https://doi.org/10.5194/egusphere-2023-1637
Preprint. Discussion started: 27 July 2023

Atmospheric teleconnections between the Arctic and the Baltic Sea region as simulated by CESM1-LE

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Abstract. This paper examines teleconnections between the Arctic and the Baltic Sea region and is based on two cases of CESM-LE climate model simulations': the stationary case with pre-industrial radiative forcing and the climate change case with measured and RCP8.5 radiative forcing.

Stationary control simulation 1800-year long time-series were used for stationary teleconnection and 40-member ensemble from the period 1920–2100 for teleconnections during ongoing climate change. We analyzed seasonal temperature at a 2-meter level, sea-level pressure, sea ice concentration, precipitations, geopotential height and 10-meter level wind speed. The Arctic was divided into seven areas.

the Baltic Sea region climate has strong teleconnections with the Arctic climate; the strongest connections are with Svalbard and Greenland region. There is high seasonality in the teleconnections, with the strongest correlations in winter and the lowest correlations in summer, when the local factors are stronger. The majority of teleconnections in winter and spring can be explained by climate indexes NAO and AO. During ongoing climate change, the teleconnection patterns did not show remarkable developments by the end of the 21st century. Minor pattern changes are between the Baltic Sea region temperature and the sea ice concentration.

To estimate different Arctic regions' collective statistical connections with the Baltic Sea region, we calculated the correlation between the parameter and its Ridge regression estimation. Seasonal coefficient of determination, R^2, were highest for winter: for temperature $R^2 = 0.64$, for surface pressure $R^2 = 0.44$ and for precipitation $R^2 = 0.35$. When doing the same for the seasons' previous month values in the Arctic, the relations are considerably weaker with the highest $R^2 = 0.09$ for temperature in the spring. Hence, the forecasting capacity of Arctic climate data for the Baltic Sea region is weak.

Although there are statistically significant teleconnections between the Arctic and Baltic Sea region, the Arctic impacts are regional and mostly connected with climate indexes. There are no simple cause-and-effect pathways. By the end of the 21st century, the Arctic ice concentration has significantly decreased. Still, the general teleconnections pattern between the Arctic and the Baltic Sea region will not change considerably by the end of the 21st century.

1 Introduction

The Arctic region is warming at least twice as fast as the whole planet (IPCC, 2021; Nakamura & Sato 2022; Overland et al., 2018; Meleshko et al., 2020); also, the Baltic Sea region is warming faster than average (BACC 2015). The question of the faster warming in the Arctic region affecting mid-latitudes has been under debate for a long time. We want to address the Baltic Sea region and find out if it is affected by the changing Arctic and if this information can be used in long-term weather forecasts.

The faster warming in the Arctic compared to the global mean, a phenomenon known as Arctic amplification (AA), results from a number of positive feedbacks that are relatively large in the Arctic, including the albedo feedback, lapse rate feedback and Planck feedback (Pithan and Mauritzen 2014). However, the relative weight of these different factors is still under debate (Dai et al., 2019). The assessment of the potential for AA to influence broader hemispheric weather (referred to as linkages) is complex and controversial (Dai and Song 2020, Francis and Vavrus 2015; Barnes and Screens 2015; Sun et al., 2016) and many details of linkage mechanisms remain elusive (Sun et al., 2018). AA is expected to be related to further changes that affect mid-latitudes and the rest of the world (Jung et al., 2015; Vihma et al., 2019). According to Overland et al. (2015), potential Arctic teleconnections with Europe are less clear than with North America and Asia. The linkages between the Arctic and mid-latitudes depend strongly on the season and geographical region (Jakobson et al., 2017; Coumou et al., 2018). Furthermore, it has been recognized that extratropical impacts depend highly on the regional structure of the anomalous Arctic climate state (Kug et al., 2015). It appears that Arctic impacts will be regional and intermittent, clouding the identification of cause-and-effect and raising the issue of how to effectively communicate potential Arctic impacts (Cohen et al., 2018).

The Baltic Sea region is very sensitive to climate change; it is a region with spatially varying climate and diverse ecosystems (Christensen et al., 2022). Climate change may bring profound ecological changes in the region (Halkka 2022). During the last half-century, the duration of permanent snow cover and snow depth have decreased (Viru and Jaagus 2020); during the last decades, there has been a major increase in both extreme mild ice winters and severe ice winters; minor increase in the intense precipitations, heat waves and cold spells (Rutgersson et al., 2022). Because of the closeness to the Arctic, the Baltic Sea region receives influences from the Arctic either remotely (teleconnections) or directly. The weather in the region depends highly on the position of the polar front: it can be located northward as well as southward of the area (Jakobson et al., 2017).

