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Atmospheric Chemistry and Physics Discussions

Revisiting the trend in the occurrences of the "warm Arctic-cold Eurasian continent" temperature pattern

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Abstract. The recent increasing trend of "warm Arctic, cold continents" has attracted much attention, but it remains debatable as to what forces are behind this phenomenon. Here, we revisited surface-temperature variability over the Arctic and Eurasian continent by applying the Self-Organizing-Map (SOM) technique to gridded daily surface temperature data. Nearly 40% of the surface temperature trends are explained by the nine SOM patterns that depict the switch to the current warm Arctic-cold Eurasia pattern at the beginning of this century from the reversed pattern that dominated the 1980s and the 90s. Further, no cause-effect relationship is found between the Arctic sea-ice loss and the cold spells in high-mid latitude Eurasian continent suggested by earlier studies. Instead, the increasing trend in warm Arctic-cold Eurasia pattern appears to be related to the anomalous atmospheric circulations associated with two Rossby wavetrains triggered by rising sea surface temperature (SST) over the central North Pacific and the North Atlantic Oceans. On interdecadal timescale, the recent increase in the occurrences of the warm Arctic-cold Eurasia pattern is a fragment of the interdecadal variability of SST over the Atlantic Ocean as represented by the Atlantic Multidecadal Oscillations (AMO), and over the central Pacific Ocean.

Key words: Warm Arctic-cold Eurasian continent, Arctic Sea ice, the Kara-Barents Sea, the Self-Organizing-Map (SOM), the Pacific Decadal Oscillation (PDO), the Atlantic Multidecadal Oscillation (AMO)

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1 Introduction

In recent decades, winter season temperature in the Arctic has been rising at a rate faster than the warming experienced in any other region of the world (Stroeve et al., 2007; Screen and Simmonds, 2010; Stroeve, 2012). In contrasts, there has been an increasing trend in colder than normal winters over the northern mid-latitude continents (Mori et al., 2014). This pattern of opposite winter temperature trend between the Arctic and high-mid latitude continents, referred to as the warm Arctic-cold continents pattern (Overland et al., 2011; Cohen et al., 2014; Walsh, 2014), has also been observed on the interannual timescale (Mori et al., 2014; Kug et al., 2015). The question as to what processes are responsible for the opposite change of winter air temperature between the Arctic and mid-latitudes remain open (Vihma, 2014; Barnes and Screen, 2015).

A number of studies have attributed the recent warm Arctic-cold continents pattern to the Arctic sea ice loss (Inoue et al., 2012; Tang et al., 2013; Mori et al., 2014; Kug et al., 2015; Cohen et al., 2018; Mori et al., 2019). Sea ice variability in different parts of the Arctic Ocean has been linked to climate variability in different parts of the world. Specifically, sea ice loss in the Barents and Kara Seas has been linked to cold winters over East Asia, while a similar connection has been found between cold winters in North America and sea ice retreat in the East Siberian and Chukchi Seas (Kug et al., 2015). A most recent study (Matsumura and Kosaka, 2019) attributed the warm Arctic-cold continents pattern to the combined effect of Arctic sea ice loss and the atmospheric teleconnection induced by tropical Atlantic sea-surface temperature (SST) anomalies. Some recent studies have suggested that the mid-latitude atmospheric circulation anomalies play a role in the formation of the warm Arctic-cold continents pattern (Luo et al., 2016; Peings et al., 2019).

Other studies, however, found no cause-and-effect relationship between Arctic sea ice loss and

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mid-latitude climate anomalies (Blackport et al., 2019; Fyfe, 2019). Numerical modeling studies using coupled ocean and atmospheric models simulated no cold mid-latitude winters when the models were forced with reduced Arctic sea ice cover (McCusker et al., 2016; Sun et al., 2016; Koenigk et al., 2019; Blackport et al., 2019; Fyfe, 2019). The results from these studies pointed to internal atmospheric variability as the likely cause for cold winters in mid-latitudes. Some studies have also suggested that on the interannual timescale mid-latitude atmospheric circulation anomalies triggered by the Pacific and Atlantic SST oscillations may explain both the Arctic sea ice loss and the cooling of the high-mid latitudes (Lee et al., 2011; Matsumura and Kosaka, 2019; Clark and Lee, 2019). The Gulf Stream has also been linked to the Barents Sea ice loss and Eurasian cooling (Sato et al., 2014).

