A Study of Causal Links Between the Arctic and The Midlatitude Jet-streams

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Abstract—This paper investigates causal links between Arctic temperatures and the jet-streams. We apply two different frameworks for this application based on the concepts of (1) *Granger causality* and (2) *Pearl causality*. Both methods show that Arctic temperature and jet speed each exhibit strong auto-correlation (as expected), and that jet speed drives Arctic temperature at timescales of 5-15 days, while Arctic temperature drives jet speed at timescales of up to 5 days, in the North Pacific. A positive feedback loop is also identified and discussed, among additional findings. This study is only the beginning of a larger effort to apply and compare different causality methods in order to gain a deeper understanding of the causal connections between the Arctic and weather at lower latitudes.

I. Motivation

Arctic amplification–that is, the phenomenon of Arctic temperatures rising much faster than the global mean ([1])–and its present and future effects on midlatitude weather and climate have received substantial attention in recent years. While it is well known that the midlatitude circulation can drive changes in Arctic temperatures and sea ice, it is unclear how and to what extent the Arctic influences midlatitude weather ([2]). Some argue that Arctic amplification is already influencing midlatitude weather (e.g. [3], [4], [5], [6]), while others state that any possible signal is too small to have been observed amidst the background of atmospheric variability (e.g. [7], [8], [9]). Regarding Arctic influence on midlatitudes under climate change, idealized and fully-coupled climate model simulations have shown an equatorward shift of the jet-stream and weakening of the zonal winds in response to Arctic warming and sea ice loss (e.g. [10], [11], [12], [13]), but little is understood about the underlying dynamics behind this response in models or whether the models can adequately simulate the processes involved. Making progress requires that we study the two-way causal connections between Arctic temperatures and the midlatitude circulation, and

place the different pathways in context of one another and the background of atmospheric variability.

The typical approach for assessing causal links in climate dynamics (including studying the links between the jet-streams and Arctic warming/sea ice loss) is targeted modeling studies. While incredibly useful for understanding the physical mechanisms at play, this approach only allows for studying cause and effect in isolation, and does not allow for the feedbacks to fully develop. In addition, we have entered a period where atmospheric science tends to be "data rich" both in observations and model output [14]. There is great need for additional tools that can aid scientists in identifying and extracting signals. Causal discovery techniques provide (1) robust definitions of causality, (2) can have direct ties to forecasting/prediction, (3) augment targeted model studies, (4) place pathways in context relative to other drivers and feedbacks, and (5) allow for a direct comparison of results from observations and models.

Here we use two different frameworks to learn about causal relationships for this system. The first framework uses vector autoregression (VAR) type models (plain VAR and LASSO), combined with the concept of *Granger causality*. The second framework is based on the concept of *Pearl causality*. We apply both frameworks to the study of causal links between the Arctic and midlatitude jet-streams. The purpose is twofold: (1) by comparing the results of two very different frameworks we hope to obtain robust results; (2) we hope to make more geoscientists aware of the different types of causal analysis tools.

II. Related work

In recent years significant work has been done on using causal reasoning for climate applications, including [15] [16] [17] [18] [19] [20] [21], on developing tools for that purpose [22] [23], and on causal attribution of climate events [24]. Of highest relevance to this work are causality studies specifically for the Arctic: Strong and Magnusdottir [25]; Kretschmer et al. [26]. These studies demonstrate the utility of causality techniques for studying Arctic-midlatitude connections, however, each employs a different approach. Thus, it is unclear whether different causality approaches would produce

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similar results, or whether a particular technique is best suited for this topic. In addition, neither study investigates the relationship between Arctic temperatures and the jet-streams - the focus of this work.

III. DATA

We use daily data from the NCAR CESM1 Large Ensemble Control run. We use Years 402 to 2,200, resulting in 656,634 days (1,799 years) of data. For our analysis we use only one season per year, either DJF or JJA, roughly dividing the number of data samples for each experiment by four. We focus on the North Pacific (120°E - 230°E) and the following three indices: jet latitude, $\mathcal{L}$; jet speed, $\mathcal{S}$; Arctic temperature (averaged over 70°N-90°N), $\mathcal{T}$. For each time series the seasonal cycle was subtracted in order to focus on anomalies, then it was averaged into non-overlapping chunks of 5 days to smooth out *weather noise*. Then we extract the values corresponding to the season of choice. Finally, each time series is standardized, i.e. we subtract its mean and divide by its standard deviation.

IV. METHODS BASED ON GRANGER CAUSALITY

We first explain two closely related models, *VAR* models and *LASSO* models, then discuss how they can each be linked to the concept of *Granger causality*.

