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**
- pathways may not be easily pulled-apart
- requires the model adequately simulates relevant processes
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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

where past values of ENSO significantly influence surface T

where past values of T significantly influence surface ENSO

McGraw and Barnes (submitted)
Granger Causality

the extent to which X provides information on Y beyond what is already provided by Y itself

Clive Granger (1934-2009)
2003 Nobel Prize in Economic Sciences
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Step 1: \[ Y_t = a_1 Y_{t-1} + a_2 Y_{t-2} + \ldots + a_k Y_{t-k} + \epsilon_{Y,t} \]

Step 2: \[ Y_t = c_1 Y_{t-1} + c_2 Y_{t-2} + \ldots + c_k Y_{t-k} + b_1 X_{t-1} + b_2 X_{t-2} + \ldots + b_k X_{t-k} + \epsilon_{X,t} \]
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use Y to predict itself

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*use Y to predict itself*

*use X to predict Y*
Granger Causality

**the extent to which X provides information on Y beyond what is already provided by Y itself**

**Step 1:** \( Y_t = a_1 Y_{t-1} + a_2 Y_{t-2} + \ldots + a_k Y_{t-k} + \epsilon_{Y,t} \)

- use Y to predict itself

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- use X to predict Y

- there exists at least one significant \( b \) (t-test)
- all of the \( b \) terms collectively add power to the regression (F-test)
Lagged regression

McGraw and Barnes (submitted)
Granger causality

(c) Granger causality, ENSO -> T, lag 7

(d) Granger causality, T -> ENSO, lag 7

where past values of ENSO significantly influence surface T

where past values of T significantly influence surface ENSO

ENSO leads T

T leads ENSO

McGraw and Barnes (submitted)
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

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

*results are not sensitive to 10-days, e.g. could be 5-days

Calculation of the jet position

The latitude of the monthly-mean jet position over Eastern North America is defined as the latitude of 500 hPa maximum zonal-mean zonal winds (\(u_{ave}\) over the sector). Typically, the eddy-driven, midlatitude jet is defined using lower-tropospheric winds in order to distinguish it from the zonal winds associated with the subtropical jet (Barnes and Polvani, 2013; Woollings et al., 2010). The subtropical jet winds increase with height, with easterlies near the surface, whereas the eddy-driven winds are largely barotropic, with westerlies near the surface. Thus, lower-tropospheric winds exhibit a jet peak associated with the midlatitude jet, but not the subtropical jet. Here, we use 500 hPa instead of the lower-troposphere winds in order to ensure that we are not finding a relationship between the jet location and ozone variability purely because we use near-surface winds and near-surface ozone. The 500 hPa level thus allows us to still distinguish the eddy-driven and subtropical jets, but is also well-removed from the surface.

For each month, the latitude of maximum zonal-mean zonal wind is found, and the wind profile is interpolated to a 0.01° latitude grid and a quadratic is fit about the maximum. The jet position is defined as the latitude of the maximum interpolated zonal-mean zonal wind.

As an example, the figure below shows the sector-averaged zonal wind for August 1998. The black dotted line shows the original MERRA profile, the red curve denotes the fitted quadratic at the peak, and the star denotes the position of the jet according to the methodology outlined above. Note that even though the resolution of the data is 2° latitude, the latitude of the jet can be defined up to much higher precision since monthly zonal wind is continuous and smooth variable.

Calculation of the position of maximum ozone variability

We define the latitude of the seasonal-mean ozone variability by finding the latitude of maximum variability each season of each year. Similar to the jet, the latitude of the maximum ozone variability is found, and then the profile is interpolated to a 0.01° latitude grid and a quadratic is fit about the maximum. The position of maximum ozone variability is then defined as the latitude of the interpolated field maximum.
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Supplementary Figure 3: Zonally averaged 500 hPa zonal winds over Eastern North America for August 1998 from MERRA. The red curve denotes the fitted quadratic at the peak and the star depicts the position of the jet.
the extent to which information of ARCTIC TEMP provides information on the JET beyond what is already provided by the JET itself

Clive Granger (1934-2009)
2003 Nobel Prize in Economic Sciences
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\[ J = \text{JET} \quad T = \text{ARCTIC TEMP} \]
Granger Causality