One of the reasons scientists are so interested in knowing the Arctic and its influence on mid-latitude weather is that there is a possibility to glance to the future. The pace of climate change is a crucial metric in risk assessment surrounding future climate predictions and directly impacts the efforts required to adapt (Rondeau-Genesse and Braun 2019; Lehner et al., 2017). The planning processes of decision-makers are very limited if the pace of changes is unknown (Klein et al., 2014). However, for short timescales, this pace can be masked by internal variability. Over a few decades, this can cause climate change effects to exceed what would be expected from the greenhouse gas (GHG) emissions alone or, to the contrary, cause slowdowns or even hiatuses (Rondeau-Genesse and Braun, 2019). Slowdowns, temporary hiatuses, and negative trends can be expected, regardless of the spatial scale (Medhaug et al., 2017; Fyfe et al., 2016). However, cooling trends should become less common or even nonexistent (Risbey et al., 2017; Grenier et al., 2015; Kay et al., 2015). At the same time, extremely warm decades should become more likely to happen (Risbey et al., 2017; Chavaillaz et al., 2016).

Widely used climate model simulations, such as those from the Coupled Model Intercomparison Project (CMIP5), combines internal and inter-model variability caused by differing physics, dynamical cores, and resolutions, making it almost impossible to assess the portion of uncertainty caused by internal variability alone (Kay et al., 2015). To enable quantification of internal variability in the midst of transient climate change, large ensembles with individual models have been performed. Comparison across ensemble members that are simulated with the same model and the same external forcing provides a measure of simulated internal variability. Here we use the Community Earth System Model version 1 large ensemble (CESM-LE; Kay et al., 2015) to diagnose connections between the Arctic and Baltic regions. In the last few years, CESM-LE has aimed at better understanding internal variability (Rondeau-Genesse and Braun, 2019). The CESM-LE has been used in multiple studies of Arctic sea ice cover, performing well overall (Smith and Jahn, 2019; Labe et al., 2018; Jahn, 2018; Massonnet et al., 2018; Barnhart et al., 2016; Jahn et al., 2016; Swart et al., 2015). The CESM-LE also produces credible NAO interannual aspects, given the length of the observational record available for assessment (93 years) (Deser et al., 2017).

Our previous research studied Arctic-Baltic teleconnections and physical mechanisms behind Arctic-Baltic teleconnections (Jakobson et al., 2017), using ERA-Interim and NCEP-CFSR reanalyzes. In this paper, we used CESM-LE model time-series to verify previous results, search climate change influence on teleconnections and study different Arctic regions' collective forecasting capabilities. CESM-LE differs from reanalyzes by a much longer time-series and the aspect that it is not constrained by observations, allowing projections. The purpose of the study is to understand which Arctic factors influence the Baltic Sea, how strong these connections are, how is AA affecting these relationships, and if the knowledge can be used in long-term weather forecasting in the Baltic Sea region.

The paper is organized as follows: Section 2 describes the used datasets and methodology. Section 3 explains the results of the spatial correlations of climatic variables (stationary, 20-year periods up to the year 2100 and lagged correlations), whereas Section 4 provides a discussion of the results and completes with conclusions.

2 Data and methodology

We used the CESM Large Ensemble Project (CESM-LE) set of climate model simulations on a 1º×1º horizontal grid (Kay et al., 2015). The CESM1 is a fully coupled model as described by Hurrell et al. (2013). A control simulation under pre-industrial (1850) radiative forcing conditions was run for 1800 years. A single ensemble member was branched from this control and ran from 1850 to 1920 with transient forcing. A 40-member ensemble was then performed for the period 1920-2100. All 40 CESM-LE ensemble members use the same model and the same external forcing. Each ensemble member has a unique climate trajectory because of small round-off level differences in their initial atmospheric conditions. Simply put, the CESM-LE ensemble spread results from internally generated climate variability alone (Kay et al., 2015). Each member is subject to the same radiative forcing scenario (historical up to 2005 and RCP8.5 thereafter).

We used Pearson's correlation coefficient to measure of dependence between two variables. To measure the strength of a relationship between two variables without the possible controlling effect of a third variable, we used partial correlation:

$$R(X,Y|Z) = \frac{R(X,Y) - R(X,Z)\cdot R(Y,Z)}{\sqrt{(1-R^2(X,Z))\cdot(1-R^2(Y,Z))}}, \qquad (1)$$

where R(A, B) is the regular Pearson correlation. Partial correlation difference from Pearson correlation reveals the controlling factor Z effect on input variables X and Y.

