New Insights on Arctic-Midlatitude Dynamics from Causal Discovery

Marie C. McGraw and Elizabeth A. Barnes
Atmospheric Science, Colorado State University
in collaboration with Savini Samarasinghe and Imme Ebert-Uphoff

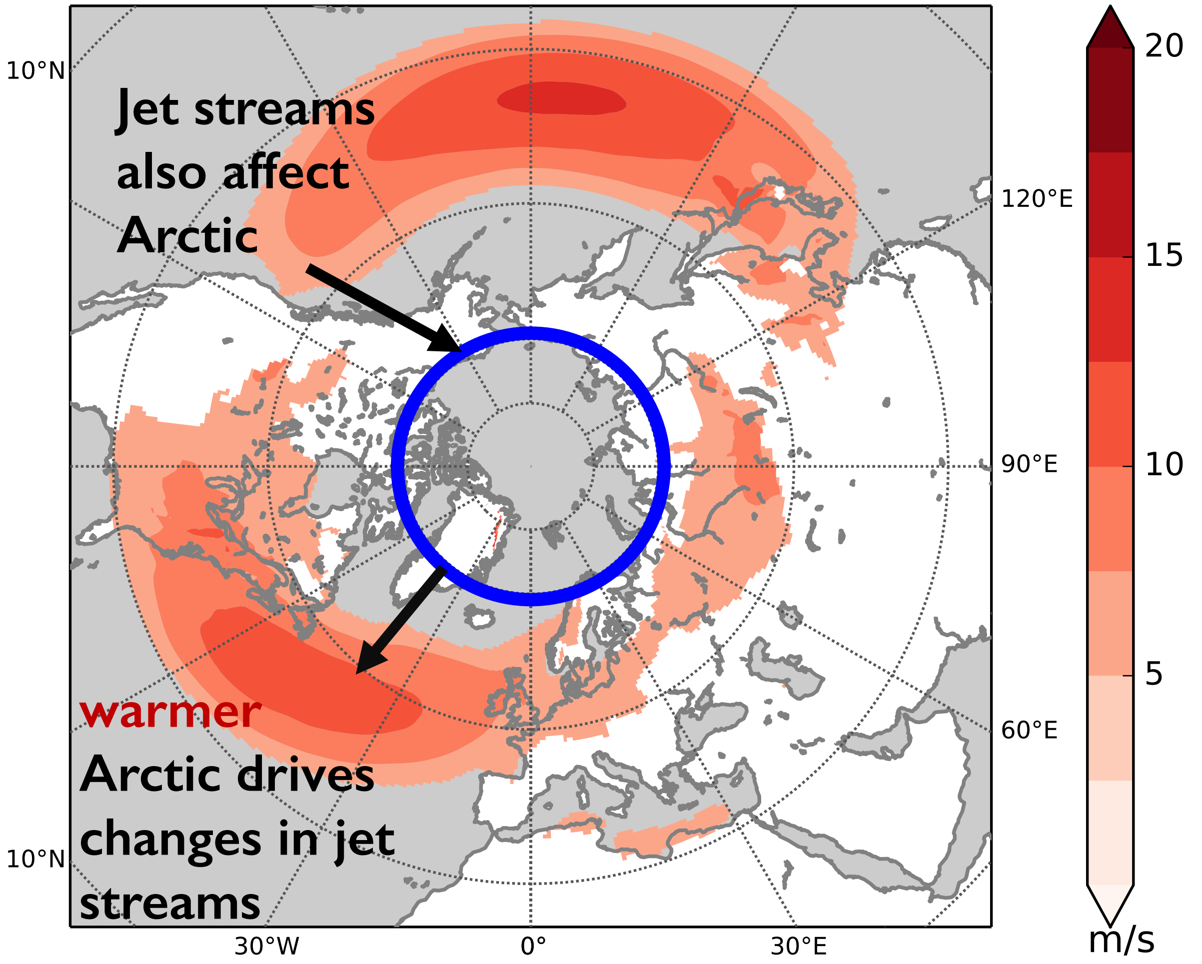
NCAR Climate Variability and Change Working Group Meeting
January 29, 2018

Why Use Causal Discovery for Studying Arctic—Midlatitude Connections?

Directly compare models and reanalysis (same techniques)

Construct and explore **feedback loops**

Utilize relatively **large amounts of data** available



DJF zonal winds from MERRA-2

Granger Causality: Our Framework for Causal Discovery

Does the inclusion of X significantly improve the predictability of Y **beyond** Y's ability to predict itself?

Granger Causality: Our Framework for Causal Discovery

Does the inclusion of X significantly improve the predictability of Y **beyond** Y's ability to predict itself?

…that is, does using X and Y to predict Y do a better job than if we had just used Y to predict itself?

Creating a Granger Causality Model with Vector Autoregression

p: number of lags
(model order)

residuals

$$\mathcal{U}(t) = \overbrace{\boldsymbol{a_1}\mathcal{U}(t-1) + \cdots + \boldsymbol{a_p}\mathcal{U}(t-p)}^{\mathcal{U}\text{ influencing }\mathcal{U}} + \overbrace{\boldsymbol{b_1}\mathcal{T}(t-1) + \cdots + \boldsymbol{b_p}\mathcal{T}(t-p)}^{\mathcal{T}\text{ influencing }\mathcal{U}} + \boxed{e_1}$$

$$\mathcal{T}(t) = \underbrace{\boldsymbol{c_1}\mathcal{U}(t-1) + \cdots + \boldsymbol{c_p}\mathcal{U}(t-p)}_{\mathcal{U}\text{ influencing }\mathcal{T}} + \underbrace{\boldsymbol{d_1}\mathcal{T}(t-1) + \cdots + \boldsymbol{d_p}\mathcal{T}(t-p)}_{\mathcal{T}\text{ influencing }\mathcal{T}} + \boxed{e_2}$$

following general framework laid out by Strong, Magnusdottir, and Stern (2009)