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**Step 1:** \( \mathcal{J}_t = a_1 \mathcal{J}_{t-1} + a_2 \mathcal{J}_{t-2} + \ldots + a_k \mathcal{J}_{t-k} + \epsilon_{\mathcal{J},t} \)

**Step 2:** \( \mathcal{J}_t = c_1 \mathcal{J}_{t-1} + c_2 \mathcal{J}_{t-2} + \ldots + c_k \mathcal{J}_{t-k} + b_1 T_{t-1} + b_2 T_{t-2} + \ldots + b_k T_{t-k} + \epsilon_{T,t} \)
Granger Causality

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*how much?*
Applying Granger Causality

Step 1: \[ J_t = a_1 J_{t-1} + a_2 J_{t-2} + \ldots + a_k J_{t-k} + \epsilon_J, t \]

Step 2: \[ J_t = c_1 J_{t-1} + c_2 J_{t-2} + \ldots + c_k J_{t-k} + b_1 T_{t-1} + b_2 T_{t-2} + \ldots + b_k T_{t-k} + \epsilon_T, t \]

- 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)
jet shifts **equatorward** more in warm months
How Much?: jet position

Jet shifts equatorward more in warm months

40-60% of simulations exhibit Granger-causality

Barnes and Simpson (submitted)
How Much?: jet position

(a) North Pacific jet latitude regression coefficients

Jet position shifts more in warm months, with 40-60% of simulations exhibiting Granger-causality.

Barnes and Simpson (submitted)
How Much?: jet position

(a) North Pacific
jet latitude regression coefficients

(b) Jet Latitude
variance explained by regression

Barnes and Simpson (submitted)
How Much?: jet speed

jet strengthens in most months

large seasonality in number of models exhibiting Granger-causality
How Much?: jet speed

(a) North Pacific jet speed regression coefficients

(b) Jet Speed variance explained by regression

North Pacific

- Jet (Eq. 2)
- Jet + Arctic Temp. (Eq. 3)

Barnes and Simpson (submitted)
Granger Causality

the extent to which information of ARCTIC TEMP provides information for WINDS beyond what is provided by the WINDS

\[ U = \text{ZONAL WINDS} \quad T = \text{ARCTIC TEMP} \]

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**how much?**
Granger Causality

the extent to which information of **ARCTIC TEMP** provides information for **WINDS**
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U = \text{ZONAL WINDS} \quad T = \text{ARCTIC TEMP}
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\[
U_t = a_1 U_{t-1} + a_2 U_{t-2} + \ldots + a_k U_{t-k} + \epsilon_{U,t}
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\]

**how much?**
Looking closer at the seasonality

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

*Barnes and Simpson (submitted)*
Looking closer at the seasonality

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

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

*Barnes and Simpson (submitted)*
Looking closer at the seasonality

Figure 9. The CMIP5 model median sector-averaged zonal wind regression coefficients as a function of latitude and month. Thin gray lines denote each members' mean jet position, and the black dashed line denotes the CMIP5 multi-model average. Results are from the RCP8.5 scenario.

(a) North Pacific zonal wind regression coefficients

colors = CMIP5 model mean regression coefficients (via GC)

jet axis

Barnes and Simpson (submitted)

CSU

Elizabeth A. Barnes
Looking closer at the seasonality

(a) North Pacific zonal wind regression coefficients

colors = CMIP5 model mean regression coefficients (via GC)

-0.5 -0.4 -0.3 -0.2 -0.1 0 0.1 0.2 0.3 0.4 0.5

-11-

Fig. 9. The CMIP5 model median sector-averaged zonal wind regression coefficients as a function of latitude and month. Thin gray lines denote each members' mean jet position, and the black dashed line denotes the CMIP5 multi-model average. Results are from the RCP8.5 scenario.

