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# Using Causal Effect Networks to analyze different Arctic drivers of mid-latitude winter circulation

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## Abstract

In the past years, the northern hemisphere mid-latitudes have suffered from severe winters like the extreme 2012/2013 winter in Eastern USA. 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 mid-latitude 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

28 validity. Our findings confirm that sea ice concentrations in autumn in the Barents and Kara Seas  
29 are an important driver of winter circulation in the mid-latitudes.

30

## 31 **1. Introduction**

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

40 Classical atmosphere dynamic theories relate a meandering jet stream structure to above  
41 normal sea surface temperatures in the tropical Pacific [*Palmer and Mansfeld*, 1984; *Palmer and*  
42 *Owen*, 1986; *Trenberth et al.*, 1998]. Warming of the tropical Pacific intensifies evaporation,  
43 increasing thunderstorm activity in that region. The associated latent heat release can then  
44 trigger large-amplitude planetary waves affecting the mid-latitude flow.

45 In contrast, some recently proposed theories focus on the polar region, claiming that anomalous  
46 atmospheric circulations can be linked to low Arctic sea ice concentrations as observed during  
47 the last two decades [*Petoukhov and Semenov*, 2010; *Francis and Vavrus*, 2012; *Jaiser et al.*,  
48 2012; *Handorf et al.*, 2015]. A reduction in sea ice cover in summer leads to the ocean taking up  
49 more energy in this season. Since sea ice works as an insulating shield blocking the ocean-  
50 atmosphere interaction, less sea ice in autumn and early winter facilitates larger heat fluxes  
51 from the relatively warm ocean into the atmosphere. Kim et al. focus on the Barents and Kara  
52 Seas in particular and argue that reduction in sea ice concentration preferentially in this area  
53 lead to a weakened AO via the stratospheric polar vortex [*Kim et al.*, 2014]. They link the  
54 additional heat release to the atmosphere caused by sea ice loss in early winter to anomalously

55 high geopotential heights over the Barents and Kara Sea region in addition to lower than normal  
56 geopotential heights over Northern Western Europe and Eastern Asia. This observed wave-like  
57 structure indicates upward propagation of large scale planetary waves into the Stratosphere,  
58 interfering with the predominantly zonal flow in the lower Stratosphere. As a result, the  
59 stratospheric zonal flow weakens and the geopotential heights and wind anomalies descend to  
60 the Troposphere, which is also called a “breakdown” of the polar vortex. As a consequence, cold  
61 Arctic air reaches lower latitudes thereby forming large meanders. Those pressure anomalies,  
62 respectively meandering of the jet stream, are then most often reflected in a negative phase of  
63 AO. Kim et al. (2104) base their analysis on theoretical physical considerations and observational  
64 data. They validate their results using climate model simulations, which reproduce similar  
65 patterns, supporting their proposed theory.

66 A similar mechanism was proposed by Cohen et al. who linked increased fall snow cover in  
67 Eurasia to changes in surface pressure anomalies, causing a likewise chain of effects [*Cohen et*  
68 *al.*, 2007, 2013, 2014a]. Based on observational data and correlation analysis they hypothesize  
69 that an extended Eurasian snow cover in fall, likely resulting from decreasing Arctic sea ice,  
70 leads to increasing sea level pressures over Central Asia in early winter. As a result a disturbed  
71 pressure pattern in the polar region is observed, leading to increased vertical wave activity and  
72 poleward heat flux. This is followed by anomalously high geopotential heights in the  
73 Stratosphere, associated with stratospheric warming and weakening of the polar vortex, and  
74 respectively a negative surface AO as described by Baldwin and Dunkerton (1999).

75 In order to study the atmospheric response to changes in the Arctic, different methods have  
76 been used. Cross-correlation analysis is widely applied to detect linear relationships and their  
77 time delays between different processes [*Polvani and Waugh*, 2004; *Cohen et al.*, 2014a].  
78 However, correlation can be highly biased by auto-correlation effects, by indirect connections  
79 via a third process, or by a common driver leading to non-causal, spurious correlations that  
80 limits its interpretability [*Runge et al.*, 2014]. Also, it does not give any answer on the direction  
81 of the relationship, such that it is not an adequate tool to study causal effects. Therefore climate  
82 models are used, to investigate atmospheric changes due to a controlled perturbation of the  
83 system [*Deser et al.*, 2010; *Petoukhov and Semenov*, 2010; *Handorf et al.*, 2015]. This approach

84 allows interpreting results as causal effects forced by the input data. However, conclusions are  
85 strictly limited to the extent of the physical realism of the climate model used. It remains  
86 questionable whether models capture important processes like ocean-ice feedbacks [*Tremblay*  
87 *et al.*, 2007], land-snow interactions [*Furtado et al.*, 2015], troposphere-stratosphere  
88 interactions [*Manzini et al.*, 2014] and Rossby wave propagation [*Gray et al.*, 2014] accurately.  
89 Thus, both climate model experiments and correlation analysis of observational data are  
90 restricted in their interpretability [*Barnes and Screen*, 2015].

91 Here we analyze observational data with a novel method based on graphical models called  
92 *Causal Effect Networks (CEN)*. This method overcomes spurious correlations due to  
93 autocorrelation, indirect effects or common drivers (at least among the observed variables  
94 included) using a causal discovery algorithm as proposed by Runge et al. (2012a, 2012b, 2014).  
95 This algorithm is a modified version of the PC-algorithm [*Spirtes et al.*, 2000] (named after its  
96 inventors Peter Spirtes and Clark Glymour) which has first been applied to climate research by  
97 Ebert-Uphoff and Deng [*Ebert-Uphoff and Deng*, 2012] to study interactions between major  
98 climate modes. Causal discovery approaches have since then been used to study atmospheric  
99 flows [*Deng and Ebert-Uphoff*, 2014], causal relationships in the Walker Cell in the Tropics  
100 [*Runge et al.*, 2014], the monsoonal dynamics in the Pacific-Indian Ocean [*Runge et al.*, 2015]  
101 and decadal ocean circulation in the Atlantic [*Schleussner et al.*, 2014].

102 The aim of this paper is to explain how to apply this method and show how it can be used for  
103 hypothesis testing in the context of teleconnections in climate research. We apply CEN to  
104 observational and reanalysis data in order to understand how different mechanisms which  
105 might cause a negative AO in winter are causally related with each other. In this study, we limit  
106 ourselves to testing a set of proposed Arctic mechanisms. In contrast to tropical mechanisms,  
107 those operate on similar sub-seasonal timescales, which facilitates a simultaneous analysis.

108 The article is structured as follows: In section 2 the data selection is motivated and section 3  
109 gives a detailed description of the two different steps of the CEN-algorithm on the basis of an  
110 example. In section 4 the sensitivity of the parameter settings and temporal resolution is  
111 analyzed and structure and robustness of the graphs are discussed in the framework of the

112 tested hypothesis. Finally, in section 5 we conclude and assess the potentials and limitations of  
113 the presented method.

114

115

## 116 **2. Data**

117 Different actors can influence mid-latitude winter circulation. The first step of our analysis is  
118 hence to come up with a reasonable choice of processes which are expected to be relevant for  
119 the analysis. This includes the decision for physical variables which should serve as proxies for  
120 the considered processes, the selection of suitable data sources and a reasonable time  
121 resolution of the data.