Creating a Granger Causality Model with Vector Autoregression

p: number of lags (model order)

residuals

$$\mathcal{U}(t) = \overbrace{\boldsymbol{a_1}\mathcal{U}(t-1)+\cdots+\boldsymbol{a_p}\mathcal{U}(t-p)}^{\mathcal{U}\text{ influencing }\mathcal{U}} + \cancel{\overbrace{\boldsymbol{b_1}\mathcal{T}(t-1)+\cdots+\boldsymbol{b_p}\mathcal{T}(t-p)}^{\mathcal{T}\text{ influencing }\mathcal{U}}} + \boxed{e_1}$$

$$\mathcal{T}(t) = \underbrace{\boldsymbol{c_1}\mathcal{U}(t-1)+\cdots+\boldsymbol{c_p}\mathcal{U}(t-p)}_{\mathcal{U}\text{ influencing }\mathcal{T}} + \underbrace{\boldsymbol{d_1}\mathcal{T}(t-1)+\cdots+\boldsymbol{d_p}\mathcal{T}(t-p)}_{\mathcal{T}\text{ influencing }\mathcal{T}} + \boxed{e_2}$$

$\mathcal{U}$: 5-day mean 850 mb zonal winds

$\mathcal{T}$: 5-day mean 850 mb temperature (70-90 N)

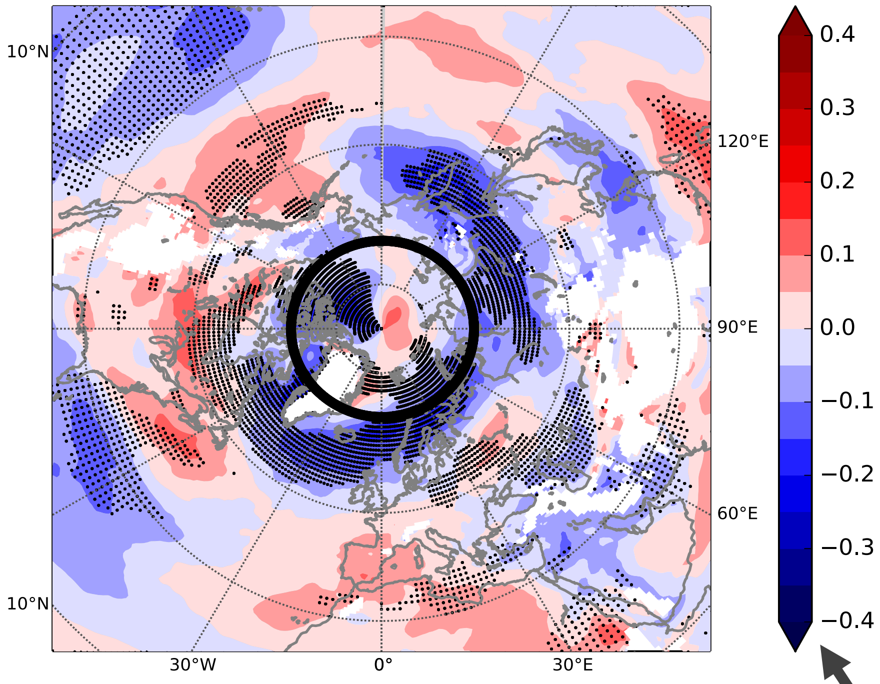
Applying the VAR Model to Reanalysis Data

$\mathcal{T}$ driving $\mathcal{U}$

lag: 5 days

DJF only

MERRA-2



$$\mathcal{U}(t) = \boldsymbol{a_1}\mathcal{U}(t-1) + \cdots + \boldsymbol{a_p}\mathcal{U}(t-p) + \boldsymbol{b_1}\mathcal{T}(t-1) + \cdots + \boldsymbol{b_p}\mathcal{T}(t-p) + e_1$$

regression coefficients

stippling: full model (**all lags**) significant at 95%

McGraw and Barnes (in prep)

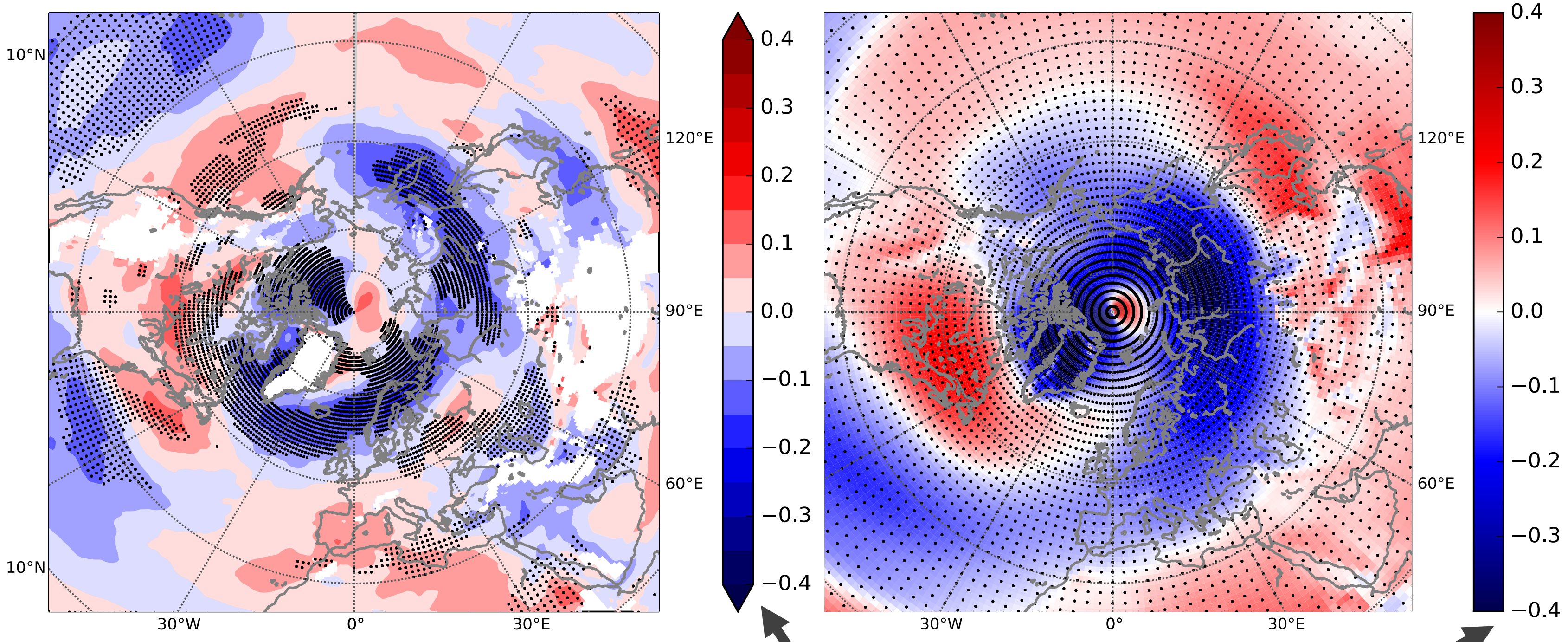
How Well Does the Model Compare with Observations?