Despite the recent attention given to the warm Arctic-cold continents pattern, it remains debatable as to what processes may be responsible for this phenomenon. In this study, we revisit surface temperature variability over the Arctic and Eurasia continent (40-90°N, 20-130°E), where the warm Arctic-cold continents pattern is a prominent feature (Cohen et al., 2014; Mori et al., 2014), by applying the Self-Organizing-Map (SOM) technique to daily surface temperature over the recent four decades. We will show that while the warm Arctic-cold Eurasian continent pattern has dominated the recent two decades, its opposite pattern, cold Arctic-warm Eurasia continent, appeared frequently in the 1980s and the 90s. Using century-long data, we will further show that the warm Arctic-cold Eurasian continent pattern is an intrinsic climate mode and the recent increasing trend in its occurrence is a reflection of an interdecadal variability of the pattern. Using regression method, we explain the reason for the recent increasing occurrences of the warm Arctic-cold continents pattern. We also assess the role of the SST anomalies over the North Pacific and Atlantic Oceans in the variability of the warm Arctic-cold Eurasia pattern on the interdecadal time scale.

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2 Datasets and methods

From the perspective of nonlinear dynamic, a region’s climate has its intrinsic modes of variability, but the frequency of occurrence of these internal modes can be modulated by remote forces external to the region (Palmer, 1999l; Hoskins and Woollings, 2015; Shepherd, 2016). In this study we will first obtain the main modes of variability of wintertime surface temperature in a region (40-90 °N, 20-130 °E) by applying the SOM method (Kohonen, 2001) to daily surface temperature data for the 40 winters in the 1979-2019 period. The use of daily data over four decades allows for capturing the variability across two time scales (synoptic and decadal). We will then determine, through regression and composite analyses, the relationships of these modes of climate variability of surface air temperature to known climate variability modes at corresponding time scales.

2.1 Datasets

Daily surface air temperature and other climate variables used in the current analyses, including 500 hPa geopotential height, 800-hPa wind and mean sea level pressure, all come from the European Centre for Medium-Range Weather Forecasts Re-Analysis (ERA), the interim version (ERA-Interim; Dee et al., 2011). Compared to the earlier versions of ERA (e.g., ERA-40, Uppala et al., 2005) and other global re-analysis products (e.g. the NCEP reanalysis, Kalnay et al., 1996), ERA-Interim has been found to be more accurate in portraying the Arctic warming trend (Dee et al., 2011; Screen and Simmonds, 2011) despite its known warm and moist bias in the surface layer (Jakobson et al., 2012). Gridded monthly SST data used in the current analysis are obtained from the US National Oceanic and Atmospheric Administration (NOAA) data archives (ftp://ftp.cdc.noaa.gov/Datasets/noaa.oisst.v2.highres/) (Reynolds et al. 2007).

The results obtained from the data within the recent four decades are put into the context of the

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variability over longer time scales using data from the Twentieth Century Reanalysis project, version 2c (20CR) that spans more than a century from 1851 through 2015 (Compo et al., 2011). The 20CR reanalysis data has a horizontal resolution of 2° latitude by 2° longitude and temporal resolution of 6 hours. Through the assimilation of surface observational pressure data, the 20CR reanalysis was produced by the model whose lower boundary condition is derived from monthly SST and sea ice conditions. Various indices used to describe known modes of climate variability are obtained from NOAA's Climate prediction Center (CPC) (https://www.esrl.noaa.gov/psd/data/climateindices/list/), which include Arctic oscillation (AO), Northern Atlantic Oscillation (NAO), Atlantic Multidecadal Oscillation (AMO) (Enfield et al., 2001) and PDO (Mantua et al., 1997) indices.

2.2 Methods

The 40-year, daily surface temperature over the study region (40-90°N, 20-130°E) is decomposed using the SOM method. SOM is a clustering method based on neural network that can transform multi-dimensional data into a two-dimensional array without supervised learning. The array includes a series of nodes arranged by a Sammon map (Sammon, 1969). Each node in the array has a vector that can represent a spatial pattern of the input data. The distance of any two nodes in the Sammon map represents the level of similarity between the spatial patterns of the two nodes. Because SOM has fewer limitations than most other commonly used clustering methods, (e.g., orthorgonality required by the empirical orthogonal function or EOF method), the SOM method can describe better the main variability patterns of the input data (Reusch et al., 2005).