122 As stated, we limit the analysis to Arctic processes and follow Kim et al. (2014) and Cohen et al.  
123 (2014) with respect to data selection. We therefore include Barents and Kara sea ice  
124 concentrations (BK-SIC) as well as Eurasia snow cover (EA-snow) in our analysis, as possible  
125 causal drivers of a negative Arctic Oscillation Index (AO). We further include sea level pressure  
126 in the Ural Mountains region (Ural-SLP) as defined in [Cohen et al., 2014] and sea level pressure  
127 in the Lake Baikal area as a proxy for Siberian High variability (Sib-SLP). Following Kim et al. and  
128 Cohen et al. we include the zonally averaged poleward heat flux  $v^*T^*$  at 100 mb (v-flux) to  
129 capture the Troposphere-Stratosphere coupling. This is a widely used proxy for vertical wave  
130 activity, whereby  $v$  denotes the meridional wind velocity,  $T$  stands for temperature and the  
131 asterisk denotes deviations from the zonal mean [Polvani and Waugh, 2004; Dunn-Sigouin and  
132 Shaw, 2015]. There are many possible ways to describe polar vortex activity (PoV), but for  
133 consistency with Kim et al. (2014) and Cohen et al. (2014) we calculate geopotential height  
134 anomalies poleward of 65°N, averaged over pressure levels from 10mb to 100mb to define the  
135 strength of the stratospheric polar vortex. Eurasia snow data is described in [Robinson et al.,  
136 1993] and is provided by NOAA<sup>1</sup>. Sea ice concentration data was taken from the Nimbus-7  
137 SMMR and DMSP SSM/I-SSMIS passive microwave data set provided by the National Snow & Ice

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<sup>1</sup> <http://gis.ncdc.noaa.gov/all-records/catalog/search/resource/details.page?id=gov.noaa.ncdc:C00756>

138 Data Center<sup>2</sup>. The Arctic Oscillation Index (AO) is provided by NOAA<sup>3</sup> and for the remaining  
139 variables we used ERA-Interim reanalysis data<sup>4</sup>.

140 In summary, our analysis contains seven different actors (Tab. 1): Barents and Kara sea ice  
141 concentrations (BK-SIC), Eurasia snow cover (EA-snow), the Arctic Oscillation Index (AO), vertical  
142 wave activity (v-flux), polar vortex strength (PoV), sea level pressure over the Ural Mountains  
143 (Ural-SLP) and Siberian High activity (Sib-SLP). For each variable we consider the time-period  
144 01/1979-12/2014, which is most reliable in the reanalysis due to availability of satellite data.

145 We calculate monthly means of daily data for each variable as we are testing mechanisms which  
146 are expected to act on monthly time scales. Thereby we perform linear interpolation of the  
147 snow data and for some years of the sea ice concentration data set, where daily data is not  
148 available. To gain additional information on the time-scale of the considered processes we  
149 perform additional analysis using half-month means as well as quarter-month means of every  
150 variable (Fig. 1). For half-monthly data we take the mean from the 1<sup>st</sup> - 15<sup>th</sup> and from the 16<sup>th</sup>-  
151 30<sup>th</sup> of each month and for February from 1<sup>st</sup> - 14<sup>th</sup> and 15<sup>th</sup> - 28<sup>th</sup> respectively (thus ignoring the  
152 31<sup>th</sup> of all applicable months as well as the 29<sup>th</sup> of February in leap years). To construct quarter-  
153 monthly time series we calculate the mean from 1<sup>st</sup> - 7<sup>th</sup>, 9<sup>th</sup> - 15<sup>th</sup>, 16<sup>th</sup> - 22<sup>th</sup> and 24<sup>th</sup> - 30<sup>th</sup>  
154 (neglecting hence the 8<sup>th</sup>, 23<sup>th</sup> and 31<sup>th</sup> of all applicable months) and for February from 1<sup>st</sup> - 7<sup>th</sup>,  
155 8<sup>th</sup> - 14<sup>th</sup>, 15<sup>th</sup> - 21<sup>th</sup> and 22<sup>th</sup> - 28<sup>th</sup> respectively. This approach has the advantage that the  
156 different time-series are still in sync with each other facilitating the comparison of associated  
157 CENs.

158 For each variable and time-resolution we calculate climatological anomalies (observed value  
159 minus the multi-year mean), from which we then compute the area-weighted spatial average  
160 over the defined region (see last column in Tab. 1). This way we create single time-series for  
161 each time-resolution and each actor (see Fig. 2 for monthly data). Since CEN construction

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<sup>2</sup> <http://nsidc.org/data/nsidc-0051>

<sup>3</sup> [http://www.cpc.ncep.noaa.gov/products/precip/CWlink/daily\\_ao\\_index/ao.shtml](http://www.cpc.ncep.noaa.gov/products/precip/CWlink/daily_ao_index/ao.shtml)

<sup>4</sup> <http://apps.ecmwf.int/datasets/data/interim-full-daily/>



162 requires stationary time-series, we remove the linear trend if present. For our analysis this is  
163 only the case for Barents and Kara sea ice concentrations (BK-SIC). Additionally we change the  
164 sign of PoV, such that positive values (negative geopotential height anomalies) indicate a strong  
165 polar vortex.

166

167

### 168 **3. Method**

169 The Causal Effect Networks approach is based on two steps: (1) Reconstructing the causal  
170 parents of each actor using a causal discovery algorithm [Runge *et al.*, 2012a, 2012b, 2014],  
171 which is a modification of the PC-algorithm [Spirtes *et al.*, 2000] for time series. As explained in  
172 the following, this step is based on iterative conditional independence tests using partial  
173 correlation. (2) In a second step, the strength of causal links is quantified using a linear version  
174 of Pearl's causal effect measures [Pearl, 2013]. Thereby the parents are used in a multiple linear  
175 regression analysis to test the significance and strength of causal dependencies between all  
176 pairs of actors at a range of time-lags.

177 Here we use a linear approach to estimate and interpret causal links, but the two-step  
178 procedure of causal reconstruction and quantification can also be embedded in an information-  
179 theoretic framework to study causal information transfer accounting for nonlinear relationships  
180 between variables. For a detailed explanation of the method, including a mathematical analysis  
181 as well as numerical testing, we refer to Runge *et al.* (2012a, 2012b, 2014). All calculations  
182 presented in this study were performed using the Python package TiGraMITe (*Time series graph*  
183 *based Measures of Information Transfer*) which provides the CEN-algorithm and is freely  
184 available<sup>5</sup>.

185 In the following we explain how to apply CEN to test causality of the hypotheses discussed in  
186 the introduction.

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<sup>5</sup> <https://www.pik-potsdam.de/members/jakrunge>

187

## 188 **Step 1: Detecting Causal Effects**

189 The first step of the CEN-algorithm aims to find causal relationships between the different  
190 actors and their associated time lags. The scope of this step is to identify past processes which  
191 directly influence each actor. We call those processes the parents of an actor and they will be  
192 used later to determine the actual strength and the sign of the causal relationships.

193 Cross-correlation can give a first impression of the pairwise linear relationship between two  
194 processes X and Y. However, it is not able to identify causal links because the bivariate analysis  
195 can be biased by autocorrelation of the two variables, by common drivers or by indirect links via  
196 a third process Z (Fig. 3a, b, c). For example cross-correlation of two independent processes X  
197 and Y can be high if one of the processes is strongly auto-correlated (Fig. 3a). Also, imagine that  
198 Z causes X and Y (Fig. 3c) then cross-correlation analysis would find a strong correlation  
199 between X and Y even though there is no direct link between them. In order to detect causal  
200 links, a multivariate analysis is required which takes all potential actors into account.

201 Recall that two processes X and Y are conditionally independent given a third process Z if  
202  $P(X \cap Y | Z) = P(X | Z)P(Y | Z)$ , whereby P denotes the probability function. In the linear case this can  
203 be tested by removing the linear influence of Z from both X and Y and testing for the correlation  
204 between their residuals (partial correlation). In the previous case (Fig. 3c), X and Y would then  
205 be conditionally independent given Z. In the example illustrated in Fig. 3b, process X causes Z  
206 which in turn influences Y. Process X and Y are thus conditionally independent given Z and a  
207 high correlation coefficient between X and Y only occurs due to the indirect link via Z.

208 This section discusses how the CEN-algorithm uses iterative partial correlations to identify non-  
209 causal correlations as depicted in Fig. 3. The extent to which such a data-based analysis allows  
210 to conclude on a physical causal mechanism depends on the included variables, time resolution  
211 of the data and assumptions such as stationarity. Two free parameters are involved: the  
212 significance level  $\alpha$  for the partial correlation tests and the maximum time delay  $\tau_{\max}$ .