$\mathcal{T}$ driving $\mathcal{U}$

lag: 5 days

DJF only

MERRA-2 | CESM Control Run



regression coefficients

stippling: full model (all lags) significant at 95%

McGraw and Barnes (in prep)

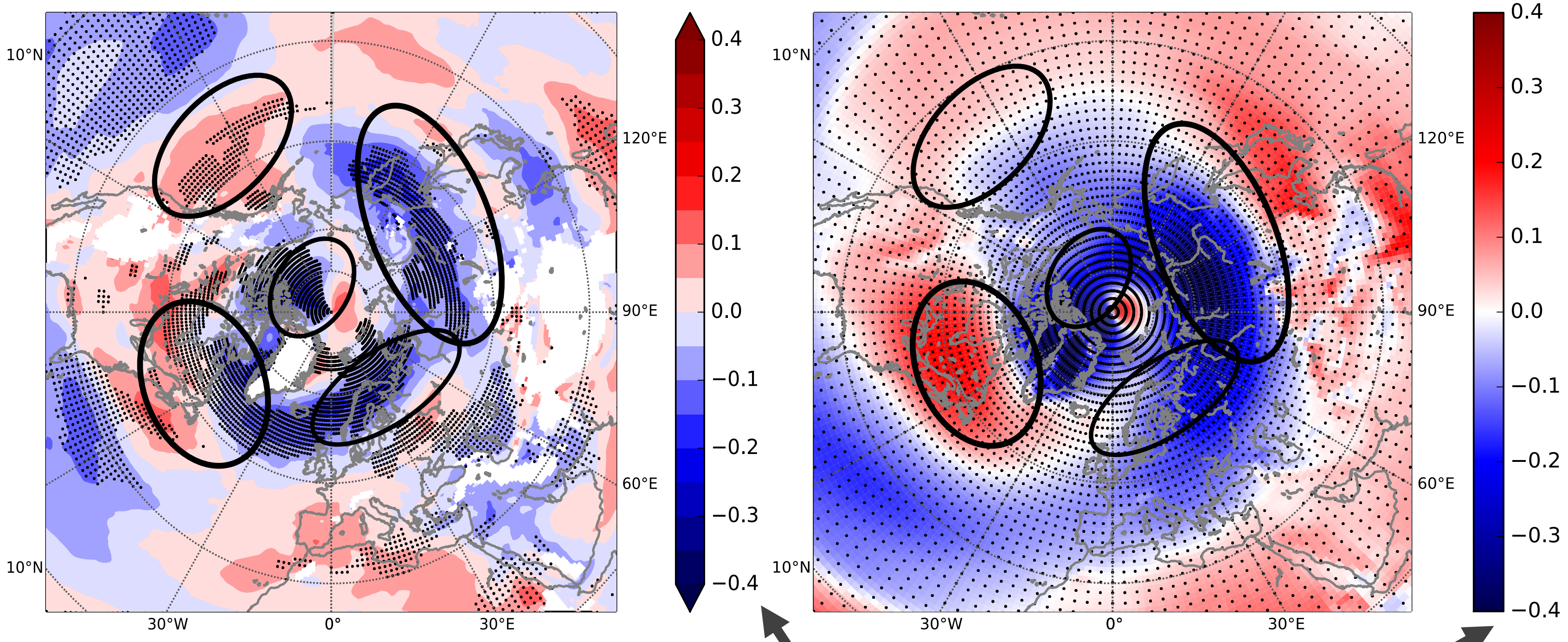
…Actually, It Compares Pretty Well!

$\mathcal{T}$ driving $\mathcal{U}$

lag: 5 days

DJF only

MERRA-2 CESM Control Run



regression coefficients

stippling: full model (all lags) significant at 95%

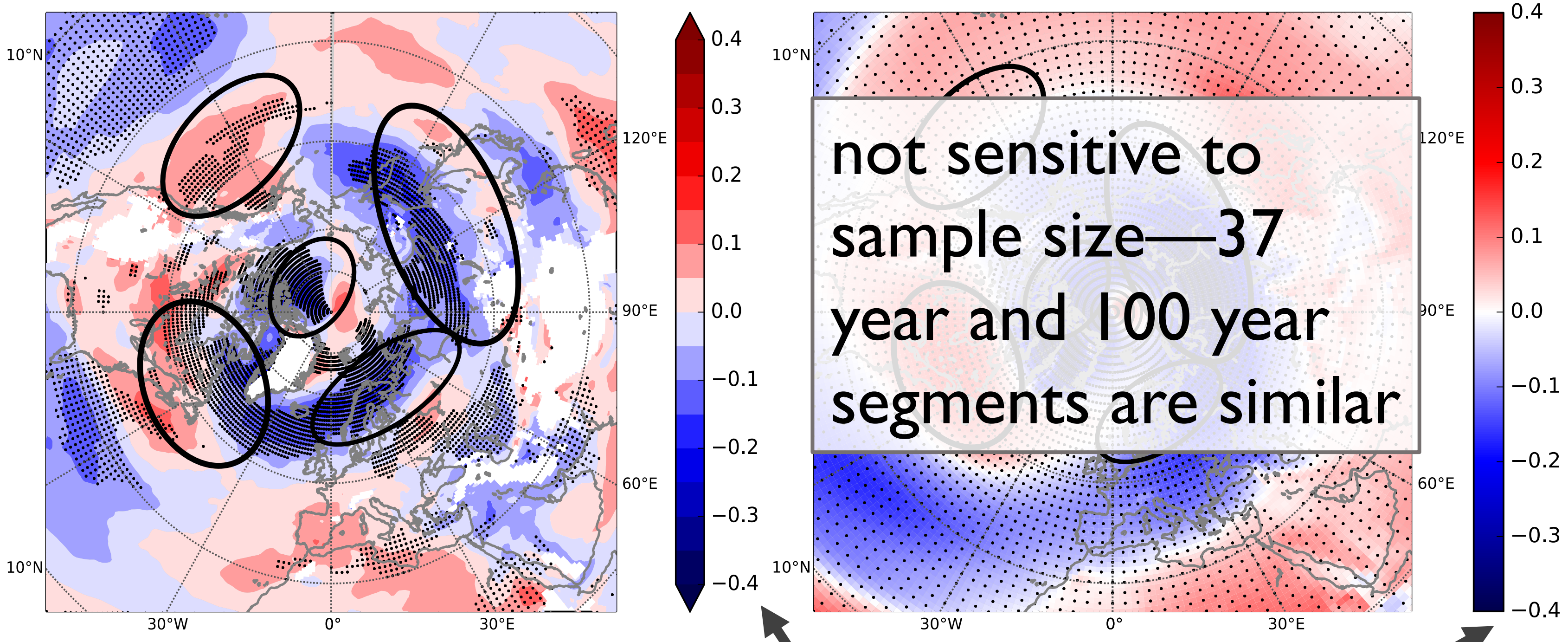
McGraw and Barnes (in prep)

