Causal links between sea-ice variability in the Barents-Kara Seas and oceanic and atmospheric drivers

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Abstract

The sea-ice cover in the Barents and Kara Seas (BKS) displays pronounced interannual variability. Both atmospheric and oceanic drivers have been found to influence sea-ice variability, but their relative strength and regional importance remain under debate. Here, we use the Liang-Kleeman information flow method to quantify the causal influence of oceanic and atmospheric drivers on the annual sea-ice cover in the BKS in the Community Earth System Model large ensemble and reanalysis. We find that atmospheric drivers dominate in the northern part, ocean heat transport dominates in the central and northeastern part, and local sea-surface temperature dominates in the southern part. Furthermore, the large-scale atmospheric circulation over the Nordic Seas drives ocean heat transport into the Barents Sea, which then influences sea ice. Under future sea-ice retreat, the atmospheric drivers are expected to become more important.

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7	Key Points:
8	• Ocean heat transport drives sea-ice variability in the central and northeastern Bar-
9	ents Sea
10	• Atmospheric temperature drives sea-ice variability in the northern Barents-Kara
11	Seas
12	• Atmospheric circulation over the Nordic Seas drives ocean heat transport, which
13	then influences sea-ice variability

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14 Abstract

The sea-ice cover in the Barents and Kara Seas (BKS) displays pronounced interannual 15 variability. Both atmospheric and oceanic drivers have been found to influence sea-ice 16 variability, but their relative strength and regional importance remain under debate. Here, 17 we use the Liang-Kleeman information flow method to quantify the causal influence of 18 oceanic and atmospheric drivers on the annual sea-ice cover in the BKS in the Commu-19 nity Earth System Model large ensemble and reanalysis. We find that atmospheric drivers 20 dominate in the northern part, ocean heat transport dominates in the central and north-21 eastern part, and local sea-surface temperature dominates in the southern part. Further-22 more, the large-scale atmospheric circulation over the Nordic Seas drives ocean heat trans-23 port into the Barents Sea, which then influences sea ice. Under future sea-ice retreat, 24 the atmospheric drivers are expected to become more important. 25

26

Plain Language Summary

The sea ice in the Barents and Kara Seas is melting due to Arctic warming, but 27 this is overlaid by large natural variability. This variability is caused by variations in the 28 ocean and the atmosphere, but it is not clear which is more important in which parts 29 of the region. We use a relatively new method that allows us to quantify cause-effect re-30 lationships between sea ice and atmospheric and oceanic drivers. We find that in the north 31 of the Barents and Kara Seas, the atmosphere has the biggest impact, in the central and 32 northeastern parts, it is the heat from the ocean, and in the south, it is the local sea tem-33 perature. We also find that wind patterns over the Nordic Seas affect how much oceanic 34 heat comes into the Barents Sea, and that, in turn, affects the sea ice. Looking ahead, 35 as the ice is expected to melt more in the future, the atmosphere is likely to become more 36 important in driving sea ice variability in the Barents and Kara Seas. This study helps 37 us better understand how the ocean and atmosphere work together to influence the yearly 38 changes in sea ice in this region. 39

40 **1 Introduction**

Arctic sea ice has been retreating in all seasons since the late 1970s, mainly as a
result of anthropogenic greenhouse gas emissions and associated global warming (Notz
& Stroeve, 2016). In winter, sea ice in the Arctic is currently retreating fastest in the
Barents and Kara Seas (BKS), which are already almost ice-free in summer (Onarheim

et al., 2018) and will continue to lose their winter sea-ice cover unless emissions are strongly
reduced (Årthun et al., 2021). However, the externally forced retreat of sea ice in the
BKS is overlaid by substantial internal variability on interannual to decadal timescales,
which may have contributed substantially to the recent decline in the region (Onarheim
& Årthun, 2017; England et al., 2019; Dörr et al., 2023). Internal variability is the dominant source of uncertainty in sea-ice projections in the Barents Sea over the next 30 years
(Bonan et al., 2021), and it is therefore important to understand the underlying drivers.

Oceanic and atmospheric processes both drive sea-ice variability in the BKS, but 52 their relative contributions remain under debate. Variable ocean heat transport toward 53 the Arctic, mainly through the Barents Sea Opening (Figure 1) and to a lesser extent 54 through Fram Strait, has been found to influence sea-ice variability in the BKS on sea-55 sonal to decadal timescales (Årthun et al., 2012; Sandø et al., 2014; Nakanowatari et al., 56 2014; Yeager et al., 2015; Årthun et al., 2019; Dörr et al., 2021; Lien et al., 2017; Doc-57 quier & Königk, 2021; Oldenburg et al., 2023). On the other hand, studies also find that 58 atmospheric variability dominates interannual sea-ice variability in the BKS through the 59 advection of warm air and enhancement of downward long-wave radiative fluxes, and that 60 ocean heat transport plays a smaller role on interannual timescales (Sorokina et al., 2016; 61 Woods & Caballero, 2016; Kim et al., 2019; Olonscheck et al., 2019; Liu et al., 2022; Zheng 62 et al., 2022). 63

Common to most studies about oceanic or atmospheric drivers of sea-ice variabil-64 ity is the use of (lagged) anomaly correlations to infer causal mechanisms. Correlation 65 in itself, however, does not imply causality. To identify cause and effect, causal inference 66 frameworks can be used (examples of climate applications include Deza et al. (2015); Kretschmer 67 et al. (2016); Vannitsem and Ekelmans (2018); Rehder et al. (2020)). One such frame-68 work, the Liang-Kleeman information flow (Liang & Kleeman, 2005; Liang, 2021), is par-69 ticularly interesting because it can quantify the direction and magnitude of causal re-70 lationships. It has been used to determine causal drivers of variability in global mean 71 temperature (Stips et al., 2016), Antarctic ice sheet surface mass balance (Vannitsem 72 et al., 2019), and pan-Arctic sea-ice area (Docquier et al., 2022). Docquier et al. (2022) 73 identified air temperature, sea surface temperature, and ocean heat transport as impor-74 tant drivers of sea ice variability, but did not consider the spatially non-uniform char-75 acter of sea ice changes and their drivers, potentially mixing signals from different re-76 gions in the Arctic. Considering spatial differences in the drivers of sea-ice variability 77

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rs especially important in the BKS because of the large changes in the last decades which
may lead to changes in the importance of atmospheric and oceanic drivers.

In this work, we apply the Liang-Kleeman information flow method to data from a large ensemble of climate model simulations and reanalysis products, allowing us to determine the past and future relationships between interannual variability in BKS seaice cover and its potential oceanic and atmospheric drivers. In section 2, we describe the data and methodology, in section 3, we present our results, and we then discuss our results and conclude in section 4.

⁸⁶ 2 Materials and Methods

We focus our analysis on output from the Community Earth System Model 1 Large 87 Ensemble (CESM-LE; Kay et al. (2015)). CESM-LE has been widely used to assess Arc-88 tic sea-ice changes and is one of the best-performing large ensembles in reproducing the 89 patterns and amplitude of sea-ice variability (England et al., 2019; Årthun et al., 2019). 90 CESM-LE consists of 40 members, of which we analyze output from 1920–2079, simu-91 lated using the historical scenario before 2005 and the high emission scenario RCP8.5 92 (Riahi et al., 2011) after 2005. To assess changes in causal relationships, we split the pe-93 riod into two 80-year sub-periods (1920–1999 and 2000–2079). The large number of en-94 semble members ensures a robust analysis of causal drivers. Before the analysis, we re-95 move the ensemble mean (i.e., the forced signal) from each member, such that we only 96 analyze internal variability. Additionally, we analyze causal relationships in reanalysis 97 data from 1979 – 2021, using ERA5 atmospheric reanalysis (Hersbach et al. (2020); 850hPa air temperature, 300hPa geopotential height, sea-level pressure) and ORAS5 ocean re-99 analysis (Zuo et al. (2019); sea-ice concentration, ocean velocity and temperature, sea-100 surface temperature). ORAS5 shows skill in reproducing observed variability and trends 101 in temperatures in the BKS (Li et al., 2022; Shu et al., 2021; Polyakov et al., 2023). We 102 note that the results based on this relatively short single realization will be less robust 103 than those from CESM-LE. To remove the forced signal in reanalysis data, we detrend 104 the data using a linear fit. The forced response is likely not linear over time, and remov-105 ing a linear fit is thus not the perfect way of isolating internal variability. Nevertheless, 106 our results remain similar if we instead remove a second-order polynomial fit (not shown). 107