## 213 **Calculating the parent processes**

214 As an illustrative example, we start with finding those processes on a monthly time-scale among  
 215 our actors which have a direct causal effect on the winter (December, January, February) polar  
 216 vortex (PoV). We look at the monthly time-series for every actor (Fig. 2) having thus a sample-  
 217 length of 108 time-steps. We define a two-sided significance level  $\alpha=0.01$  and a maximum time-  
 218 lag of  $\tau_{\max}=3$  months implying that parent processes more than three months ago or those with  
 219 a significance below 99% will be neglected.

220 First, for every actor  $X$  the cross-correlation function  $\rho(X_{t-\tau}, \text{PoV}_t)$  is calculated for time shifts of  
 221  $\tau=1$  up to the maximum time-shift  $\tau_{\max}=3$  months. Note that, if we study causal effects *on* winter  
 222 PoV, this implies that the monthly time-series  $\text{PoV}_t$  only consists of winter data but the lagged  
 223 or driving variable contains data from other seasons (in particular autumn but also summer  
 224 when  $\tau>3$ ). Here the expression “driver” is used in its statistical meaning of being conditional-  
 225 dependent and shifted in time. For  $\tau=1$  the expression  $\rho(X_{t-1}, \text{PoV}_t)$  denotes the Pearson  
 226 correlation coefficient of November-December-January data of process  $X$  and December-  
 227 January-February data of PoV (see Fig. 4) whereas for  $\tau=3$  the linear influence of the three  
 228 months shifted September-October-November data of actor  $X$  on PoV in winter (DJF) is  
 229 measured. For example, for the influence of Eurasia snow cover ( $X=\text{EA-snow}$ ) on the polar  
 230 vortex with a time delay of  $\tau=1$  we obtain:

$$231 \quad \rho(\text{EA-snow}_{t-1}, \text{PoV}_t) = -0.262$$

232 which is significant at the  $\alpha=0.01$  level. This indicates that there is a negative linear relationship  
 233 between early winter (NDJ) snow and the winter polar vortex. This seems reasonable since a  
 234 large snow cover in Eurasia is indicated to induce a weakened polar vortex [Cohen *et al.*, 2014].  
 235 The cross-correlation function is now calculated and evaluated for every actor  $X \in \{\text{BK-SIC}_{t-\tau}, \text{EA-}$   
 236  $\text{snow}_{t-\tau}, \text{AO}_{t-\tau}, \text{v-flux}_{t-\tau}, \text{PoV}_{t-\tau}, \text{Sib-SLP}_{t-\tau}, \text{Ural-SLP}_{t-\tau}\}$  and every time-lag  $\tau \in \{1,2,3\}$ . We find that  
 237 besides EA-snow (with  $\tau=1$ ), also Ural-SLP (with  $\tau=1$  and  $\tau=2$ ), AO (with  $\tau=1$ ), PoV (with  $\tau=1$ ) and  
 238 v-flux (with  $\tau=1$ ) are significantly correlated with winter PoV. Sorted by the strength of  
 239 correlation starting with the strongest in absolute value, the set of potential parent-processes of  
 240 PoV in this zeroth iteration step without any conditioning is:

$$241 \quad \mathbf{P}^0 = \{\text{v-flux}_{t-1}, \text{PoV}_{t-1}, \text{Ural-SLP}_{t-1}, \text{Ural-SLP}_{t-2}, \text{AO}_{t-1}, \text{EA-snow}_{t-1}\}.$$

242 To test these potential drivers for conditional independence, we next calculate partial  
243 correlations:

$$244 \quad \rho(X_{t-\tau}, Y_t | \mathbf{Z})$$

245 which measure the linear influence from process X on Y, excluding the influence of some set of  
246 variables  $\mathbf{Z}$ . This thus checks if X and Y are conditionally independent given  $\mathbf{Z}$ . We choose  $\mathbf{Z}$  as a  
247 subset of  $\mathbf{P}^0$  such that  $\mathbf{Z}$  denotes a set of other processes which potentially influences the  
248 bivariate correlation coefficient  $\rho(X_{t-\tau}, Y_t)$ . In each iteration step  $\mathbf{P}^1, \mathbf{P}^2, \dots$  we condition on a new  
249  $\mathbf{Z}$ , whereby the algorithm first takes only one condition and starts with the process which is  
250 strongest correlated (in absolute value) with process Y. Then the dimension of the subset  
251 selected from the remaining parents is increased and different two-dimensional conditions are  
252 tested and so on for higher dimensions. If the partial correlation significance test of a pair  $X_{t-\tau}$   
253 and  $Y_t$  is non-significant given  $\mathbf{Z}$ , the process  $X_{t-\tau}$  is removed from the set of potential parents. If,  
254 however, the partial correlation  $\rho(X_{t-\tau}, Y_t | \mathbf{Z})$  remains significant for all tested  $\mathbf{Z}$ , then actor X is  
255 considered to directly influence Y with a time-lag of  $\tau$ .

256 Returning to our example, we first test condition  $\mathbf{Z}=\{v\text{-flux}_{t-1}\}$  and find:

$$257 \quad \rho(\text{EA-snow}_{t-1}, \text{PoV}_t | v\text{-flux}_{t-1}) = -0.147$$

258 which is not significantly different from zero at our chosen level and hence we find that EA-  
259 snow and PoV are conditionally independent (at a time-delay of one month) if the influence of  
260 v-flux from the same time shift is excluded. We thus conclude that there is no direct influence  
261 from EA-snow on PoV with a delay of one month and that the significant correlation between  
262 them  $\rho(\text{EA-snow}_{t-1}, \text{PoV}_t) = -0.261$  is due to the influence of v-flux. For example, EA-snow could  
263 be linked to PoV indirectly via v-flux (as in Fig. 3b). On the other hand, if we take  $X=\text{Ural-SLP}_{t-1} \in$   
264  $\mathbf{P}^0$  and condition on the same  $\mathbf{Z}=\{v\text{-flux}_{t-1}\}$  we find

$$265 \quad \rho(\text{Ural-SLP}_{t-1}, \text{PoV}_t | v\text{-flux}_{t-1}) = -0.281$$

266 which is still significantly different from zero. In other words, the linear influence of  $\text{Ural-SLP}_{t-1}$   
267 on  $\text{PoV}_t$  cannot exclusively be explained by the linear influence of v-flux.

268 We calculate partial correlations for all the elements from  $\mathbf{P}^0$  conditioning on  $\mathbf{Z}=\{\text{v-flux}_{t-1}\}$  and  
 269 find that some of them are conditionally independent from PoV given  $\text{v-flux}_{t-1}$ , which can thus be  
 270 neglected as potential drivers of winter PoV. This way we obtain a much smaller set of potential  
 271 parent processes of PoV:

$$272 \quad \mathbf{P}^1 = \{\text{v-flux}_{t-1}, \text{PoV}_{t-1}, \text{Ural-SLP}_{t-1}\} \subset \mathbf{P}^0.$$

273 Now the algorithm proceeds by conditioning on the process which was second strongest  
 274 correlated with PoV, i.e.  $\mathbf{Z}=\{\text{PoV}_{t-1}\}$ . We thus check if some of the potential drivers of PoV only  
 275 occur due to the auto-correlation of PoV. Calculating partial correlations of the elements of  $\mathbf{P}^1$   
 276 conditioning on  $\mathbf{Z}=\{\text{PoV}_{t-1}\}$  gives only values significantly different from zero such that  $\mathbf{P}^2 = \mathbf{P}^1$ .  
 277 The last possibility of picking only one condition is  $\mathbf{Z}=\{\text{Ural-SLP}_{t-1}\}$ , where we find again that all  
 278 the partial correlations remain significantly different from zero such that  $\mathbf{P}^3 = \mathbf{P}^2 = \mathbf{P}^1$ . Sorting the  
 279 elements by the strength of their partial correlation value in the last iteration step we have:

$$280 \quad \mathbf{P}^3 = \{\text{v-flux}_{t-1}, \text{Ural-SLP}_{t-1}, \text{PoV}_{t-1}\}.$$

281 Now we increase the dimension of  $\mathbf{Z}$  and condition on two possible drivers from  $\mathbf{P}^3$ . Thus we  
 282 start with  $\mathbf{Z} = \{\text{v-flux}_{t-1}, \text{Ural-SLP}_{t-1}\} \subset \mathbf{P}^3$  and calculate:

$$283 \quad \rho(\text{PoV}_{t-1}, \text{PoV}_t \mid \text{v-flux}_{t-1}, \text{Ural-SLP}_{t-1}) = 0.268$$

284 which is still significantly different from zero. When testing for the other possibilities ( $\mathbf{Z}=\{\text{v-flux}_{t-1},$   
 285  $\text{PoV}_{t-1}\}$  and  $\mathbf{Z}=\{\text{Ural-SLP}_{t-1}, \text{PoV}_{t-1}\}$ ), the partial correlations remain significant. Since there are  
 286 no more combinations for choosing  $\mathbf{Z}$  the algorithm converges and stops.