…Actually, It Compares Pretty Well!

$\mathcal{T}$ driving $\mathcal{U}$

lag: 5 days

DJF only



not sensitive to sample size—37 year and 100 year segments are similar

regression coefficients

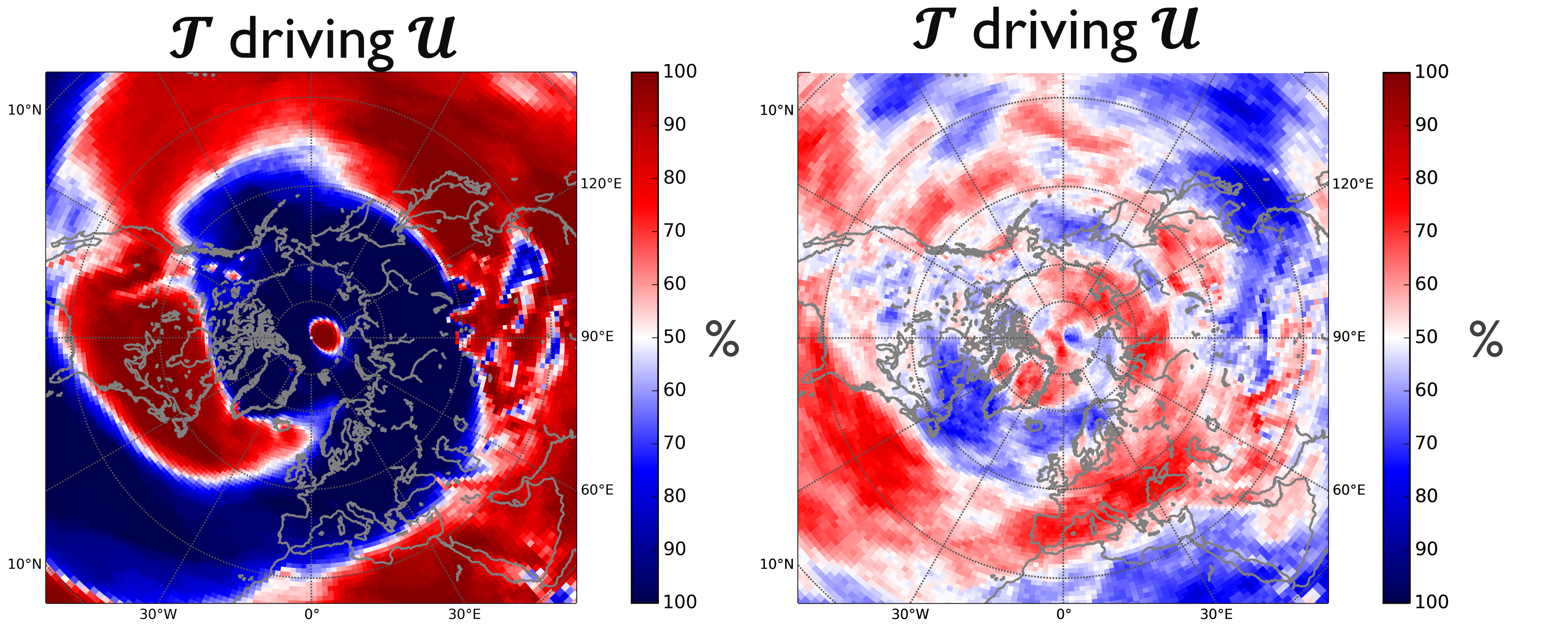
stippling: full model (all lags) significant at 95%

McGraw and Barnes (in prep)