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To represent the sea-ice cover in the BKS, we calculate the sea-ice area (SIA) in 108 the region, multiplying the sea-ice concentration with the grid cell area and summing 109 up over all grid cells in the region (Fig. 1a). The drivers analyzed herein were chosen 110 based on the literature on the atmospheric and oceanic influences on Arctic and BKS 111 sea ice: ocean heat transport through the Barents Sea Opening (BSO; Årthun et al. (2012)) 112 and the northward ocean heat transport in the Fram Strait (Fig. 1b), sea-surface tem-113 perature over the southwestern Barents Sea (SST_{AW}, Fig. 1c, Sandø et al. (2014)), air 114 temperature at 850 hPa (T850, Fig. 1d, Olonscheck et al. (2019); Liu et al. (2022), Schlichtholz 115 (2011)), the 300 hPa geopotential height over the extended BKS (Fig. 1e, Liu et al. (2022)), 116 and the sea-level pressure over the northern Nordic Seas (Fig. 1f; Dörr et al. (2021); Rieke 117 et al. (2023)). We compute the ocean heat transport on the original grids of CESM and 118 ORAS5 through the sections shown in Fig. 1, using a reference temperature of 0° C, fol-119 lowing Dörr et al. (2021). We compute annual means for all variables, to focus on inter-120 annual variability. CESM-LE shows trends similar to the reanalysis in all variables (Fig. 121 1), but simulates a lower sea-surface temperature and ocean heat transport, and more 122 sea ice. 123

We use the atmospheric temperature above the boundary layer (T850) since it is 124 less directly tied to sea ice than surface temperatures (Pavelsky et al., 2011; Olonscheck 125 et al., 2019), and, hence, better captures the dynamical link between atmospheric vari-126 ability and variability in sea ice. The influence of atmospheric temperature on sea ice 127 occurs mostly through changes in the surface turbulent heat (latent and sensible) and 128 long-wave radiative fluxes (Sorokina et al., 2016; Liu et al., 2022; Kim et al., 2019; Woods 129 & Caballero, 2016). Since our analysis is based on annual means and spatial averages 130 over areas with seasonal ice cover, it will integrate flux anomalies that both drive and 131 are driven by sea-ice anomalies. We, therefore, do not include surface fluxes as a poten-132 tial driver of sea-ice variability. Thermodynamic forcing through anomalous downwelling 133 longwave radiative flux at the surface, which is suggested to be a main atmospheric driver 134 of sea ice variability, is related to anticyclonic anomalies over the eastern BKS (Liu et 135 al., 2022) and is captured by the geopotential height index. 136

To reveal the causal relationships between BKS sea ice and its potential drivers, we use the Liang-Kleeman information flow method (Liang & Kleeman, 2005; Liang, 2021). The method computes the absolute rate of information transfer from variable X_j to vari-

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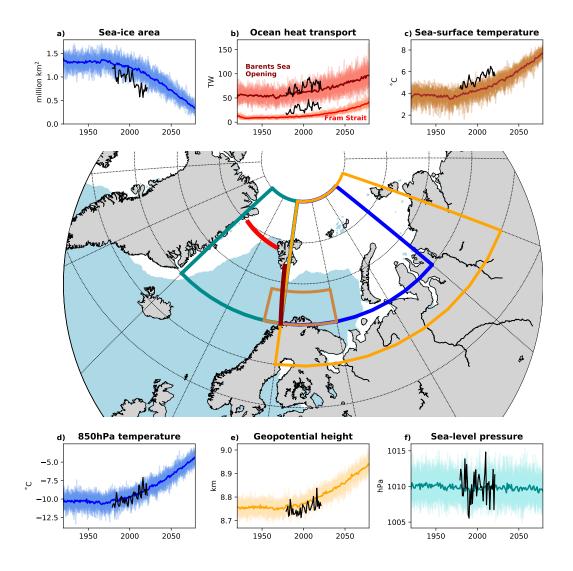


Figure 1. Potential drivers of sea-ice variability Barents-Kara Seas. a) Sea-ice area averaged over the Barents-Kara Seas (blue area; 20–80°E, 70–85°N), b) ocean heat transport through the Fram Strait (red line) and Barents Sea Opening (dark red line), c) sea-surface temperature averaged over the southwestern Barents Sea (brown area; 15–40°E, 70–74°N), d) 850 hPa temperature averaged over the BKS, e) 300 hPa geopotential height averaged over the extended BKS (orange area; 20–100°E, 65–85°N), and f) sea-level pressure averaged over the Nordic Seas (dark cyan area; -20–20°E, 70–85°N). Colored lines and shading show the ensemble mean and all individual members, respectively. Black lines show data from ERA5/ORAS5 reanalysis. White/blue shading on the map shows the annual mean sea-ice cover (based on 15% sea-ice concentration) in ORAS5 over 1979–2021.

140 able X_i as

$$T_{j \to i} = \frac{1}{\det \mathbf{C}} \cdot \sum_{k=1}^{N} \Delta_{jk} C_{k,dj} \cdot \frac{C_{ij}}{C_{ii}}$$
(1)

where \mathbf{C} is the covariance matrix, N is the number of variables (7 in our case; SIA and 141 6 potential drivers), Δ_{jk} are the cofactors of **C**, $C_{k,dj}$ is the sample covariance between 142 X_k and the Euler forward difference in time of X_j , C_{ij} is the sample covariance between 143 X_i and X_j and C_{ii} is the sample variance of X_i . When X_j has a causal influence on X_i , 144 $T_{j \to i}$ is significantly different from zero, whereas when there is no influence, $T_{j \to i}$ is zero. 145 We compute statistical significance using bootstrap resampling with replacement of all 146 terms in Eq. (1) using 1000 realizations. We further normalize the rate of information 147 transfer and express it in percent, as the absolute value of the relative rate of informa-148 tion transfer $|\tau_{j\to i}|$ (see Liang (2021) for more details). A value of $|\tau_{j\to i}|$ of 100% means 149 a maximum influence, while 0% means no influence. Note that the percentage cannot 150 be quantitatively interpreted as an explained variance, however, values can be compared 151 to determine which variables have the largest influence. 152

We apply the Liang-Kleeman information flow method to the BKS sea ice area and 153 the six potential drivers mentioned above. For CESM-LE, we follow Docquier et al. (2022) 154 and compute $|\tau|$ for each member's detrended data (ensemble mean removed) and then 155 compute the mean across ensemble members. Statistical significance is calculated using 156 Fisher's method for multiple tests (Fisher, 1992). Furthermore, to analyze spatial dif-157 ferences in the causal relationships between BKS sea ice and its drivers, we repeat the 158 analysis for each grid point in the BKS and replace the total SIA with the annual mean 159 sea-ice concentration at this grid point. We then obtain spatial maps of the relative rate 160 of information transfer between local sea-ice concentration and the same regional drivers 161 mentioned above. We calculate significance for each grid point in the same way as for 162 the sea-ice area, but we additionally apply a False Discovery Rate (FDR; Wilks (2016); 163 Docquier et al. (2023)) to account for the multiplicity of tests. 164

165 **3 Results**

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3.1 Causal links in CESM-LE

We first assess the causal relationships between the BKS sea-ice area and its potential drivers in CESM-LE for the two different periods, 1920–1999 and 2000–2079. Figure 2 shows matrices of the relative rates of information transfer and correlation coef-

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ficients between sea ice and all its potential drivers, averaged over all CESM-LE members. In both periods, the self-influence (diagonal) shows the highest $|\tau|$, ranging from 29% to 62%. Self-influence can be interpreted as the influence of the variable state on the dynamics of the variable itself (Liang, 2021; Docquier et al., 2022).

As for the causal influence between sea ice and the other variables, the heat trans-174 port through the Barents Sea Opening has the largest influence on sea ice area in the 175 BKS during the two periods ($|\tau| = 10\%$ in 1920–1999 and 6% in 2000–2079; Fig. 2a,c), 176 despite not being the variable with the highest correlation (R = -0.63 in 1920–1999 and 177 -0.45 in 2000–2079; Fig. 2b,d). The second variable having a significant influence on sea 178 ice is T850 ($|\tau| = 4\%$ in 1920–1999 and 7% in 2000–2079). SST_{AW} is highly correlated 179 to the sea-ice area (R = -0.81 in 1920–1999 and -0.69 in 2000–2079) but does not have 180 a significant causal influence on sea ice in either period. This shows the usefulness of the 181 causal analysis, as it identifies actual causal links rather than simple correlations between 182 variables. Despite being significantly correlated with the sea ice area, the influence of 183 the atmospheric circulation indices (geopotential height and sea-level pressure) on the 184 sea ice is not significant. 185