287 We have now found the set of direct drivers of winter PoV (relative to the variables taken into  
 288 account), which we call its parents denoted by:

$$289 \quad \mathcal{P}_{\text{PoV}} = \{\text{v-flux}_{t-1}, \text{Ural-SLP}_{t-1}, \text{PoV}_{t-1}\}.$$

290 In other words we found that (given the settings of  $\tau_{\text{max}}=3$  and  $\alpha=0.01$ ) winter polar vortex (PoV)  
 291 is directly driven by itself with a delay of one month and by vertical wave activity (v-flux) and  
 292 pressure variability in the Ural Mountains region (Ural-SLP) with a delay of one month, but is  
 293 (linearly) conditionally independent of all other processes.

294 The procedure described for PoV is performed for all actors yielding a set of parents for every  
295 actor (see Tab. 2):

$$296 \quad \mathcal{P} = \{\mathcal{P}_{AO}, \mathcal{P}_{BK-SIC}, \mathcal{P}_{EA-snow}, \mathcal{P}_{v-flux}, \mathcal{P}_{PoV}, \mathcal{P}_{Sib-SLP}, \mathcal{P}_{Ural-SLP}\}.$$

297 Note that the interpretation of the significance level  $\alpha$  as the probability of false rejections of  
298 the hypothesis of a non-causal link is not strictly valid here since we tested every possible link  
299 multiple times by conditioning on different processes (see discussion section).

300

## 301 **Step 2: Quantifying Causal Effects**

302 In the second step, we use the sets of parents to determine the strength of causal relationships.  
303 The case of  $\tau=0$ , i.e., when there is no time shift between the actors was omitted when  
304 calculating the parents. In this step we will nevertheless quantify the significant instantaneous  
305 relationships conditional on the parents. As stated above, such contemporaneous links can in  
306 general not be interpreted in a causal way. Some might turn out to be causal parents at a higher  
307 time resolution, but some might be just due to excluded common drivers. We address this issue  
308 later by studying different time lags.

309 As mentioned, the set of derived parents depends on the significance level  $\alpha$ , which here is,  
310 however, not well interpretable due to the multiple testing problem. In order to better assess  
311 significance, we therefore test every possible combination of actors and time-lags again  
312 (including links from parents) using the causal parents as a conditioning set.

313 In general, multiple linear regression can be used to measure the influence a system of variables  
314 (the independent variables) has on a different (dependent) variable. However, it can often be  
315 challenging to define a set of independent variables which can explain the dependent variable.  
316 The list of causal parents provides a reasonable choice for those variables with their associated  
317 time-lags. We calculate the link strength using standardized multiple linear regression  
318 coefficients based on our list of parents for the case of  $\alpha=0.01$  and up to a maximum lag of  
319  $\tau_{max}=3$ . We found that PoV is influenced from the past by  $\mathcal{P}_{PoV} = \{v-flux_{t-1}, Ural-SLP_{t-1}, PoV_{t-1}\}$ . To

320 calculate if process X significantly influences PoV with a time-lag of  $\tau \geq 0$  we formulate the  
321 standardized linear regression model

$$322 \quad \text{PoV}_t^* = \beta_0 + \beta_1 \text{v-flux}_{t-1}^* + \beta_2 \text{Ural-SLP}_{t-1}^* + \beta_3 \text{PoV}_{t-1}^* + \beta_4 X_{t-\tau}^* + \varepsilon.$$

323 Here the beta coefficients  $\beta_i$  with  $i \in \{0,1,2,3,4\}$  denote the standardized regression coefficients,  $\varepsilon$   
324 stands for the error term and the asterisk indicates that the time-series have been normalized  
325 and standardized. The regression coefficients express how much the different independent  
326 variables contribute to variability in PoV in terms of standard deviations. Interpreted causally  
327 [Pearl, 2013], this means that if X is increased by one standard-deviation keeping the other  
328 variables fixed, then PoV increases by  $\beta_4$  standard-deviations. The  $\beta$ -coefficient of X is tested for  
329 significance at  $\alpha=0.01$  with the null-hypothesis  $\beta=0$ , which would mean that variable X does not  
330 contribute significantly to the dependent variable PoV.

331 To test if, for example, X=EA-snow significantly influences winter PoV with a delay of one month  
332  $\tau=1$  we calculate the standardized linear regression model and choose EA-snow<sub>t-1</sub> as well as the  
333 parents of PoV as independent variables to explain PoV:

$$334 \quad \text{PoV}_t^* = \beta_0 + \beta_1 \text{v-flux}_{t-1}^* + \beta_2 \text{Ural-SLP}_{t-1}^* + \beta_3 \text{PoV}_{t-1}^* + \beta_4 \text{EA-snow}_{t-1}^* + \varepsilon$$

335 We get  $\beta_4 = -0.076$  which is not significant at the  $\alpha=0.01$  level such that the influence from EA-  
336 snow on PoV with a delay of one month is considered to be absent. If we, however, calculate  
337 the influence of v-flux with  $\tau=1$  (which is also in  $\mathcal{P}_{\text{PoV}}$ ) on winter PoV we obtain a significant beta  
338 coefficient  $\beta_1 = -0.514$ . Thus, v-flux is concluded to be causally influencing the winter polar  
339 vortex with a delay of one month and with a strength of  $\beta_1 = -0.514$ , i.e., a one-standard  
340 deviation increase in v-flux leads to a negative change of about half a standard deviation in PoV.

341 We test the influence of every actor  $X \in \{\text{BK-SIC}_{t-\tau}, \text{EA-snow}_{t-\tau}, \text{AO}_{t-\tau}, \text{v-flux}_{t-\tau}, \text{PoV}_{t-\tau}, \text{Sib-SLP}_{t-\tau},$   
342  $\text{Ural-SLP}_{t-\tau}\}$  and every time-lag  $\tau \in \{0,1,2,3\}$  on PoV as well as on every other actor in form of  
343 standardized linear regression. The remaining significant links form our *Causal Effect Network*.

344 Note, that it is possible that in this step significant direct links are identified which had been  
345 rejected in the first step. Nevertheless, by testing every potential link again, we can better  
346 interpret the statistical meaning of  $\alpha$  as the probability of falsely rejecting the null hypothesis

347 that a lagged variable  $X_{t-\tau}$  is independent of  $Y_t$  given the parents of  $Y_t$  selected with the causal  
348 algorithm. However, we will see that our list of parents strongly coincides with the significant  
349 strong links identified in the second step.

350

351

## 352 **4. Results & Discussion**

353 We construct CEN for winter circulation and with different  $\alpha$  and  $\tau_{\max}$  settings. Visualization of  
354 CEN as a process graph gives an easy to interpret picture of the underlying complex  
355 teleconnection pattern. Only the significant links are presented in the graph and the numbers  
356 next to the links stand for the associated time lag  $\tau$ . Instantaneous links are represented by  
357 dashed links and have no direction or time-shift. The node color (in case the variable influences  
358 itself) and the link color represent the standardized regression coefficient (beta values) and  
359 hence capture the strength of the causal relationship. If two processes are linked for more than  
360 one time-lag then all lags are given (sorted by strength) with the link color based on the  
361 strongest connection. The time-lag for auto-driven data is not shown in the graph, but  
362 predominantly actors are lag-1 auto-correlated.