SOM method has been used in atmospheric research at mid and high latitudes of the northern hemisphere (Skific et al., 2009; Johnson and Feldstein, 2010; Horton et al., 2015; Loikith and Broccoli, 2015; Vihma et al., 2019). For example, Johnson and Feldstein (2010) identified the spatial patterns of

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the daily wintertime North Pacific sea level pressure and related the variability of the occurrences of those patterns to some large-scale circulation indices. Loikith and Broccoli (2015) compared observed and model-simulated circulation patterns across the North American domain. SOM method was used to detect circulation pattern trends in a subset of North America during two periods (Horton et al., 2015). In this study, the SOM method is applied to wintertime daily temperature anomalies obtained by subtracting 40-year averaged daily temperature from the original daily temperature at each grid point. Prior to SOM analysis, it is necessary to determine how many SOM nodes are needed to best capture the variability in the data. According to previous studies (Lee and Feldstein, 2013; Gibson et al., 2017; Schudeboom et al., 2018), the rule for determining the number of SOM nodes is that the number should be sufficiently large to capture the variability of the data analyzed, but not too large to introduce unimportant details. Table 1 shows the averaged spatial correlation between all daily surface air temperature and their matching nodes. There is an increase in correlation coefficients from 0.26 for a 3×1 grid to 0.51 for a 4×4 grid, but the gain from a 3×3 grid to a 4×4 grid is relatively small. Hence, a 3×3 grid seems to meet the above-mentioned rule and will be utilized in this study.

The contribution of each SOM node to the trend in wintertime surface temperature is calculated by the product of each node pattern and its frequency trend normalized by the total number of wintertime days (90, Lee and Feldstein, 2013). The sum of the contributions from all nodes denotes the SOM-explained trends. Residual trends are equal to the subtraction of SOM-explained trends from the total trends. The statistical significance in this study is tested by using the Student's t test.

3 Results

3.1 Surface temperature variability

The majority of the 9 SOM nodes depict a dipole pattern characterized by opposite changes in surface temperature between the Arctic Ocean and the Eurasian continent, although the sign switch does not always occur at the continent-ocean boundary (Figure 1). The position of the boundary between the warm and cold anomalies reflect the transition between the cold Arctic-warm Eurasia pattern (denoted, in descent order of the occurrence frequency, by nodes 3, 9, 6), to the warm Arctic-cold Eurasia pattern (depicted, in descent order of the occurrence frequency, by nodes 1, 7, 4). The spatial patterns represented by the first group of nodes (3, 9, 6) are almost mirror images of the patterns denoted by the corresponding nodes in the second group (1, 7, 4). For example, the first node in group 1 (node 9, 15.4%) and in group 2 (node 1, 17.1%) show a mirror image pattern with cold (warm) anomalies in the Arctic Ocean extending into northern Eurasia and warm (cold) anomalies in the rest of the Eurasia continent in the study domain. In both cases, the region of maximum anomalies is centered near Svalbard, Norway. The second most frequent pattern, denoted by node 3 (17.2%) and 7 (13.7%) in the two groups, respectively, has the boundary of separation moved northward from northern Eurasia continent toward the shore of the Arctic Ocean. While the maximum anomaly in the Arctic Ocean remains close to Svalbard, maximum values over the continent are found in central Russia. Nodes 4-6 display a noticeable transition from node 1 to node 7 and from node 3 to node 9, respectively. Although nodes 2 and 8 show an approximate monopole spatial pattern, they also represent a transition between nodes 1 and 3, and between nodes 7 and 9, respectively. Above SOM analysis cannot consider the trend in surface air temperature. The result is similar while removing the trend (Not shown).

The temporal variability on this time scale is typically related to synoptic processes and hence the questions are what synoptic patterns are responsible for the occurrence of the spatial patterns depicted by each of the 9 SOM nodes and how these patterns are related to those of the Arctic sea ice anomalies? These questions can be answered by using the composite method. Specifically, for each node, composite maps are made respectively for the anomalous 500-hPa geopotential height, mean sea level pressure, 850-hPa wind, downward longwave radiation, surface turbulent heat flux, and sea ice concentration over all the days when the spatial variability of the surface temperature anomalies is best matched by the spatial pattern of that node.

3.2 Large-scale circulation patterns

For all nodes, the spatial pattern of the composited 500 hPa-geopotential height anomalies (Figure 2) is similar to that of mean sea level pressure anomalies (Not shown), indicating an approximately barotropic structure. For nodes 1, 4 and 7, 500-hPa height anomalies show a dipole structure of positive values over Siberia and negative values to its south. Anomalous southwesterly winds on the western side of the anticyclone over Siberia transport warm and moist air from northern Europe and the North Atlantic Ocean into the Atlantic sector of the Arctic Ocean (Figure 3), providing a plausible explanation of the warm surface temperature anomalies in the region (Figure 1). On the eastern side of the anticyclone, anomalous northwesterly winds bring cold and dry air from the Arctic Ocean into Eurasia continent, which is consistent with the negative surface temperature anomalies there. The opposite occurs for nodes 3, 6 and 9. A similar explanation involving anomalous pressure and wind fields can be applied to other nodes. The dipole structure that dominates the anomalous 500-hPa height fields over the North Atlantic Ocean for most nodes resembles the spatial pattern of the NAO. In addition, the patterns for a few nodes, such as nodes 4 and 7, have some resemblance to the spatial pattern of the AO over larger geographical region. The possible connection to NAO and AO is further investigated by averaging the daily index values of NAO or AO over all occurrence days for each node. The results (Table 2) show that nodes 1, 2, 3 (5, 8, 9) correspond to a significant positive (negative) phase of the NAO index characterized by negative (positive) height anomalies over Iceland and

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positive (negative) values over the central North Atlantic Ocean. Association is also found between nodes 1, 2, 3, and 6 (5, 7, 8, and 9) and the positive (negative) phases of the AO index.