Besides influencing the sea ice area, the heat transport through the Barents Sea 186 Opening also influences SST_{AW} in both periods (fourth row in Fig. 2a,c). This under-187 scores the importance of the oceanic heat imported into the Barents Sea in setting the 188 ocean temperatures and ice cover (Årthun et al., 2012). Furthermore, CESM-LE shows 189 a significant correlation between the heat transport through Fram Strait and the Bar-190 ents Sea Opening in the first period (R = 0.49), which is likely due to similar atmospheric 191 influence (Dörr et al., 2021). The information flow method picks up this connection as 192 an influence from the Barents Sea Opening to the Fram Strait ($|\tau| = 10\%$), which is ex-193 pected since the Barents Sea Opening is upstream of the Fram Strait. Finally, the vari-194 ability in Barents Sea Opening heat transport is significantly influenced by sea-level pres-195 sure over the Nordic Seas during the first period ($|\tau| = 5\%$), confirming that interannual 196 variability of ocean heat transport is driven by atmospheric circulation (Muilwijk et al., 197 2019; Dörr et al., 2021; Madonna & Sandø, 2022; Brown et al., 2023). These results sug-198 gest that for annual means, the direct influence of the large-scale atmospheric circula-199 tion on sea ice in the BKS is weak, but a causal chain exists whereby the Nordic sea-level 200 pressure influences the oceanic heat transport into the BKS, which then influences sea 201 ice. 202

In the second period, as the sea ice retreats northward, the influence of the Bar-203 ents Sea Opening heat transport on sea ice becomes weaker ($|\tau| = 6\%$, Fig. 2c). On the 204 other hand, the influence of T850 becomes larger ($|\tau| = 7\%$), indicating that atmospheric 205 temperatures will be increasingly important for sea-ice variability in the future BKS. The 206 influence of sea-level pressure over the Nordic Seas on the Barents Sea Opening heat trans-207 port weakens and is no longer significant in the second period, while their correlation stays 208 high. We note that when we expand the area over which we average the sea-level pres-209 sure to the south, its influence is still significant in both periods (not shown), indicat-210 ing that the large-scale influence of the atmospheric circulation over the Nordic Seas re-211 mains an important driver of ocean heat transport into the Barents Sea. 212

We next look at the spatial distribution of the causal relationships between sea ice 213 and its potential drivers in CESM-LE by replacing the BKS sea ice area with the local 214 sea ice concentration and repeating the analysis for every grid point in the BKS. We show 215 the causal relationship in both directions for sea ice and the Barents Sea Opening heat 216 transport, T850, SST_{AW} , and the geopotential height index for the second period in Fig-217 ure 3. We choose to show the second period only (2000-2079) because it is the period 218 where the average sea-ice area is closer to the reanalysis data (Fig. 1). We show the in-219 teraction of sea ice with all variables during both periods in Supplementary Figures S1 220 and S2. 221

The causal method reveals that atmospheric temperatures (T850) mainly influence 222 sea ice in the northern and eastern BKS, while sea-surface temperatures in the south-223 ern Barents Sea (SST_{AW}) mainly influence sea ice in the central and southern Barents 224 Sea (Fig. 3a,b left). The regions of significant influence are broadly consistent with the 225 regions of maximum correlation (right column in Fig. 3a,b), although the correlations 226 are significant in the entire BKS region for both variables. The local influence of the Bar-227 ents Sea Opening heat transport on sea ice is significant in the northeastern Barents Sea, 228 approximately in between the influence regions of T850 and SST_{AW} (Fig. 3c). However, 229 unlike the correlation, which also shows a maximum in the southern BKS, $|\tau|$ is not sig-230 nificant there, indicating no direct influence of the Barents Sea Opening heat transport 231 on sea ice in this region. The results show a similar tripartition in the earlier period (Sup-232 plementary Fig. S2). However, the influence of SST and T850 is more limited, and the 233 influence of the Barents Sea Opening ocean heat transport is strong across the entire Bar-234

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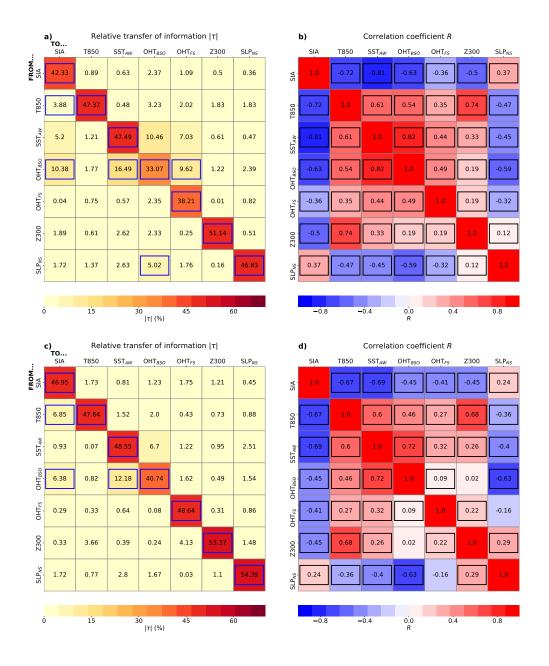


Figure 2. Causal drivers of sea ice variability in the Barents-Kara Seas (BKS). Matrix with relative rates of information transfer (a,c) and correlation coefficients (b,d) between each variable in the BKS for 1920–1999 (a,b) and 2000–2079 (c,d) averaged over 40 members from CESM-LE. Variables include the sea-ice area over the BKS (SIA), the 850 hPa air temperature (T850), the sea-surface temperature over the southwestern Barents Sea (SST_{AW}), the ocean heat transport through the Barents Sea Opening (OHT_{BSO}), the ocean heat transport through the Fram Strait (OHT_{FS}), the 300-hPa geopotential over the extended region (Z300), and the sea-level pressure over the Nordic Seas (SLP_{NS}). The highlighted elements are significant at the 5% confidence level based on Fisher's method for multiple tests.

ents Sea, which confirms results obtained with sea ice area instead of sea ice concentration (Fig. 2).

The atmospheric geopotential height index (Z300) is well correlated with the sea 237 ice concentration in the northern BKS (as also shown in Liu et al. (2022)). The signif-238 icant influence on sea ice is, however, restricted to the area south of Svalbard in the first 239 period (Fig. S2) and almost disappears in the second period (Fig. 3e). The sea-level pres-240 sure over the Nordic Seas is well correlated to sea ice in the southern BKS, but the in-241 formation flow method shows no significant influence (Fig. S1). This corroborates the 242 result from Fig. 2 that the sea-level pressure influences sea ice in the southern Barents 243 Sea mainly via the Barents Sea Opening heat transport. 244

In summary, we find that in CESM-LE, the Barents Sea Opening heat transport has the strongest influence on sea ice in the first period, mostly affecting sea ice in the central and northeastern Barents Sea. Sea ice in the northern BKS is mostly affected by atmospheric temperature, which has the strongest total influence in the second period. Sea ice in the southern Barents Sea is mostly affected by local sea-surface temperature. We further find a causal chain in which the atmosphere influences ocean heat transport into the Barents Sea, which then influences sea ice.

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3.2 Causal links in reanalysis

To evaluate the results from CESM-LE, we briefly analyze causal relationships be-253 tween BKS sea ice and its drivers in reanalysis data from 1979 - 2021. Because of the 254 relatively short observational period, large internal variability, and only one realization, 255 the relative transfer of information between the BKS sea-ice area and the other variables 256 is not significant (Fig. S3 in the supplemental material). We therefore directly turn to 257 the regional relationships between sea-ice concentration and T850, SST_{AW} , the Barents 258 Sea Opening heat transport, and the geopotential height index in Figure 4. Note that 259 we use a significance level of 10% to account for the short observational period. Even 260 though most values are not significant, it is still useful to compare the results with those 261 from CESM-LE. The relationship of sea ice with all variables is shown in Figure S4. Like 262 in CESM-LE, the Barents Sea Opening heat transport significantly influences sea ice con-263 centration in the northern and northeastern Barents Sea, although over a smaller area 264 than in CESM-LE, and a bit more to the west. The influence of SST_{AW} is limited in re-265

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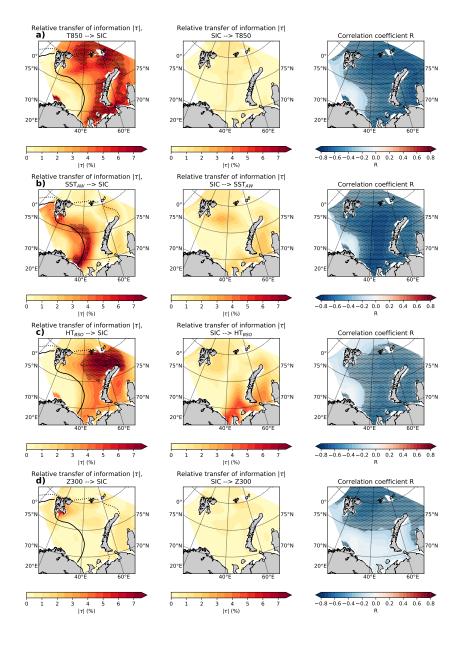


Figure 3. Regional influence on Barents-Kara Seas (BKS) sea ice. Maps of relative rates of information transfer (in the two directions) and correlation coefficients between annual mean sea-ice concentration and a) 850 hPa temperature (T850) over the BKS, b) sea-surface temperature (SST_{AW}) over the southwestern BKS, c) heat transport through the Barents Sea Opening (HT_{BSO}, and d) 300 hPa geopotential height (Z300) over the BKS, for CESM-LE over 2000–2079. The black contour line in the left panels denotes the ensemble mean sea-ice edge (based on 15% sea-ice concentration) in 2000, and the dashed line the sea-ice edge in 2079. Black stippling denotes statistically significant values (FDR 5%; 1000 bootstrap samples).

analysis. Similar to CESM-LE, the reanalysis data shows the largest (although not significant) influence of T850 in the northern BKS.