Barnes and Simpson (submitted)
Models with higher latitude jets shift further
Models with higher latitude jets shift further

(b) North Pacific
correlation of mean jet latitude and jet latitude regression coefficient

larger equatorward jet shifts for higher-latitude jets
Barotropic Model

Easterly torque of amplitude -1 applied to 45°N jet, at 65°N

Initial stirred jet
Resulting forced jet
Applied easterly torque (*2)

Distribution of jet latitudes, (T.amp.1, T.lat.65°N, Stir lat.45°N)

- No Forcing (Mean: 49.22, StdDev: 3.62)
- Forcing (Mean: 46.88, StdDev: 3.21)

std. dev. = 3.21
std. dev. = 3.62

Ronalds and Barnes (in prep)
Barotropic Model

Impacts of applying an easterly torque at 65°N

Ronals and Barnes (in prep)

CSU

Elizabeth A. Barnes
Barotropic Model

Impacts of applying an easterly torque at 65°N

- Larger equatorward shift

Ronalds and Barnes (in prep)
Conditional Independence of $X$ & $Y$

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

The 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)
By understanding the physical processes involved we can describe the causal connections intuitively in the graphical form shown in Fig. 1a. Note that Fig. 1a shows arrows from SPaper to Temp and from Temp to Fire. However, there is no edge between SPaper and Fire because the cause–effect relationship between SPaper and Fire always goes through the variable Temp. In other words, if we want to make a prediction for whether the match is on fire, and we already know the temperature of the match head, we do not gain any additional information by knowing whether the match recently touched the sand paper. In essence the variable Temp blocks the information flow from SPaper to Fire. In probabilistic terms we say that random variable Fire is conditionally independent of SPaper given Temp.

C. Independence and conditional independence

Since it is well known that correlation of two variables does not imply causation, tests other than cross correlation must be used to identify potential causal relationships. The basis of causal discovery is to use—in addition to the common independence tests that only involve two variables—also conditional independence tests that involve three or more variables.

Two discrete random variables, X and Y, are said to be independent of each other if
\[ P(X=x, Y=y) = P(X=x) P(Y=y) \]
for any x, y. Denoting as
\[ P(X=x | Y=y) \]
the conditional probability that X takes the state x, conditioned on the fact that Y is in state y, two discrete random variables, X and Y, are conditionally independent given a third random variable, Z, if
\[ P(X=x | Y=y, Z=z) = P(X=x | Z=z) \]
for any x, y, and z with
\[ P(Z=z) \neq 0. \]
If X and Y are conditionally independent given Z, then if one is interested in the state of X and already knows the state of Z, knowing Y in addition does not add any new information. In other words Z blocks the information flow from X to Y. The definition of conditional independence applies not only if Z represents a single random variable, but also for a set of several random variables, \( Z = (Z_1, \ldots, Z_k) \). Although defined here only for discrete variables for the sake of simplicity, the above definitions generalize to continuous variables.

We saw an example of a conditional independence relationship in the match example above (Fire is conditionally independent of SPaper given Temp). In this example the conditional independence was concluded from our understanding of the physical problem. However, in structure learning we want to learn unknown conditional independencies in a system based on data. For that we need tests for independence and CI. A great variety of measures can be used to test for independence and conditional independence, see Borgelt (2010) for a review. Ideally, any such measure is supposed to yield a value of zero if the variables are (conditionally) independent and nonzero otherwise. In statistics the traditional choice is cross correlation as measure for independence and partial correlation for conditional independence.
Causal Effect Networks/Bayesian Networks

Correlation Graph

Directed independence graph

Ebert-Uphoff and Deng (2012; JCLI)
Causal Effect Networks/Bayesian Networks

Correlation Graph

Directed independence graph

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.
Causal Effect Networks

1. Introduction

The recent cold winters in North America and Eurasia were characterized by a meandering jet stream pattern and a negative Arctic Oscillation index (AO). 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 et al. 2001; Comiso 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
Another tool for our toolbox

- Lagged Regression/Correlations
- Targeted Model Experiments
- Forecasting Approach

Diagram:
- Stratosphere
- Arctic warming & ice loss
- Jet-stream changes
- Tropical forcing
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

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

\[ X_t = Y_{t-1} + \epsilon_t \]

red noise (AR1)

Y drives X one day later

+ noise

memory in Y

noise in X

ENSO

\[ T \]

\[ X \]

\[ Y \]

\[ \alpha = 0.85, \quad \epsilon_n = 0.5 \]