The following parameters were analyzed: the temperature at 2-meter level (T2m); sea-level pressure (PSL); sea ice concentration (ICEC); precipitations (PREC) as the sum of large-scale and convective precipitation; geopotential height at 500 mb (Z500); and wind speed at 10-meter level (U10). The following teleconnection indices – North Atlantic Oscillation (NAO), Arctic Oscillation (AO) and Barents Oscillation (BO) were calculated from the model data using eofs.xarray module in Python. NAO is defined as EOF–1 of seasonal SLP anomalies for 20–80N, 80W–40E, BO as EOF–2 of seasonal SLP anomalies for 30–90N, 90W–90E, and AO as EOF–1 of seasonal geopotential anomalies for 20–90N.

Correlations with and without the effect of teleconnection indices were analyzed. For that purpose, partial correlations between atmospheric variables with the controlling impact of the teleconnection index were calculated.

For the testing area (TA), we chose a region around the Baltic Sea (50–65N, 10–40E). For the Arctic, we looked at the area above 50N. We chose 7 important areas (IA) in the Arctic to analyze the relationships between regions in the Arctic and TA (Figure 1, Table 1). Initially, we looked also at the Chukchi Sea and Canada Basin regions, but all these regions' correlations with TA were clearly weaker than with the remaining regions.

Table 1. Important Areas (IA)

	Area	Lat 1	Lat 2	Lon1	Lon 2	Mask
1	Central Arctic	85	90	0	360	No
2	Greenland	60	85	297	340	Land
3	West-Greenland	60	77	295	315	Sea
4	East-Greenland	60	75	315	340	Sea
5	Svalbard	75	82	10	30	No
6	Kara Sea	66	80	60	100	Sea
7	Laptev Sea	66	80	100	170	Sea

We assessed the control simulation to reveal statistically significant seasonal correlations between TA and the Arctic region. For control simulation 1800-year long time-series, all correlations stronger than ±0.046 are statistically significant at the confidence level of 95%. To analyze teleconnections transformations during climate change, we looked at 20-year periods of the ensemble simulation from 1980 to 2100. For every ensemble simulation, 20-year long periods with 40 ensemble members (in a total of 800 events), all correlations stronger than ±0.069 are statistically significant at the confidence level of 95%. This paper only looks at correlations stronger than ±0.1, as weaker correlations are supposedly not important. For control simulation, this gives a confidence level of 99.998%, while for ensemble simulations 20-year long series, the confidence level is 99.5%. Still, the relationship shown by the correlations may not be causal, there can be indirect connections, and we cannot rule out model internal feedback-generated correlations.

For understanding correlation maps, the first correlation parameter marks always the TA areal average, and the second one is from the Arctic. We also calculated correlations between TA and IA areal seasonal averages. We computed correlations with IA previous month's averages to investigate the Arctic region's capability to forecast TA seasonal averages. We used the Ridge regression method to estimate IA-s collective forecasting capability, using the module sklearn.linear_model in Python with parameter alpha = 1.0.

3 Results

3.1 Stationary spatial correlations of climatic variables

The climatic variables of separate areas are usually dependent, but correlations in space depend highly on the distance and climatic variables. In addition to natural spatial correlations between climatic variables within near distances, also correlations emerge within longer distances. To reveal stationary connections between remote regions, we used CESM-LE 1800 year-long control run. This model run is very stable without significant trends, as the radiative forcing conditions were constantly at the year 1850 level during the whole period.

We found significant correlations between several variables between the Baltic Sea testing area (TA; shown with the rectangle in our Figures) and different Arctic areas. The most robust results were found for 2-meter temperature (T2m): the negative correlation between TA and the Greenland area is $R < -0.6$ in winter and only slightly weaker in spring and autumn (Figure 2, row 1). The summer is more influenced by local circulations, and remote correlations are weak. Most of these correlations are related to the NAO index – the same partial correlation with the controlling factor NAO has values in the Greenland area in winter weaker than –0.2 (Figure 2, row 2) and in spring and autumn mostly weaker than –0.3. Teleconnections with TA that are not controlled by the NAO index are strongest at the Atlantic Ocean east to Iceland, but the correlation strength exceeds 0.3 only in spring and autumn. The AO index effect is similar to the NAO index, with a slightly weaker impact in the Iceland region but stronger in Siberia (not shown). The BO index effect was clearly lower than that of NAO and AO (not shown).

Table 2. Seasonal correlations of control run 1800 years-long data between areal averages of testing area (TA, rows) and important area (IA, columns) parameters. The first column is the correlation between the parameter in TA and its estimation using Ridge regression over all parameters in IA-s. All shown correlations are statistically significant at the 95% confidence level. For each TA parameter in each IA-s the strongest correlation is highlighted in bold.