A. Vector Autoregression (VAR) model

A VAR(p) model estimates vector $\mathbf{y}_t$ in terms of its p lags as follows:

$$\mathbf{y}_t = \mathbf{c} + \mathbf{A}_1\mathbf{y}_{t-1} + ... + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{e}_t, \quad (1)$$

where p denotes the number of lags considered; vector $\mathbf{y}_t$ contains the values of k considered variables at time t; $\mathbf{c}$ is a coefficient vector; $\mathbf{A}_i$ are the $k \times k$ coefficient matrices (for $i = 1, \ldots, p$); and $\mathbf{e}_t$ is the vector of error terms (residuals). Eq. (1) is a standard regression problem and a standard least-squares approach is used to calculate the model parameters [27], vector $\mathbf{c}$ and matrices $\mathbf{A}_i$. We derive such a VAR model for several different values of p, then look at convergence characteristics to choose the smallest p for which the model no longer changes significantly.

B. LASSO model (Regularized Regression)

For an interpretation based on Granger causality we need to distinguish which of the coefficients, a_{ij}^k, of matrices $\mathbf{A}_i$ are non-zero. (The reasons will become apparent in the next subsection.) For a standard VAR model that requires using a cut-off value, since, due to noise and numerical accuracy, none of the coefficients is likely to be *exactly* zero. The LASSO (least absolute shrinkage and selection operator) [28], [29] approach solves this problem in a more elegant and robust way.

It adds constraints, namely it limits the sum of the magnitude of the elements of all $\mathbf{A}_i$ ($i = 1, \ldots, 10$) matrices to be below a chosen threshold [30]. This forces small coefficients to become exactly zero, while the remaining coefficients compensate for that change. As such it performs *variable selection* along with prediction, i.e. it tells us which input variables (and at which lags) are actually important in the model. LASSO results in a model of the exact same form as Eq. (1), but where many coefficients are exactly zero, which makes the subsequent Granger analysis more straightforward.

C. Connection to Granger causality

Once a model of the form in Eq. (1) is obtained, we perform validation tests to assure the model is stable [27],[31], then apply the concept of Granger causality by inspection of the coefficients in $\mathbf{A}_i$. Let a_{ij}^k denote the element of row i and column j of matrix $\mathbf{A}_k$. Then a_{ij}^k denotes the effect of $y_{j,(t-k)}$ (the jth variable, lagged by k) on $y_{i,t}$ (the ith variable, without lag). Furthermore, since the data was normalized, a_{ij}^k indicates for a change of one standard deviation of $y_{j,(t-k)}$ how much change to expect (approximately) in $y_{i,t}$. (This quantitative interpretation should be used with caution, as many geophysical relationships are non-linear, and the model is thus only a rough approximation.) Then, for $i \neq j$, we see in this model that $y_{j,(t-k)}$ is useful for the prediction of $y_{i,t}$, if and only if $a_{ij}^k \neq 0$. Consequently, the jth variable, y_j, is said to *Granger-cause* the ith variable, y_i, if and only if at least one of the coefficients $a_{ij}^k \neq 0$ for any lag $k = 1, \ldots, p$.

V. METHOD BASED ON PEARL CAUSALITY

The concept of *Granger causality* is related to *predictability*. In contrast Pearl and Rebane developed the framework of *causal calculus* [32] based on the concept of *intervention*, which forms the basis for graphical models and for the concept of *Pearl causality* (see also [33], [34]). The method we use builds on the fact that it is impossible to *prove* a cause-effect relationship between two variables based on just observations, but that one can nevertheless *disprove* such relationships based on observations. We thus use an elimination method that first assumes that all variables have cause-effect connections to each other (for all lags), then uses conditional independence tests to *eliminate* the great majority of these connections. This method usually yields a small set of *potential* cause-effect relationships, each of which may or may not be a true causal relationship. Nevertheless, the sets of actual causal relationships is a subset of the resulting set. The specific method used is the temporal version [15], [18] of the *PC stable* algorithm [35], which is a variant of the classic *PC* algorithm [36] (so named after the first names of the two authors, i.e. no relation to PCA). For more information, see [18]. For brevity, we refer to PC stable as simply PC in the remainder of this document.

VI. Results and Interpretation

Our primary focus for now is on the boreal winter (DJF) results, and the relationship between jet speed ($\mathcal{S}$) and Arctic temperature ($\mathcal{T}$). The results of the LASSO model run for a maximum lag of 25 days (p = 5) is shown in Figure 1a, while the results of the PC model run using 11 time slices is shown in Figure 1b. To create the time slices, we used the original variables (y) and 10 time shifted versions of y, namely shifted by -25, -20, ..., -5, +5, ..., +25 days [18]. All three methods– VAR (not shown), LASSO, and PC–agree quite well with each other.

