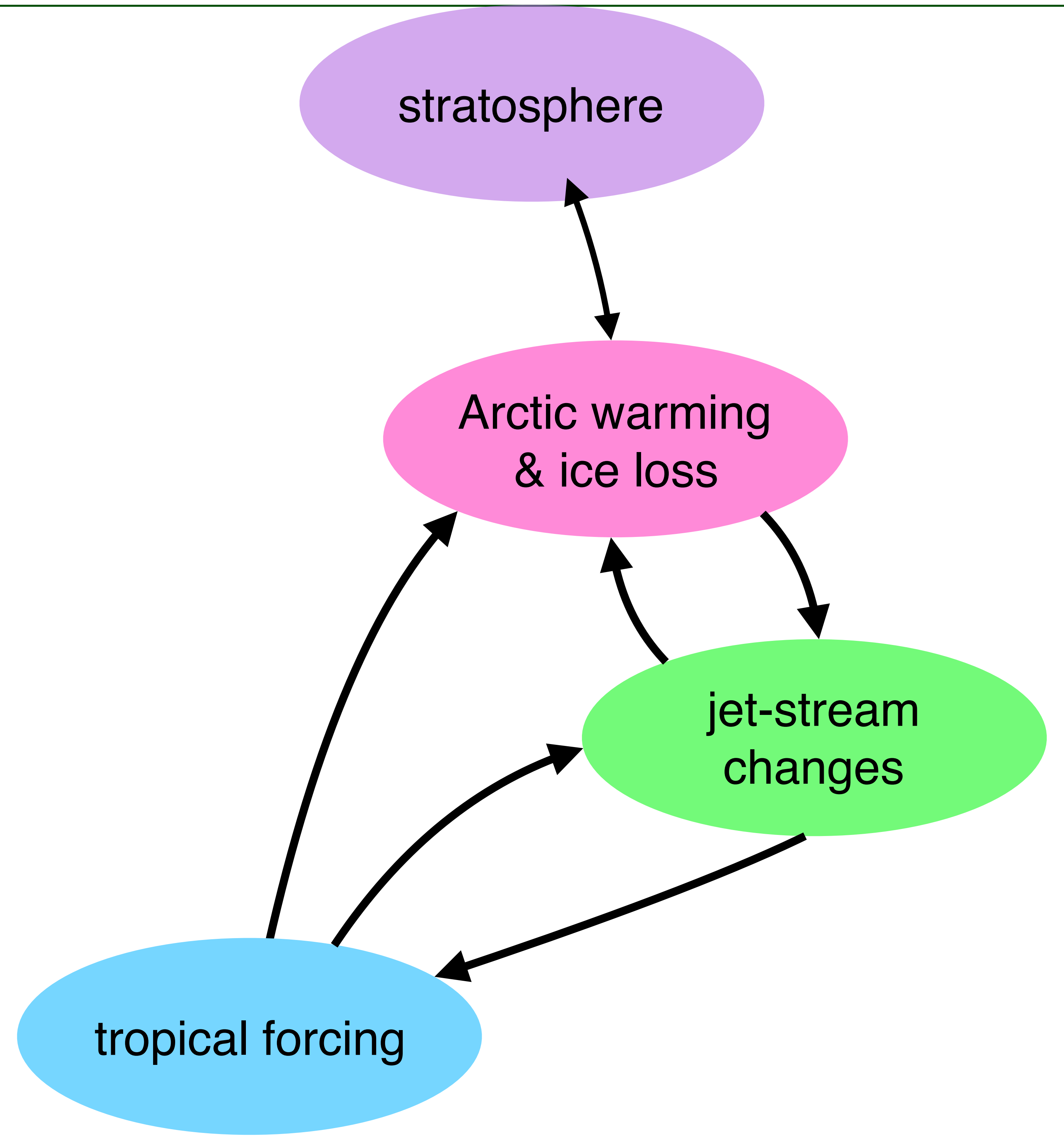
Lagged Regression/Correlations

Targeted Model Experiments

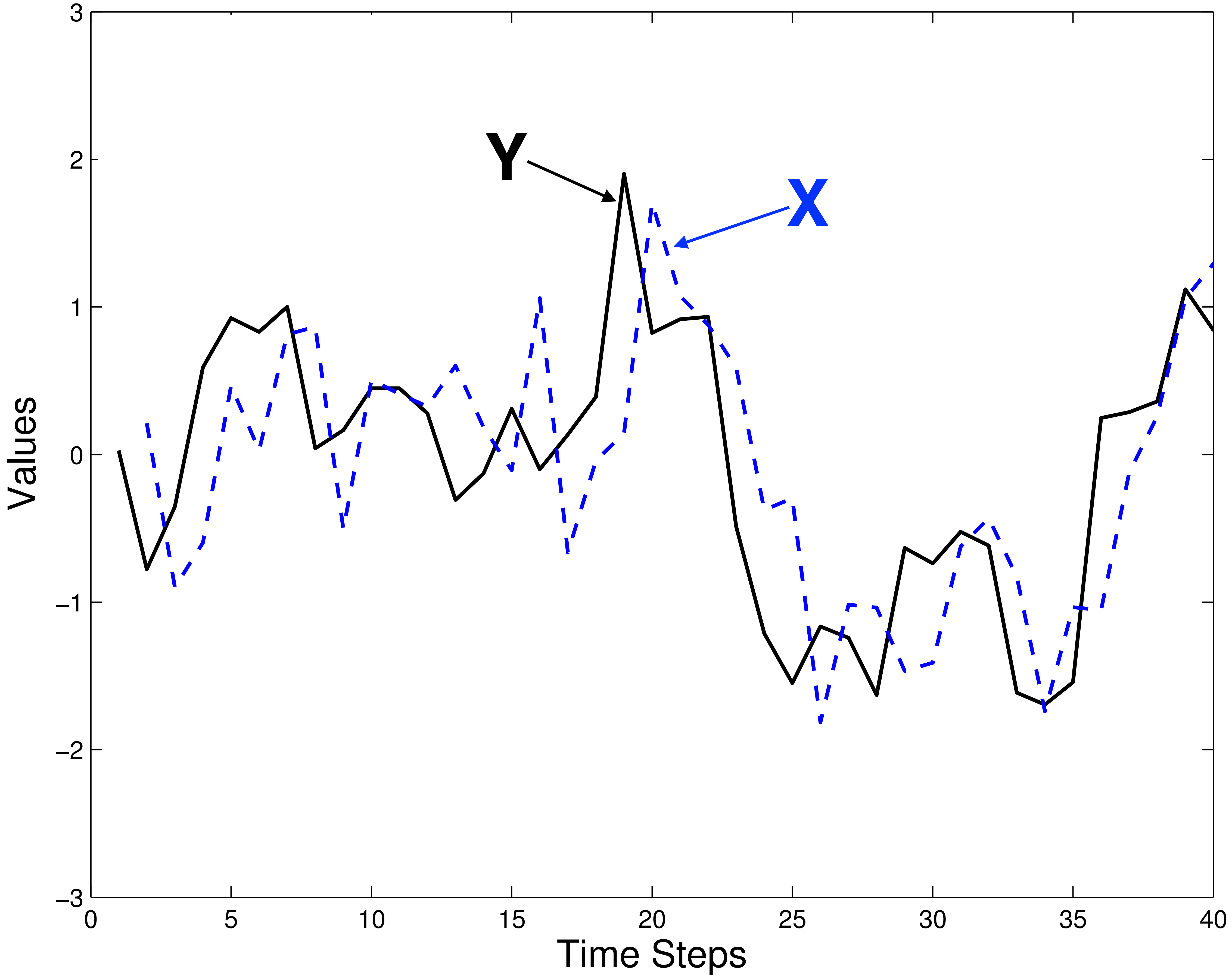
Forecasting Approach

Causal Discovery Techniques

- ✓ robust definitions of causality
- ✓ ties to forecasting/prediction
- ✓ does not suffer from the autocorrelation issues of lagged regression
- ✓ augments targeted model studies
- ✓ **can quantify strong pathways in observations and directly compare to model simulations**
- ✓ **puts pathways in context relative to other drivers and allows for feedbacks**



Lagged regression



memory in Y

$$Y_t = \alpha Y_{t-1} + \beta_t$$

red noise (AR1)

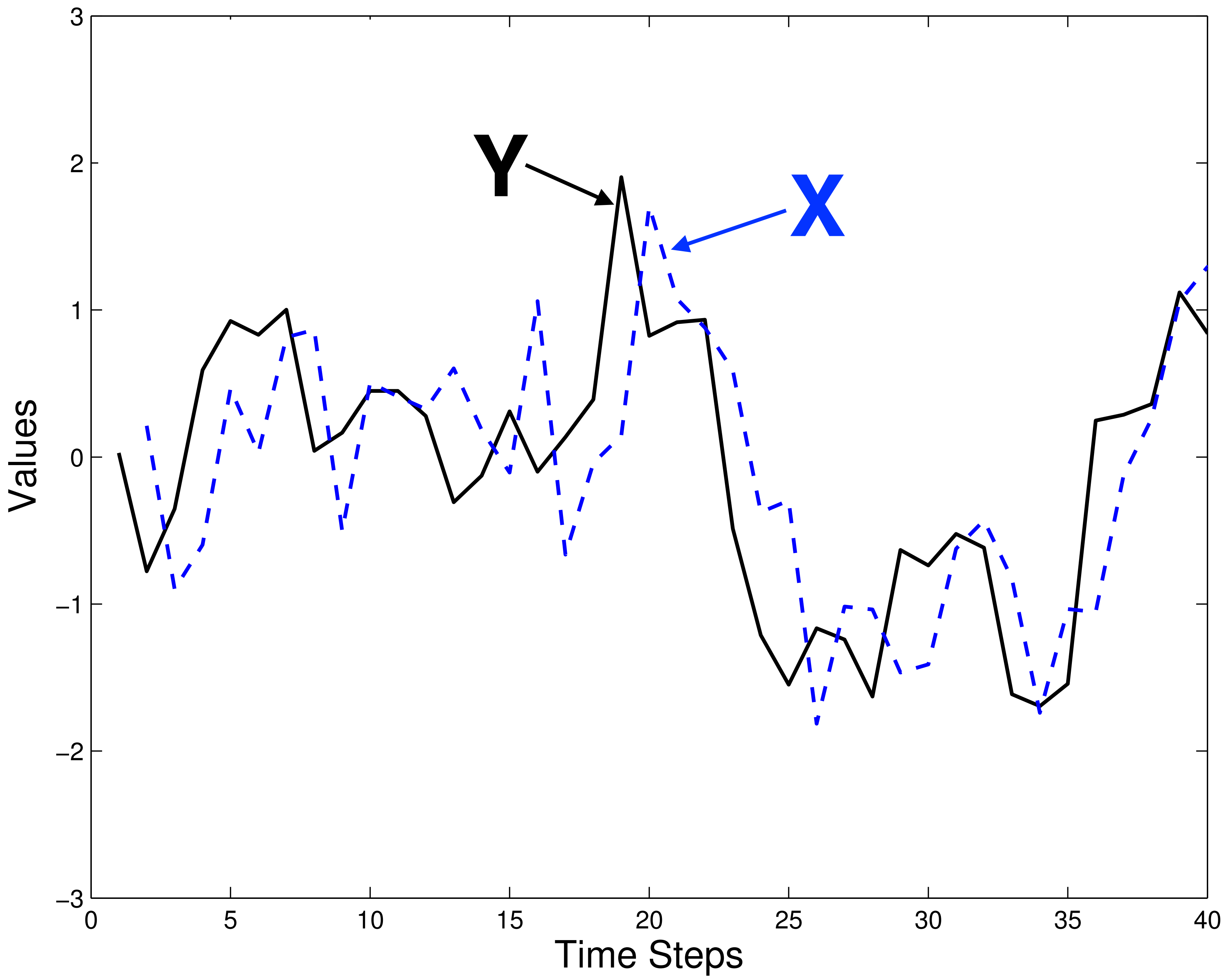
$$X_t = Y_{t-1} + \epsilon_t$$

noise in X

Y drives X one day later
+
noise

McGraw and Barnes (submitted)

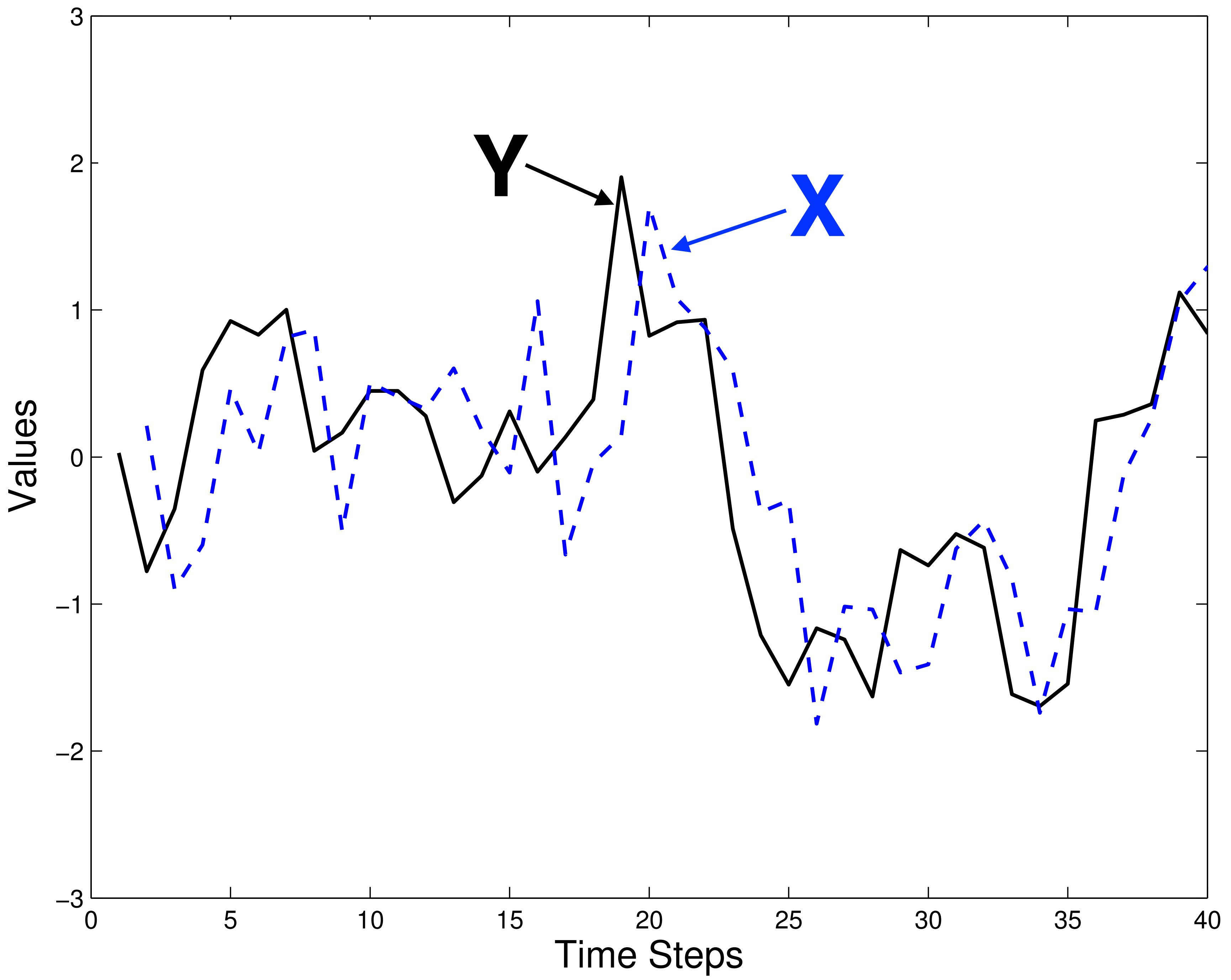
Lagged regression



- Pretend we don't know the relationship between X and Y
- **Step 1:** test whether Y —> X [*right*]
- **Step 2:** test whether X —> Y [*wrong*]

McGraw and Barnes (in prep)

Lagged regression



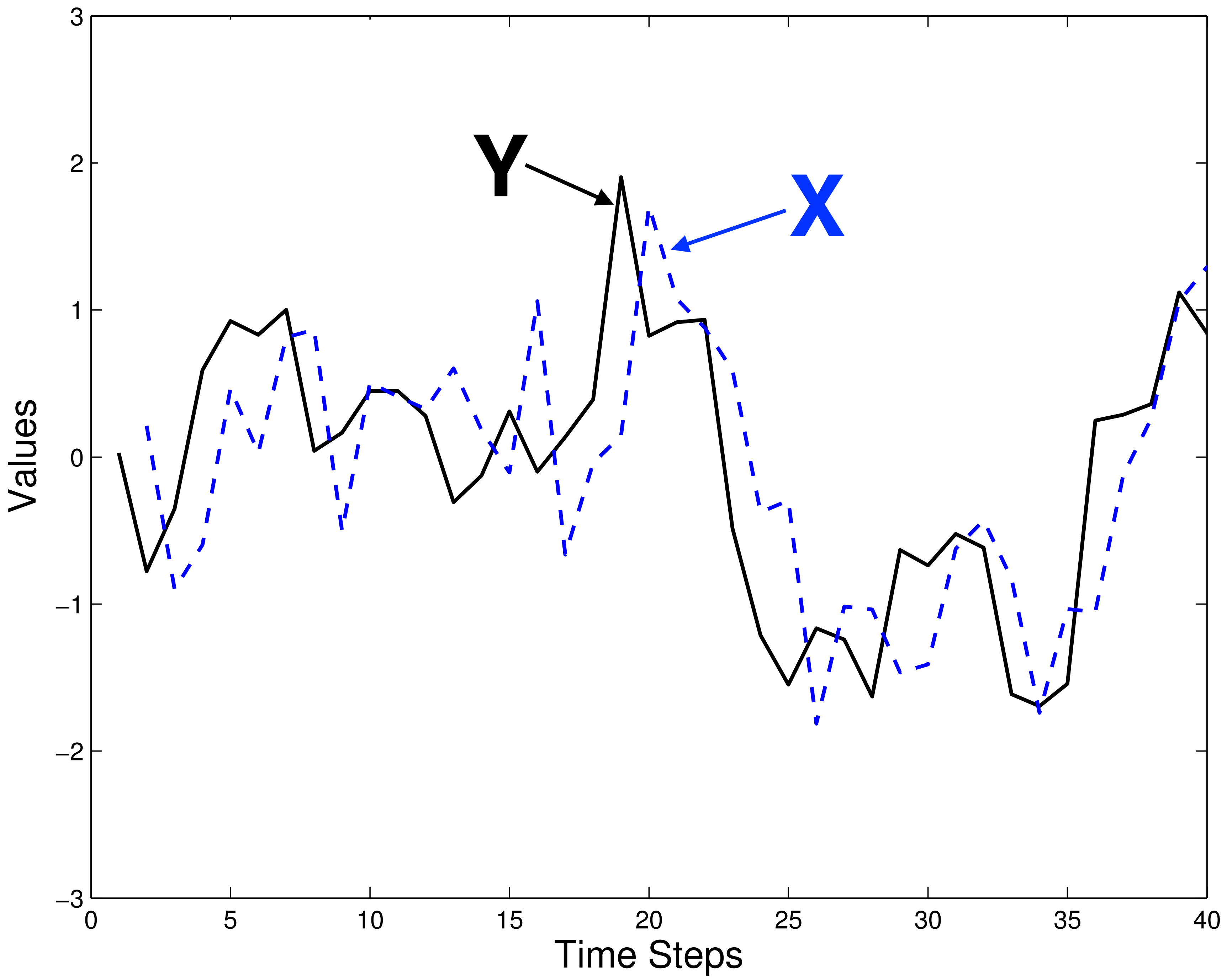
- Pretend we don’t know the relationship between X and Y
- **Step 1:** test whether Y —> X **[*right*]**
- **Step 2:** test whether X —> Y **[*wrong*]**

$$X_t = bY_{t-1} + \epsilon_t$$

$$Y_t = bX_{t-1} + \epsilon_t$$

McGraw and Barnes (in prep)

Lagged regression



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- **Step 1:** test whether Y —> X **[*right*]**
- **Step 2:** test whether X —> Y **[*wrong*]**