McGraw and Barnes (submitted)
Lagged regression

- Pretend we don’t know the relationship between X and Y
  - Step 1: test whether Y $\rightarrow$ X $\mathbf{[right]}$
  - Step 2: test whether X $\rightarrow$ Y $\mathbf{[wrong]}$

McGraw and Barnes (in prep)
Lagged regression

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

\[ X_t = b Y_{t-1} + \epsilon_t \]

\[ Y_t = b X_{t-1} + \epsilon_t \]

McGraw and Barnes (in prep)
Lagged regression

- Pretend we don’t know the relationship between $X$ and $Y$
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- **Step 2**: test whether $X \rightarrow Y$  

\[
X_t = bY_{t-1} + \epsilon_t
\]

\[
Y_t = bX_{t-1} + \epsilon_t
\]

* McGraw and Barnes (in prep)
Lagged regression

\[ X_t = bY_{t-1} + \epsilon_t \]

McGraw and Barnes (in prep)
Lagged regression

\[ Y_t = bX_{t-1} + \epsilon_t \]

McGraw and Barnes (in prep)
Lagged regression

(a) Lag Regression, ENSO

memory in $\alpha$

noise in $X$

0 2 4 6 8 10 12 14

0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9

0 10 20 30 40 50 60 70 80 90 100

right

wrong

McGraw and Barnes (submitted)
Lagged regression

(a) Lag Regression

$\alpha$ = 0.85, $\epsilon_n$ = 0.5

McGraw and Barnes (submitted)
Granger causality

(a) Lag Regression, ENSO

(b) Granger Causality, ENSO

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 $X$

$\alpha = 0.05$

McGraw and Barnes (submitted)
Models with higher latitude jets shift further
Models with higher latitude jets shift further
Models with higher latitude jets shift further
Models with higher latitude jets shift further

**Barnes and Simpson (submitted)**

**Correlation of mean jet latitude and jet latitude regression coefficient**

- **larger equatorward jet shifts for higher-latitude jets**

**CMIP5 RCP8.5 u700 response to 1K POLE warming for warming in North Pacific**

- **low-latitude jet models**
- **high-latitude jet models**
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

(a) North Pacific
jet speed regression coefficients

(b) Jet Speed
variance explained by regression

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, $T_{pol} \rightarrow U700$
(b) Lagged regression, $U700 \rightarrow T_{pol}$
(c) Granger causality, $T_{pol} \rightarrow U700$
(d) Granger causality, $U700 \rightarrow T_{pol}$

420 421 422

Significance is assessed at 95%.

McGraw and Barnes (submitted)
Implications for models biases

North Pacific
position of the maximum zonal wind regression coefficient

higher-latitude jets: coefficient axis
lower-latitude jets: coefficient axis
higher-latitude jets: position
lower-latitude jets: position

jet position

coefficient maximum
Implications for models biases
Implications for models biases

**North Pacific**

- *position of the maximum zonal wind regression coefficient*

- dashed line: higher-latitude jets: coefficient axis
- dashed line: lower-latitude jets: coefficient axis
- solid line: higher-latitude jets: position
- solid line: lower-latitude jets: position

**CMIP5 RCP8.5 u700 response to 1K POLE warming for warming in North Pacific**

- June

- **low-latitude jet models**
- **high-latitude jet models**
Implications for models biases

more negative regression coefficients for higher-latitude jets

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**

(a) North Pacific zonal wind regression coefficients

- **Equatorward jet**
- **Stronger jet**

Barnes and Simpson (in prep)
How Much?: **North Pacific vs North Atlantic**

(a) North Pacific zonal wind regression coefficients

(b) North Atlantic zonal wind regression coefficients

Barnes and Simpson (in prep)
How Much?: **North Pacific vs North Atlantic**

(b) North Atlantic
jet speed regression coefficients

**stronger jet**

**weaker jet**

(b) North Atlantic zonal wind regression coefficients

**weaker jet**

**stronger jet**

Barnes and Simpson (in prep)
Forecasting evidence

% reduction in RMS forecast error for days 11-30 when Arctic is relaxed toward reanalysis

- 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
Modeling evidence

The bimonthly changes in SIT and SIC between the late-twentieth and twenty-first centuries are shown in the top two rows of Fig. 2. The magnitude and pattern of sea ice is accompanied by a thinning of the ice pack. SIT reductions are generally realistic compared to the available observations (Holland et al. 2006).