363 For the settings  $\alpha=0.01$ ,  $\tau_{\max}=3$  and using monthly data we obtain the CEN as in figure 5a. We  
364 find evidence that Barents Kara sea ice concentrations (BK-SIC) have a negative effect on sea  
365 level pressure over the Ural Mountains region (Ural-SLP) with a time-delay of three months.  
366 Thus, low sea ice in autumn can lead to increased surface pressure in winter. We also find a  
367 positive link from Ural-SLP to v-flux with a delay of one month which means that higher surface  
368 pressure can increase the poleward heat flux, respectively the vertical wave activity. This is  
369 consistent with the mechanisms proposed by Cohen et al. (2014) and Kim et al. (2014).  
370 Moreover we can see in figure 5a, that increasing vertical wave activity induces a weakening of  
371 the stratospheric polar vortex with a delay of one month. Hence, the CEN depicts the  
372 Troposphere-Stratosphere coupling described by Kim et al. (2014) and Cohen et al. (2014). We  
373 also see a reverse relation from the Stratosphere into the Troposphere, whereby a weak polar



374 vortex (PoV) leads to increasing sea ice in the Barents and Kara Seas and to less vertical wave  
375 activity. We find no causal link connecting a weak polar vortex to a negative AO. However, we  
376 have a positive instantaneous link between them, which might indicate that this connection is  
377 happening on a sub-monthly time-scale. In addition to the mechanisms involving the  
378 Stratosphere we also detect a direct positive link from BK-SIC to AO. Thus, we find that Barents  
379 and Kara sea ice in fall induces a weakening of AO in winter without any stratospheric  
380 connection. However, AO is also instantaneously related to sea level pressure in the Ural  
381 Mountains region (Ural-SLP) with a negative sign which is in turn strongly positively related with  
382 sea level pressure in Siberia (Sib-SLP). Even though the instantaneous links provide no direction,  
383 they are in accordance with the expectation that AO is negative when sea level pressure in the  
384 Arctic is high. The same is true for the instantaneous link connecting Sib-SLP and Ural-SLP to  
385 each other resp. to BK-SIC. In addition to the influence of Ural-SLP on PoV via v-flux we also find  
386 a weaker direct causal link between them with a delay of one month, suggesting that high sea  
387 level pressure in Central Asia can induce a weakening of the polar vortex directly, or via  
388 processes which are not part of the tested hypothesis. The positive instantaneous link between  
389 EA-snow and Sib-SLP is indicating that increasing snow cover in Eurasia is associated to a  
390 strengthened Siberian High which is consistent with the hypothesis of Cohen et al. (2014). The  
391 auto-regressive influence (with a time-lag of one month) is as expected especially high for BK-  
392 SIC and EA-snow and weaker for PoV and AO. Ural-SLP, Sib-SLP and v-flux are not significantly  
393 causally influenced by their values in the months before.

394 We performed sensitivity analyses of the CEN to the parameter settings used and found the  
395 detected links to be robust. We limit ourselves to analyzing only links which go back to late  
396 summer. Figure 5 shows the winter months CENs associated with different significance levels ( $\alpha$   
397 = 0.01, 0.025, 0.05 in the rows) and for maximum time-lags of three and five months (columns).  
398 Not surprisingly, the number of significant links increases when we increase  $\alpha$ , most of them  
399 involving the two actors based on sea level pressure (Fig. 5b, e, c, f). Also links associated with  
400 time-lags of more than three months (Fig. 5d-f) appear when increasing the maximum time-lag  
401  $\tau_{max}$ , however only for larger  $\alpha$  values. We see that all links in Fig. 5a appear in all other graphs  
402 as well. For a significance level  $\alpha > 0.01$  (Fig. 5b, e, c, f), we see that decreasing sea ice

403 concentrations in the Barents and Kara Seas (BK-SIC) induce stronger sea level pressure over  
404 Siberia (Sib-SLP) with a lag of two months. This is in accordance with the mechanism described  
405 by Kim et al. (2014). We also see for  $\alpha > 0.01$  that increasing snow cover in Eurasia (EA-snow) is  
406 also instantaneously positively linked to surface pressure over the Ural Mountains region (Ural-  
407 SLP). For a longer time lag we find that EA-snow is negatively influencing sea level pressure in  
408 the Ural Mountains region (Ural-SLP) with a delay of five months (Fig. 5e, f). For  $\alpha = 0.05$  we even  
409 find some evidence that EA-snow can influence AO directly, and thus it seems again that  
410 processes not involving the Stratosphere are present. Overall, the CEN structure as in figure 5a  
411 appears for all tested parameters.

412 As explained in the method section, instantaneous links provide no information on the  
413 direction. To gain further information on the direction of those links and to further test the  
414 robustness of our findings, we construct CENs also for half-monthly and quarter-monthly time-  
415 series (see Fig. 6a, b). Since the data sets are then two-times respectively four-times longer and  
416 consist of shorter time-steps we adjust our settings for the CEN-algorithm. In order to make the  
417 results comparable with figure 5a we therefore double respectively quadruple  $\tau_{max}$  to refer to  
418 the same time-shift. Since for higher time-resolutions more potential links are tested for  
419 significance we adjust the  $\alpha$  value accordingly<sup>6</sup>. Comparing figure 5a with CENs based on half-  
420 monthly (Fig. 6a) and quarter-monthly (Fig. 6b) time series with the same maximum time-shift  
421 of three months and an adjusted significance level  $\alpha = 0.005625$  for half-monthly and  $\alpha = 0.003$  for  
422 quarter-monthly data, we find a robust pattern of the involved causal processes. Especially the  
423 Troposphere-Stratosphere connection is clearly visible in all CENs. For the CEN based on half-  
424 monthly data (Fig. 6a) the connection to vertical wave propagation (v-flux) is via the Siberian  
425 region (Sib-SLP) whereby this region is directly influenced by the Ural Mountains (Ural-SLP) area.  
426 On a quarter-monthly time-scale both regions directly influence v-flux which in turn influences  
427 PoV (Fig. 6b). On the other hand we have a direct link from PoV to AO (Fig. 6b) in the quarter-

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<sup>6</sup> If  $n$  denotes the number of actors, then  $N = n^2(\tau_{max} + 1) - n$  potential links are tested. Thus,  $N = 189$  (monthly),  $N = 336$  (half-monthly) and  $N = 630$  (quarter-monthly). To calculate the adapted  $\alpha$  we use a simple Bonferroni-correction and divide  $\alpha = 0.01$  by the multiplicity of the performed tests.

428 monthly based CEN, which indicates that a breakdown of the polar vortex causes a negative AO  
429 on a weekly time-scale. Also, there are direct links connecting Ural-SLP to EA-snow, BK-SIC and  
430 Sib-SLP, which shows that the Ural Mountains region has a strong influence on the surrounding  
431 regions on sub-monthly time-scales, which is in accordance with the tested hypothesis.  
432 However, the strong instantaneous links between tropospheric based actors (AO, Ural-SLP, Sib-  
433 SLP and EA-snow) remain for all time-scales, indicating that those causal processes are occurring  
434 on sub-weekly time-scales or are due to common drivers. The darker node-colors show that at  
435 sub-monthly time scales auto-regressive processes become larger.