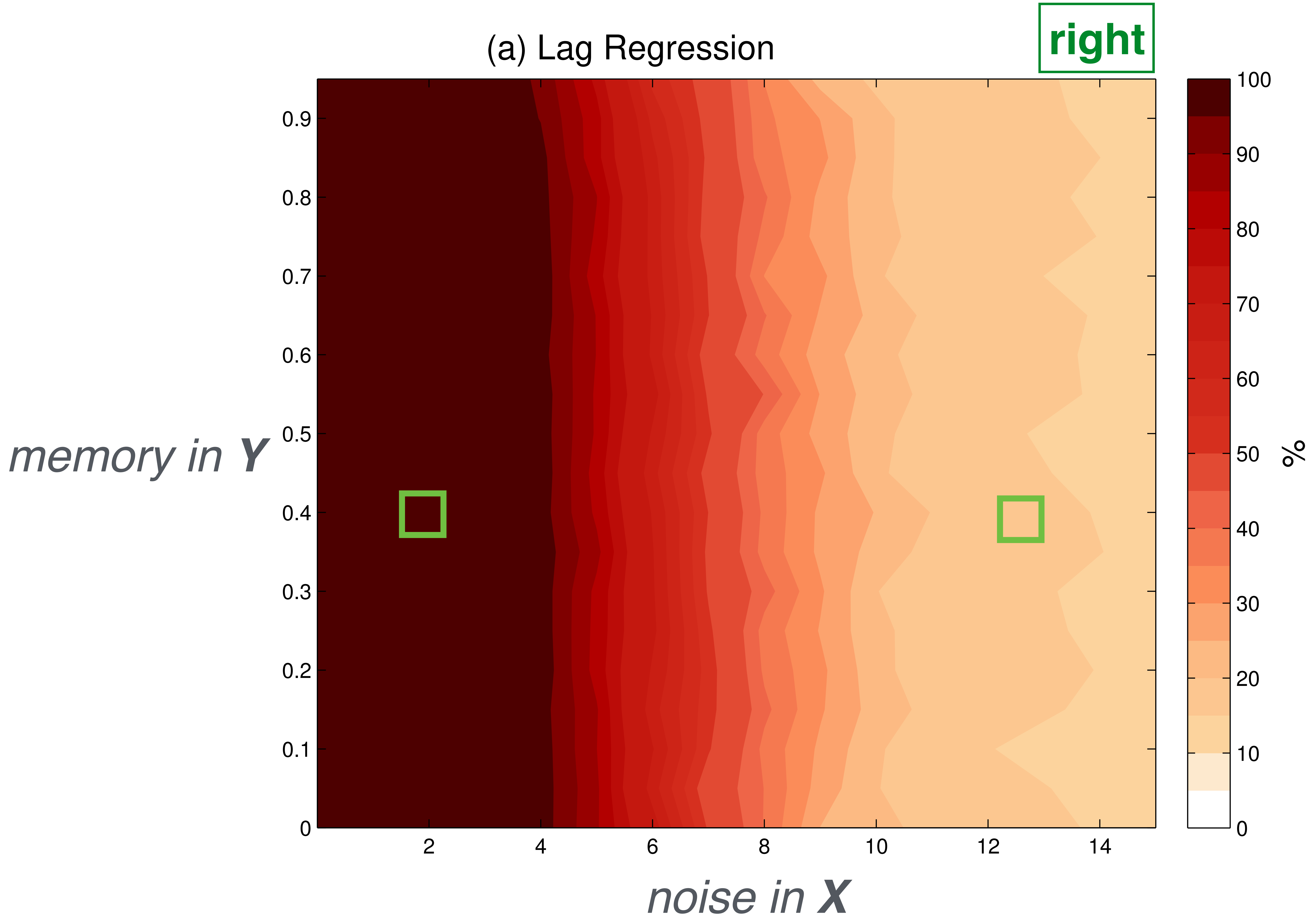
$$X_t = bY_{t-1} + \epsilon_t$$

how much?

$$Y_t = bX_{t-1} + \epsilon_t$$

McGraw and Barnes (in prep)

Lagged regression



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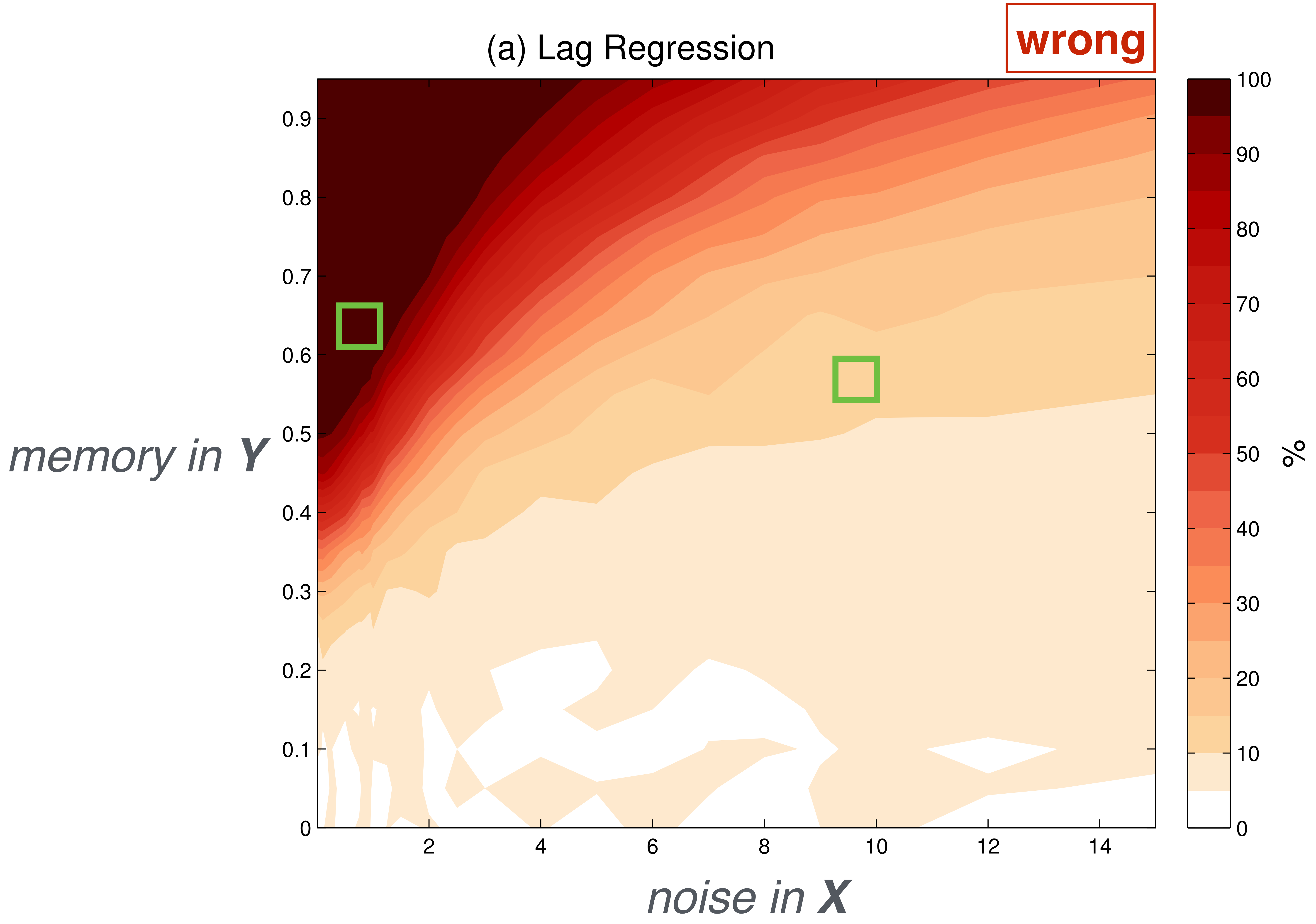

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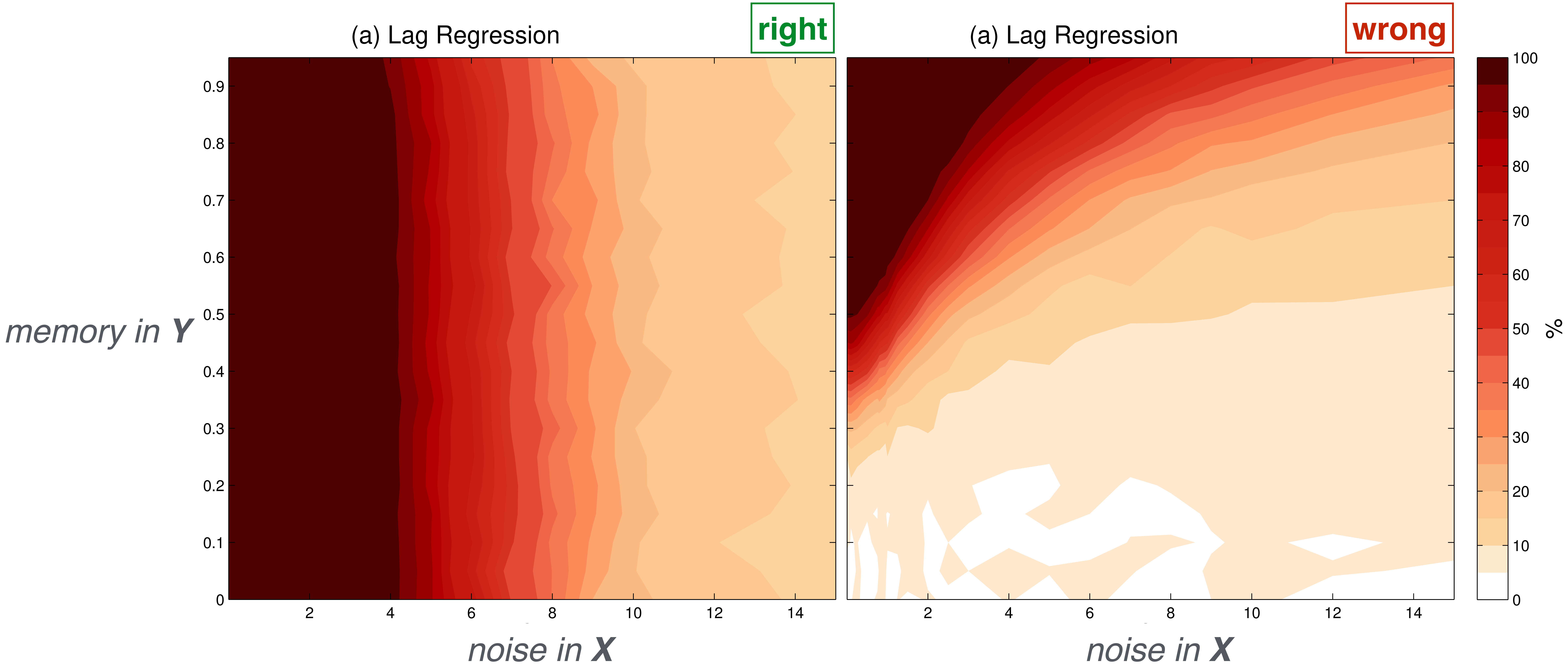
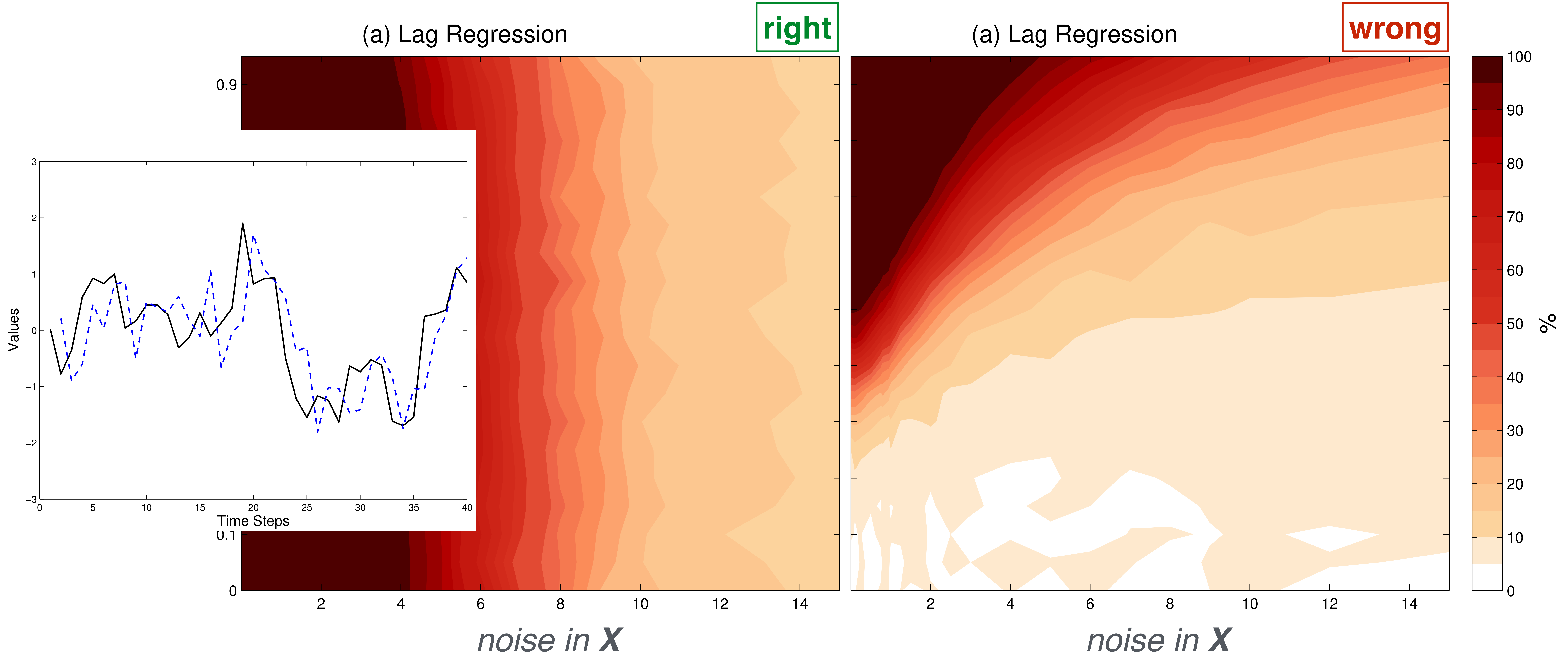


McGraw and Barnes (submitted)

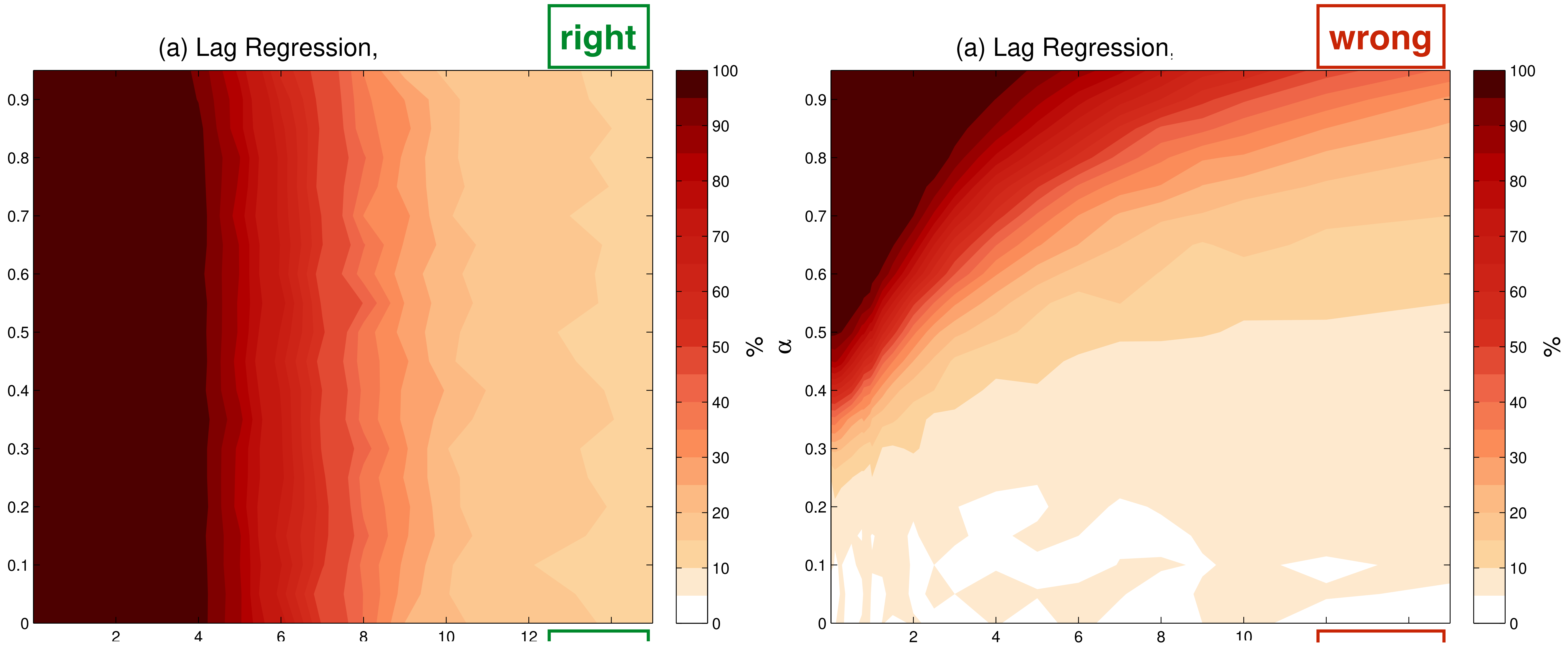
Elizabeth A. Barnes

Lagged regression



McGraw and Barnes (submitted)

Granger causality

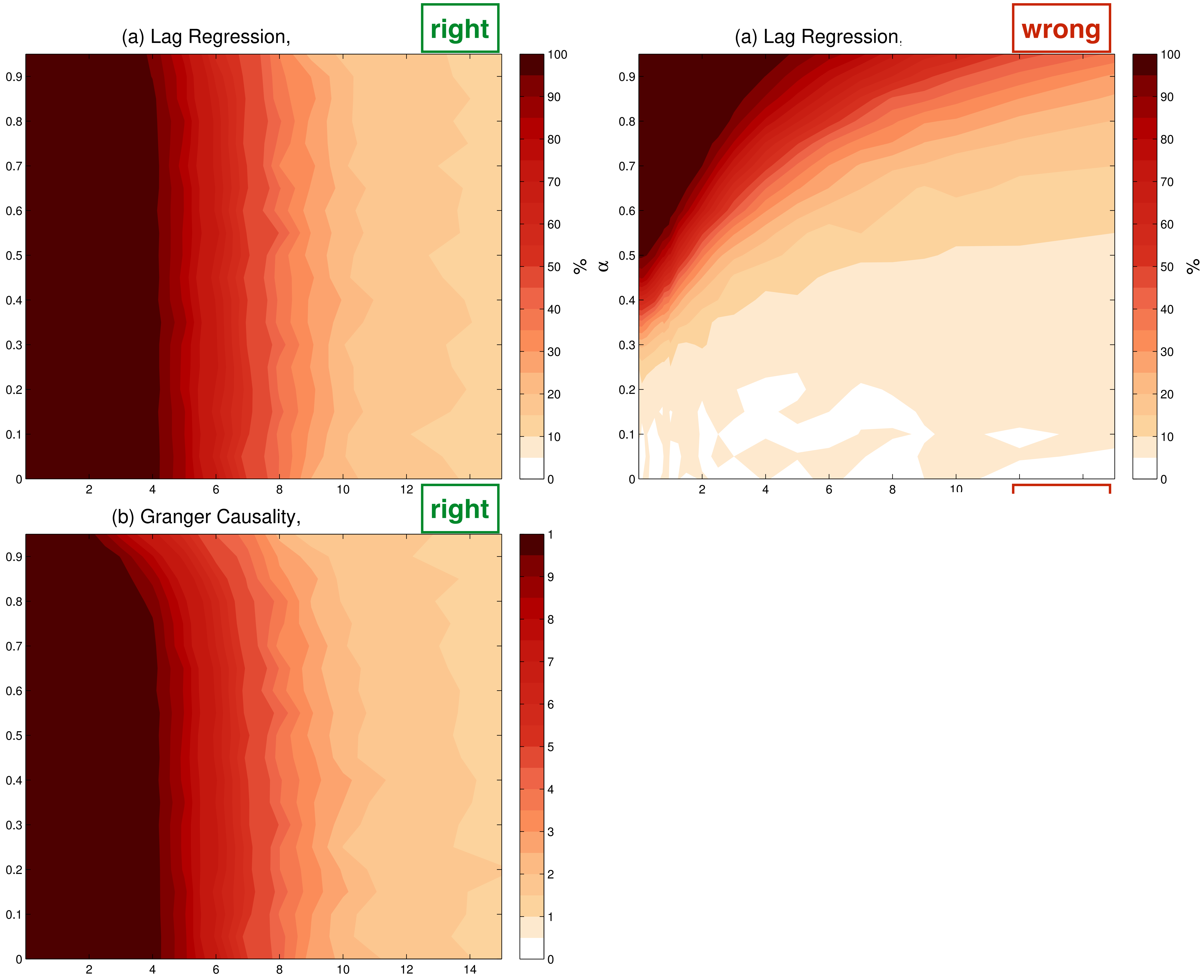


*memory in **Y***

*noise in **X***

McGraw and Barnes (submitted)

Granger causality



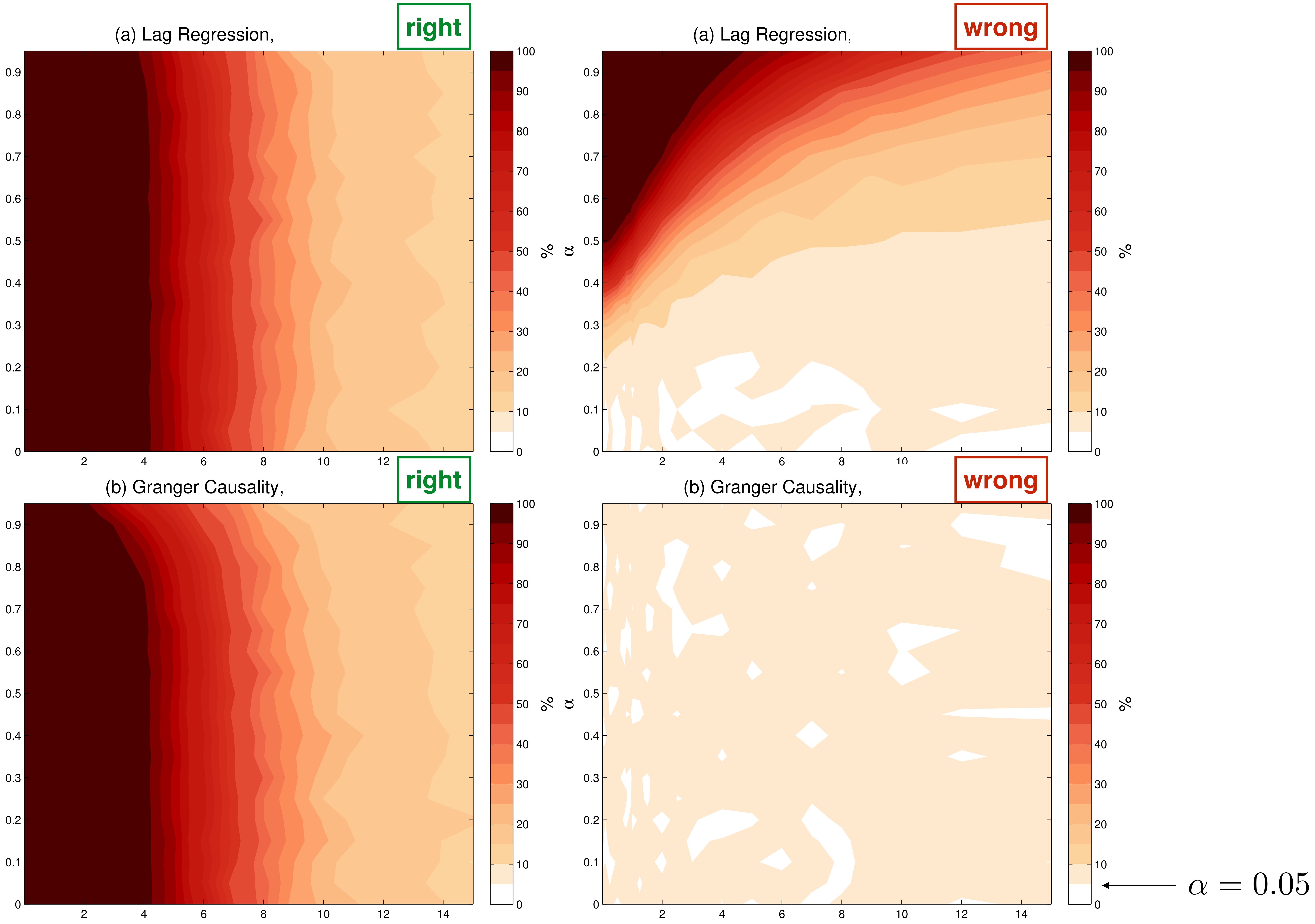
memory in ***Y***

noise in ***X***

McGraw and Barnes (submitted)