The late-twentieth-century SIC and SIT distributions are seasonally dependent, with the largest decreases (50%–60%) within the marginal seas in winter. The areal reduction in Arctic ice thinning is relatively uniform throughout the year, with maximum values in February; not shown). In this season, the Arctic is dominated by an upper-level ridge response (maximum amplitude at 500 hPa, and an equivalent barotropic (e.g., 10 m and not statistically significant) during the warm season (June–September), in accord with the small response of the net surface energy fluxes. Although the Student's t-test shows a significance level of 5% confidence, the response in November–December (and in each month of the month of February (not shown)).

More detail on the vertical structure of the circulation responses is given in Fig. 13, which shows transects of the momentum balances of the circulation response. A quantitative analysis of the momentum balances of the circulation response is beyond the scope of this paper. The shallow baroclinic atmospheric circulation response over the Arctic in midwinter is due to the near cancellation of the NAO (although this occurs mainly in November–December (and in each month). A different circulation response is seen in midwinter, with the notable exception of the net surface energy fluxes. Although the Student's t-test shows a significance level of 5% confidence, the response in November–December (and in each month).

Further, the shallow baroclinic atmospheric circulation response over the Arctic in early and late winter may be understood as a linear dynamical response to enhanced boundary layer heating induced by the underlying loss of sea ice (Hoskins and Karoly 1981). On the other hand, farther south, the ocean-induced near-surface warming. Farther south, the atmosphere-only CAM3 simulations have been shown to play a role in shaping the structure of the marginal seas in winter. The changes in Arctic sea ice are communicated to the marginal seas. The areal reduction in Arctic ice thinning is relatively uniform throughout the year, with maximum values in February; not shown). In this season, the Arctic is dominated by an upper-level ridge response (maximum amplitude at 500 hPa, and an equivalent barotropic (e.g., 10 m and not statistically significant) during the warm season (June–September), in accord with the small response of the net surface energy fluxes. Although the Student's t-test shows a significance level of 5% confidence, the response in November–December (and in each month). A different circulation response is seen in midwinter, with the notable exception of the net surface energy fluxes. Although the Student's t-test shows a significance level of 5% confidence, the response in November–December (and in each month).
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.”
Mediators of Surface Temperature Persistence

As expected, the annual cycle of near-surface persistence has been computed for all land grid points and then area-averaged between the 10–40 cm layer, soil temperature above 40 cm, and snow depth. This coincides with increased precipitation, which then has an influence on the near-surface temperature in the extratropical NH, and the results are shown in Figure 2. In October/November (O/N), other mediators start to emerge as well, but the lowest persistence overall still occurs in late autumn/early winter since temperature is somewhat enigmatic, as large parts of Greenland are covered with some exceptions. Snow depth exhibits a slightly more little interannual variability, and hence no significant correlation between snow and temperature. The regions where snow depth variability (not shown). Rather than in persistence in spring appears to be a result of a decline in the mediation by soil moisture and snow depth, and an abrupt expiry of shallow soil temperature mediation. By January/February (J/F), when the domain is limited to specific regions and is not consistent between the maps.

Steps 1–4 are satisfied. The letters in the title of each panel are the first letters of months 1 and 2. The area-averaged temperature persistence is low in late autumn/early winter since summertime continental heating over both Eurasia and North America. Soil temperature is the dominant mediator over large areas. The regions where soil temperature is the best mediator in 20CR. This is consistent with the patterns of mediation by the dominant mediators of near-surface temperature persistence. Considerable overlap exists between the maps for ERA-20C and 20CR, with some exceptions. As previously mentioned, the approach used to produce Figure 3 for each variable in standardised units. The α value is shown when the dominant mediator in month 1 is equal to 1, as shown by the dark red bar in Figure 2(a). In 20CR for the same month pair, the area-averaged temperature persistence in the warm season in ERA-20C follow Figure 2 as sets of nine coloured bars for each month pair, one for ERA-20C in Figure 2(a) and for 20CR in Figure 2(b).