436 In summary, the CEN-algorithm provides robust results, whereby additional links can  
437 predominantly be explained by changing parameter settings and by the temporal resolution of  
438 the underlying time-series. Barents and Kara sea ice (BK-SIC) is detected to play an important  
439 role on winter-circulation, especially on the monthly time-scale (Fig. 5) being responsible for  
440 changes in the pressure profile over the Ural Mountains region as well as by influencing AO  
441 directly. Thus, mechanisms effecting AO not involving the Stratosphere seem to be important,  
442 too. We assume that other processes for example as described by Petoukhov and Semenov  
443 [Petoukhov and Semenov, 2010] not represented by our choice of actors play a role, connecting  
444 Arctic sea ice and AO. As stated by Cohen and Kim, we find a connection of surface pressure  
445 (Ural-SLP) and upward wave activity (v-flux) into the Stratosphere for all parameter settings and  
446 time-scales (Fig. 5, 6). On lower time-scales we also have a direct link from Sib-SLP to v-flux (Fig.  
447 6). These findings confirm the hypothesis that higher pressure over Central Asia leads to  
448 increasing vertical wave activity into the Stratosphere [Cohen et al., 2014]. The Ural Mountains  
449 region as a preferred location for atmospheric blocking [Wang et al., 2009] seems to play a  
450 central role for winter circulation, being linked to the tropospheric actors AO, BK-SIC, Sib-SLP  
451 and EA-snow on all time-scales. Further, the region is responsible for coupling with the  
452 Stratosphere (Fig. 5, 6). In this context, we expect that the link connecting Ural-SLP to PoV  
453 directly, and not via v-flux, can at least partly be explained by hemispheric-wide averaging of the  
454 actors v-flux and PoV (in contrast to the regional actor Ural-SLP). Additionally, it is possible that  
455 a common driver not included in this analysis is responsible for this direct link. For example,  
456 tropical teleconnections like ENSO could influence both the Arctic Stratosphere and sea level

457 pressure in Central Asia [Butler et al., 2014]. Additionally, we find that the increased vertical  
458 wave activity can induce a weakening of the polar vortex (PoV), whereas PoV is positively  
459 connected to surface AO (Fig. 5, 6). Thus, our findings are consistent with the Troposphere-  
460 Stratosphere-Troposphere mechanisms described by Cohen et al. (2014) and Kim et al. (2014).  
461 We also find a reverse connection, linking a weak polar vortex (PoV) to increasing Barents and  
462 Kara sea ice and decreasing vertical wave activity (v-flux). This provides a negative feedback on a  
463 time-scale of approximately one to two months. The role of Eurasia snow cover (EA-snow)  
464 seems to be more complex. We find no evidence that late autumn snow fall in Eurasia  
465 influences the sea level pressure in Central Asia as proposed by Cohen et al. (2014). However,  
466 we find that EA-snow is instantaneously linked to Sib-SLP with positive sign and for  $\alpha > 0.01$  also  
467 to Ural-SLP (Fig. 5, 6). On a monthly time-scale we also have a direct negative link to Ural-SLP  
468 (with a lag of five months) and for  $\alpha = 0.05$  also to AO (with a lag of two months). Overall our  
469 findings are less robust for EA-snow.

470

471

## 472 **5. Conclusion**

473 In the context of hypothesis testing, we constructed *Causal Effect Networks* (CEN) in order to  
474 unravel causal relationships and their time delays between different actors of mid-latitude  
475 winter circulation. We restricted ourselves to studying Arctic mechanisms, based on those  
476 proposed by Kim et al. (2014) and Cohen et al. (2014). For each of the seven actors we  
477 constructed one index at different temporal resolutions. CEN-construction was performed by  
478 first deriving a set of parents for each actor, consisting of the conditional dependent processes  
479 (Step 1). Then those parents were used to estimate the strength and statistical significance of  
480 links employing linear regression models (Step 2). We only considered effects on winter  
481 circulation and applied the method to monthly, half-monthly and quarter-monthly time-series.  
482 We found that the method provides robust results for different values of the significance level  $\alpha$   
483 and maximum time delay  $\tau_{\max}$  as well as for the considered range of temporal resolutions.

484 Figure 7 (respectively Fig. 5a) contains the most robust links on a monthly scale whereby results  
485 are presented according to the approximate geographical location of the actors. Overall, our  
486 findings are largely consistent with previously proposed hypotheses under consideration,  
487 whereby especially Barents and Kara sea ice is detected to be an important external driver for  
488 winter circulation. Our CENs confirm the proposed Troposphere-Stratosphere coupling, which is  
489 evident for all tested parameter settings. However, we also find a robust pattern indicating a  
490 direct tropospheric connection of Barents and Kara sea ice and AO, such as for example  
491 proposed by Petoukhov and Semenov (2010). The direct link connecting Ural-SLP to PoV might  
492 be due to not considered tropical mechanisms influencing both the Stratosphere and sea level  
493 pressure in Eurasia as documented by Butler et al. (2014). The role of Eurasia snow cover is less  
494 robust but seems to influence sea level pressure in Asia significantly.

495 Since the CEN-algorithm requires the choice of the free parameters  $\tau_{\max}$  and  $\alpha$  and depends on  
496 the temporal resolution of the underlying data, changing settings can produce different graphs.  
497 However, by including sensitivity tests for different parameter settings and time scales, we  
498 report robust results. Also, it should be noted that the CEN approach assumes stationary time-  
499 series. Long term trends or changing trends within the studied time period might affect the  
500 results [Overland and Wang, 2005] and require a careful treatment of the data. However, here  
501 we only found a clear negative linear trend in the sea ice data. The causal interpretation of the  
502 resulting CENs also depends on the choice of actors such that the inferred parents can still be  
503 due to not-yet-included other variables. The challenge of how to choose adequate actors can  
504 also be assessed by different methods such as dimension reduction via Principal Component  
505 Analysis [Runge et al., 2015]. Nonetheless, the CEN-algorithm is especially useful for testing  
506 hypothesis if consistency of the data choice is assured.

507 The scope of this paper was to introduce and explain the CEN-algorithm and how it can be  
508 applied to address questions associated with teleconnections in the global climate system. In  
509 this context, CENs can overcome ambiguities of correlation analyses and provide a practical  
510 supplemental method to model experiments in order to test hypothesis. Moreover, CENs could  
511 be used also on model data to assess their validity. Here we limited ourselves to linear  
512 measurements, but CENs can also be constructed using non-parametric approaches, e.g., from

513 information theory [Runge *et al.*, 2012a, 2012b]. Further research should address the question  
514 of how tropical mechanisms contribute to mid-latitude winter circulation [Palmer, 2014;  
515 Trenberth *et al.*, 2014] and also the different hypotheses related to summer circulation  
516 [Overland *et al.*, 2012; Coumou *et al.*, 2014].

517

518

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635 **Tables**

<b>Abbreviation</b>	<b>Actor</b>	<b>Variable/Unit</b>	<b>Region (Level)</b>
<b>BK-SIC</b>	Barents Kara sea ice	Sea ice area fraction	70° - 80°N, 30° - 105°E
<b>EA-snow</b>	Eurasia snow cover	snow covered area fraction	40° - 80°N, 30° - 180°E
<b>AO</b>	Arctic Oscillation Index	Geopotential height in m	20° - 90°N (1000 mb)
<b>v-flux</b>	Vertical wave propagation	Pole-ward eddy heat flux $v \cdot T^*$ in K*m/s	45° - 75°N (100 mb)
<b>PoV</b>	Polar Vortex	Geopotential height in m	65° - 90°N (10 - 100 mb)
<b>Sib-SLP</b>	Siberian High	Sea level pressure in mb	40° - 65°N, 85° - 120°E
<b>Ural-SLP</b>	Ural Mountains sea level pressure	Sea level pressure in mb	45° - 70°N, 40° - 85°E

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637 *Table 1: Table of variables and regions of every considered actor*

638

<b>Actor</b>	<b>Parents <math>\mathcal{P}</math></b>
<b>AO</b>	AO <sub>t-1</sub> , BK-SIC <sub>t-2</sub>
<b>BK-SIC</b>	BK-SIC <sub>t-1</sub> , PoV <sub>t-2</sub>
<b>EA-snow</b>	EA-snow <sub>t-1</sub>
<b>v-flux</b>	PoV <sub>t-1</sub>
<b>PoV</b>	v-flux <sub>t-1</sub> , Ural-SLP <sub>t-1</sub> , PoV <sub>t-1</sub>

Sib-SLP	None
Ural-SLP	BK-SIC <sub>t-3</sub>

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640 *Table 2: Table of parent processes of each actor for winter (DJF) data and with the settings*  
641  *$\alpha=0.01$  and  $\tau_{max}=3$ . The subscript denotes the time lag in months. The parent processes are then*  
642 *used in the second step of the CEN-algorithm in order to quantify the link strength in terms of*  
643 *linear regression coefficients.*

## 644 **FIGURE CAPTIONS**

645 **Figure 1:** Schematic picture of different time scales, whereby each box indicates one time-step.  
646 Quarter-monthly time series (bottom row) consists of four times respectively two times more  
647 data points than monthly (top row) and half-monthly (middle row) time series.