Granger causality

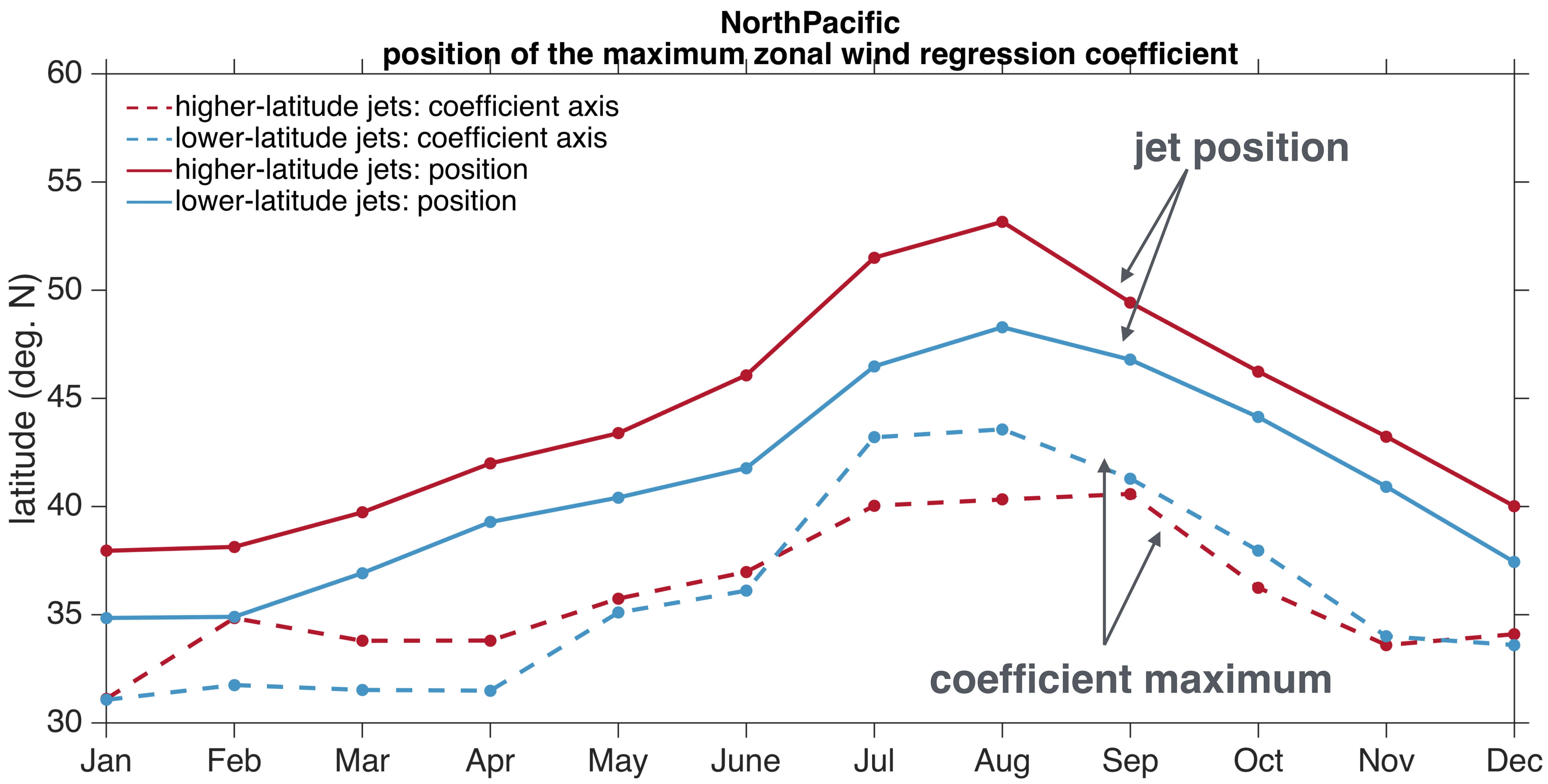
memory in ***Y***



noise in ***X***

McGraw and Barnes (submitted)

Models with higher latitude jets shift further



Barnes and Simpson (submitted)

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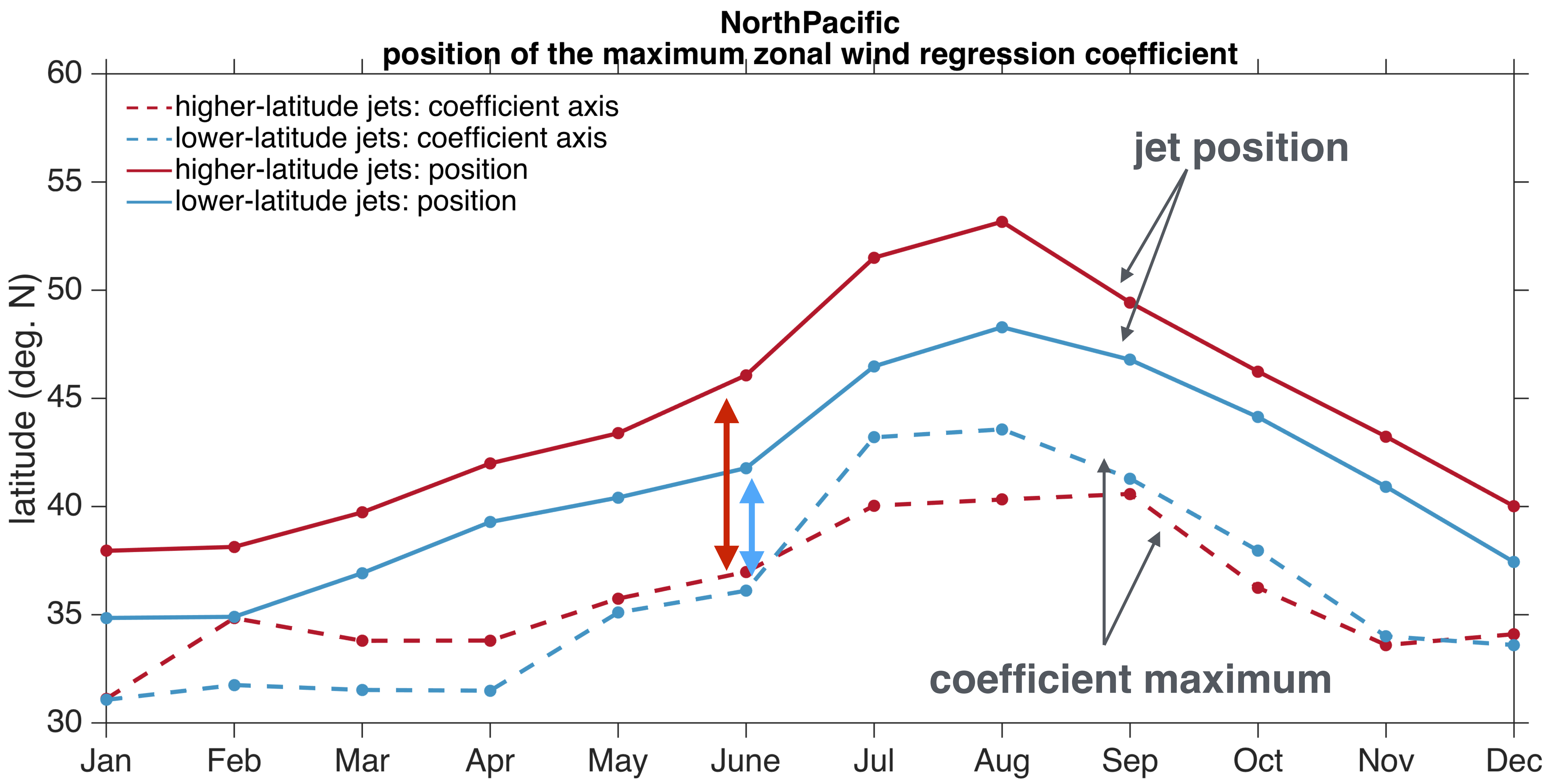

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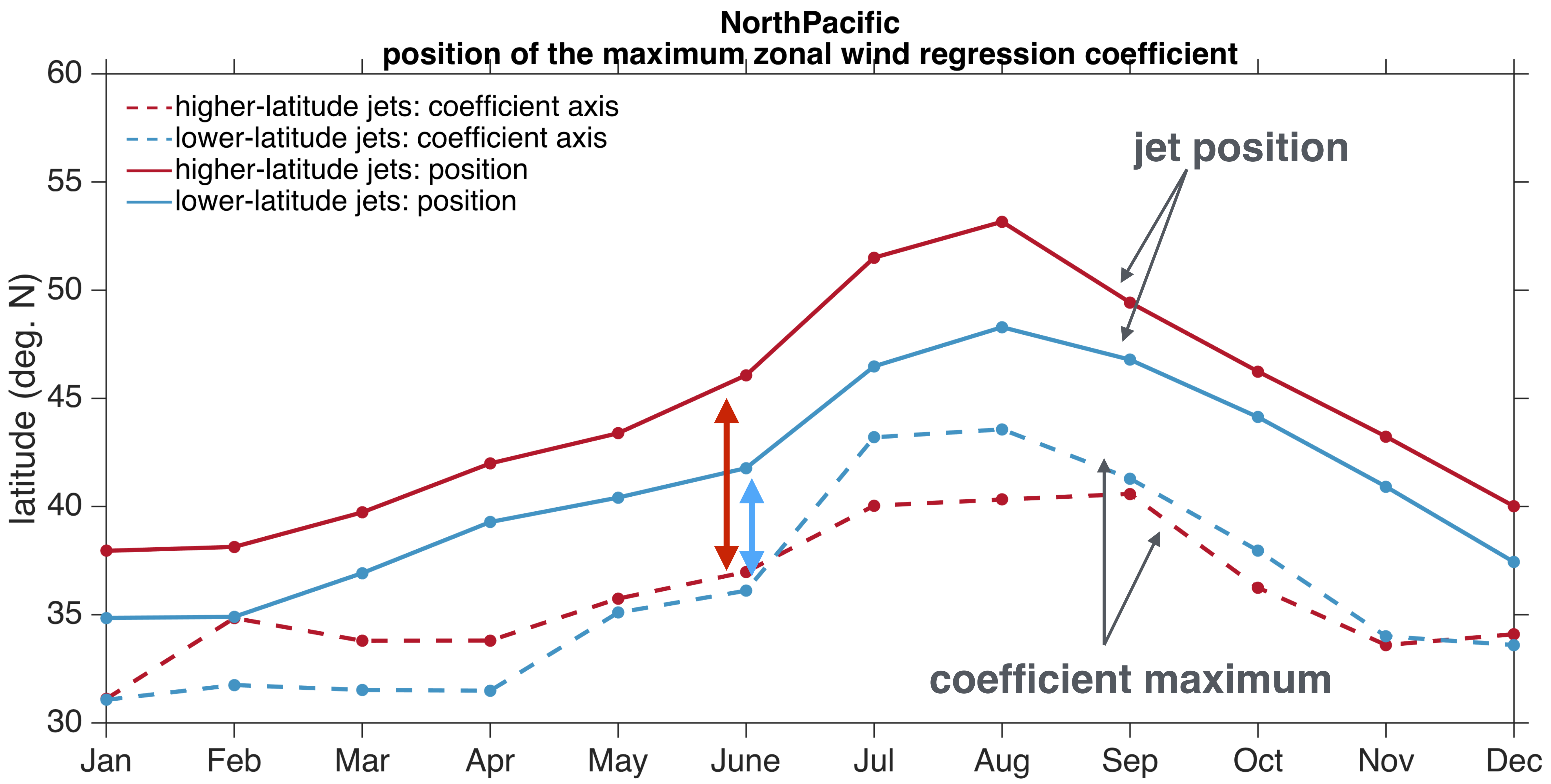