		Correl	Central Arctic			Greenland			West-Greenland			East-Greenland			Svalbard			Kara Sea			Laptev Sea		
		Ridge	PSL	T2m	ICEC	PSL	T2m	ICEC	PSL	T2m	ICEC	PSL	T2m	ICEC	PSL	T2m	ICEC	PSL	T2m	ICEC	PSL	T2m	ICEC
MAM	T2m (TA)	0.68	-0.42		0.05	-0.49	-0.55	0.36	-0.39	-0.51	0.14	-0.52	-0.49	0.33	-0.54	0.07	-0.07	-0.41	0.43	-0.15	-0.38	**0.39**	-0.27
JJA		0.54	-0.31		-0.13	-0.25	-0.17	0.13	-0.18	-0.21	0.17	-0.28	-0.1		-0.29	0.23	-0.29	-0.15	-0.12	0.06	-0.17	0.19	-0.16
SON		0.59	-0.21	-0.09		-0.28	-0.47	0.16	-0.15	-0.38	0.14	-0.34	-0.41	0.08	-0.42	0.09	-0.13	-0.13	0.19			0.06	
DJF		0.8	**-0.47**	-0.2	0.29	-0.58	**-0.65**	0.28	-0.46	**-0.61**	0.21	**-0.61**	-0.57	0.23	**-0.68**	-0.07		**-0.52**	0.47	-0.28	-0.37	0.2	-0.31
MAM	PSL (TA)	0.51		0.11		-0.09	0.16	-0.07	-0.11		0.08	-0.07	0.28	-0.13	0.08	**0.31**	-0.22	0.21	-0.08		0.17		
JJA		0.47	**-0.19**	-0.06	-0.06	-0.24	-0.24	0.06	-0.16	-0.19		-0.27	-0.17		-0.28	0.09	-0.07		0.05		0.09	0.13	-0.05
SON		0.6	-0.08			-0.31	0.08	0.08	-0.3	-0.14	0.12	-0.31	0.28			0.25	-0.1	0.08	-0.12				-0.07
DJF		0.66	0.1	0.13	-0.23	0.12	**0.39**	-0.12	0.07	**0.21**		0.15	**0.47**	-0.15	0.28	0.29	-0.17	**0.31**	-0.19	0.07	**0.18**		
MAM	PREC (TA)	0.47	0.12			0.28	0.05		0.28	0.22	-0.12	0.27	-0.11	0.06	0.13	-0.23	0.18					-0.08	0.08
JJA		0.53	**0.22**			0.35	0.26	-0.12	0.28	0.27	-0.13	0.37	0.16		**0.37**	-0.12	0.12	**0.22**	-0.09			**-0.17**	0.07
SON		0.56	0.16			**0.39**	0.02	-0.1	**0.37**	0.2	-0.15	0.38	-0.16		0.19	-0.15	0.07	0.11	0.07		0.1		0.06
DJF		0.59	-0.06	-0.07	0.17		-0.31	0.09		-0.14	-0.05	-0.07	**-0.41**	0.13	-0.19	-0.22	0.15	-0.19	0.2		-0.12		0.06

To generalize the results, we divided the Arctic region into important areas (IA, Figure 1) and calculated correlations between IA and TA seasonal averages (Table 2).

The strongest correlations for IA-s are between T2m in TA and PSL in Svalbard, seasonally the correlation was strongest in winter (R = –0.68). Meanwhile, correlations with Svalbard T2m and ICEC are much weaker with |R| < 0.31 in all seasons. TA T2m correlations with the Greenland region IA-s PSL are comparable to Svalbard, but correlations with T2m are much stronger. The correlations between T2m values in the Greenland region in winter and spring are –0.65 ≤ R ≤ – 0.49 and in autumn –0.47 ≤ R ≤ –0.38.

Correlations between TA and IA-s parameters are the weakest in summer, where the strongest correlations are R = 0.37 between PREC in TA and PSL in both East Greenland and Svalbard. Correlations in summer between T2m in TA and PSL are even weaker, with the strongest correlation R = –0.31 in Central Arctic. ICEC in IA-s has generally weaker correlations with TA parameters than PSL or T2m.

Central Arctic parameters correlation with TA is stronger than 0.4 only between TA T2m and Central Arctic PSL in winter and spring. Laptev Sea parameters correlations with TA parameters were weaker than in other IA-s, with a correlation stronger than |R| > 0.3 occurring with TA T2m only in spring and winter.

To estimate IA-s collective forecasting capability, we calculated the correlation between the parameter in TA and its Ridge regression estimation (Table 2 first column). All IA-s seasonal PSL, T2m and ICEC values were used for the Ridge regression estimation. The correlation between T2m in TA and its Ridge regression estimation varies from 0.54 in summer to 0.8 in winter. The correlation between PSL in TA and its Ridge regression estimation is from 0.47 in summer to 0.66 in winter. The correlation between PREC in TA and its Ridge regression estimation is from 0.47 in spring to 0.59 in winter. When examining the coefficient of determination R^2, then 0.82 = 64% of T2m variability in TA in winter can be explained by PSL, T2m and ICEC variability in Arctic IA-s. The weakest connection with the Arctic is TA PSL in summer and PREC in spring, with R^2 = 0.472 = 22%.