The correlation maps for sea ice and the geopotential height index (Z300) look similar to CESM-LE, with Z300 being correlated with sea-ice concentration in the northern Barents Sea (Fig. 4e). This area corresponds to elevated rates of information transfer from sea ice to Z300, albeit not significant.

Although the influences are mostly not significant, the reanalysis data generally supports the partitioning of the Barents Sea ice cover into a northern part influenced by atmospheric temperatures, and a central part influenced by ocean heat transport, although the partitioning is not as clear as in CESM-LE. Furthermore, the reanalysis also supports the notion that, for annual means and on interannual timescales, the atmospheric circulation indices have little direct influence on the sea ice cover, but instead influence the ocean heat transport into the Barents Sea (Fig. S3).

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4 Discussion and Conclusions

We have used the Liang-Kleeman information flow method (Liang & Kleeman, 2005; 280 Liang, 2021) to analyze causal relationships between annual-mean sea ice variability and 281 its atmospheric and oceanic drivers in the Barents and Kara Seas based on the CESM-282 LE large ensemble (1920–2079) and reanalysis data (1979–2021). We find that in CESM-283 LE, the ocean heat transport into the Barents Sea is a main driver of present and fu-284 ture sea ice variability, consistent with previous studies (Årthun et al., 2012; Decuypère 285 et al., 2022; Docquier et al., 2021; Dörr et al., 2021; Rieke et al., 2023). Furthermore, 286 we find a tripartition of the Barents-Kara sea ice, with the northern part being predom-287 inantly influenced by atmospheric temperature (Arctic domain), the southern part in-288 fluenced by local sea-surface temperature (Atlantic domain), and the region between the 289 two domains influenced by ocean heat transport. We further find that as the sea ice cover 290 in the Barents-Kara Seas retreats in the future, the influence of sea-surface temperature 291 and ocean heat transport decreases, while the atmospheric influence increases, as sug-292 gested by Smedsrud et al. (2013). 293

Previous studies have identified a strong influence of atmospheric circulation pat terns on subseasonal to interannual sea ice variability in the Barents and Kara Seas dur ing the cold season, both in observations/reanalysis (Kimura & Wakatsuchi, 2001; Deser

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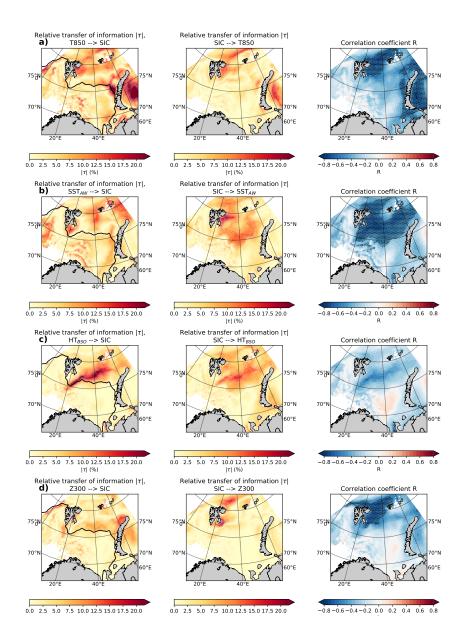


Figure 4. As Figure 3, but for ORAS5/ERA5 in 1979–2021. The black contour line in the left panels denotes the ensemble mean sea-ice edger (based on 15% sea-ice concentration) in 1979–2021. Black stippling denotes statistically significant values (FDR 10%; 1000 bootstrap samples).

et al., 2000; Sorokina et al., 2016; Blackport et al., 2019; Siew et al., 2023) and modelling 297 experiments (Blackport et al., 2019; Liu et al., 2022; Siew et al., 2023). On decadal and 298 longer time scales, large-scale atmospheric circulation as well as ocean heat transport 299 and Atlantic Water properties have been found to influence sea ice variability (Zhang, 300 2015; Yashayaev & Seidov, 2015; Polyakov et al., 2023). Our results focusing on annual 301 means indicate that the direct influence of circulation patterns on Barents-Kara sea ice 302 variability is weak and regionally confined. Rather, we show indirect influences via at-303 mospheric temperature as well as via a causal chain where the atmospheric circulation 304 over the Nordic Seas drives variability of ocean heat transport into the Barents Sea, which 305 then drives sea-ice variability, consistent with Sorteberg and Kvingedal (2006) and Muilwijk 306 et al. (2019). These indirect influences seem reasonable given our use of annual-mean 307 atmospheric circulation patterns, whose variability reflects more integrated signals of global 308 climate change. 309

A main novelty of our results is that they go beyond simple correlations, which do 310 not necessarily imply causality and do not reveal the direction of possible causal rela-311 tionships. That said, the correlation is still a useful diagnostic in the case of a known 312 relationship, such as between ocean heat transport and sea ice. Furthermore, we acknowl-313 edge the limitations of using the Liang-Kleeman information flow method. First, the method 314 is valid for linear systems and will only give an approximate solution for non-linear sys-315 tems. The method has, however, been validated using highly non-linear synthetic exam-316 ples (Liang, 2021), and has been successfully used to detect causal influences in the cli-317 mate system (Liang, 2014; Stips et al., 2016; Docquier et al., 2022). Non-linear estimates 318 of the rate of information transfer (e.g., Pires et al. (2023)) have therefore not been ap-319 plied here. Second, there might be hidden variables that have an influence on sea ice in 320 the Barents-Kara Seas but that are not included here. However, we have carefully checked 321 the literature to account for all relevant variables, so the effect of hidden variables is likely 322 limited. Despite these two limitations, this causal method provides highly valuable in-323 formation on causal drivers of annual sea ice variability in the Barents and Kara Seas 324 beyond correlation and regression analyses. 325

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- use that may be made of the Copernicus information or data it contains.

335 Open Research

All data in this study are publicly available. Output from ORAS5 is available through

the Copernicus Climate Change Service's Climate Data Store (Copernicus Climate Change

³³⁸ Service, 2021). Output from ERA5 is available through the Copernicus Climate Change

³³⁹ Service's Climate Data Store (Copernicus Climate Change Service, 2019a, 2019b). Out-

³⁴⁰ put from CESM-LE is available via the Earth System Grid (Climate Data Gateway, 2021).

³⁴¹ Python functions used to calculate the Liang-Kleeman information flow as in Docquier

et al. (2022) can be downloaded from https://github.com/Climdyn/Liang_Index_climdyn.

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1 2	Causal links between sea-ice variability in the Barents-Kara Seas and oceanic and atmospheric drivers
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7	Key Points:
8	• Ocean heat transport drives sea-ice variability in the central and northeastern Bar-
9	ents Sea
10	• Atmospheric temperature drives sea-ice variability in the northern Barents-Kara
11	Seas
12	• Atmospheric circulation over the Nordic Seas drives ocean heat transport, which
13	then influences sea-ice variability

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14 Abstract

The sea-ice cover in the Barents and Kara Seas (BKS) displays pronounced interannual 15 variability. Both atmospheric and oceanic drivers have been found to influence sea-ice 16 variability, but their relative strength and regional importance remain under debate. Here, 17 we use the Liang-Kleeman information flow method to quantify the causal influence of 18 oceanic and atmospheric drivers on the annual sea-ice cover in the BKS in the Commu-19 nity Earth System Model large ensemble and reanalysis. We find that atmospheric drivers 20 dominate in the northern part, ocean heat transport dominates in the central and north-21 eastern part, and local sea-surface temperature dominates in the southern part. Further-22 more, the large-scale atmospheric circulation over the Nordic Seas drives ocean heat trans-23 port into the Barents Sea, which then influences sea ice. Under future sea-ice retreat, 24 the atmospheric drivers are expected to become more important. 25