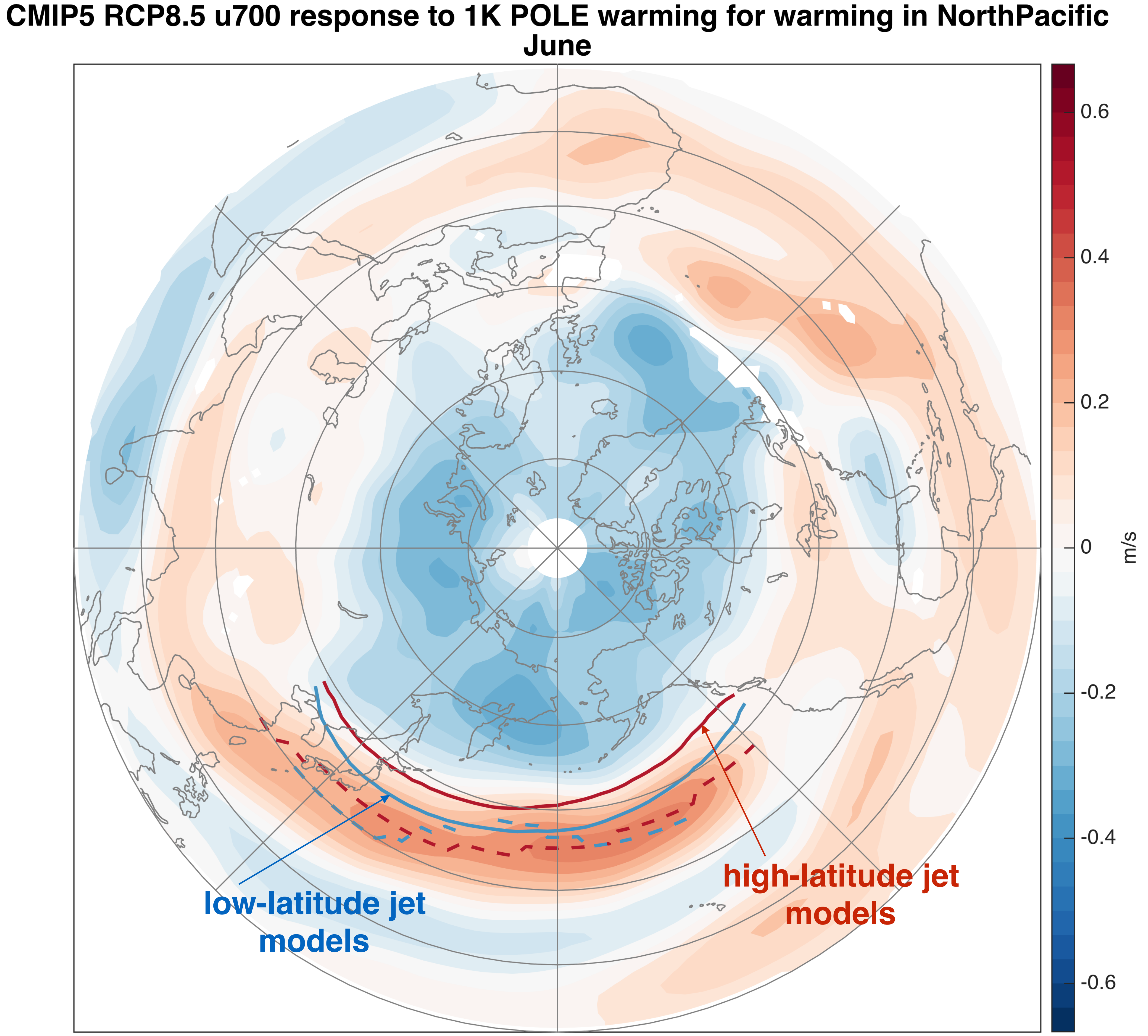

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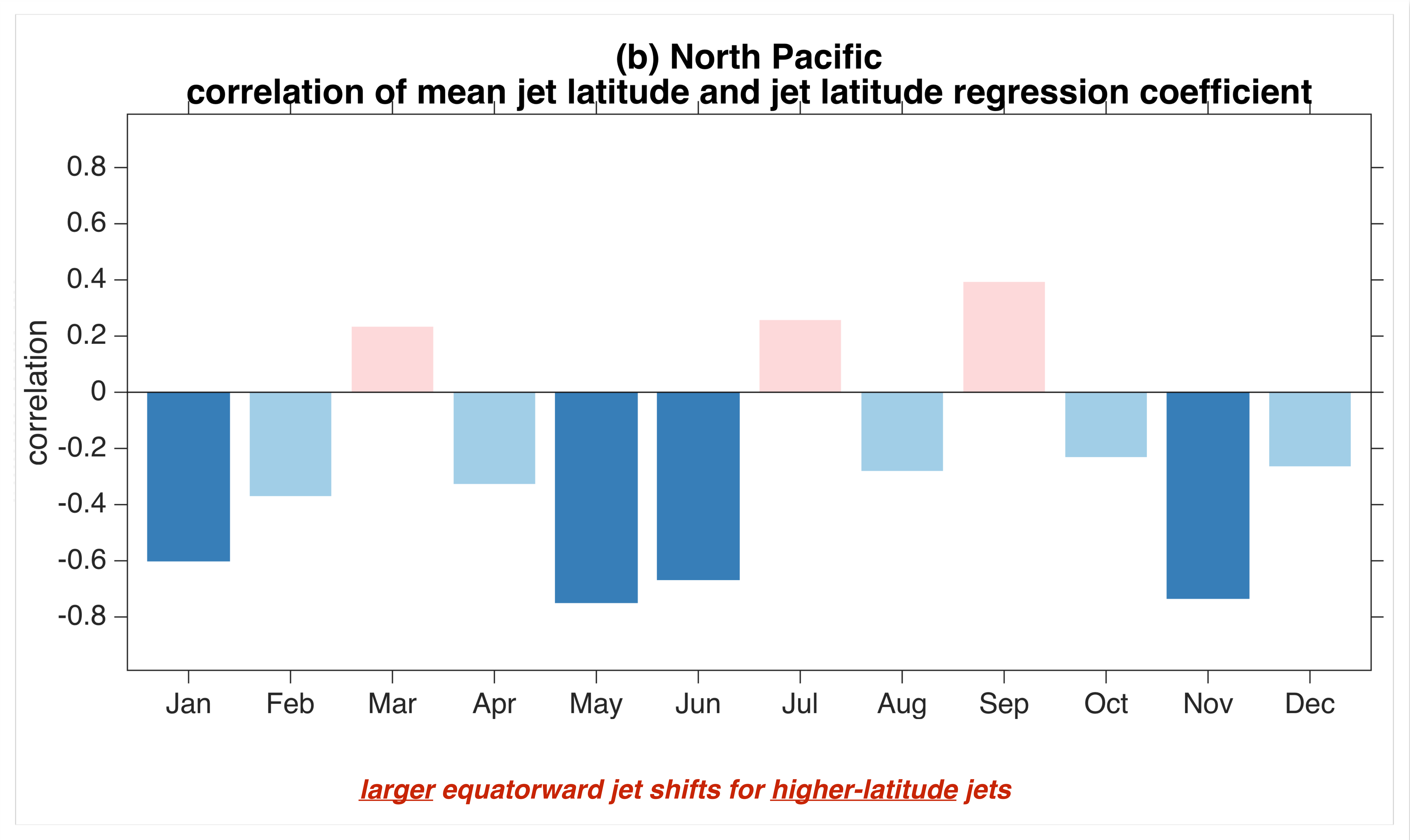
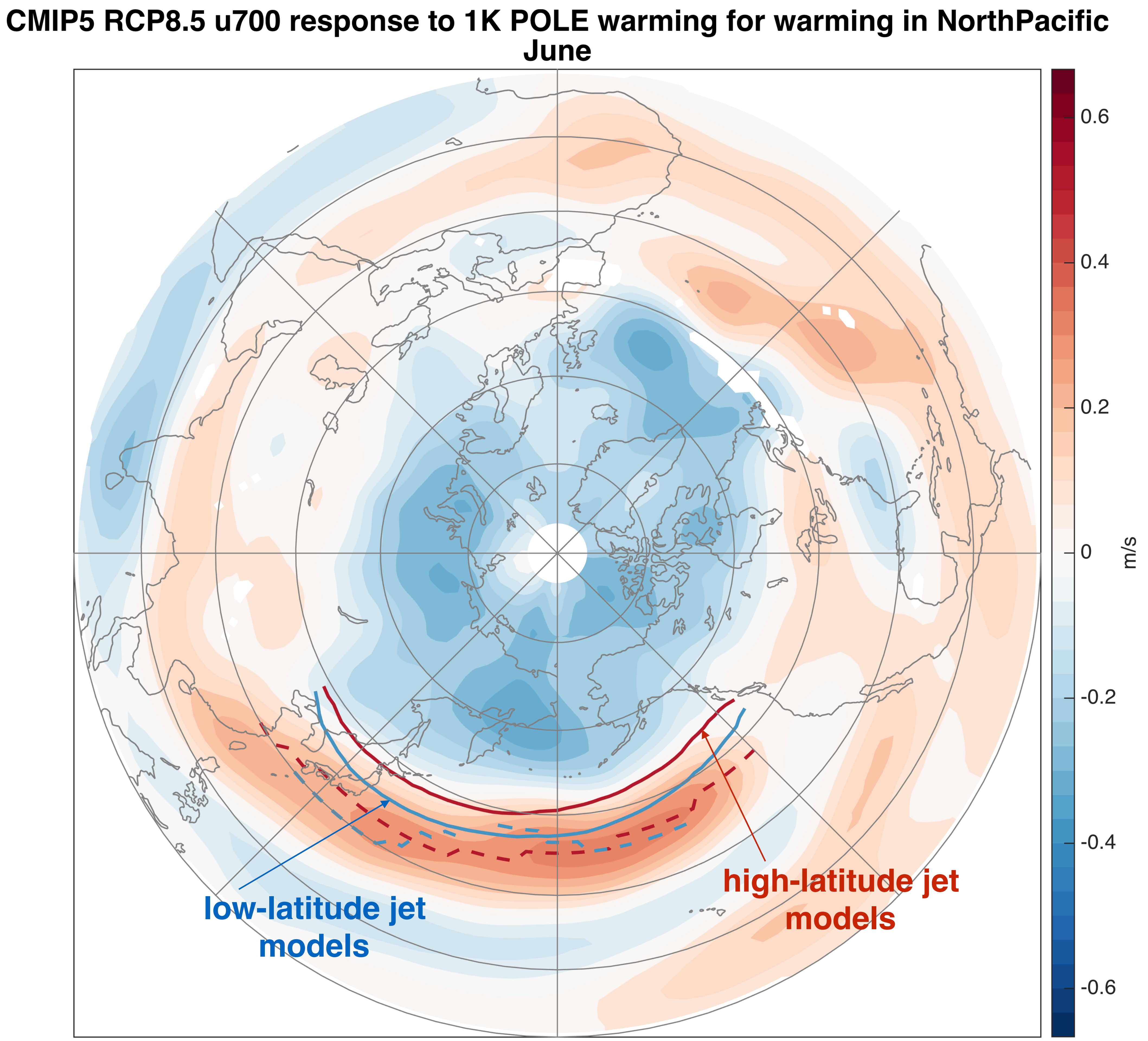
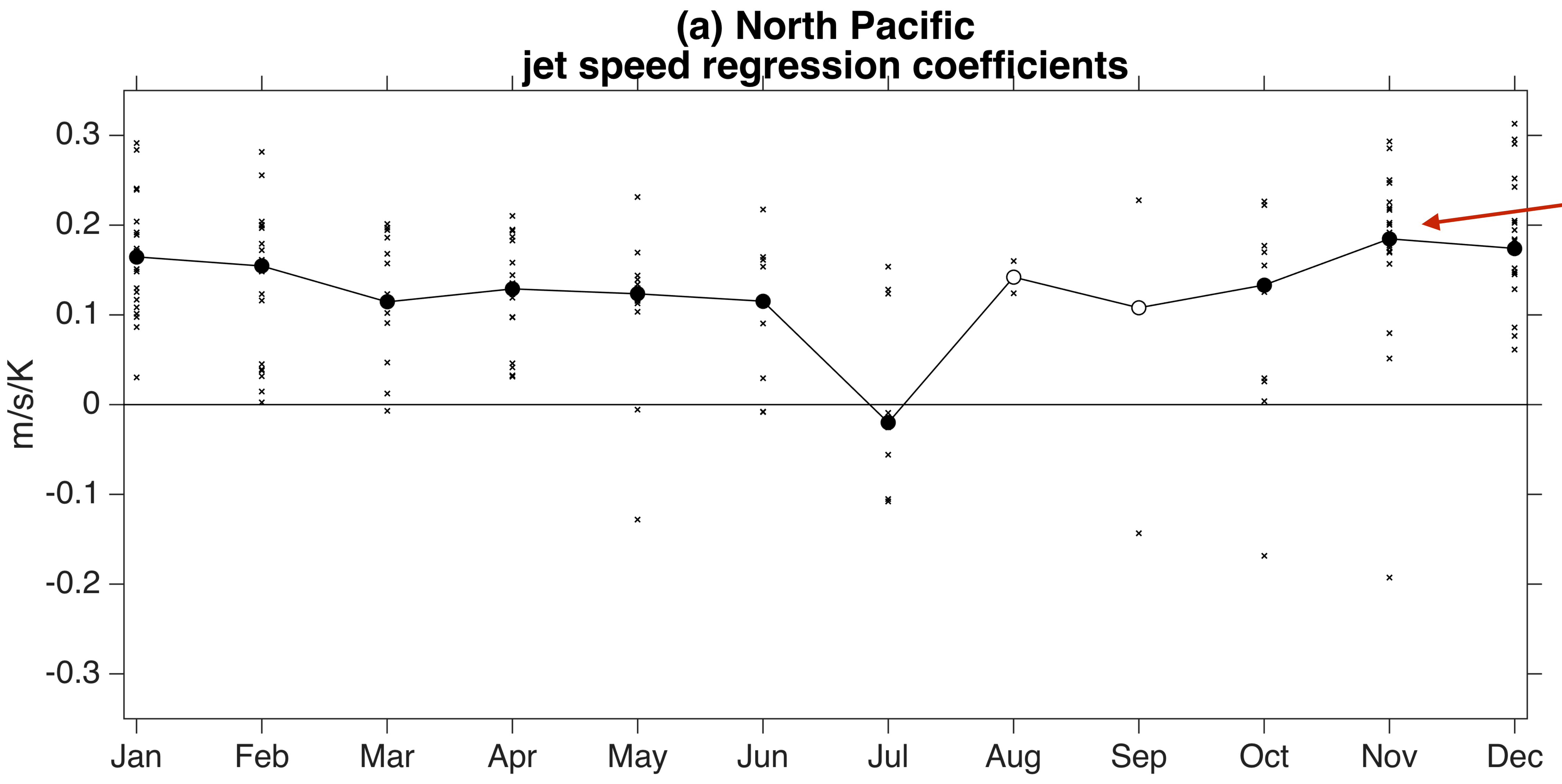


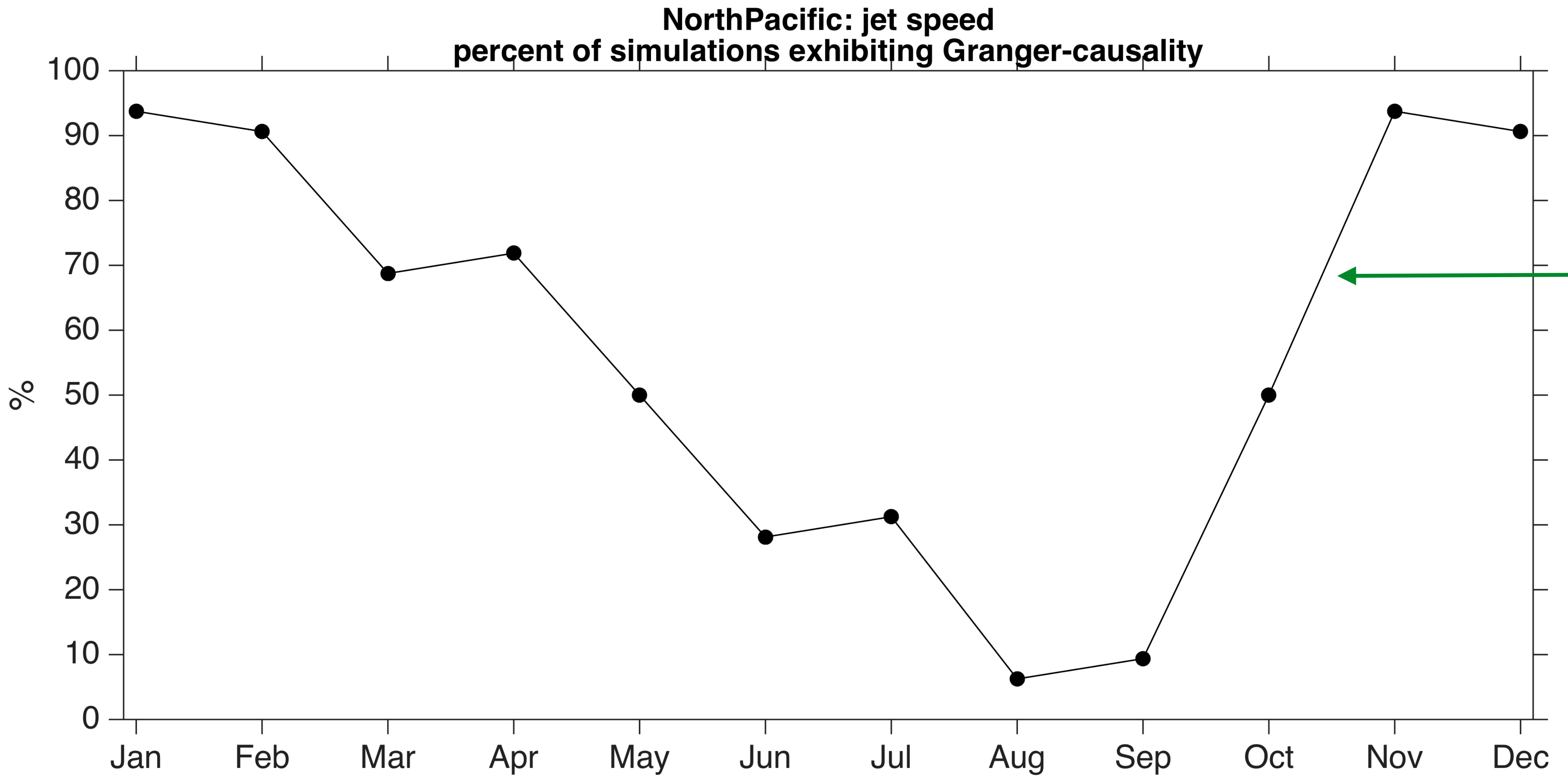


Barnes and Simpson (submitted)

How Much?: **jet speed**



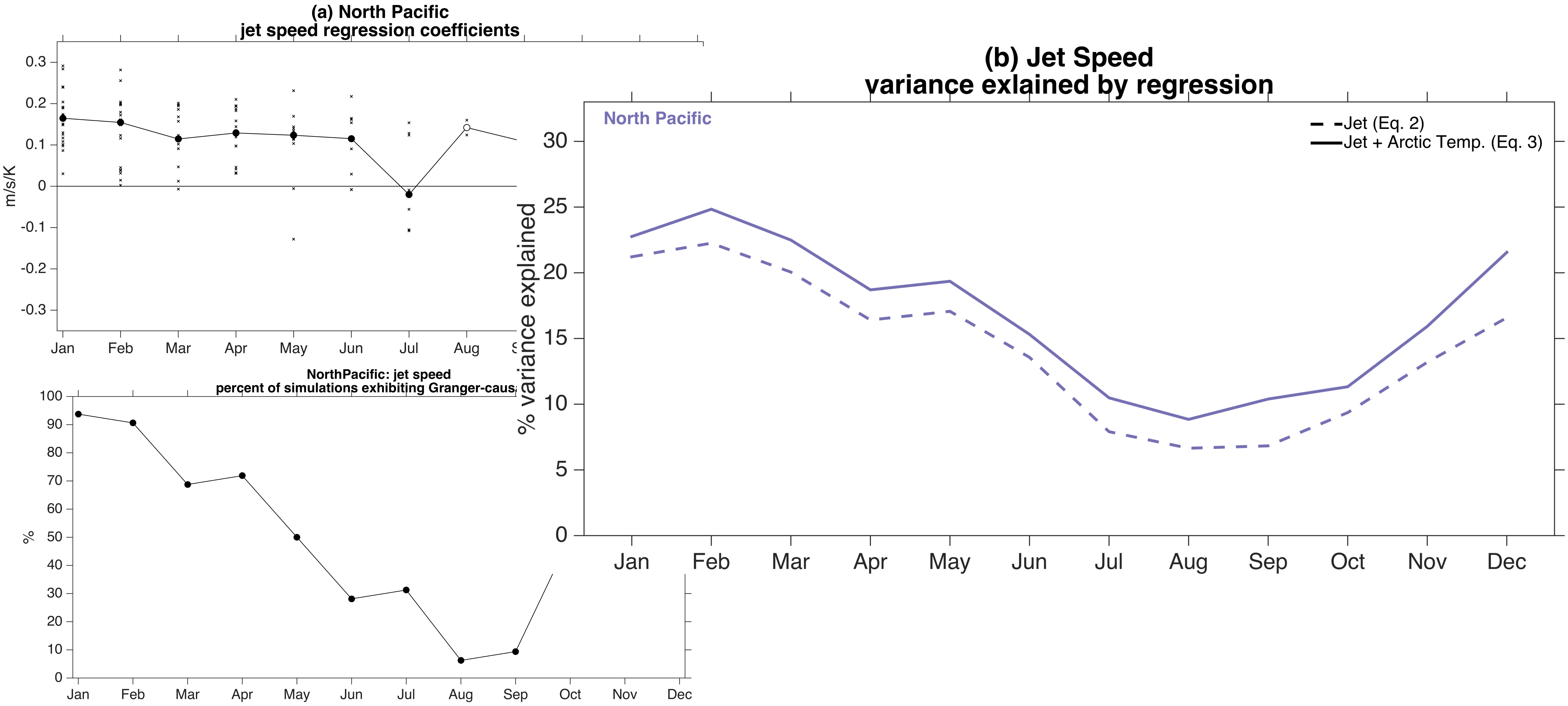
jet **strengthens** in most months



large seasonality in number of models exhibiting Granger-causality

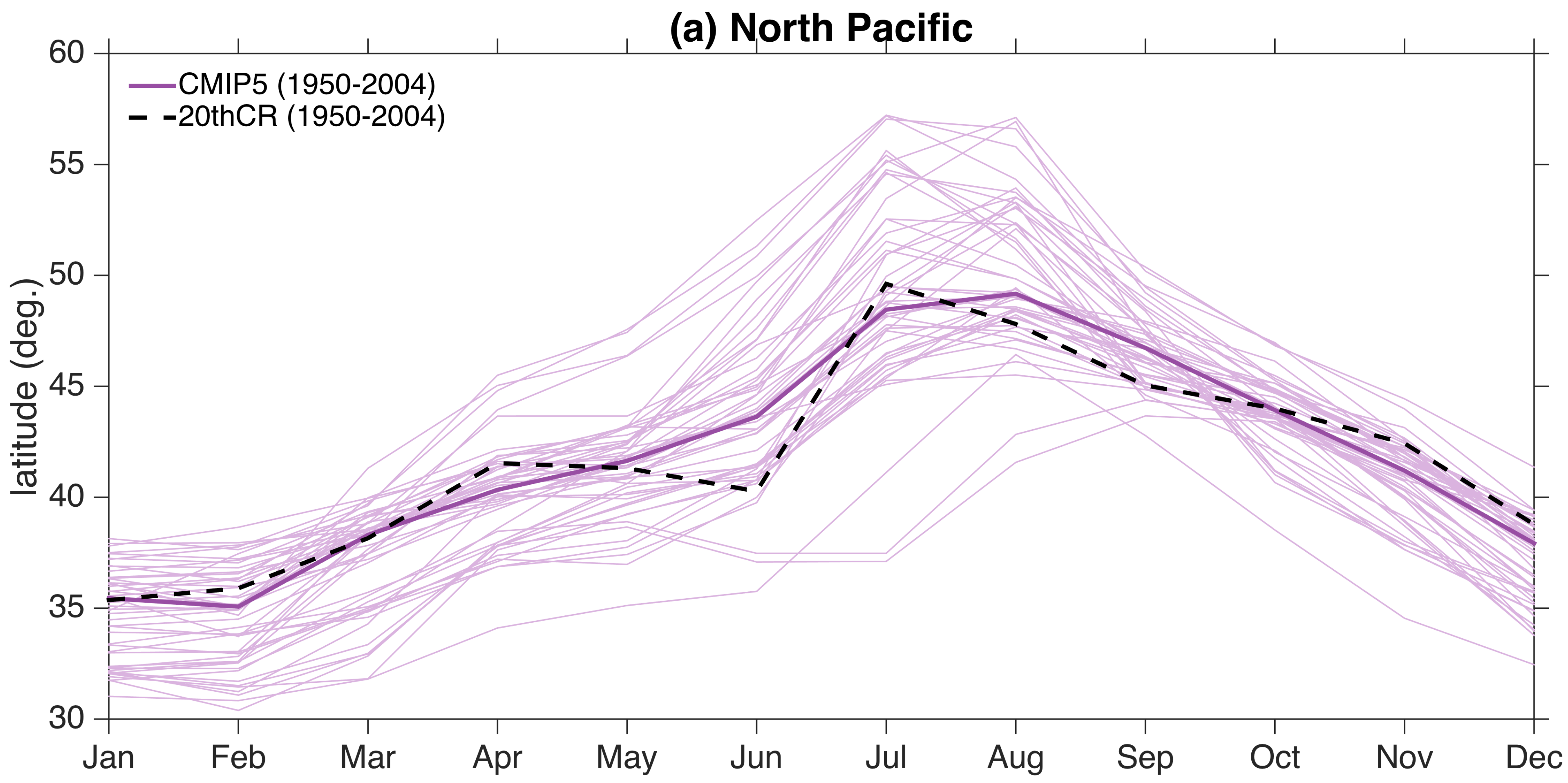
Barnes and Simpson (submitted)

How Much?: **jet speed**



Barnes and Simpson (submitted)