Local correlations (at the same spot) are necessary to better understand teleconnections between different parameters. The abovementioned strong correlation between T2m in the Greenland region and TA can be connected through local relationships with other parameters. There is a robust local connection between T2m and ICEC, especially in the areas of ice margin (R~–0.9). ICEC correlation between TA and Greenland region reaches R = –0.4; the correlation between T2m at TA and ICEC in Greenland region reaches R = 0.5.

The local correlation between ICEC and U10 is mostly strongly negative (strength up to –0.8, not shown), especially in the regions where ICEC is lower than 0.8. No significant local correlation exists between ICEC and PSL in the Greenland Sea (not shown).

3.2 Spatial correlations of climatic variables during 2020 – 2100

To analyze how teleconnections are modified by climate change, we investigated the differences between 20-year periods and the control run. Depending on the variable, the correlation might change its spatial pattern and value between different 20-year periods. The correlations between the following variables (the temperature at 2-meter level T2m; sea-level pressure PSL and sea ice concentration ICEC; precipitations PREC; geopotential height at 500 mb Z500) were analyzed. To get statistically reliable results, we used for every 20-year period all 40 ensemble members, so we had in total of 800 values for each period. Most of the correlations did not show significant changes in 20-year periods from the control run, including the most emphasized correlation between T2m in TA and the Arctic region.

However, there are some statistically significant changes in correlations between T2m in the TA and ICEC in the Arctic. Positive correlations between T2m in the TA and ICEC in the North Pole region show a remarkable weakening in winter (DJF) after 2020. At the same time, the positive correlation strengthens significantly in the Davis Strait and Hudson Bay region. The strong positive correlation in the Davis Strait is also remarkable in spring (MAM), but it does not strengthen as much as in winter (not shown). The correlation in the region between Greenland and Iceland weakens. The negative correlation between T2m and ICEC in the control run in the coastal areas of Siberia fades away after 2040, except in the Barents Sea, where it strengthens.

In regions of changing correlations, the average ICEC in winter will be lessening in the Barents Sea, Hudson Bay and between Greenland and Iceland (Figure 4). ICEC in the North Pole region and coastal areas of Siberia eastward of the Barents Sea do not decrease in winter.

3.3 Lagged correlations

We are interested in factors driving variations in the Baltic Sea region and whether prior conditions may provide predictive capability. Given this, we studied the connections between earlier average month values of different parameters in the Arctic region and seasonal values of TA conditions. The strongest correlations were between spring (MAM) T2m in TA and the previous month's (February) average T2m and PSL (Fig. 5). The correlation values were –0.22 in Svalbard and Greenland regions; correlations between other parameters showed a weaker correlation (|R|<0.2). Analogous correlations during other seasons were weaker. We used Ridge regression to determine the predictive capability of all previous months' average PSL, T2m and ICEC in all IA-s to TA next seasonal condition. Using Ridge regression did not improve the predictability much – the strongest correlation was R = 0.30 for T2m in MAM. Thus, even for the best case, the previous month's average values over the Arctic describe less than 10% of next season's TA average climate state.

We focused on the testing area and searched for information at which rate the Arctic region climate parameters are statistically connected with incoming parameters in the testing area. It turned out that quite common are also occasions where the values of the testing area variables can give information about the value of the Arctic region variables. For example, the spring average T2m in TA has R > 0.35 with ICEC in June at Greenland and East-Greenland. Stronger lagged correlations from TA to the Arctic can be explained by different averaging intervals – the monthly average in the Arctic has a lower influence on the next seasonal average in the TA than TA seasonal average to the following month's average in the Arctic.

4 Conclusion and Discussion

The advantage of this study is the length of the 1800-year long CESM-LE self-consistent control database, which also reveals relations with a weaker strength (correlations stronger than ±0.046 are statistically significant at the confidence level of 95%). CESM-LE 40-member ensemble forecast until 2100 allows us to investigate how relationships may change in the changing climate. The most important teleconnections for the testing area are T2m, PSL and ICEC in regions around Greenland and Svalbard (Figure 1, Table 1). For a long time, it has been recognized that ice conditions in the Greenland region might be connected to several variables in Europe (Hildebrandsson 1914, Wiese 1924, Schell 1956, etc.). Our results did not confirm the old hypothesis by Hildebrandsson (1914) that the mean winter conditions over Europe depend on the summer sea ice extent in the Greenland Sea. Lagged correlation between summer ICEC in the Greenland Sea did not significantly correlate with any primary TA parameter in the following winter. It has to be considered that our testing area is only part of the area Hildebrandsson investigated.