Good Agreement on Signs of Regression Coefficients

red: positive
blue: negative

DJF only



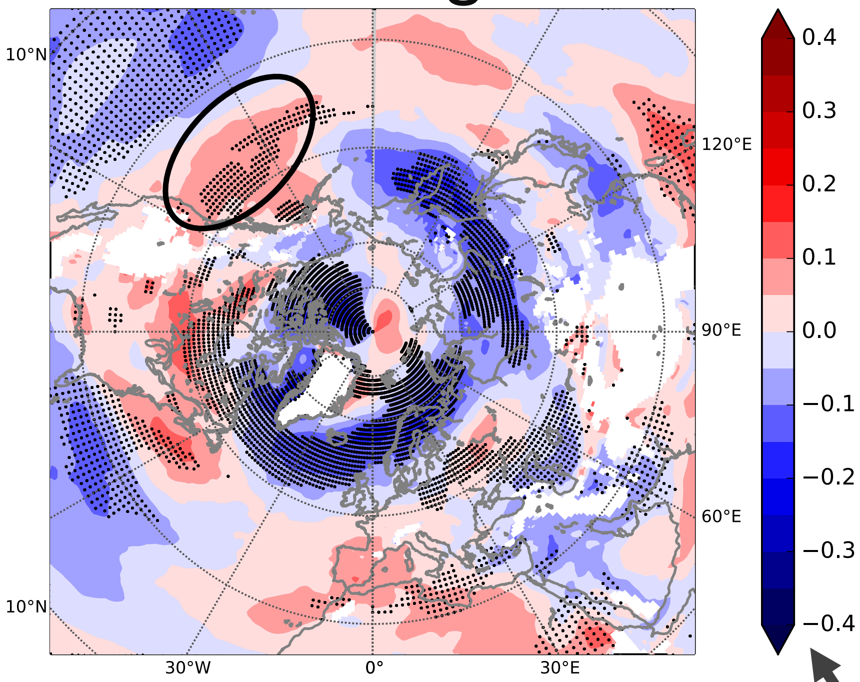
lag: 5 days

lag: 20 days

Using VAR Model to Explore Feedback Loops

DJF only

$\mathcal{T}$ driving $\mathcal{U}$



lag: 5 days

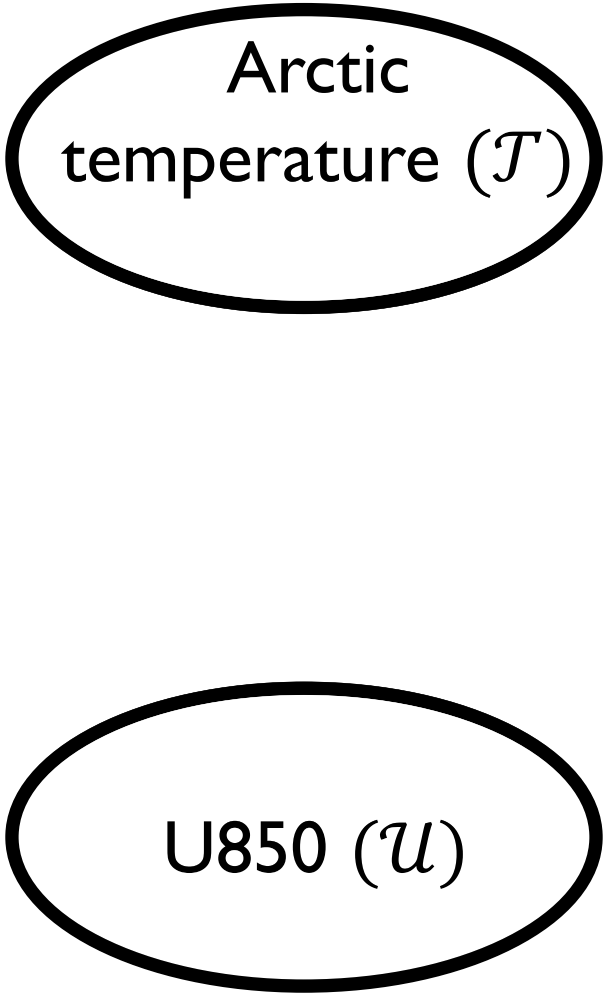
regression coefficients

McGraw and Barnes (in prep)