26

Plain Language Summary

The sea ice in the Barents and Kara Seas is melting due to Arctic warming, but 27 this is overlaid by large natural variability. This variability is caused by variations in the 28 ocean and the atmosphere, but it is not clear which is more important in which parts 29 of the region. We use a relatively new method that allows us to quantify cause-effect re-30 lationships between sea ice and atmospheric and oceanic drivers. We find that in the north 31 of the Barents and Kara Seas, the atmosphere has the biggest impact, in the central and 32 northeastern parts, it is the heat from the ocean, and in the south, it is the local sea tem-33 perature. We also find that wind patterns over the Nordic Seas affect how much oceanic 34 heat comes into the Barents Sea, and that, in turn, affects the sea ice. Looking ahead, 35 as the ice is expected to melt more in the future, the atmosphere is likely to become more 36 important in driving sea ice variability in the Barents and Kara Seas. This study helps 37 us better understand how the ocean and atmosphere work together to influence the yearly 38 changes in sea ice in this region. 39

40 **1 Introduction**

Arctic sea ice has been retreating in all seasons since the late 1970s, mainly as a
result of anthropogenic greenhouse gas emissions and associated global warming (Notz
& Stroeve, 2016). In winter, sea ice in the Arctic is currently retreating fastest in the
Barents and Kara Seas (BKS), which are already almost ice-free in summer (Onarheim

et al., 2018) and will continue to lose their winter sea-ice cover unless emissions are strongly
reduced (Årthun et al., 2021). However, the externally forced retreat of sea ice in the
BKS is overlaid by substantial internal variability on interannual to decadal timescales,
which may have contributed substantially to the recent decline in the region (Onarheim
& Årthun, 2017; England et al., 2019; Dörr et al., 2023). Internal variability is the dominant source of uncertainty in sea-ice projections in the Barents Sea over the next 30 years
(Bonan et al., 2021), and it is therefore important to understand the underlying drivers.

Oceanic and atmospheric processes both drive sea-ice variability in the BKS, but 52 their relative contributions remain under debate. Variable ocean heat transport toward 53 the Arctic, mainly through the Barents Sea Opening (Figure 1) and to a lesser extent 54 through Fram Strait, has been found to influence sea-ice variability in the BKS on sea-55 sonal to decadal timescales (Årthun et al., 2012; Sandø et al., 2014; Nakanowatari et al., 56 2014; Yeager et al., 2015; Årthun et al., 2019; Dörr et al., 2021; Lien et al., 2017; Doc-57 quier & Königk, 2021; Oldenburg et al., 2023). On the other hand, studies also find that 58 atmospheric variability dominates interannual sea-ice variability in the BKS through the 59 advection of warm air and enhancement of downward long-wave radiative fluxes, and that 60 ocean heat transport plays a smaller role on interannual timescales (Sorokina et al., 2016; 61 Woods & Caballero, 2016; Kim et al., 2019; Olonscheck et al., 2019; Liu et al., 2022; Zheng 62 et al., 2022). 63

Common to most studies about oceanic or atmospheric drivers of sea-ice variabil-64 ity is the use of (lagged) anomaly correlations to infer causal mechanisms. Correlation 65 in itself, however, does not imply causality. To identify cause and effect, causal inference 66 frameworks can be used (examples of climate applications include Deza et al. (2015); Kretschmer 67 et al. (2016); Vannitsem and Ekelmans (2018); Rehder et al. (2020)). One such frame-68 work, the Liang-Kleeman information flow (Liang & Kleeman, 2005; Liang, 2021), is par-69 ticularly interesting because it can quantify the direction and magnitude of causal re-70 lationships. It has been used to determine causal drivers of variability in global mean 71 temperature (Stips et al., 2016), Antarctic ice sheet surface mass balance (Vannitsem 72 et al., 2019), and pan-Arctic sea-ice area (Docquier et al., 2022). Docquier et al. (2022) 73 identified air temperature, sea surface temperature, and ocean heat transport as impor-74 tant drivers of sea ice variability, but did not consider the spatially non-uniform char-75 acter of sea ice changes and their drivers, potentially mixing signals from different re-76 gions in the Arctic. Considering spatial differences in the drivers of sea-ice variability 77

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rs especially important in the BKS because of the large changes in the last decades which
may lead to changes in the importance of atmospheric and oceanic drivers.

In this work, we apply the Liang-Kleeman information flow method to data from a large ensemble of climate model simulations and reanalysis products, allowing us to determine the past and future relationships between interannual variability in BKS seaice cover and its potential oceanic and atmospheric drivers. In section 2, we describe the data and methodology, in section 3, we present our results, and we then discuss our results and conclude in section 4.

⁸⁶ 2 Materials and Methods

We focus our analysis on output from the Community Earth System Model 1 Large 87 Ensemble (CESM-LE; Kay et al. (2015)). CESM-LE has been widely used to assess Arc-88 tic sea-ice changes and is one of the best-performing large ensembles in reproducing the 89 patterns and amplitude of sea-ice variability (England et al., 2019; Årthun et al., 2019). 90 CESM-LE consists of 40 members, of which we analyze output from 1920–2079, simu-91 lated using the historical scenario before 2005 and the high emission scenario RCP8.5 92 (Riahi et al., 2011) after 2005. To assess changes in causal relationships, we split the pe-93 riod into two 80-year sub-periods (1920–1999 and 2000–2079). The large number of en-94 semble members ensures a robust analysis of causal drivers. Before the analysis, we re-95 move the ensemble mean (i.e., the forced signal) from each member, such that we only 96 analyze internal variability. Additionally, we analyze causal relationships in reanalysis 97 data from 1979 – 2021, using ERA5 atmospheric reanalysis (Hersbach et al. (2020); 850hPa air temperature, 300hPa geopotential height, sea-level pressure) and ORAS5 ocean re-99 analysis (Zuo et al. (2019); sea-ice concentration, ocean velocity and temperature, sea-100 surface temperature). ORAS5 shows skill in reproducing observed variability and trends 101 in temperatures in the BKS (Li et al., 2022; Shu et al., 2021; Polyakov et al., 2023). We 102 note that the results based on this relatively short single realization will be less robust 103 than those from CESM-LE. To remove the forced signal in reanalysis data, we detrend 104 the data using a linear fit. The forced response is likely not linear over time, and remov-105 ing a linear fit is thus not the perfect way of isolating internal variability. Nevertheless, 106 our results remain similar if we instead remove a second-order polynomial fit (not shown). 107

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To represent the sea-ice cover in the BKS, we calculate the sea-ice area (SIA) in 108 the region, multiplying the sea-ice concentration with the grid cell area and summing 109 up over all grid cells in the region (Fig. 1a). The drivers analyzed herein were chosen 110 based on the literature on the atmospheric and oceanic influences on Arctic and BKS 111 sea ice: ocean heat transport through the Barents Sea Opening (BSO; Årthun et al. (2012)) 112 and the northward ocean heat transport in the Fram Strait (Fig. 1b), sea-surface tem-113 perature over the southwestern Barents Sea (SST_{AW}, Fig. 1c, Sandø et al. (2014)), air 114 temperature at 850 hPa (T850, Fig. 1d, Olonscheck et al. (2019); Liu et al. (2022), Schlichtholz 115 (2011)), the 300 hPa geopotential height over the extended BKS (Fig. 1e, Liu et al. (2022)), 116 and the sea-level pressure over the northern Nordic Seas (Fig. 1f; Dörr et al. (2021); Rieke 117 et al. (2023)). We compute the ocean heat transport on the original grids of CESM and 118 ORAS5 through the sections shown in Fig. 1, using a reference temperature of 0° C, fol-119 lowing Dörr et al. (2021). We compute annual means for all variables, to focus on inter-120 annual variability. CESM-LE shows trends similar to the reanalysis in all variables (Fig. 121 1), but simulates a lower sea-surface temperature and ocean heat transport, and more 122 sea ice. 123

We use the atmospheric temperature above the boundary layer (T850) since it is 124 less directly tied to sea ice than surface temperatures (Pavelsky et al., 2011; Olonscheck 125 et al., 2019), and, hence, better captures the dynamical link between atmospheric vari-126 ability and variability in sea ice. The influence of atmospheric temperature on sea ice 127 occurs mostly through changes in the surface turbulent heat (latent and sensible) and 128 long-wave radiative fluxes (Sorokina et al., 2016; Liu et al., 2022; Kim et al., 2019; Woods 129 & Caballero, 2016). Since our analysis is based on annual means and spatial averages 130 over areas with seasonal ice cover, it will integrate flux anomalies that both drive and 131 are driven by sea-ice anomalies. We, therefore, do not include surface fluxes as a poten-132 tial driver of sea-ice variability. Thermodynamic forcing through anomalous downwelling 133 longwave radiative flux at the surface, which is suggested to be a main atmospheric driver 134 of sea ice variability, is related to anticyclonic anomalies over the eastern BKS (Liu et 135 al., 2022) and is captured by the geopotential height index. 136

To reveal the causal relationships between BKS sea ice and its potential drivers, we use the Liang-Kleeman information flow method (Liang & Kleeman, 2005; Liang, 2021). The method computes the absolute rate of information transfer from variable X_j to vari-