As far as we know, the first attempt to reveal the teleconnections between the Baltic Sea region and the Arctic was made by our workgroup in 2017 (Jakobson et al., 2017). It was based on NCEP-CFSR and ERA-Interim reanalyses models for the period 1979 – 2015. Differences between the model parameters and different periods from CESM-LE ensemble complicated the comparison with the present study. The comparable T2m in the present study and temperature at the 1000 hPa level in the study made in 2017 showed a different extent in the Greenland region but similar negative correlation strength in winter. In the present study, spring and autumn showed a much stronger correlation in much wider regions around Greenland. Summer showed a very weak correlation in both studies, probably due to the more emphasized local circulation.

https://doi.org/10.5194/egusphere-2023-1637
Preprint. Discussion started: 27 July 2023

In investigating the influence of climatic parameters of the Arctic region on the testing area, we have to consider also the local correlations. Our results from the 1800-year long CESM-LE ensemble confirmed a strong (R~–0.9) local connection between T2m and ICEC, as found in many other studies (e.g. Olonscheck et al., 2019; Vihma et al., 2014; Outten and Esau 2012). Our results also confirm the strong negative local correlation between ICEC and U10 in the ice margin regions (strength up to –0.8), as shown in Jakobson et al. (2019). Many scientists have found a lower PSL over the shrunk ice areas (Cassano et al., 2013; Alexander et al., 2004; Deser et al., 2000; Agnew, 1993), suggesting increased surface heating as a possible cause. Although Deser et al. (2000) found that mean PSL has decreased over the retracted ice margin in the Greenland Sea (according to 1958–97 reanalysis products), our results did not show a significant correlation between ICEC and PSL in the Greenland Sea region during any season. According to Agnew (1993), the reason why the correlation is not present in the Greenland Sea may be due to the important role that ice export through Fram Strait and ocean currents play in determining ice extent in this region.

According to Chen et al. (2013), Barents Oscillation (BO) is through meridional flow and zonal wind anomalies related to natural Arctic surface air temperature (SAT) variability. Our T2m–T2m correlation pattern in winter (Figure 2) was similar to the BO winter pattern. We tested BO index influence on correlations between Arctic and TA, using partial correlation. The BO index effect was insignificant or more negligible than NAO and AO index influence on all parameters we checked in all seasons. NAO and AO index had the largest impact in winter. In summer, the local effects are more dominant, and climate indexes influence is weaker.

We also aimed to reveal the ongoing climate change, especially AA's influence on teleconnections between TA and the Arctic until the year 2100. Most of the correlations of 20-year periods did not show remarkable differences from the control run. Changes in the TA T2m correlations with ICEC in the Arctic in the areas with decreasing ICEC concur with negative trends in ICEC and positive trends in T2m in TA. Changes in the correlations in winter with regions with high and stable ICEC values are hard to suspect to have any direct physical basis. The strongest correlation between TA and Arctic region parameters was T2m in TA and in the Greenland region (Table 2). This correlation is constant up to 2100, opposite to Sun et al. (2016), who declared that the "Warm Arctic, Cold Continents" regime is transient and becoming increasingly unlikely as the climate continues to warm.

To generalize separate Arctic regions' statistical connections with the TA, we used The Ridge regression. PSL, T2m, and ICEC variability in Arctic IA-s can explain from 22% of spring PREC to 64% of winter T2m variability in TA. A substantial amount of it can be explained by climate indices. The previous month's IA-s averages forecasting capacity for TA seasonal average is much weaker – TA spring T2m has the highest coefficient of determination R^2 = 9% with the Ridge regression estimation. Thus, we have to conclude that the use of Arctic climate data could not improve the Baltic Sea region's weather forecasting.

In conclusion – the Baltic Sea region climate has strong teleconnections with the Arctic climate; the strongest connections are with Svalbard and Greenland region. There is high seasonality in the teleconnections, with the strongest correlations in winter and the weakest correlations in summer, when the local factors are stronger. The majority of teleconnections in winter and spring can be explained by climate indexes NAO and AO.

By the end of the 21st century, the Arctic ice concentration has significantly decreased. There will also be slight changes in the teleconnection locations and strength. Still, the general teleconnections pattern between the Arctic and the Baltic Sea region will not change during the 21st-century climate change.

The most important Arctic factors influencing the Baltic Sea are T2m and PSL, but the mechanisms for these teleconnections remained unknown. We have to agree with Overland et al. (2016) that there are no simple cause-and-effect pathways in the Arctic and mid-latitude weather and climate linkages.

Data availability

The CESM1-LE data are available online at https://www.cesm.ucar.edu/community-projects/lens/data-sets

Author contributions

EJ and LJ designed the experiments, analyzed the results and wrote the paper. EJ performed the experiments and generated figures.