Implications for models biases

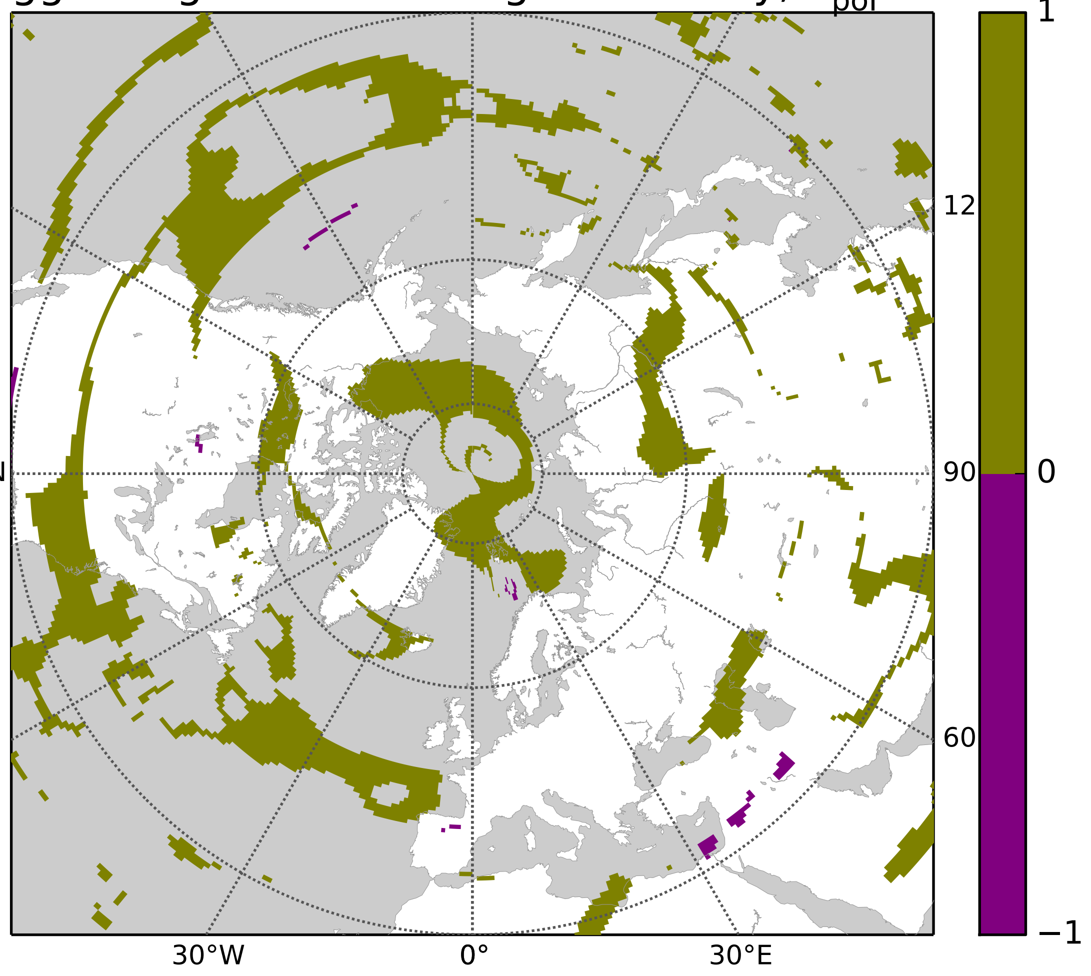


models exhibit seasonal biases in the mean jet position

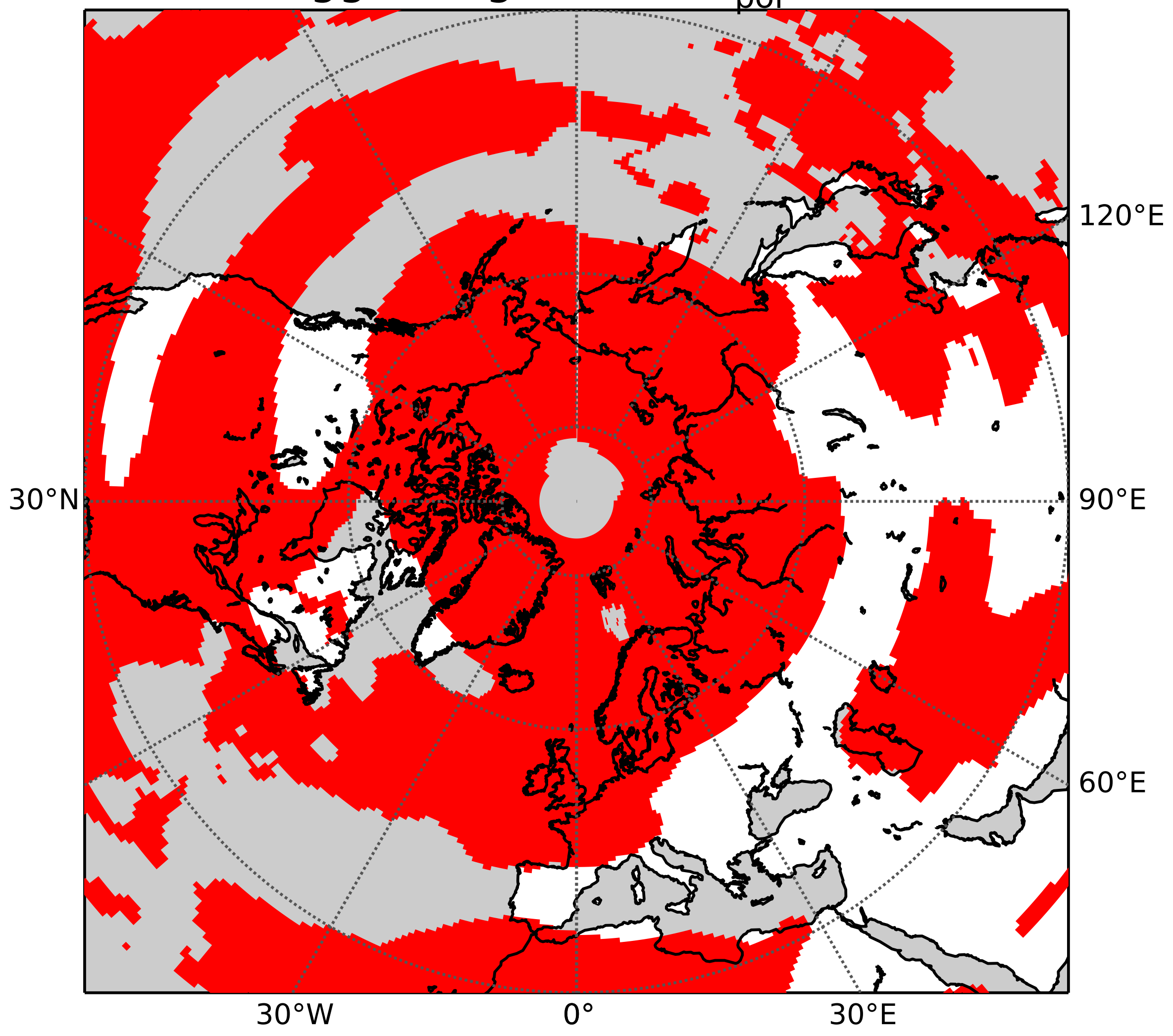
Barnes and Simpson (in prep)

Applied to Arctic temperatures and 700hPa zonal wind

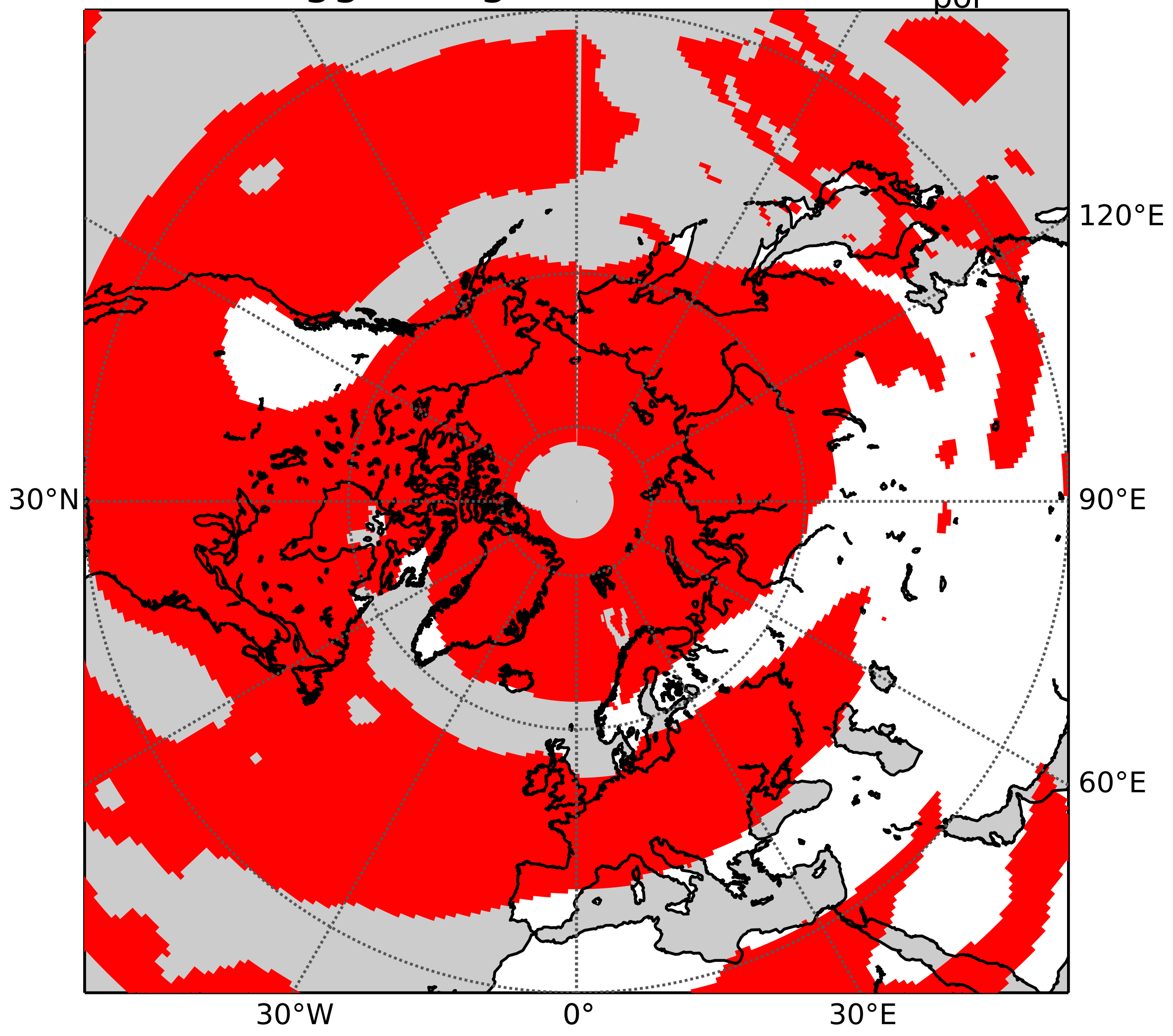
(a) Lagged regression - Granger causality, T_{pol}-> U700



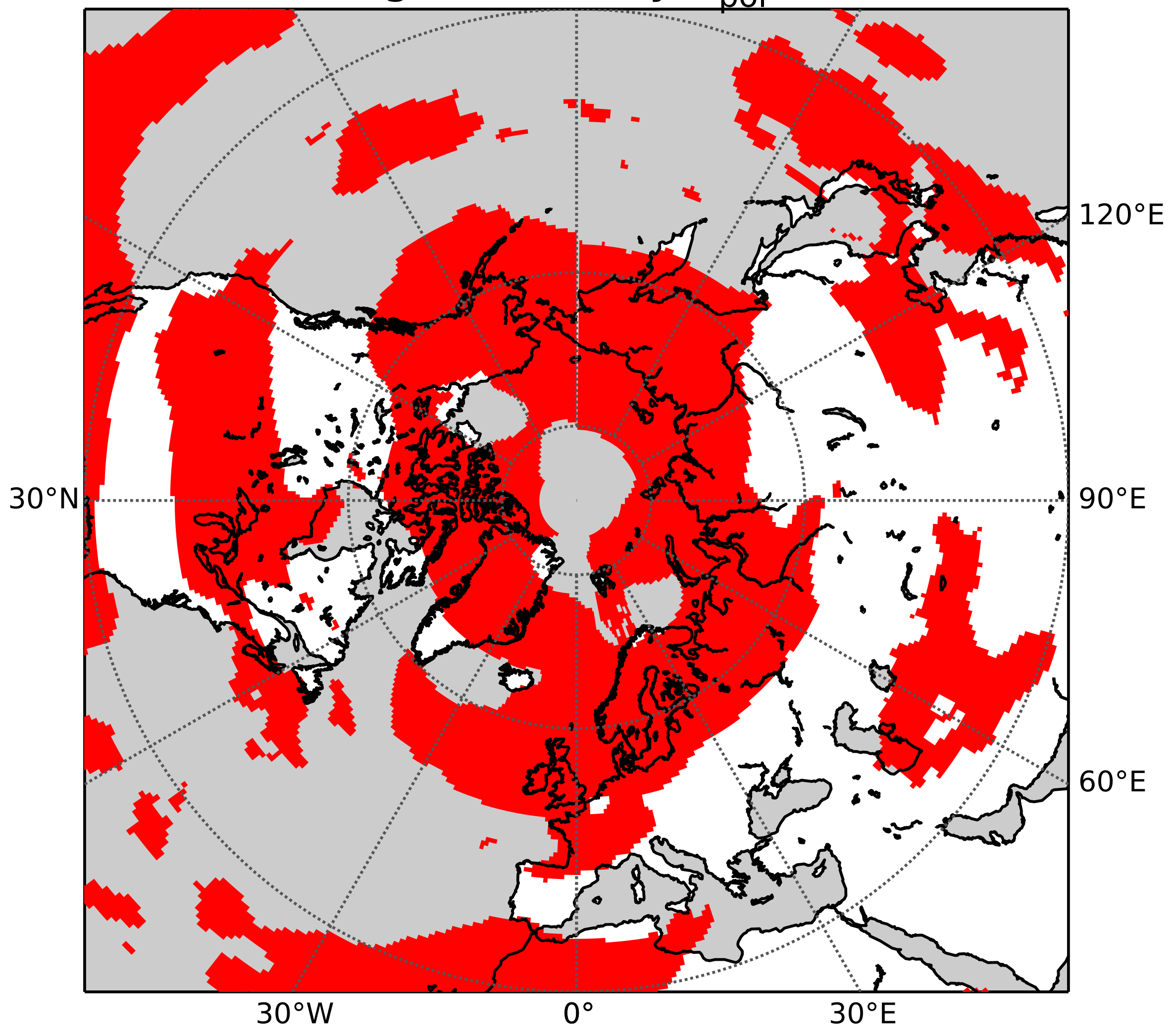
(a) Lagged regression, T_{pol}-> U700



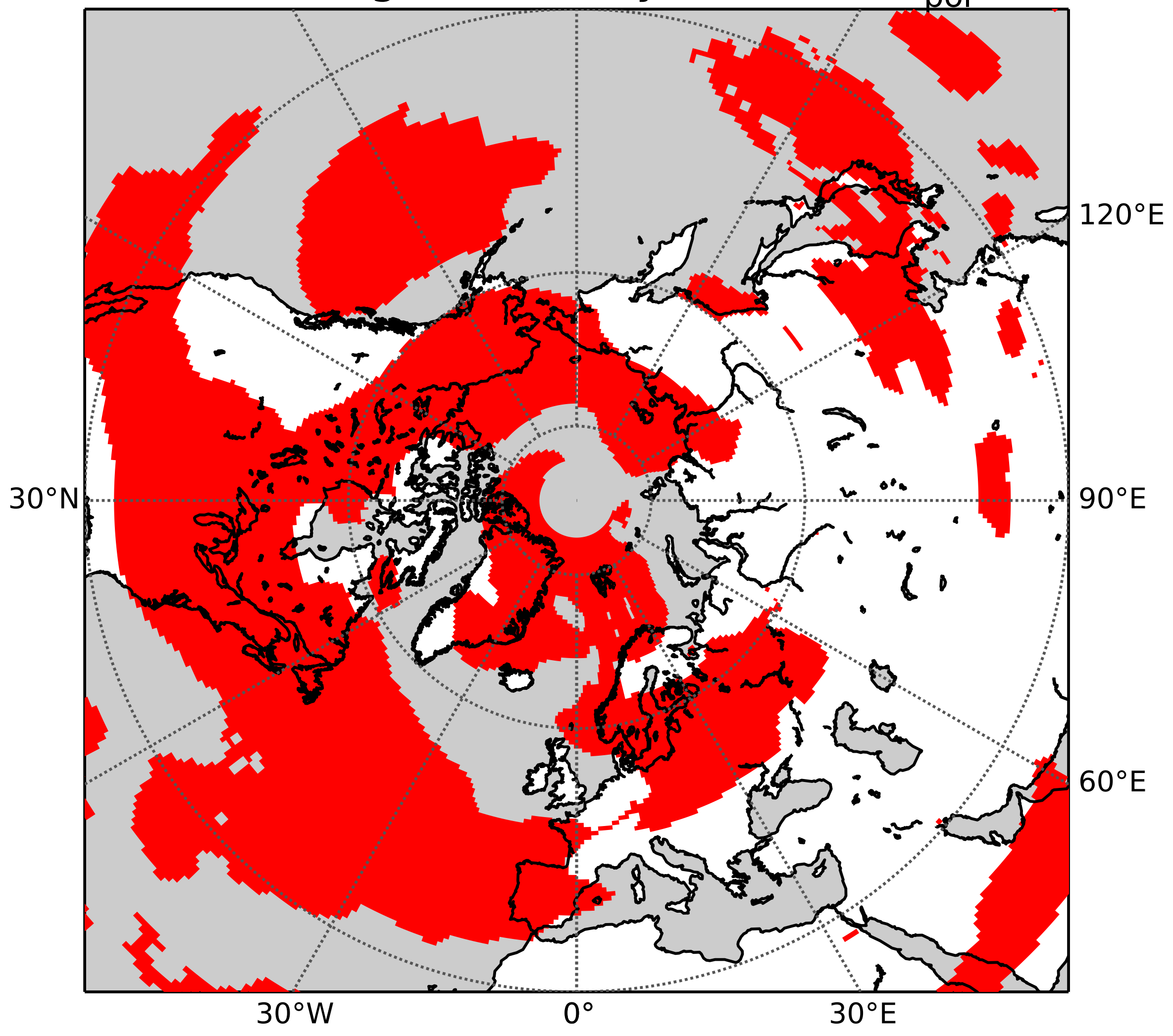
(b) Lagged regression, U700 -> T_{pol}



(c) Granger causality,T_{pol}-> U700



(d) Granger causality, U700 -> T_{pol}



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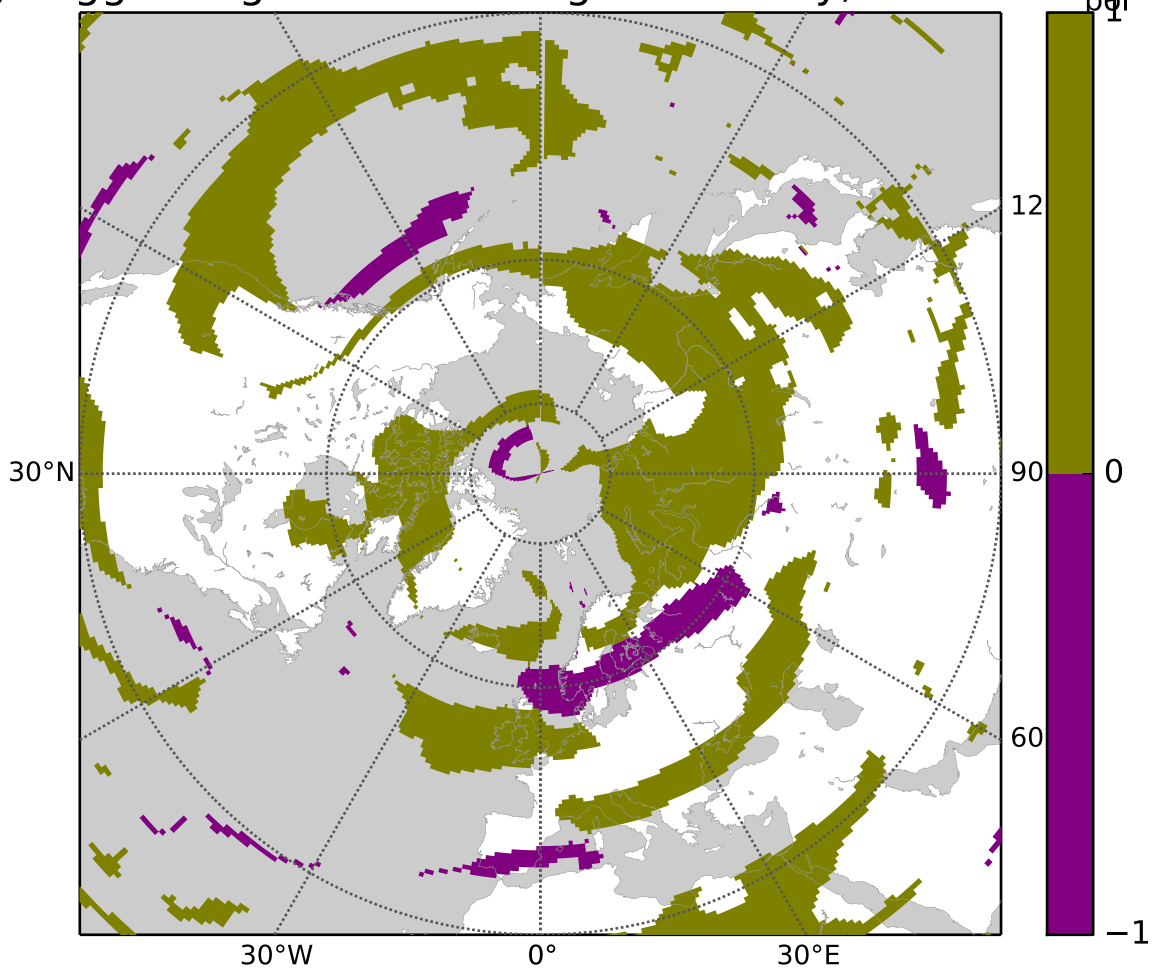
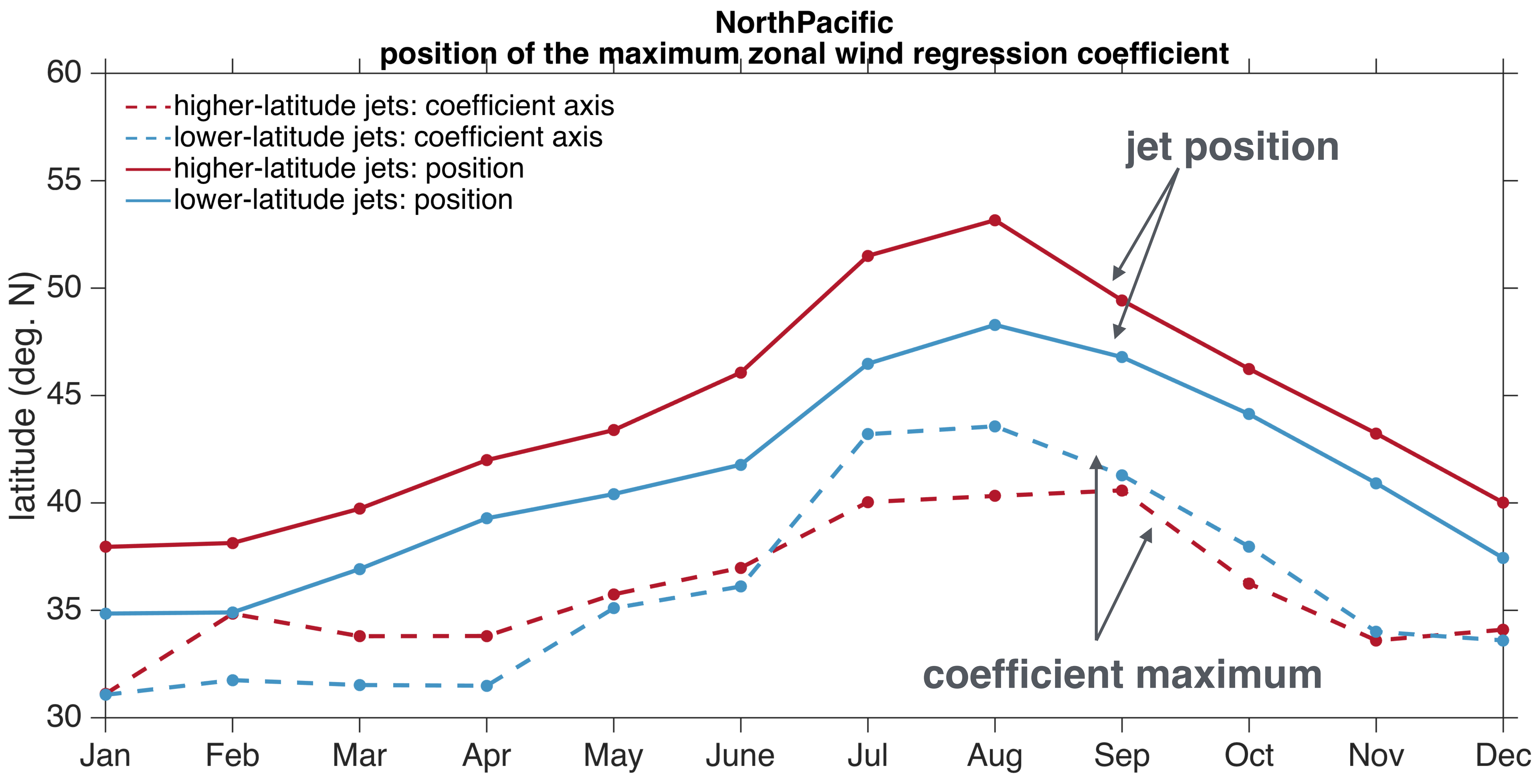