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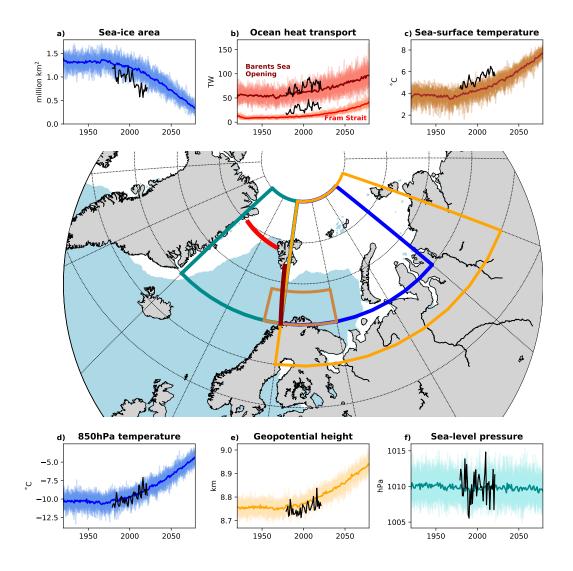


Figure 1. Potential drivers of sea-ice variability Barents-Kara Seas. a) Sea-ice area averaged over the Barents-Kara Seas (blue area; 20–80°E, 70–85°N), b) ocean heat transport through the Fram Strait (red line) and Barents Sea Opening (dark red line), c) sea-surface temperature averaged over the southwestern Barents Sea (brown area; 15–40°E, 70–74°N), d) 850 hPa temperature averaged over the BKS, e) 300 hPa geopotential height averaged over the extended BKS (orange area; 20–100°E, 65–85°N), and f) sea-level pressure averaged over the Nordic Seas (dark cyan area; -20–20°E, 70–85°N). Colored lines and shading show the ensemble mean and all individual members, respectively. Black lines show data from ERA5/ORAS5 reanalysis. White/blue shading on the map shows the annual mean sea-ice cover (based on 15% sea-ice concentration) in ORAS5 over 1979–2021.

140 able X_i as

$$T_{j \to i} = \frac{1}{\det \mathbf{C}} \cdot \sum_{k=1}^{N} \Delta_{jk} C_{k,dj} \cdot \frac{C_{ij}}{C_{ii}}$$
(1)

where \mathbf{C} is the covariance matrix, N is the number of variables (7 in our case; SIA and 141 6 potential drivers), Δ_{jk} are the cofactors of **C**, $C_{k,dj}$ is the sample covariance between 142 X_k and the Euler forward difference in time of X_j , C_{ij} is the sample covariance between 143 X_i and X_j and C_{ii} is the sample variance of X_i . When X_j has a causal influence on X_i , 144 $T_{j \to i}$ is significantly different from zero, whereas when there is no influence, $T_{j \to i}$ is zero. 145 We compute statistical significance using bootstrap resampling with replacement of all 146 terms in Eq. (1) using 1000 realizations. We further normalize the rate of information 147 transfer and express it in percent, as the absolute value of the relative rate of informa-148 tion transfer $|\tau_{j\to i}|$ (see Liang (2021) for more details). A value of $|\tau_{j\to i}|$ of 100% means 149 a maximum influence, while 0% means no influence. Note that the percentage cannot 150 be quantitatively interpreted as an explained variance, however, values can be compared 151 to determine which variables have the largest influence. 152

We apply the Liang-Kleeman information flow method to the BKS sea ice area and 153 the six potential drivers mentioned above. For CESM-LE, we follow Docquier et al. (2022) 154 and compute $|\tau|$ for each member's detrended data (ensemble mean removed) and then 155 compute the mean across ensemble members. Statistical significance is calculated using 156 Fisher's method for multiple tests (Fisher, 1992). Furthermore, to analyze spatial dif-157 ferences in the causal relationships between BKS sea ice and its drivers, we repeat the 158 analysis for each grid point in the BKS and replace the total SIA with the annual mean 159 sea-ice concentration at this grid point. We then obtain spatial maps of the relative rate 160 of information transfer between local sea-ice concentration and the same regional drivers 161 mentioned above. We calculate significance for each grid point in the same way as for 162 the sea-ice area, but we additionally apply a False Discovery Rate (FDR; Wilks (2016); 163 Docquier et al. (2023)) to account for the multiplicity of tests. 164

165 **3 Results**

166

3.1 Causal links in CESM-LE

We first assess the causal relationships between the BKS sea-ice area and its potential drivers in CESM-LE for the two different periods, 1920–1999 and 2000–2079. Figure 2 shows matrices of the relative rates of information transfer and correlation coef-

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ficients between sea ice and all its potential drivers, averaged over all CESM-LE members. In both periods, the self-influence (diagonal) shows the highest $|\tau|$, ranging from 29% to 62%. Self-influence can be interpreted as the influence of the variable state on the dynamics of the variable itself (Liang, 2021; Docquier et al., 2022).

As for the causal influence between sea ice and the other variables, the heat trans-174 port through the Barents Sea Opening has the largest influence on sea ice area in the 175 BKS during the two periods ($|\tau| = 10\%$ in 1920–1999 and 6% in 2000–2079; Fig. 2a,c), 176 despite not being the variable with the highest correlation (R = -0.63 in 1920–1999 and 177 -0.45 in 2000–2079; Fig. 2b,d). The second variable having a significant influence on sea 178 ice is T850 ($|\tau| = 4\%$ in 1920–1999 and 7% in 2000–2079). SST_{AW} is highly correlated 179 to the sea-ice area (R = -0.81 in 1920–1999 and -0.69 in 2000–2079) but does not have 180 a significant causal influence on sea ice in either period. This shows the usefulness of the 181 causal analysis, as it identifies actual causal links rather than simple correlations between 182 variables. Despite being significantly correlated with the sea ice area, the influence of 183 the atmospheric circulation indices (geopotential height and sea-level pressure) on the 184 sea ice is not significant. 185

Besides influencing the sea ice area, the heat transport through the Barents Sea 186 Opening also influences SST_{AW} in both periods (fourth row in Fig. 2a,c). This under-187 scores the importance of the oceanic heat imported into the Barents Sea in setting the 188 ocean temperatures and ice cover (Årthun et al., 2012). Furthermore, CESM-LE shows 189 a significant correlation between the heat transport through Fram Strait and the Bar-190 ents Sea Opening in the first period (R = 0.49), which is likely due to similar atmospheric 191 influence (Dörr et al., 2021). The information flow method picks up this connection as 192 an influence from the Barents Sea Opening to the Fram Strait ($|\tau| = 10\%$), which is ex-193 pected since the Barents Sea Opening is upstream of the Fram Strait. Finally, the vari-194 ability in Barents Sea Opening heat transport is significantly influenced by sea-level pres-195 sure over the Nordic Seas during the first period ($|\tau| = 5\%$), confirming that interannual 196 variability of ocean heat transport is driven by atmospheric circulation (Muilwijk et al., 197 2019; Dörr et al., 2021; Madonna & Sandø, 2022; Brown et al., 2023). These results sug-198 gest that for annual means, the direct influence of the large-scale atmospheric circula-199 tion on sea ice in the BKS is weak, but a causal chain exists whereby the Nordic sea-level 200 pressure influences the oceanic heat transport into the BKS, which then influences sea 201 ice. 202

In the second period, as the sea ice retreats northward, the influence of the Bar-203 ents Sea Opening heat transport on sea ice becomes weaker ($|\tau| = 6\%$, Fig. 2c). On the 204 other hand, the influence of T850 becomes larger ($|\tau| = 7\%$), indicating that atmospheric 205 temperatures will be increasingly important for sea-ice variability in the future BKS. The 206 influence of sea-level pressure over the Nordic Seas on the Barents Sea Opening heat trans-207 port weakens and is no longer significant in the second period, while their correlation stays 208 high. We note that when we expand the area over which we average the sea-level pres-209 sure to the south, its influence is still significant in both periods (not shown), indicat-210 ing that the large-scale influence of the atmospheric circulation over the Nordic Seas re-211 mains an important driver of ocean heat transport into the Barents Sea. 212

We next look at the spatial distribution of the causal relationships between sea ice 213 and its potential drivers in CESM-LE by replacing the BKS sea ice area with the local 214 sea ice concentration and repeating the analysis for every grid point in the BKS. We show 215 the causal relationship in both directions for sea ice and the Barents Sea Opening heat 216 transport, T850, SST_{AW} , and the geopotential height index for the second period in Fig-217 ure 3. We choose to show the second period only (2000-2079) because it is the period 218 where the average sea-ice area is closer to the reanalysis data (Fig. 1). We show the in-219 teraction of sea ice with all variables during both periods in Supplementary Figures S1 220 and S2. 221