Using VAR Model to Explore Feedback Loops

N. Pacific

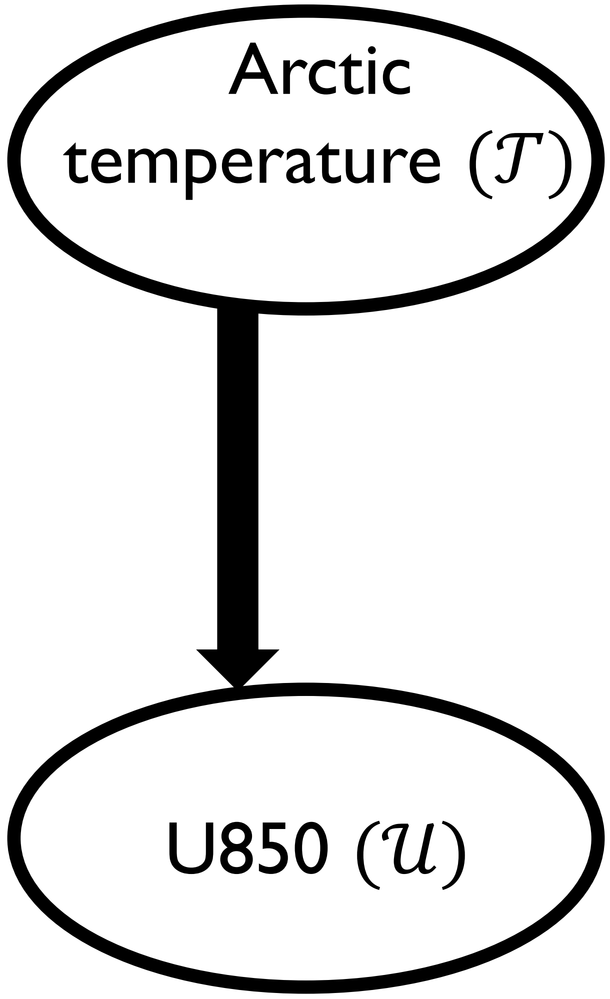
DJF only



Using VAR Model to Explore Feedback Loops

N. Pacific

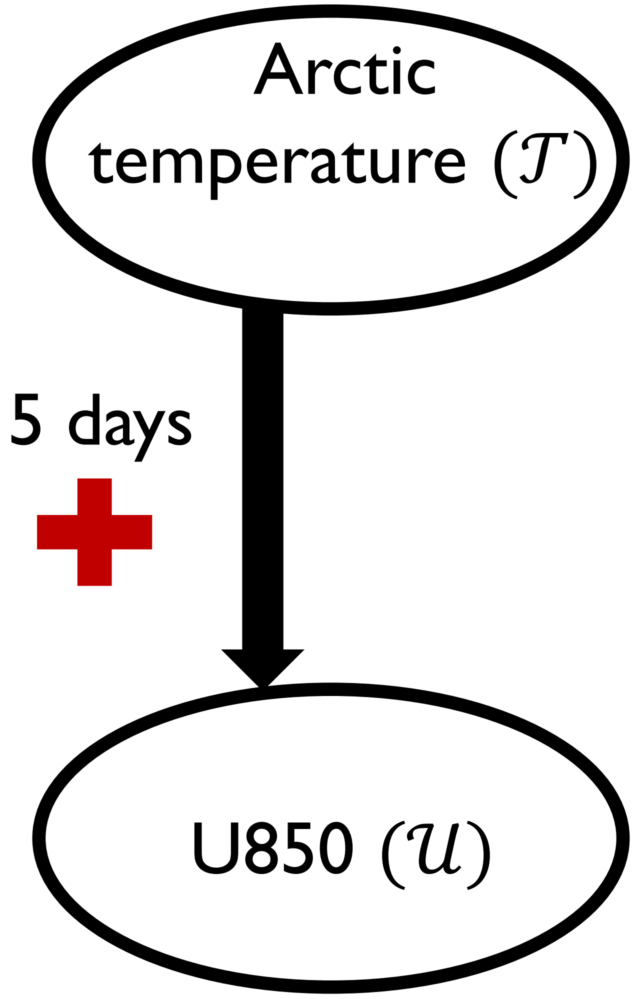
DJF only



Using VAR Model to Explore Feedback Loops

N. Pacific

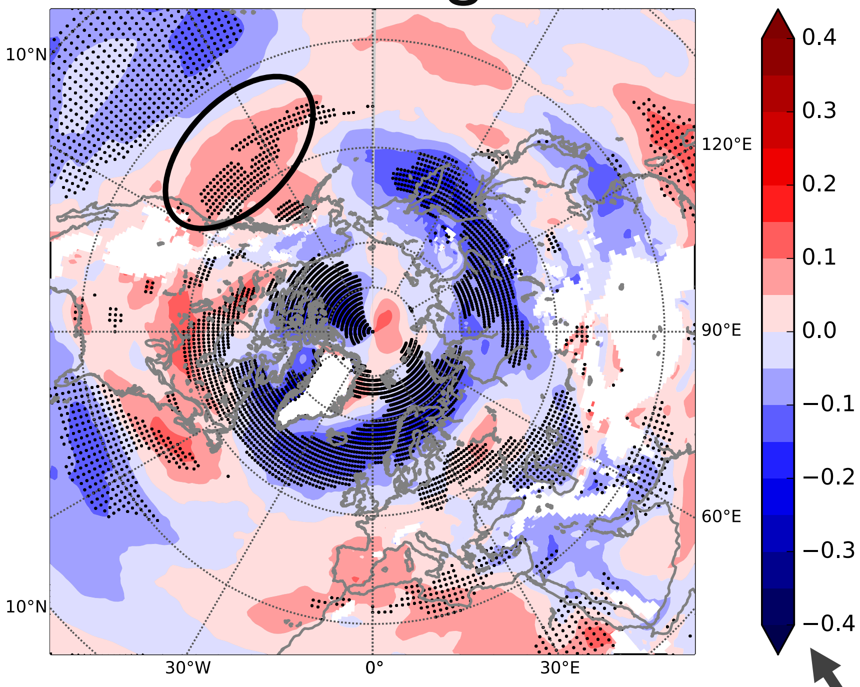
DJF only



Using VAR Model to Explore Feedback Loops

DJF only

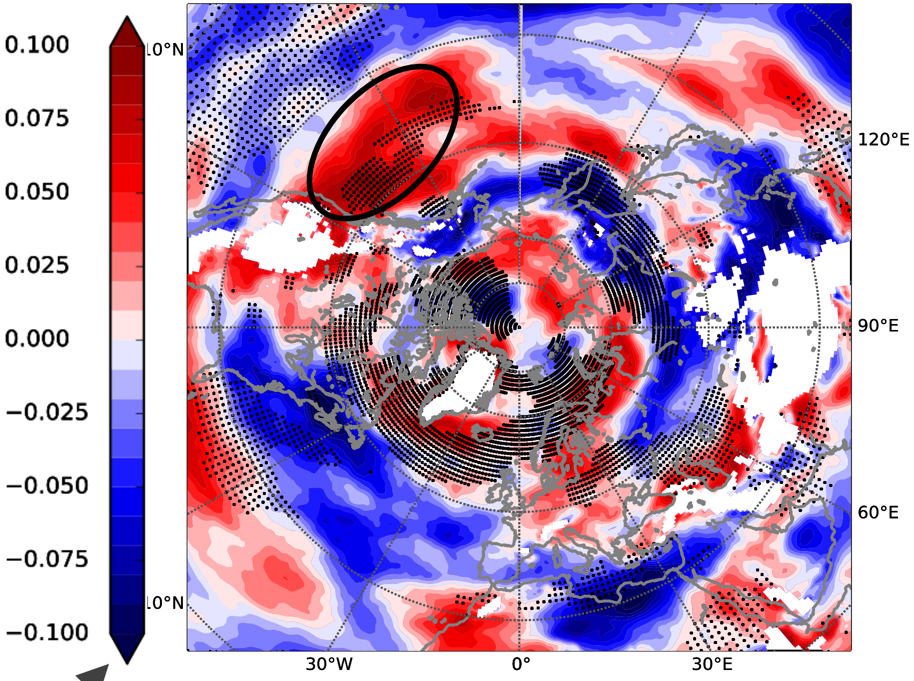
$\mathcal{T}$ driving $\mathcal{U}$



lag: 5 days

15 days earlier…

$\mathcal{U}$ driving $\mathcal{T}$



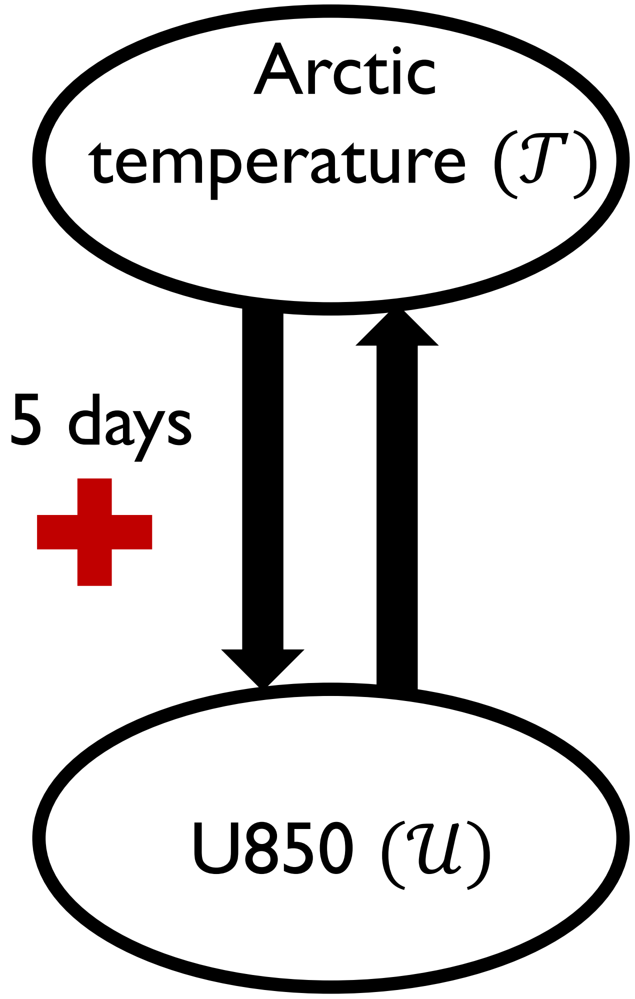
lag: 20 days

regression coefficients

Using VAR Model to Explore Feedback Loops

N. Pacific

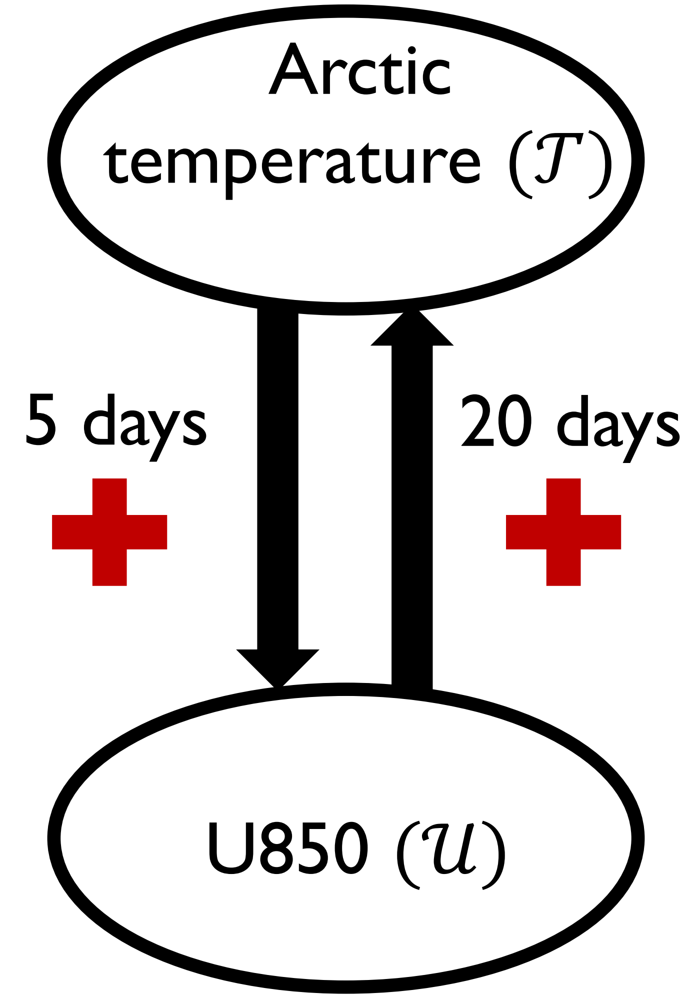
DJF only



Using VAR Model to Explore Feedback Loops

N. Pacific

DJF only

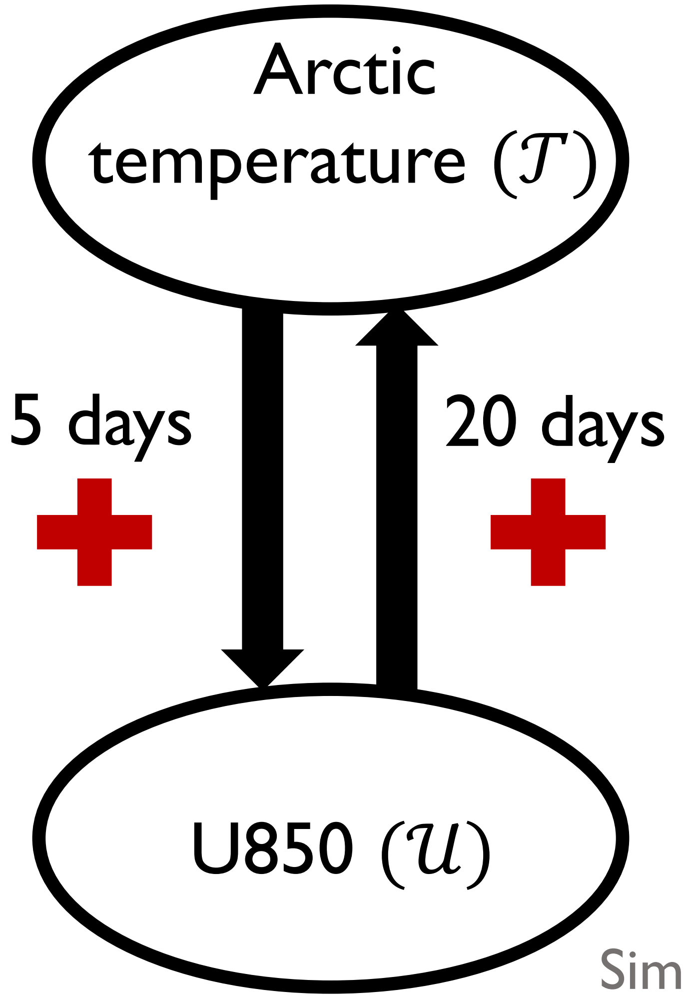


Using VAR Model to Explore Feedback Loops

N. Pacific

DJF only

Warmer Arctic drives **stronger** winds in North Pacific



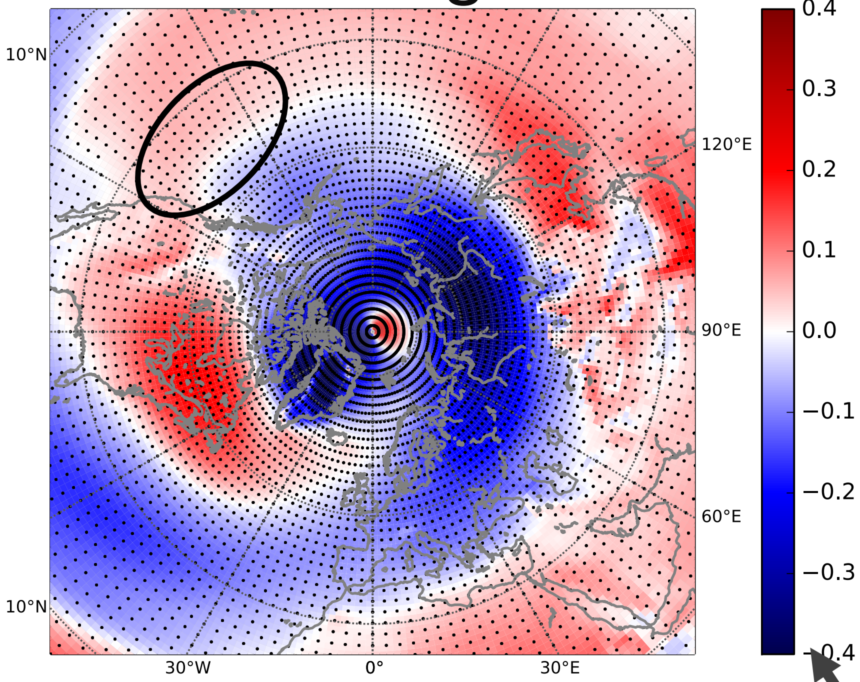