McGraw and Barnes (submitted)

Implications for models biases



Barnes and Simpson (in prep)

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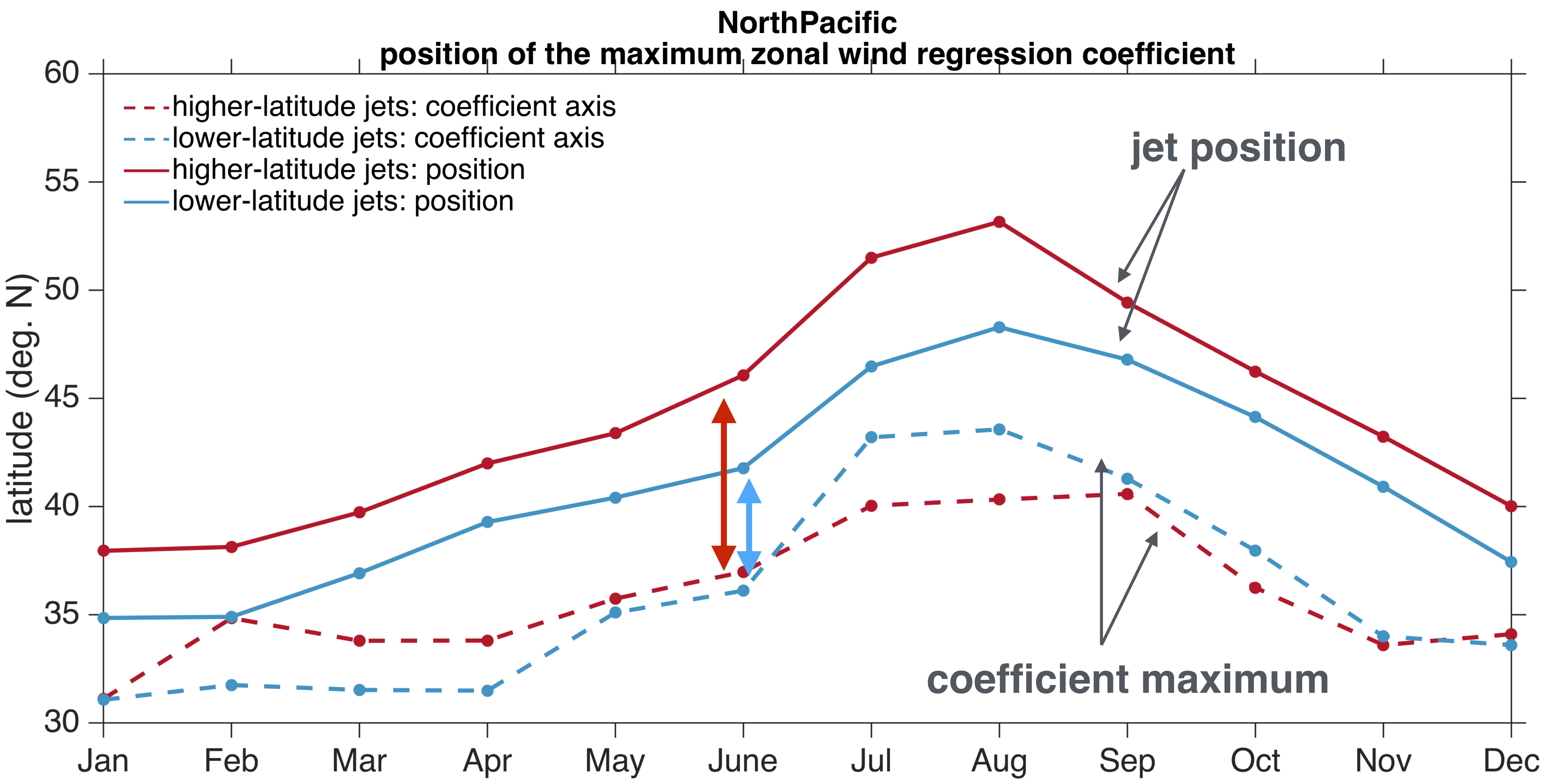

Barnes and Simpson (in prep)

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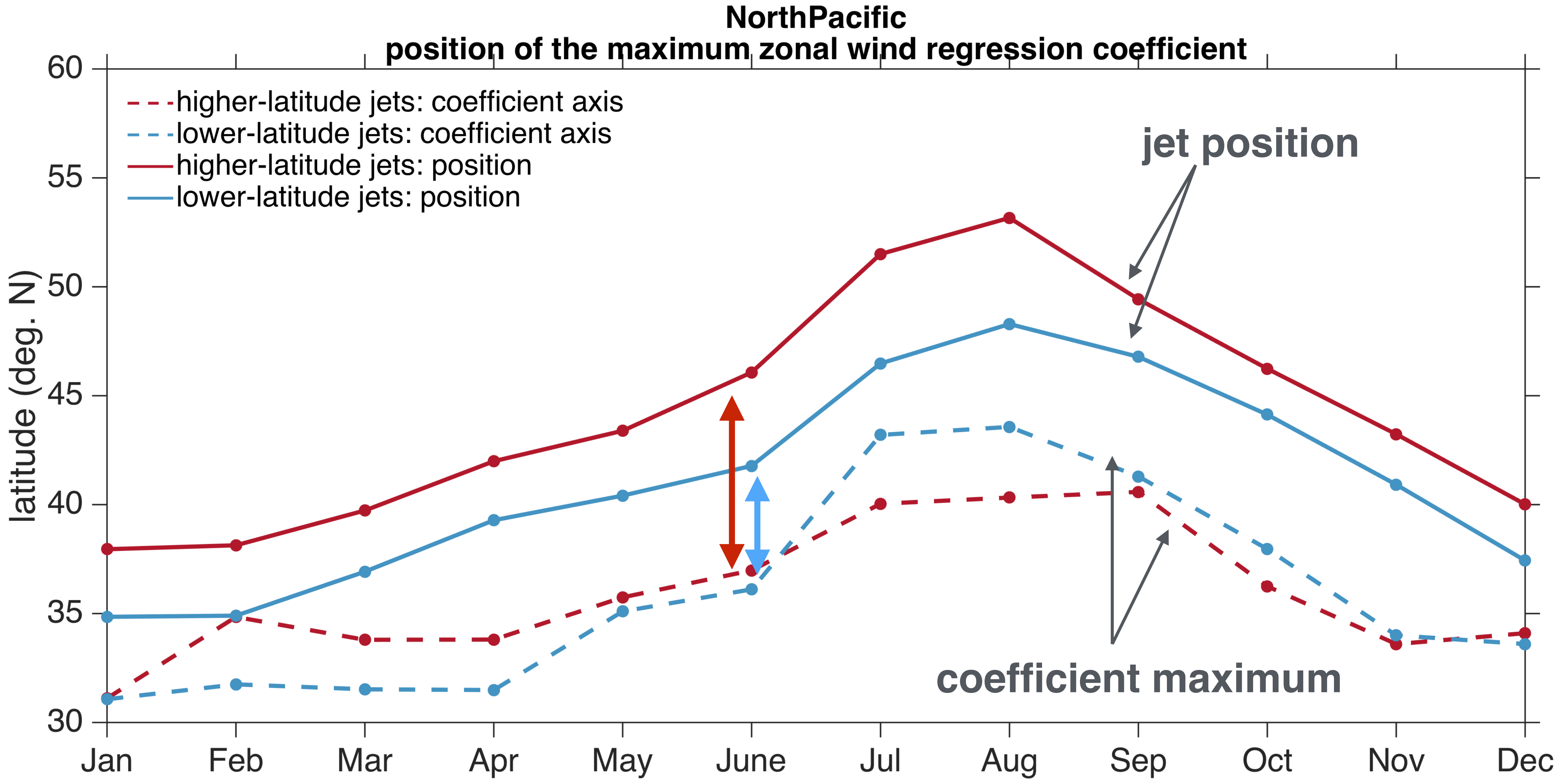

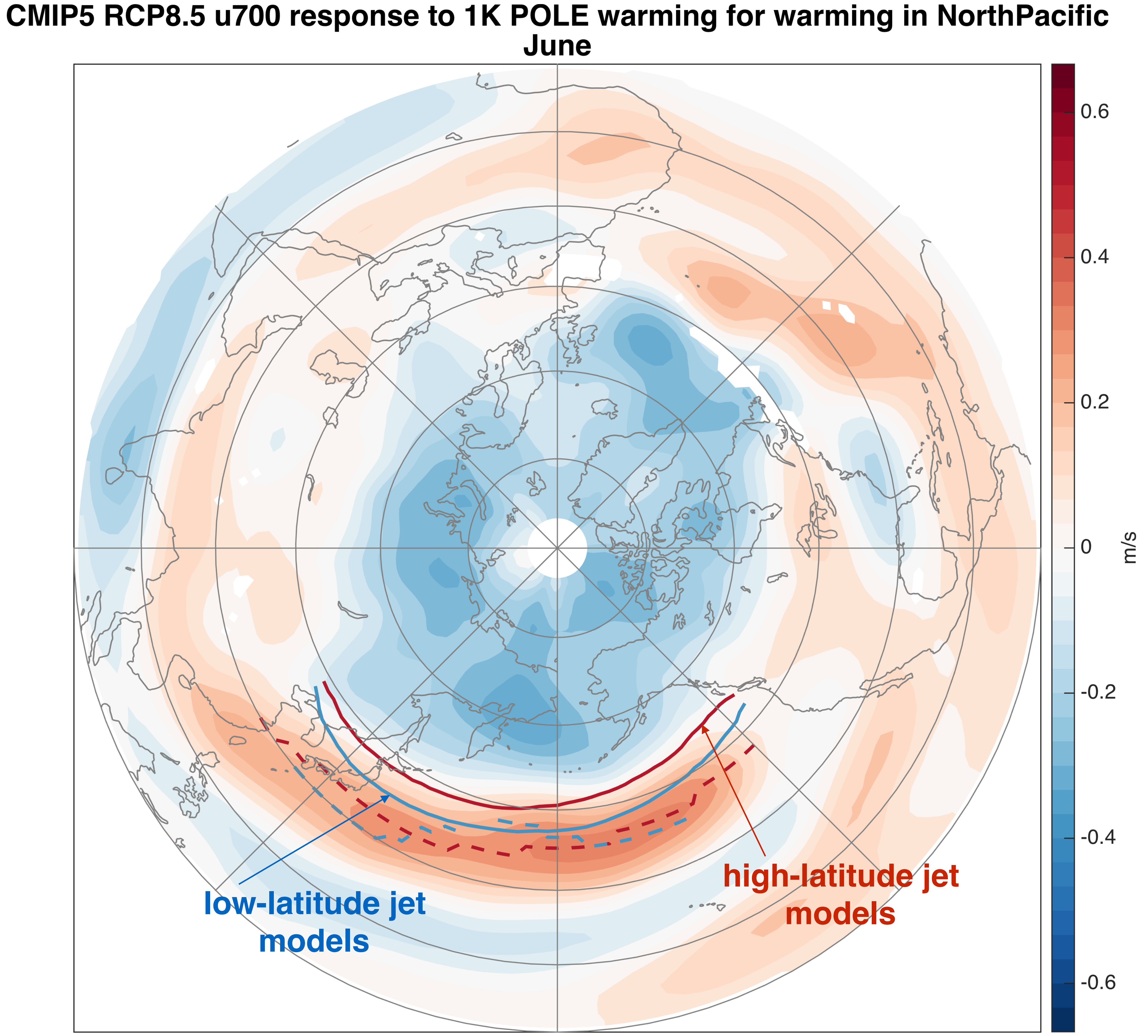

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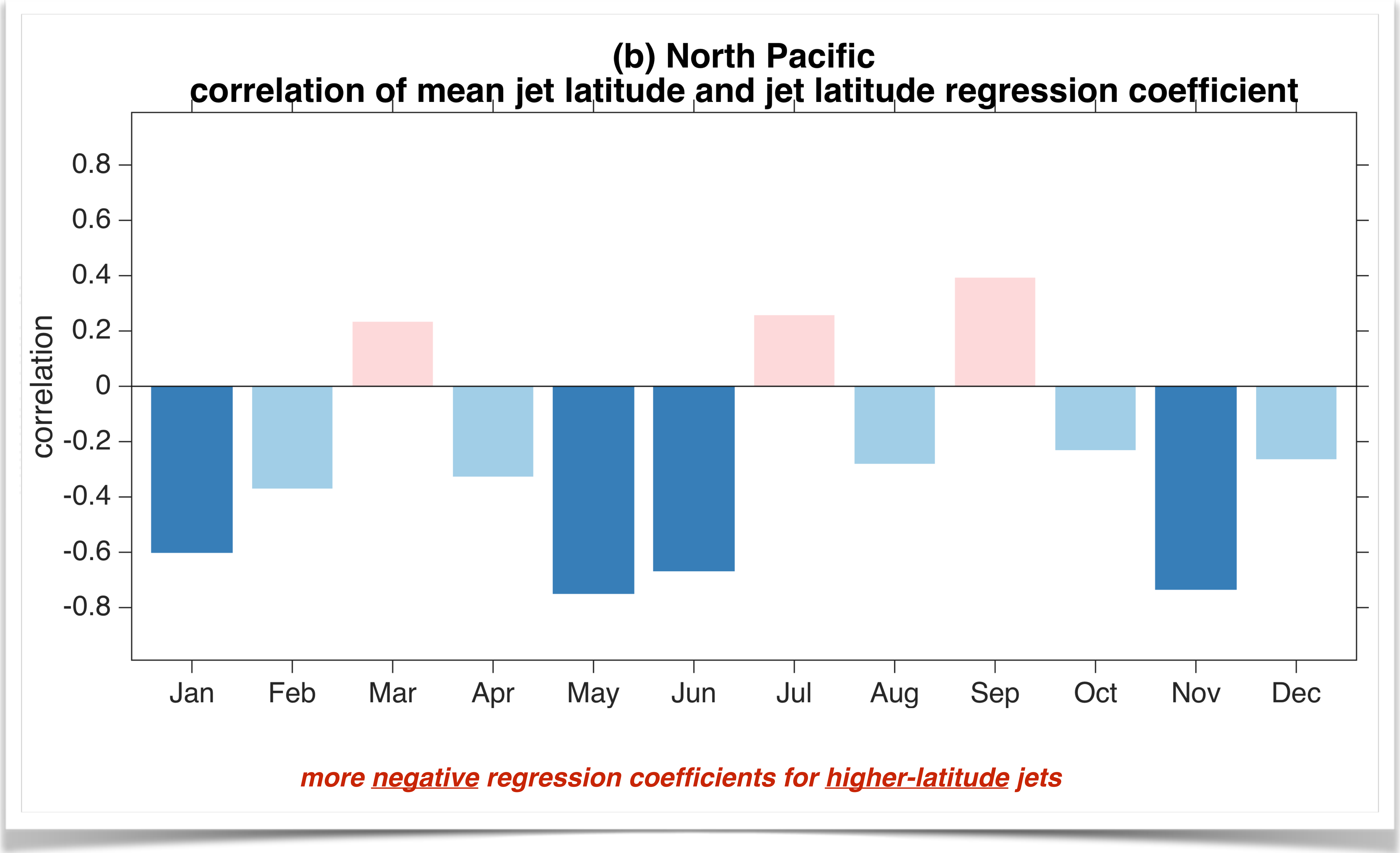
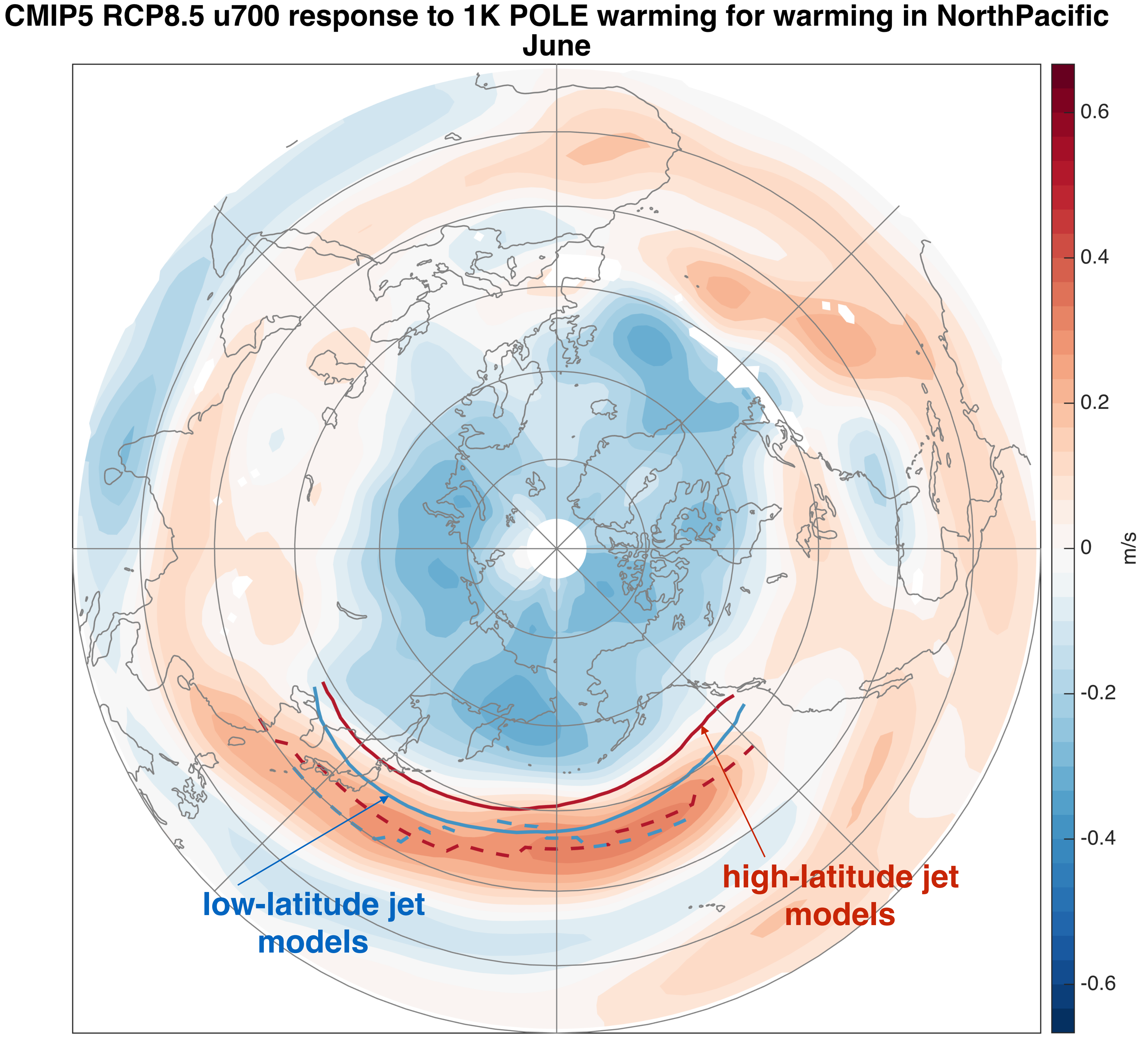
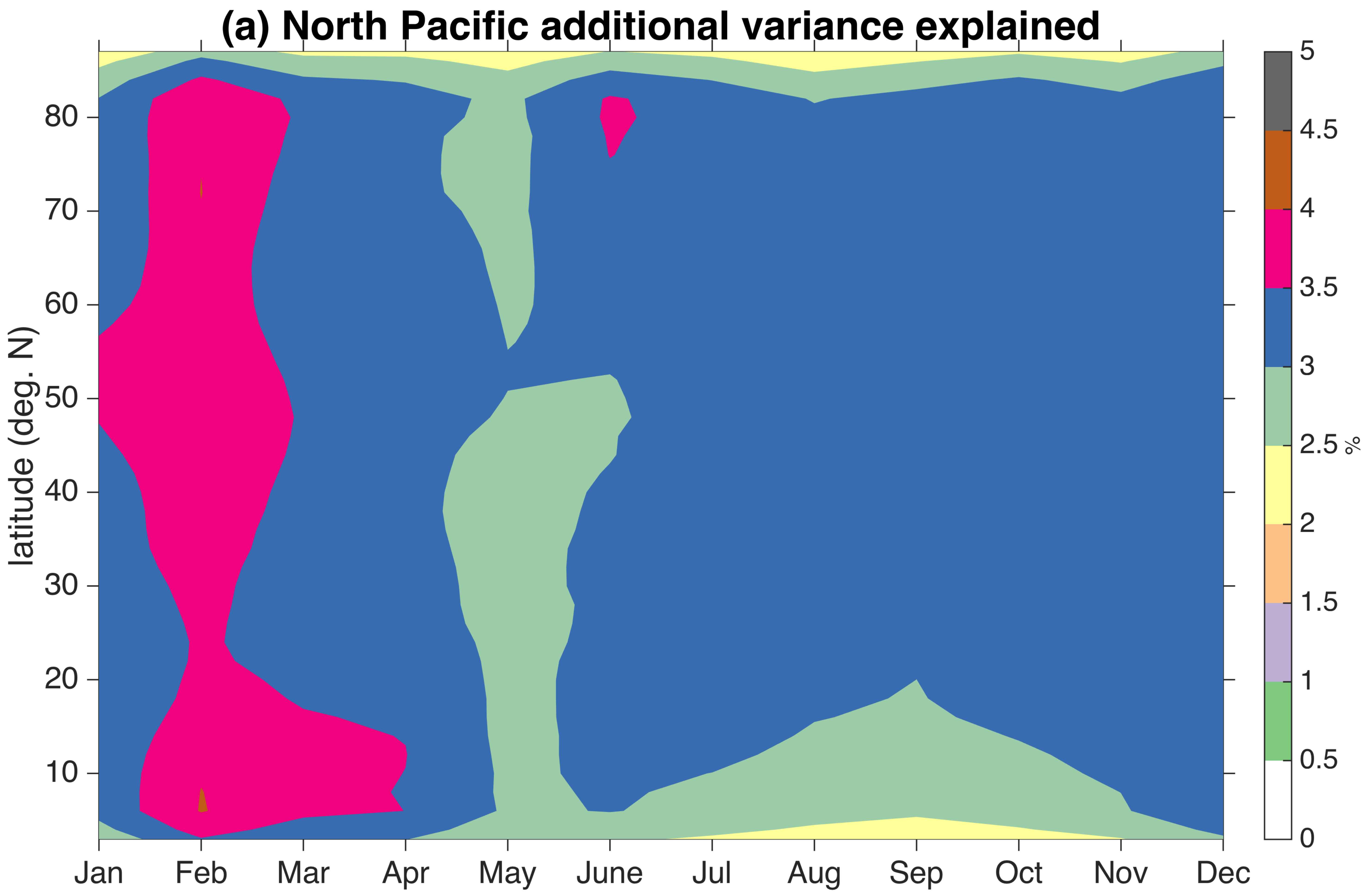