The causal method reveals that atmospheric temperatures (T850) mainly influence 222 sea ice in the northern and eastern BKS, while sea-surface temperatures in the south-223 ern Barents Sea (SST_{AW}) mainly influence sea ice in the central and southern Barents 224 Sea (Fig. 3a,b left). The regions of significant influence are broadly consistent with the 225 regions of maximum correlation (right column in Fig. 3a,b), although the correlations 226 are significant in the entire BKS region for both variables. The local influence of the Bar-227 ents Sea Opening heat transport on sea ice is significant in the northeastern Barents Sea, 228 approximately in between the influence regions of T850 and SST_{AW} (Fig. 3c). However, 229 unlike the correlation, which also shows a maximum in the southern BKS, $|\tau|$ is not sig-230 nificant there, indicating no direct influence of the Barents Sea Opening heat transport 231 on sea ice in this region. The results show a similar tripartition in the earlier period (Sup-232 plementary Fig. S2). However, the influence of SST and T850 is more limited, and the 233 influence of the Barents Sea Opening ocean heat transport is strong across the entire Bar-234

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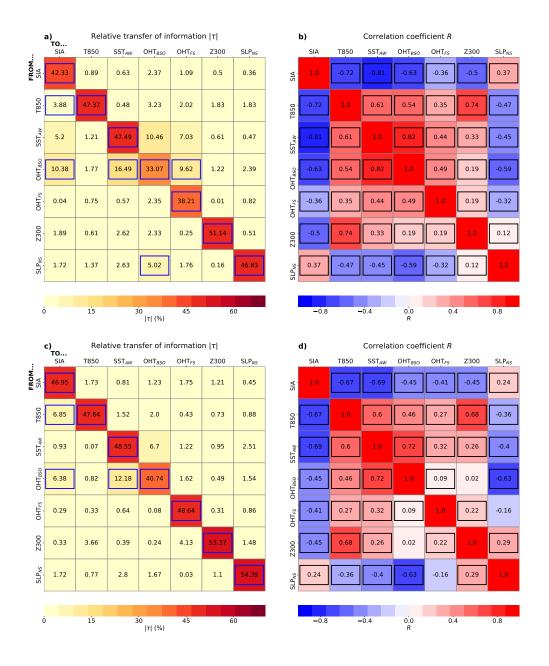


Figure 2. Causal drivers of sea ice variability in the Barents-Kara Seas (BKS). Matrix with relative rates of information transfer (a,c) and correlation coefficients (b,d) between each variable in the BKS for 1920–1999 (a,b) and 2000–2079 (c,d) averaged over 40 members from CESM-LE. Variables include the sea-ice area over the BKS (SIA), the 850 hPa air temperature (T850), the sea-surface temperature over the southwestern Barents Sea (SST_{AW}), the ocean heat transport through the Barents Sea Opening (OHT_{BSO}), the ocean heat transport through the Fram Strait (OHT_{FS}), the 300-hPa geopotential over the extended region (Z300), and the sea-level pressure over the Nordic Seas (SLP_{NS}). The highlighted elements are significant at the 5% confidence level based on Fisher's method for multiple tests.

ents Sea, which confirms results obtained with sea ice area instead of sea ice concentration (Fig. 2).

The atmospheric geopotential height index (Z300) is well correlated with the sea 237 ice concentration in the northern BKS (as also shown in Liu et al. (2022)). The signif-238 icant influence on sea ice is, however, restricted to the area south of Svalbard in the first 239 period (Fig. S2) and almost disappears in the second period (Fig. 3e). The sea-level pres-240 sure over the Nordic Seas is well correlated to sea ice in the southern BKS, but the in-241 formation flow method shows no significant influence (Fig. S1). This corroborates the 242 result from Fig. 2 that the sea-level pressure influences sea ice in the southern Barents 243 Sea mainly via the Barents Sea Opening heat transport. 244

In summary, we find that in CESM-LE, the Barents Sea Opening heat transport has the strongest influence on sea ice in the first period, mostly affecting sea ice in the central and northeastern Barents Sea. Sea ice in the northern BKS is mostly affected by atmospheric temperature, which has the strongest total influence in the second period. Sea ice in the southern Barents Sea is mostly affected by local sea-surface temperature. We further find a causal chain in which the atmosphere influences ocean heat transport into the Barents Sea, which then influences sea ice.

252

3.2 Causal links in reanalysis

To evaluate the results from CESM-LE, we briefly analyze causal relationships be-253 tween BKS sea ice and its drivers in reanalysis data from 1979 - 2021. Because of the 254 relatively short observational period, large internal variability, and only one realization, 255 the relative transfer of information between the BKS sea-ice area and the other variables 256 is not significant (Fig. S3 in the supplemental material). We therefore directly turn to 257 the regional relationships between sea-ice concentration and T850, SST_{AW} , the Barents 258 Sea Opening heat transport, and the geopotential height index in Figure 4. Note that 259 we use a significance level of 10% to account for the short observational period. Even 260 though most values are not significant, it is still useful to compare the results with those 261 from CESM-LE. The relationship of sea ice with all variables is shown in Figure S4. Like 262 in CESM-LE, the Barents Sea Opening heat transport significantly influences sea ice con-263 centration in the northern and northeastern Barents Sea, although over a smaller area 264 than in CESM-LE, and a bit more to the west. The influence of SST_{AW} is limited in re-265

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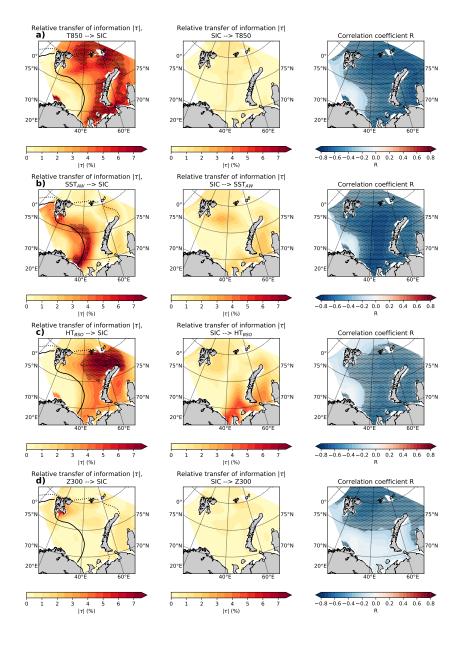


Figure 3. Regional influence on Barents-Kara Seas (BKS) sea ice. Maps of relative rates of information transfer (in the two directions) and correlation coefficients between annual mean sea-ice concentration and a) 850 hPa temperature (T850) over the BKS, b) sea-surface temperature (SST_{AW}) over the southwestern BKS, c) heat transport through the Barents Sea Opening (HT_{BSO}, and d) 300 hPa geopotential height (Z300) over the BKS, for CESM-LE over 2000–2079. The black contour line in the left panels denotes the ensemble mean sea-ice edge (based on 15% sea-ice concentration) in 2000, and the dashed line the sea-ice edge in 2079. Black stippling denotes statistically significant values (FDR 5%; 1000 bootstrap samples).

analysis. Similar to CESM-LE, the reanalysis data shows the largest (although not significant) influence of T850 in the northern BKS.

The correlation maps for sea ice and the geopotential height index (Z300) look similar to CESM-LE, with Z300 being correlated with sea-ice concentration in the northern Barents Sea (Fig. 4e). This area corresponds to elevated rates of information transfer from sea ice to Z300, albeit not significant.

Although the influences are mostly not significant, the reanalysis data generally supports the partitioning of the Barents Sea ice cover into a northern part influenced by atmospheric temperatures, and a central part influenced by ocean heat transport, although the partitioning is not as clear as in CESM-LE. Furthermore, the reanalysis also supports the notion that, for annual means and on interannual timescales, the atmospheric circulation indices have little direct influence on the sea ice cover, but instead influence the ocean heat transport into the Barents Sea (Fig. S3).