Stronger winds in North Pacific drive **warmer** Arctic

Similar results using other causality methods (Samarasinghe et al. (2017, 2018))

Using VAR Model to Explore Feedback Loops

DJF only

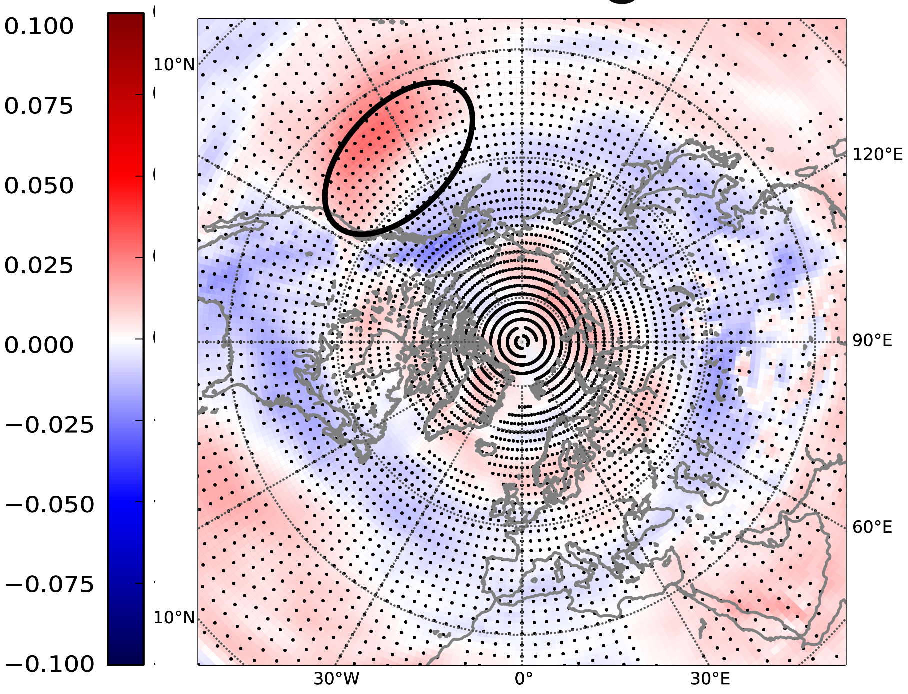
$\mathcal{T}$ driving $\mathcal{U}$



lag: 5 days

15 days earlier…

$\mathcal{U}$ driving $\mathcal{T}$



lag: 20 days

regression coefficients

Causal Discovery Techniques Like VAR Can Shed New Light on Arctic-Midlatitude Dynamics

- VAR gives us a way to directly compare models and reanalysis
  - CESM doesn't look too bad compared to reanalysis

- VAR helps us examine feedback loops—we can begin to understand how the Arctic and the midlatitudes affect each other in tandem
  - Positive feedback loop between winds and Arctic temperature in N. Pacific—warmer Arctic strengthens winds, which drives further Arctic warming

For More on Causal Discovery and Relevant Climate Science Applications, Check Out…

- Ebert-Uphoff, I., and Y. Deng (2012)—Causal discovery for climate research using graphical models. *J. Climate,* **25**, 5648-5665.
- Kretschmer, M. et al. (2016)—Using causal effect networks to analyze different Arctic drivers of midlatitude winter circulation. *J. Climate,* **29**, 4069-4081.
- McGraw, M., and E. Barnes—Memory matters: A case for Granger causality in climate variability studies. *J. Climate,* under review (revisions submitted 11/2017).
- Runge, J., V. Petoukhov, and J. Kurths (2014)—Quantifying the strength and delay of climatic interactions: the ambiguities of cross correlation and a novel measure based on graphical models. *J. Climate*, **27**, 720-739.
- Samarasinghe, S. et al. (2017)—A study of causal links between the Arctic and the midlatitude jet-streams. *Proc. Seventh Intl. Workshop on Climate Informatics (CI 2017), NCAR Technical Note NCAR/TN-536+PROC.*
- Samarasinghe, S., et al. (2018)--
- Strong, C., G. Magnusdottir, and H. Stern (2009)—Observed feedback between winter sea ice and the North Atlantic Oscillation. *J. Climate,* **22**, 6021-6032.