The LASSO model (Figure 1a) shows both the magnitudes and the signs of the jet speed-Arctic temperature ($\mathcal{S}$-$\mathcal{T}$) relationship. First, we note that both $\mathcal{S}$ and $\mathcal{T}$ are autocorrelated (curved arrows), with coefficients that decay over the 25 day period but remain non-zero. Second, $\mathcal{T}$ drives $\mathcal{S}$ 5 days earlier (as well as 15, 20, and 25 days earlier), with the positive coefficient indicating that warmer temperatures drive a faster jet in the North Pacific. $\mathcal{S}$ also drives $\mathcal{T}$ at a lag of 5 days, with the negative coefficient indicating that faster jets are associated with a colder Arctic. However, at a lag of 15 days and beyond, the relationship between $\mathcal{S}$ and $\mathcal{T}$ changes–$\mathcal{S}$ drives $\mathcal{T}$ with positive LASSO coefficients, indicating that a stronger North Pacific jet drives warmer Arctic temperatures. **Collectively, the LASSO results indicate that there is a positive feedback loop between Arctic temperature and North Pacific jet speed–a warmer Arctic drives a stronger North Pacific jet, and the stronger jet drives further Arctic warming.**

The PC model (Figure 1b) agrees quite well with the results of the LASSO model (although its formulation does not provide the magnitudes or signs of the relationships). In the PC model, we did not allow instantaneous connections between variables to make it easier to compare results with the VAR and LASSO models. The autocorrelated relationships (curved arrows) in the PC model are quite similar to those in the LASSO model. In the PC model, $\mathcal{T}$ drives $\mathcal{S}$ at a lag of 5 days only, and $\mathcal{S}$ drives $\mathcal{T}$ at lags of 15 and 20 days. These are the lags with the strongest coefficients in the LASSO model. So, the PC model and the LASSO model show very similar results, with the lags with the strongest LASSO coefficients also showing significant relationships in the PC model.

Jet latitude, $\mathcal{L}$, also shows evidence of a causal relationship with $\mathcal{T}$ in both the LASSO and PC models (not shown). The influence of $\mathcal{T}$ on $\mathcal{L}$ is not strong, with both PC and LASSO showing few significant relationships. However, the influence of $\mathcal{L}$ on $\mathcal{T}$ is stronger. The LASSO model shows that $\mathcal{L}$ drives $\mathcal{T}$ with negative coefficients at most lags, indicating that a more poleward jet drives colder Arctic temperatures (and vice versa). The PC model shows a very similar
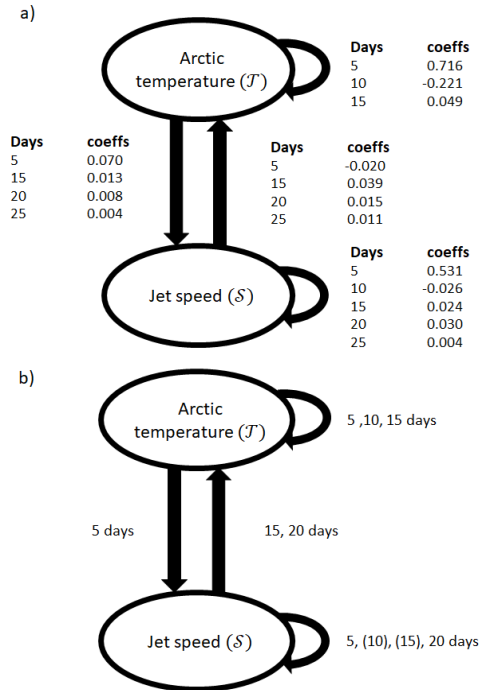

Fig. 1. Arctic temperature ($\mathcal{T}$) and jet speed ($\mathcal{S}$) relationships as described by (a) LASSO ($\lambda = 0.005, p = 5$) and (b) PC (11 time slices, $\alpha = 0.05$) models. Non-zero LASSO regression coefficients are shown next to their corresponding arrows in (a). (b) shows lags at which a significant relationship was present according to PC stable.

relationship to the LASSO model, with $\mathcal{L}$ driving $\mathcal{T}$ at similar lags.

VII. Conclusions and Future Work

Using VAR, LASSO, and PC models, we have demonstrated that Arctic temperature drives jet speed at timescales of 5-15 days in the North Pacific. This relationship is positive, with warmer Arctic temperatures driving a stronger jet, and a stronger jet driving warmer Arctic temperatures. The work described here is only the beginning of a larger study. Future steps include: (1) expansion of these methods to reanalysis, 2-D spatial fields, and inclusion of additional variables such as sea ice extent; (2) providing results from significance testing by comparing unrestricted and restricted VAR models; (3) quantifying the strength of causal relationships beyond use of regression coefficients.

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