279

4 Discussion and Conclusions

We have used the Liang-Kleeman information flow method (Liang & Kleeman, 2005; 280 Liang, 2021) to analyze causal relationships between annual-mean sea ice variability and 281 its atmospheric and oceanic drivers in the Barents and Kara Seas based on the CESM-282 LE large ensemble (1920–2079) and reanalysis data (1979–2021). We find that in CESM-283 LE, the ocean heat transport into the Barents Sea is a main driver of present and fu-284 ture sea ice variability, consistent with previous studies (Årthun et al., 2012; Decuypère 285 et al., 2022; Docquier et al., 2021; Dörr et al., 2021; Rieke et al., 2023). Furthermore, 286 we find a tripartition of the Barents-Kara sea ice, with the northern part being predom-287 inantly influenced by atmospheric temperature (Arctic domain), the southern part in-288 fluenced by local sea-surface temperature (Atlantic domain), and the region between the 289 two domains influenced by ocean heat transport. We further find that as the sea ice cover 290 in the Barents-Kara Seas retreats in the future, the influence of sea-surface temperature 291 and ocean heat transport decreases, while the atmospheric influence increases, as sug-292 gested by Smedsrud et al. (2013). 293

Previous studies have identified a strong influence of atmospheric circulation pat terns on subseasonal to interannual sea ice variability in the Barents and Kara Seas dur ing the cold season, both in observations/reanalysis (Kimura & Wakatsuchi, 2001; Deser

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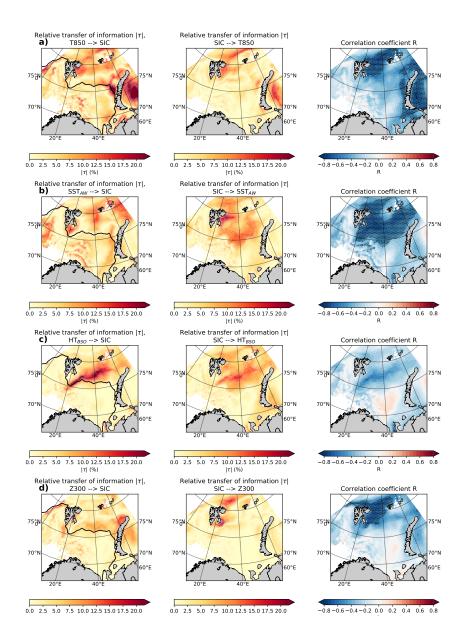


Figure 4. As Figure 3, but for ORAS5/ERA5 in 1979–2021. The black contour line in the left panels denotes the ensemble mean sea-ice edger (based on 15% sea-ice concentration) in 1979–2021. Black stippling denotes statistically significant values (FDR 10%; 1000 bootstrap samples).

et al., 2000; Sorokina et al., 2016; Blackport et al., 2019; Siew et al., 2023) and modelling 297 experiments (Blackport et al., 2019; Liu et al., 2022; Siew et al., 2023). On decadal and 298 longer time scales, large-scale atmospheric circulation as well as ocean heat transport 299 and Atlantic Water properties have been found to influence sea ice variability (Zhang, 300 2015; Yashayaev & Seidov, 2015; Polyakov et al., 2023). Our results focusing on annual 301 means indicate that the direct influence of circulation patterns on Barents-Kara sea ice 302 variability is weak and regionally confined. Rather, we show indirect influences via at-303 mospheric temperature as well as via a causal chain where the atmospheric circulation 304 over the Nordic Seas drives variability of ocean heat transport into the Barents Sea, which 305 then drives sea-ice variability, consistent with Sorteberg and Kvingedal (2006) and Muilwijk 306 et al. (2019). These indirect influences seem reasonable given our use of annual-mean 307 atmospheric circulation patterns, whose variability reflects more integrated signals of global 308 climate change. 309

A main novelty of our results is that they go beyond simple correlations, which do 310 not necessarily imply causality and do not reveal the direction of possible causal rela-311 tionships. That said, the correlation is still a useful diagnostic in the case of a known 312 relationship, such as between ocean heat transport and sea ice. Furthermore, we acknowl-313 edge the limitations of using the Liang-Kleeman information flow method. First, the method 314 is valid for linear systems and will only give an approximate solution for non-linear sys-315 tems. The method has, however, been validated using highly non-linear synthetic exam-316 ples (Liang, 2021), and has been successfully used to detect causal influences in the cli-317 mate system (Liang, 2014; Stips et al., 2016; Docquier et al., 2022). Non-linear estimates 318 of the rate of information transfer (e.g., Pires et al. (2023)) have therefore not been ap-319 plied here. Second, there might be hidden variables that have an influence on sea ice in 320 the Barents-Kara Seas but that are not included here. However, we have carefully checked 321 the literature to account for all relevant variables, so the effect of hidden variables is likely 322 limited. Despite these two limitations, this causal method provides highly valuable in-323 formation on causal drivers of annual sea ice variability in the Barents and Kara Seas 324 beyond correlation and regression analyses. 325

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- ³³² publicly accessible. The results contain modified Copernicus Climate Change Service in-
- formation 2023. Neither the European Commission nor ECMWF is responsible for any
- use that may be made of the Copernicus information or data it contains.

335 Open Research

All data in this study are publicly available. Output from ORAS5 is available through

the Copernicus Climate Change Service's Climate Data Store (Copernicus Climate Change

³³⁸ Service, 2021). Output from ERA5 is available through the Copernicus Climate Change

³³⁹ Service's Climate Data Store (Copernicus Climate Change Service, 2019a, 2019b). Out-

³⁴⁰ put from CESM-LE is available via the Earth System Grid (Climate Data Gateway, 2021).

³⁴¹ Python functions used to calculate the Liang-Kleeman information flow as in Docquier

et al. (2022) can be downloaded from https://github.com/Climdyn/Liang_Index_climdyn.

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Supporting Information for "Causal links between sea ice and its drivers in the Barents-Kara Seas"

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1. Figures S1 to S4

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Relative transfer of information |\tau| SIC --> T850

R

.

Correlation coefficient R

Relative transfer of information |τ|, a) T850 --> SIC

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Figure S1. Same as Fig. 3, but for all variables in Fig. 2 for the period 2000–2079.

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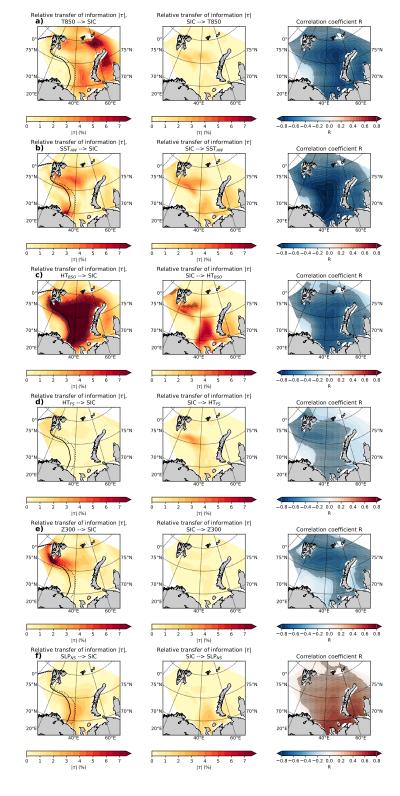


Figure S2. Same as Fig. 3, but for all variables in Fig. 2 for the period 1920–1999.

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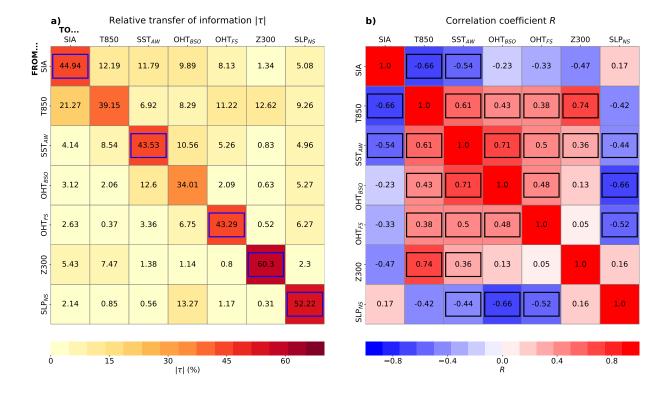


Figure S3. Same as Fig. 2, but for reanalysis in the period 1979–2021, and the highlighted elements are significant at the 10% level based on Fisher's method for multiple tests.

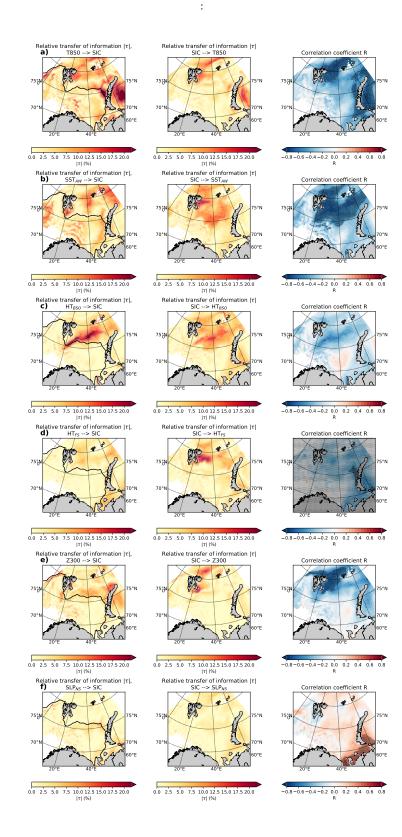


Figure S4. Same as Fig. 4, but with all variables in Fig. 2.

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