648 **Figure 2:** Monthly time-series of all calendar months of climatological anomalies of each actor  
649 from 01/1979-12/2014.

650 **Figure 3:** Possible scenarios leading to a correlation without a direct causation between process  
651 X and Y: a) inflated correlation due to autocorrelation b) indirect chain via Z c) common driver Z.

652 **Figure 4:** Schematic picture of time series considered to measure influence of actor X on winter  
653 polar vortex (PoV) with a time-lag  $\tau=1$ , whereby the time-series only consist of the dark grey  
654 boxes.

655 **Figure 5:** CENs of actors of winter (DJF) circulation based upon monthly mean data. With a  
656 maximum time-lag of  $\tau_{max}=3$  (a, b, c) and  $\tau_{max}=5$  (d, e, f) and with significance level  $\alpha=0.01$  (a,  
657 d),  $\alpha=0.025$  (b, e) and  $\alpha=0.05$  (c, f).

658 **Figure 6:** CEN of actors of winter (DJF) circulation for a) half-monthly data with  $\tau_{max}=6$  and  
659  $\alpha=0.005625$  and b) quarter-monthly data with  $\tau_{max}=12$  and  $\alpha=0.003$ .

660 **Figure 7:** Same as Fig. 5a but the network is embedded in a schematic projection of the earth  
661 and the atmosphere. The regional actors BK-SIC, Ural-SLP, Sib-SLP and EA-snow are presented  
662 according to their approximate geographical location and the hemispheric actors AO, v-flux and  
663 PoV are presented according to their approximate latitude and pressure levels. See Tab. 1 for  
664 the exact coordinates of all actors.

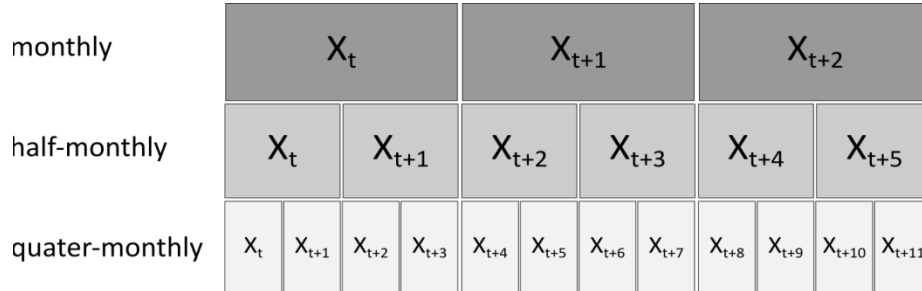
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# FIGURES

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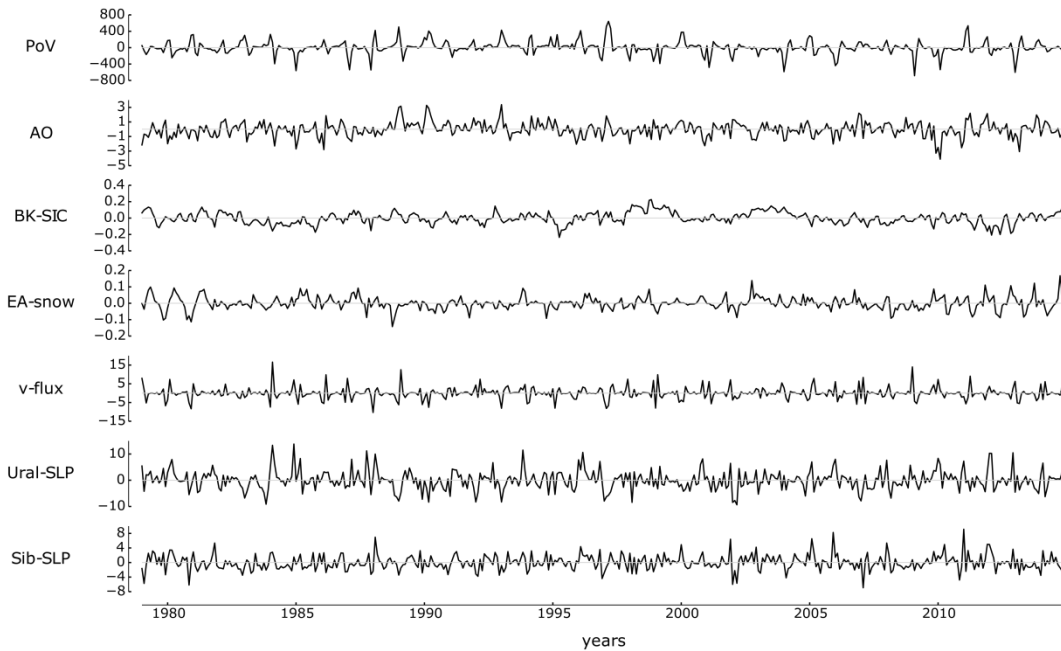