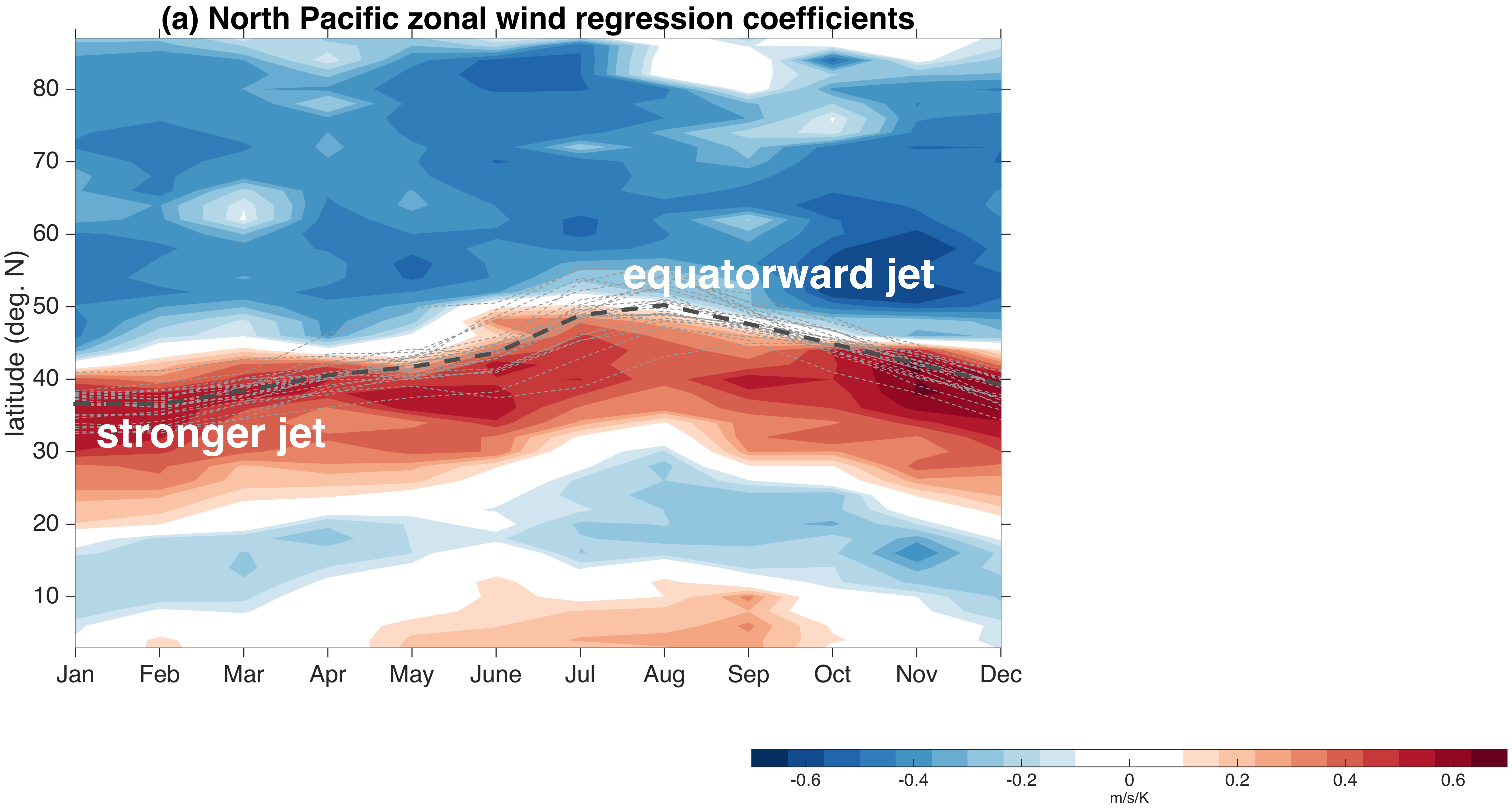
Barnes and Simpson (in prep)

Variance explained in zonal winds



2-4% of additional zonal wind variance explained by Arctic temperatures

How Much?: **North Pacific** vs **North Atlantic**



Barnes and Simpson (in prep)

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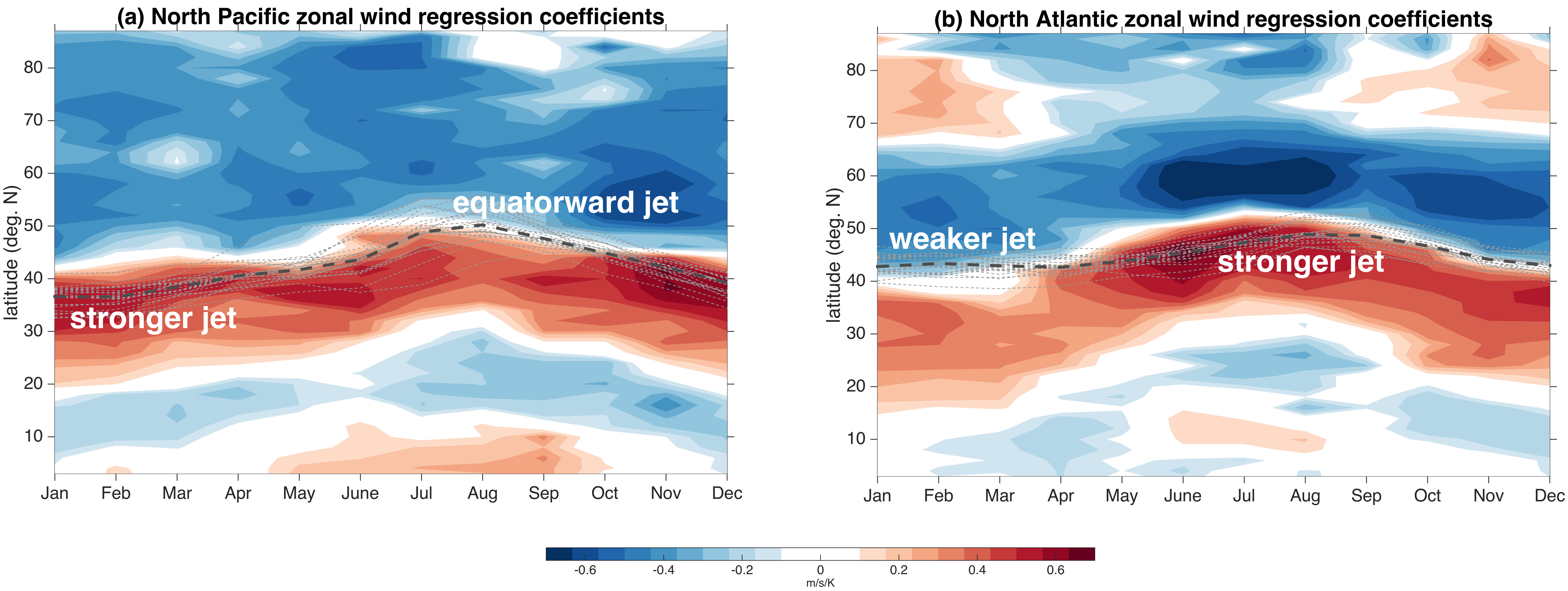

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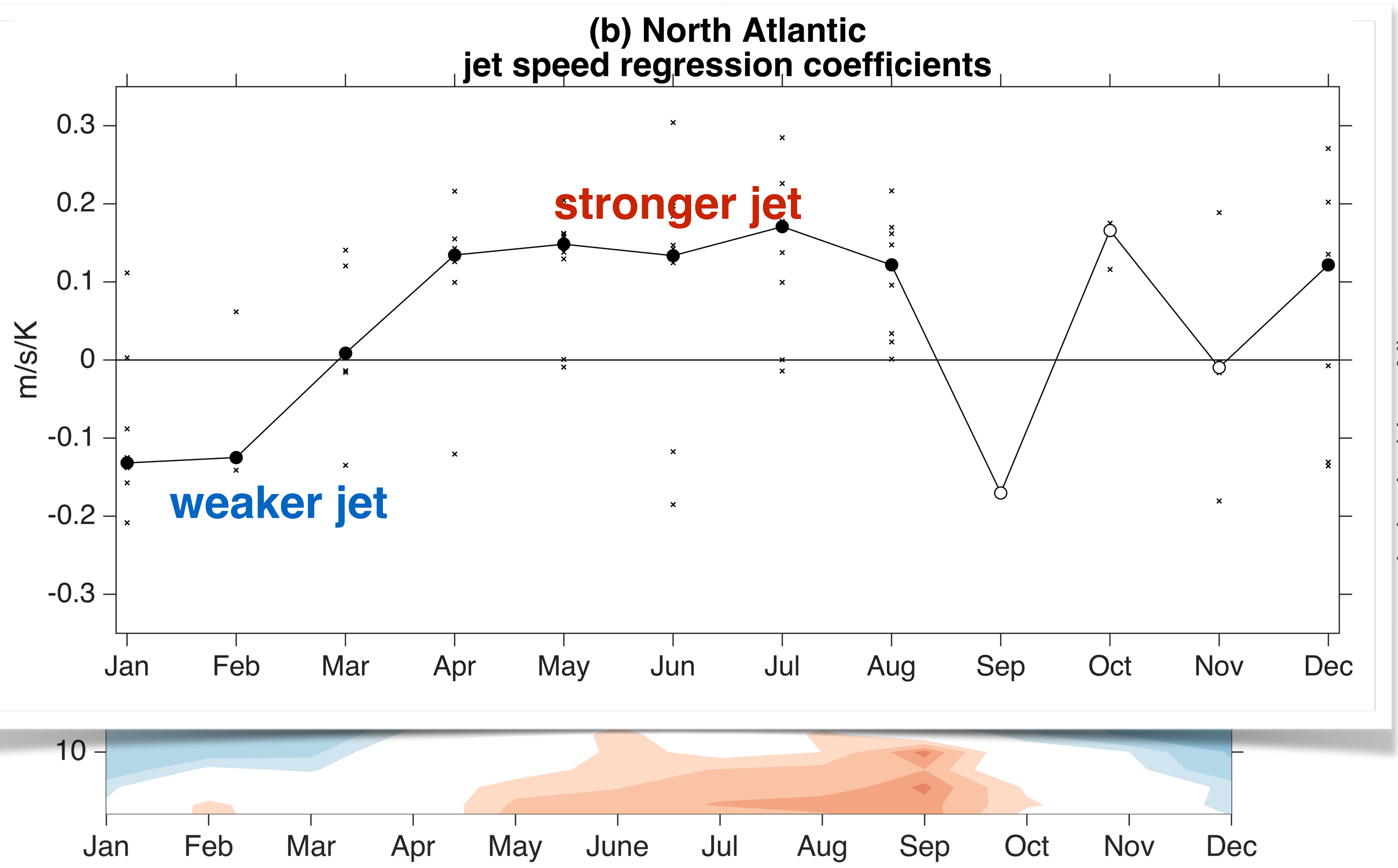
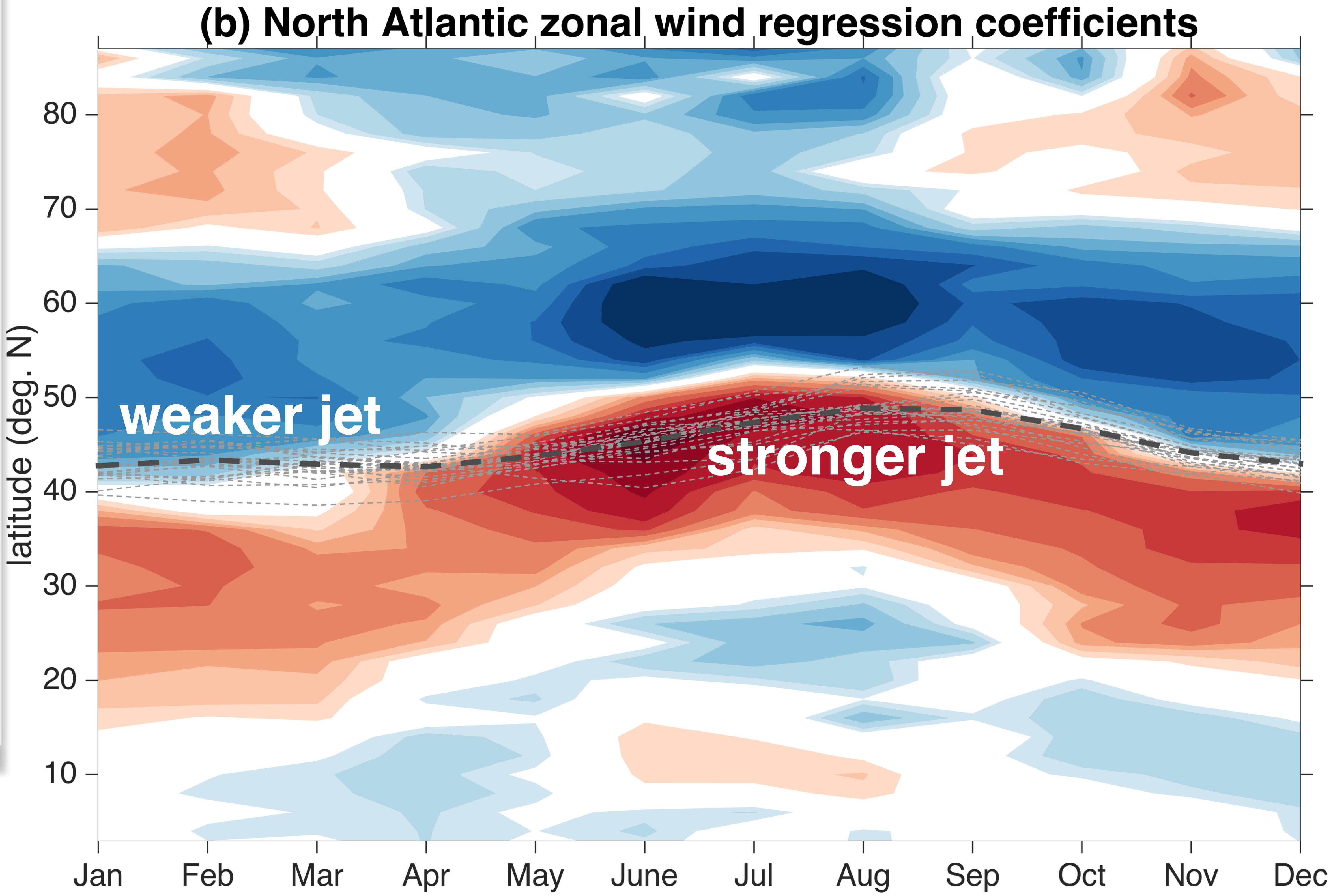
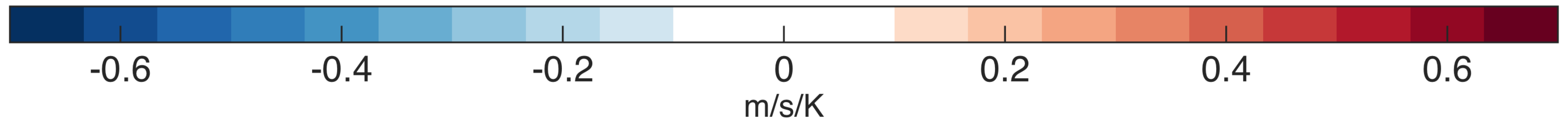
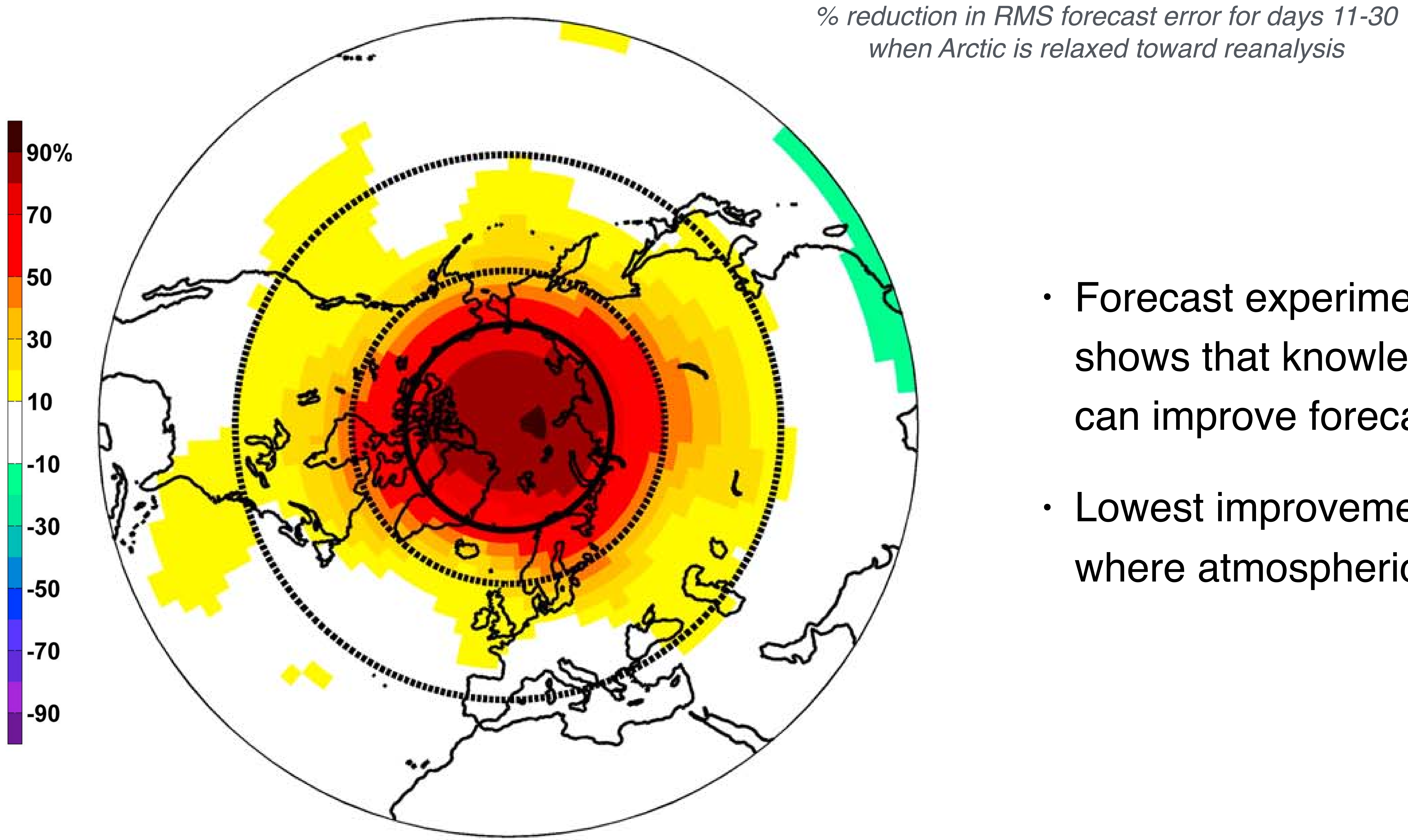






Barnes and Simpson (in prep)