Competing interests

The contact author has declared that none of the authors has any competing interests.

Acknowledgements

We thank Marika Holland, Frederic Castruccio and the whole NCAR Oceanography Section for hosting our visit, for access and support to use NCAR supercomputers and for the helpful discussions.

Financial support

We thank Baltic-American Freedom Foundation for financing EJ visit to NCAR via BAFF Research Scholar Program.

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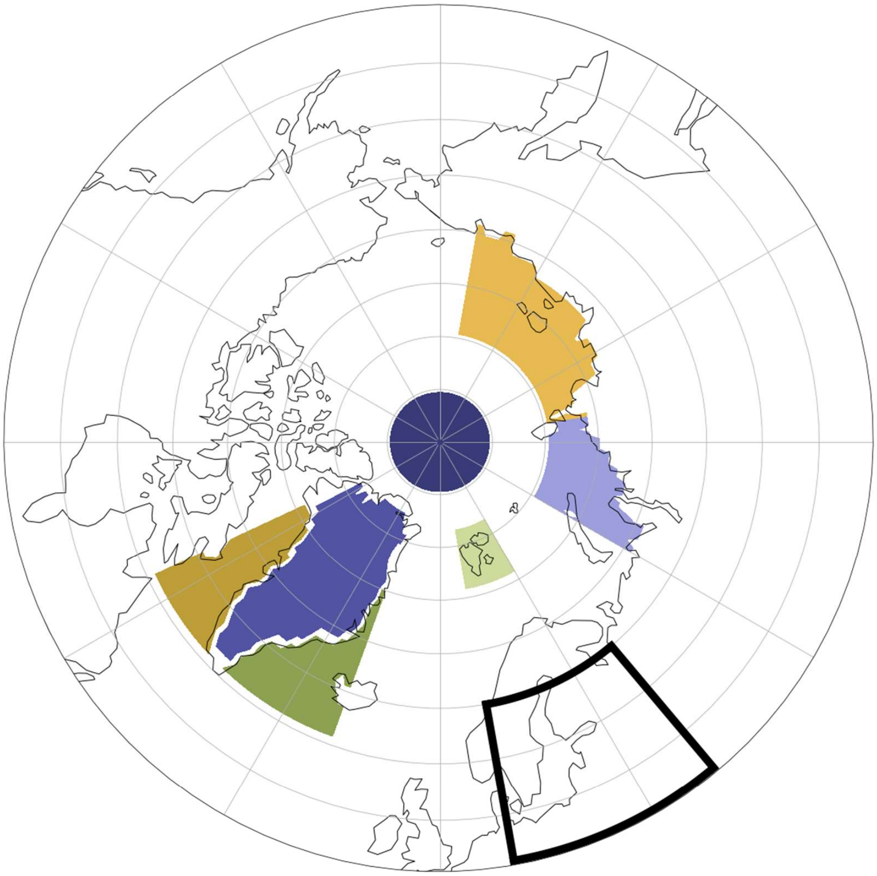

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Figure 1. Important areas (IA, coloured areas) in the Arctic and test area (TA, black rectangle).

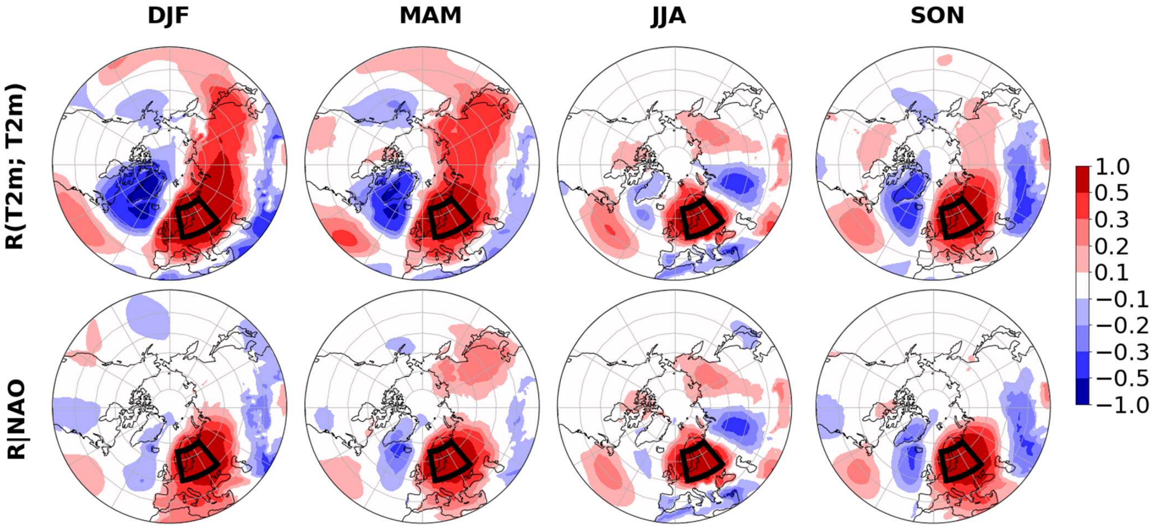

Figure 2. The 2-meter temperature (T2m) seasonal correlations between the testing area (black rectangle) and surrounding areas 435 **according to CESM-LE 1800-year control run. The second row shows the partial correlation with the controlling factor NAO.**