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671 **Figure 1:** Schematic picture of different time scales, whereby each box indicates one time-step. Quarter-monthly  
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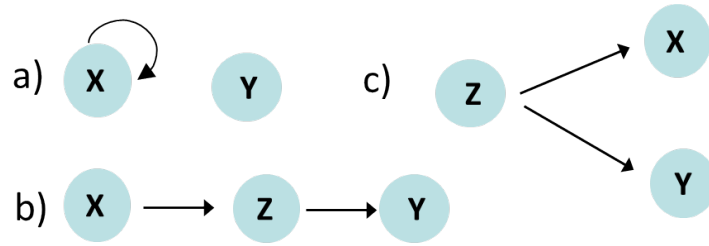
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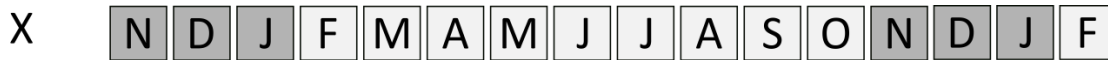
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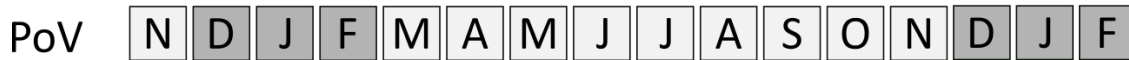
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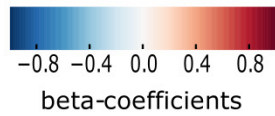
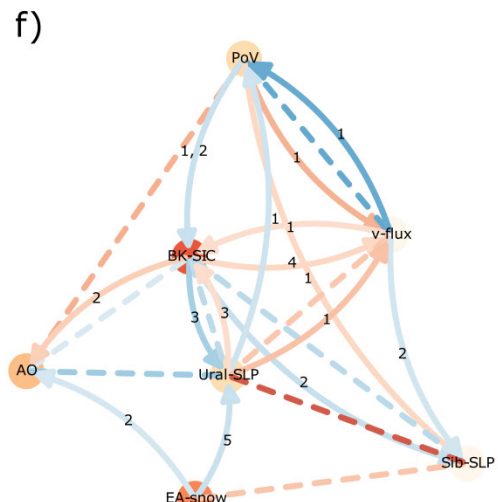
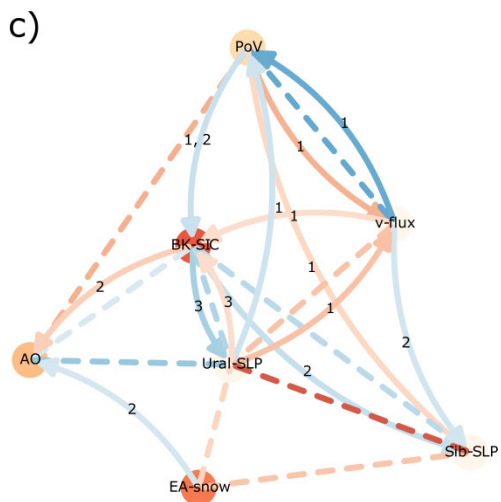
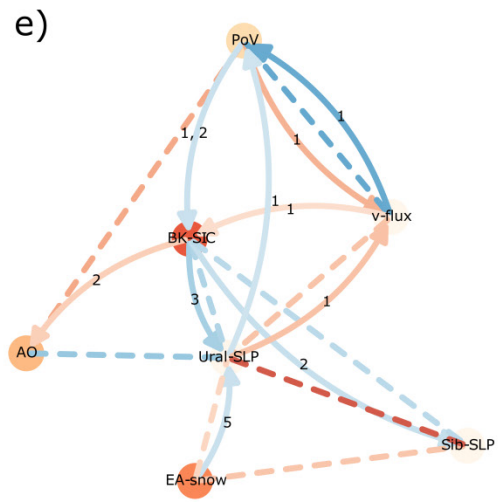
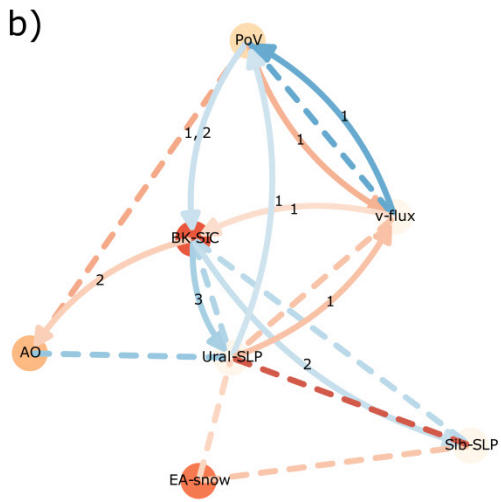
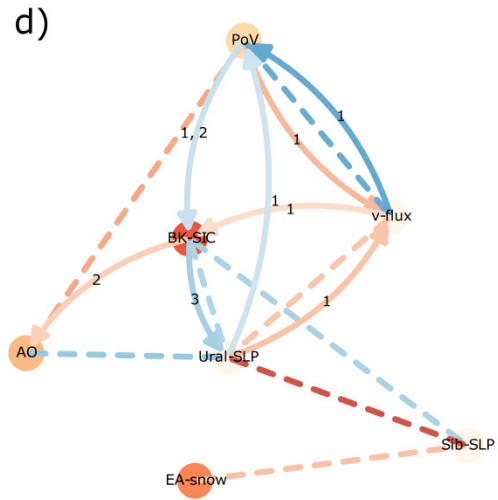
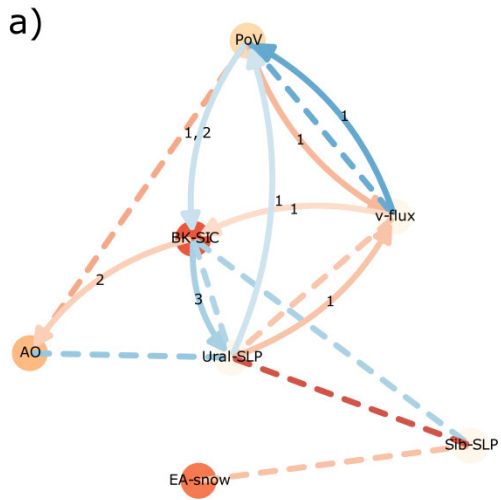
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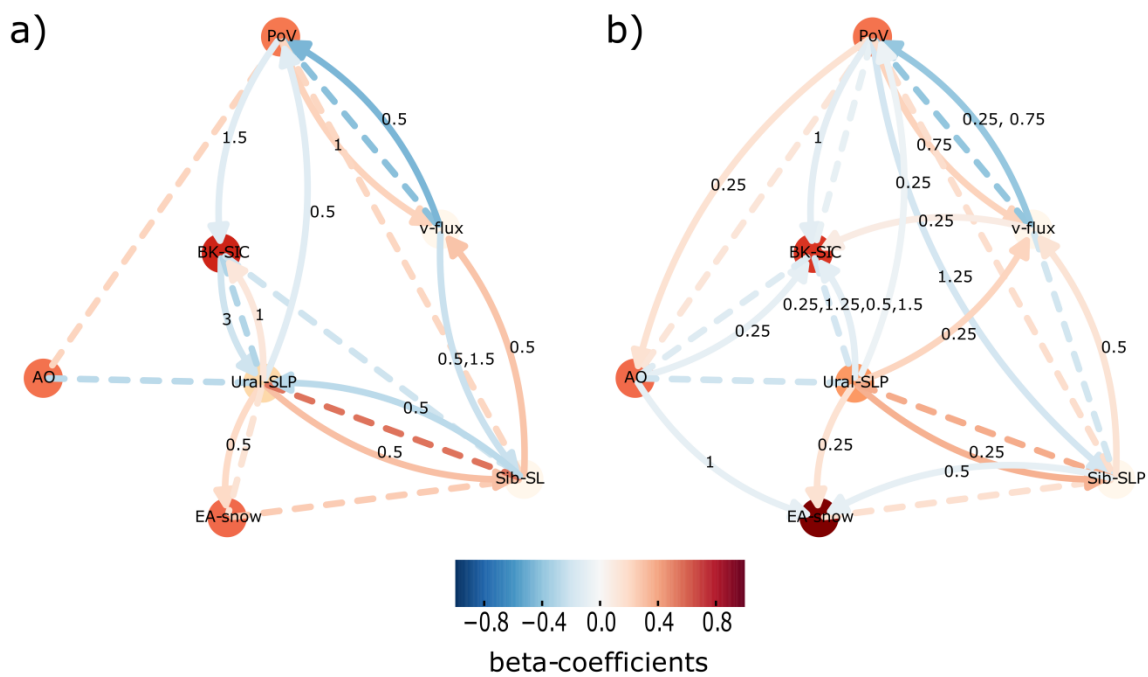


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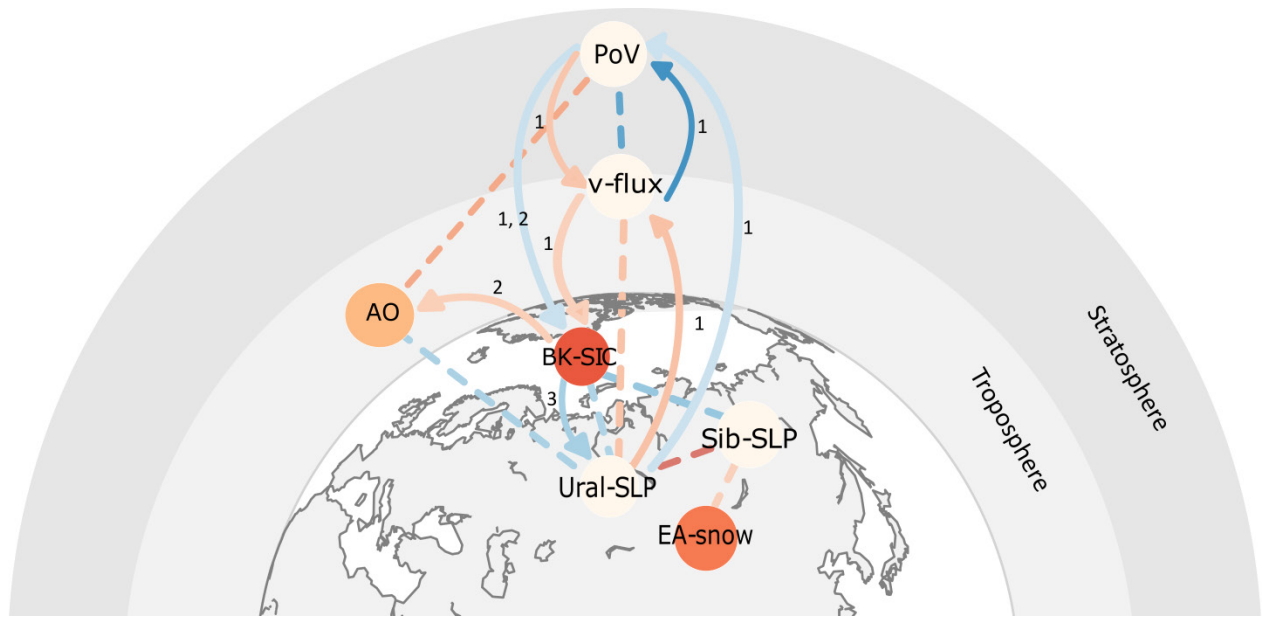
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