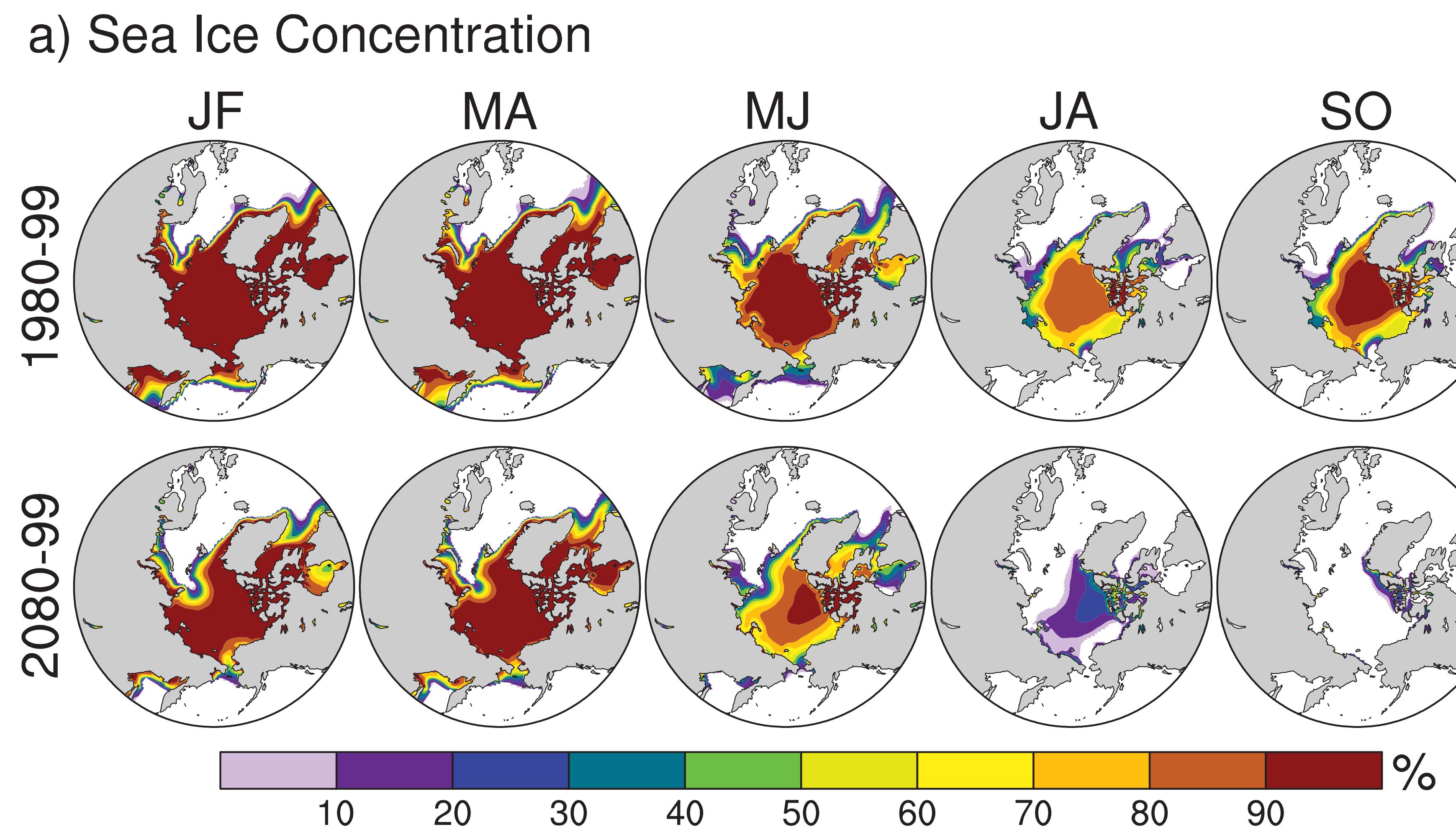
Forecasting evidence



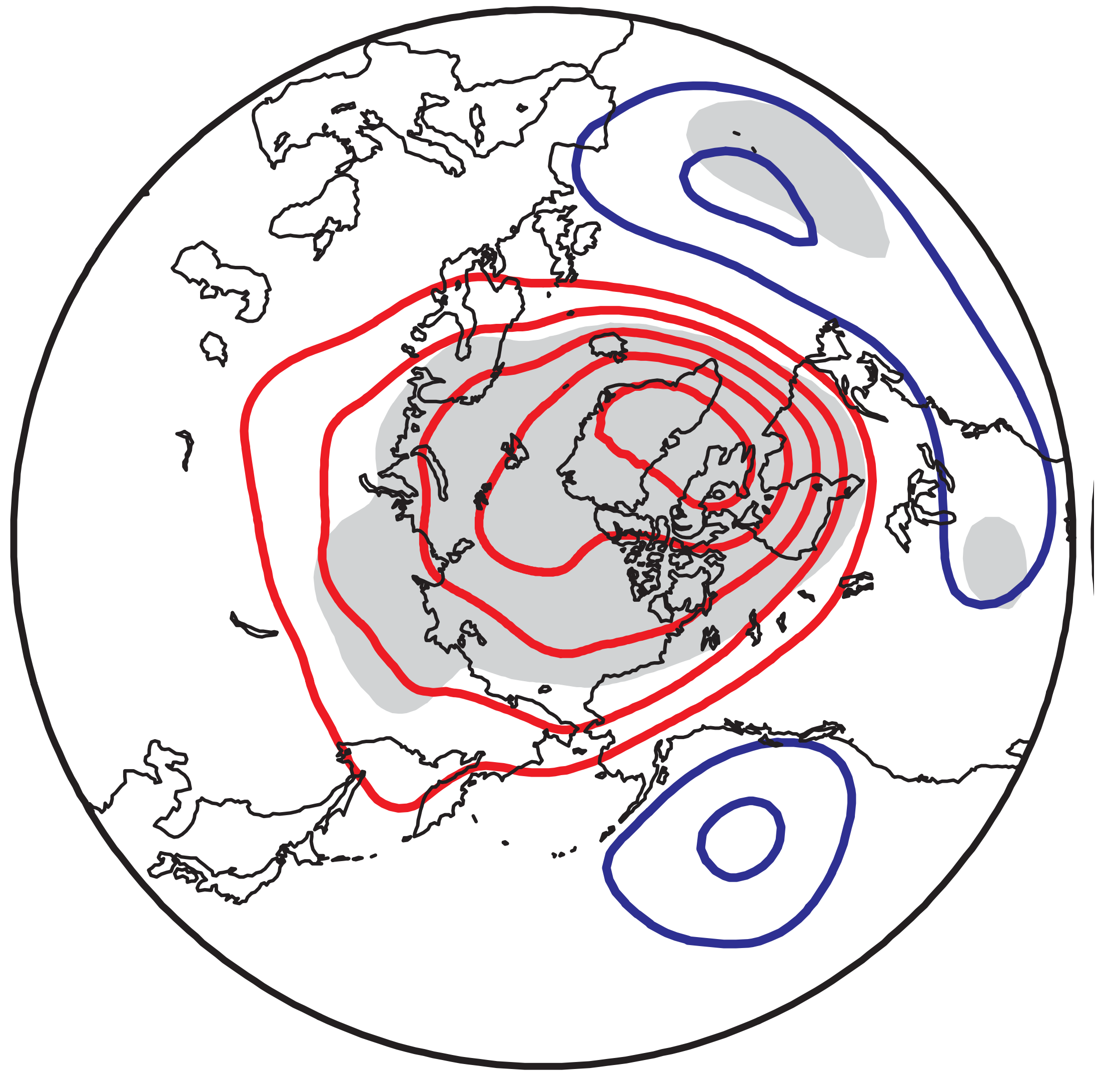
- Forecast experiments with ECMWF model shows that knowledge of the Arctic state can improve forecasts in midlatitudes
- Lowest improvement over the oceans where atmospheric variability is large

Jung et al. (2014; GRL)

Modeling evidence

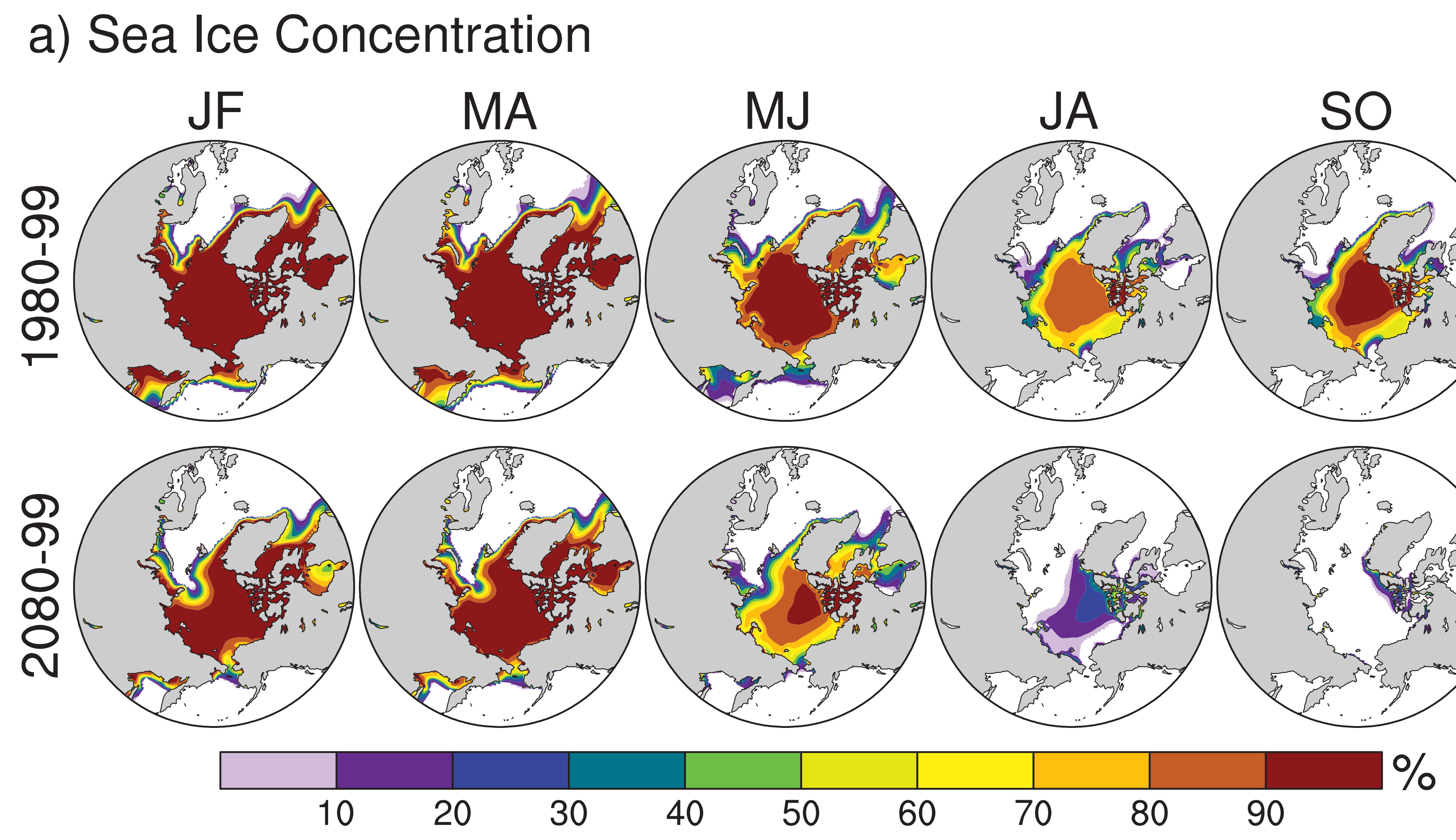


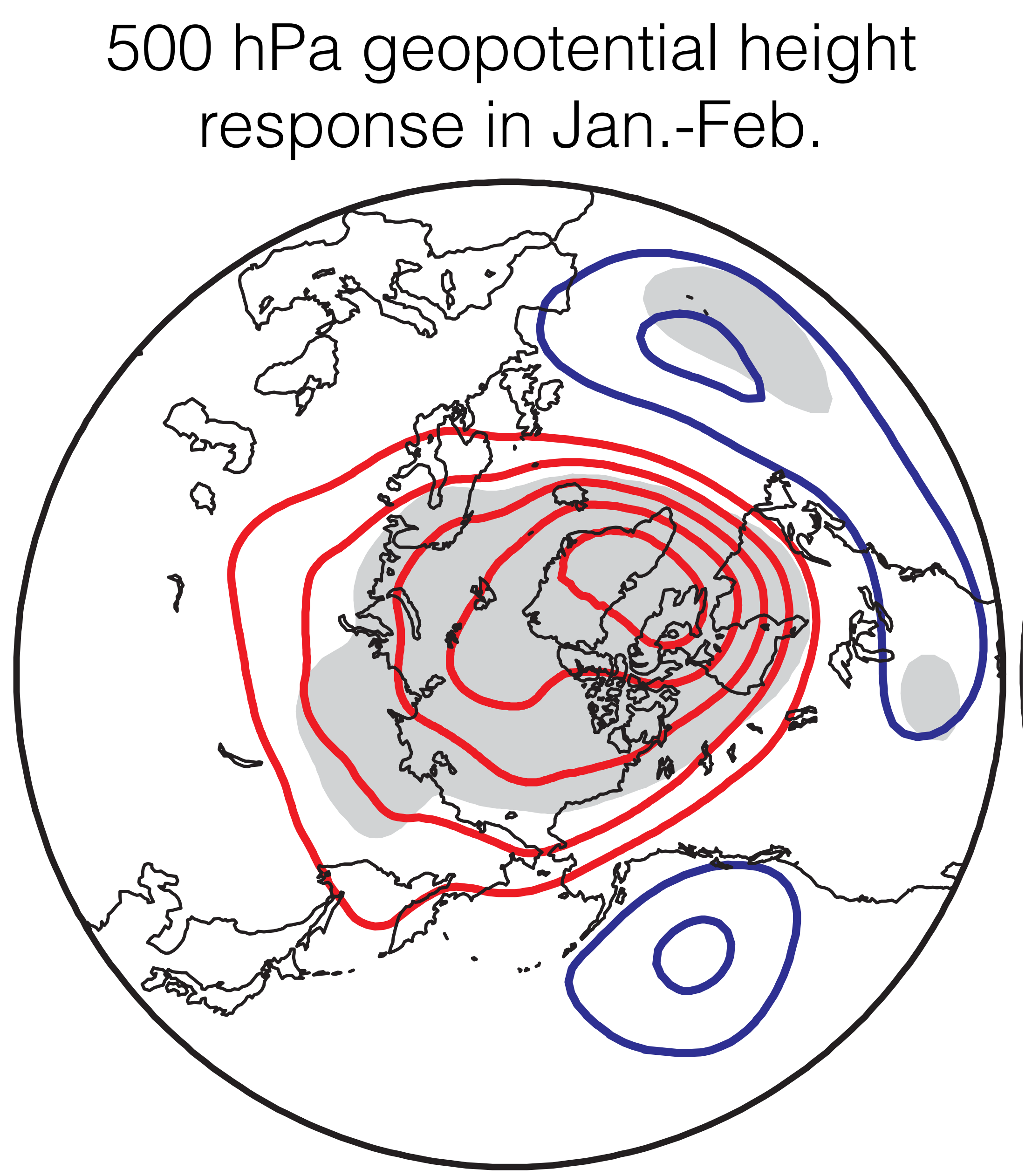
500 hPa geopotential height
response in Jan.-Feb.



atmosphere-only CAM3 simulations
Deser, Tomas, et al. (2010; JCLI)

Modeling evidence





abstract of Deser et al. (2010):

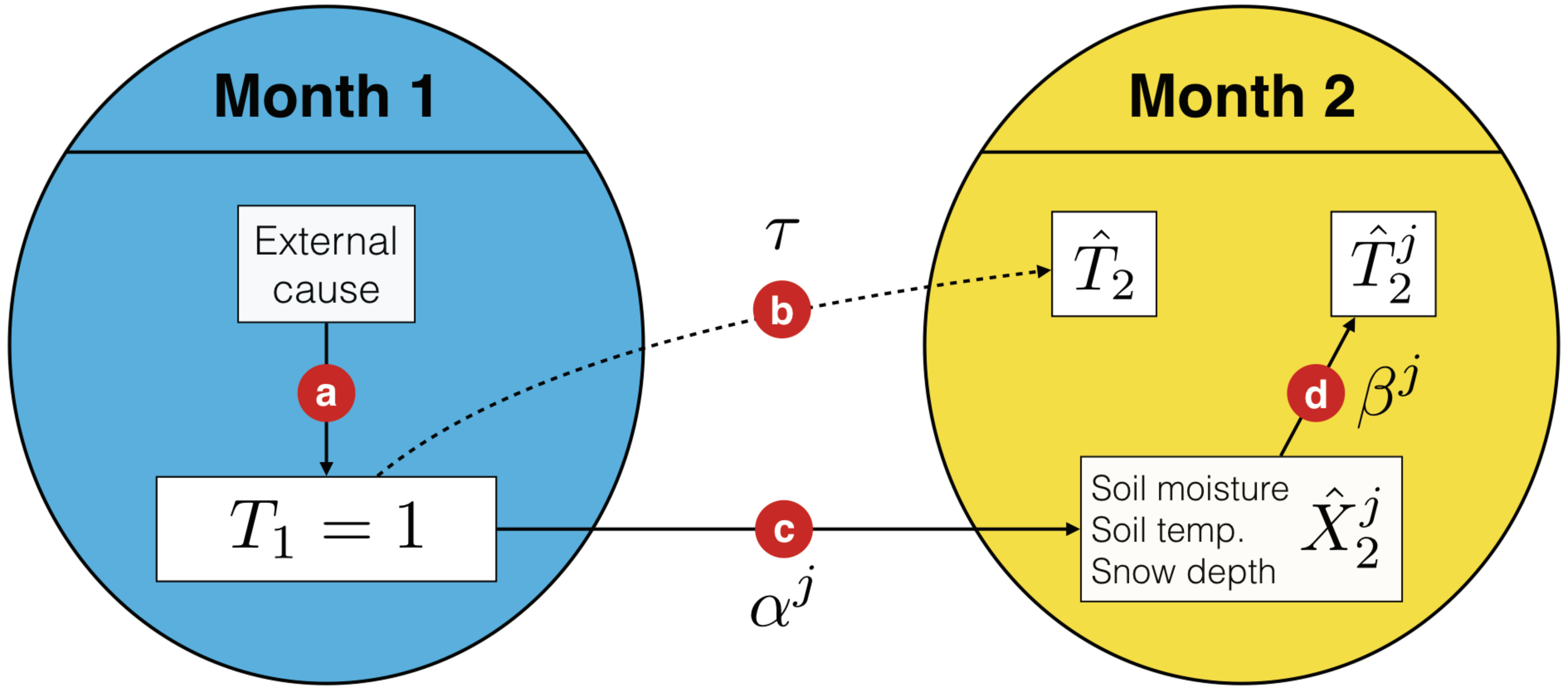
"The loss of Arctic sea ice is greatest in summer and fall, yet the response of the net surface energy budget over the Arctic Ocean is largest in winter."

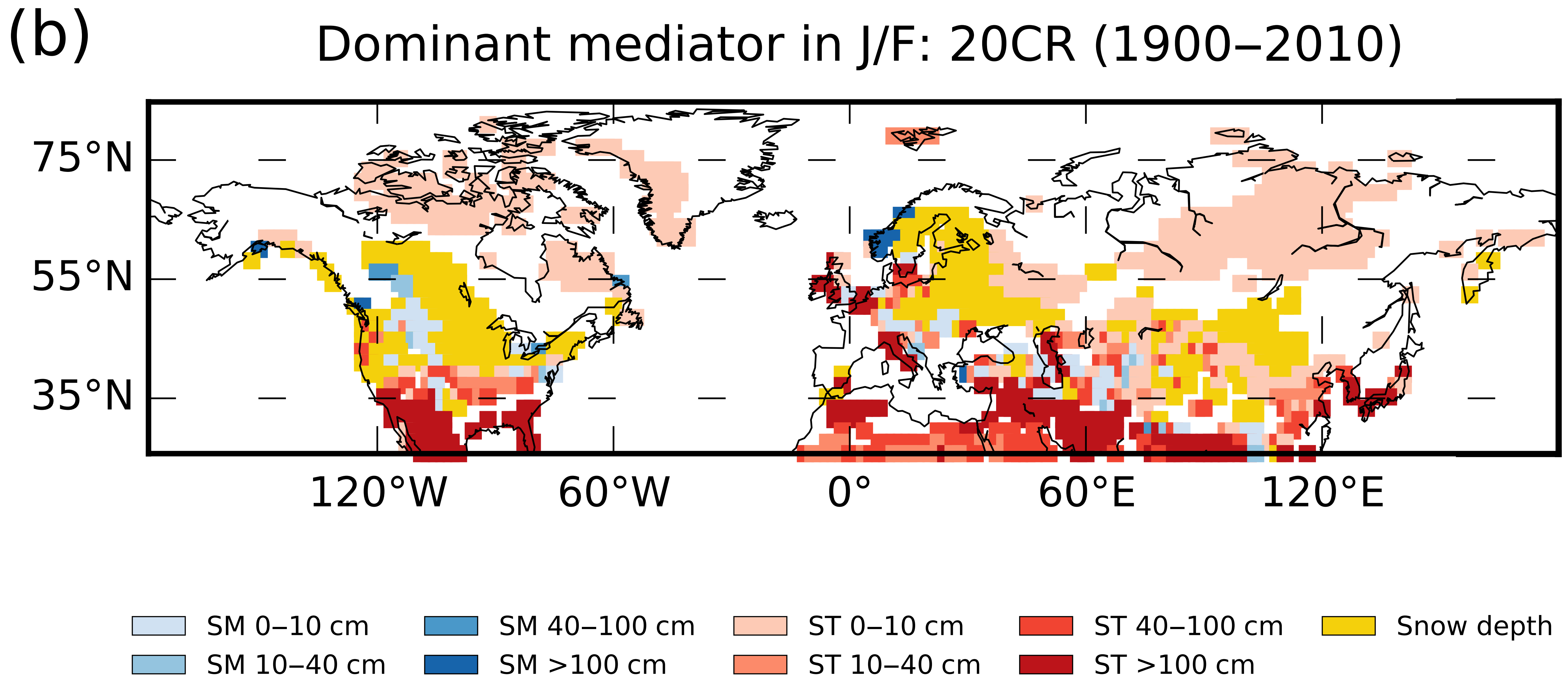
…

"[The circulation] response resembles the negative phase of the North Atlantic Oscillation in February only."

atmosphere-only CAM3 simulations
Deser, Tomas, et al. (2010; JCLI)

Mediators of Surface Temperature Persistence





Kolstad et al. (2017; QJRMS)