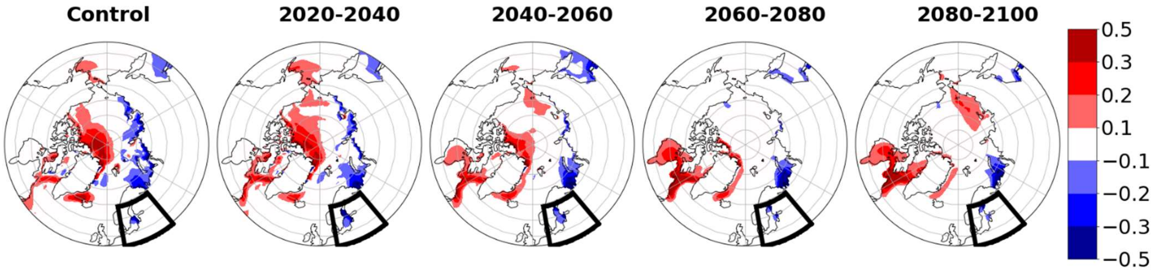

Figure 3. The correlation in DJF between 2-meter temperature (T2m) in the testing area (black box) and ice concentration (ICEC) in the control run and 20-year periods from ensemble simulations at the period 2020 – 2100.

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https://doi.org/10.5194/egusphere-2023-1637
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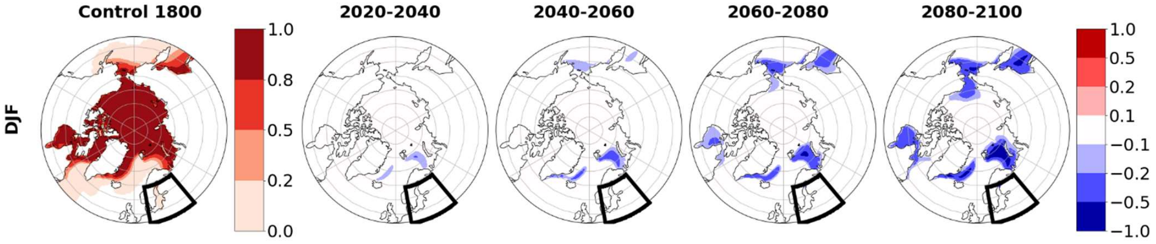

Figure 4. The difference of ice concentration (ICEC) 20-year average in DJF from the control run average (first column) at the 20-year long periods of 2020 – 2100.

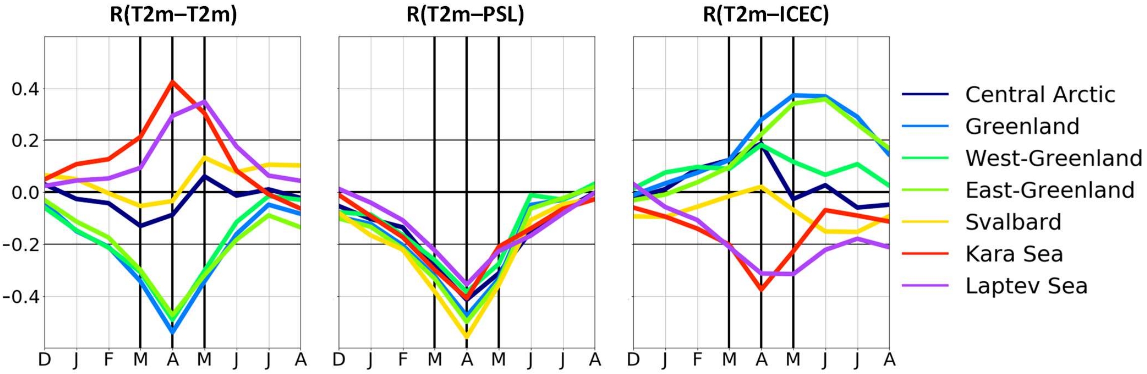

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Figure 5. Lagged correlation between spring (MAM) mean 2-meter temperature (T2m) in TA and IA-s monthly means of 1) T2m (left); 2) pressure at sea level (PSL, middle); and 3) ice fraction (ICEC, right). On the x-axis are the monthly means in IA-s. All correlations stronger than ±0.046 are statistically significant at the confidence level of 95%.