3.3 Downward radiative fluxes

Besides the anomalous circulation patterns, anomalous surface radiative fluxes may also play a role in shaping the spatial pattern of surface temperature variability. In fact, the spatial pattern of the mean anomalous daily downward longwave radiation for an individual node (Figure 4) is in good agreement with the spatial pattern of the surface temperature anomalies of that node. In other words, increased downward longwave radiation is associated with positive surface temperature anomalies, and vice versa. As expected from previous studies (e.g., Sedlar et al. 2011), there is a significant positive correlation between downward longwave radiative fluxes and the anomalous total column water vapor and mid-level cloud cover (not shown). The correlation to low- and high-level cloud cover is, however, not significant (Not shown). Most of the water vapor in both the Arctic and Eurasia is derived from the North Atlantic Ocean, but the water vapor is transported into the Arctic by southwesterly flows and into Eurasia by northwesterly winds. The anomalous shortwave radiation corresponding to each node (not shown) is an order of magnitude smaller that of the longwave radiation anomalies and has a spatial pattern opposite to that of the mid-level cloud cover and the longwave radiation anomalies.

3.4 Sea ice

The analyses presented above attempt to explain the spatial pattern of surface temperature variability for each node from the perspective of anomalous heat advection and surface radiative fluxes. As mentioned earlier, there has been a debate in the literature about the role played by the sea ice anomalies in the Barents and Kara Seas in the development of the warm Arctic-cold Eurasia pattern. Here, we examine the anomalous turbulent heat flux (Figure 5) and sea ice concentration (Figure 6) for

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each node. Turbulent heat flux is considered positive when it is directed from the atmosphere downward to the ocean or land surfaces. Thus, a positive anomaly indicates either an increase in the atmosphere-to-surface heat transfer or a decrease in the heat transfer from the surface to the atmosphere. The magnitude of anomalous turbulent heat flux is found to be comparable to that of anomalous downward longwave radiation (Figure 4). For all nodes, the heat flux anomalies are larger over ocean than over land. For node 1, positive turbulent heat flux anomalies occur mainly over the Barents Sea, the western and central North Atlantic Ocean and the eastern North Pacific Ocean, indicating an increase in heat transport from the air to the ocean due possibly to an increase in vertical temperature gradient caused by warm air advection associated with anomalous circulation. The downward heat transfer results in sea ice melt in the Greenland Sea and the Barents Sea (Figure 6). For node 4, the anomalous southerly winds over the Nordic Sea produce larger positive turbulent heat flux anomalies. For node 7, the anticyclone is located more northwards, which generates opposite anomalous winds between the Nordic and northern Barents Seas and the southern Barents Sea and thus opposite turbulent heat flux anomalies that are consistent with the opposite sea ice concentration anomalies in the two regions. For nodes 3, 6, and 9, the anomalous cold air from the central Arctic Ocean flows into warm water in the Nordic and Barents Seas, producing negative turbulent heat flux anomalies and positive sea ice concentration anomalies. Sorokina et al. (2016) noted that turbulent heat flux usually peaks 2 days before changes in surface temperature pattern occur. The pattern of the composted anomalous turbulent heat flux 2 days prior to the day when the nodes occur (not shown) is similar to the current-day pattern in Figure 6. Our results support the conclusion of Sorokina et al. (2016) and Blackport et al. (2019) that the anomalous atmospheric circulations lead to the anomalous sea ice concentration in the Barents Sea.

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3.5 Contributions of SOM nodes to the trends in wintertime surface temperature

The results above suggest that both the surface temperature anomaly patterns over the Arctic Ocean and Eurasian continent and the sea ice concentration anomalies in the Nordic and Barents Seas can be explained largely by changes in atmospheric circulations and the associated vertical and horizontal heat and moisture transfer by mean and turbulent flows. Next, we assess the contributions of these nodes to the trend in wintertime surface temperature.

We first examine the time series of the accumulated number of days for each node in each winter for the 1979-2019 period (Figure 7). The time series for nodes 1, 4, 6, and 9 exhibit variability on interannual as well as decadal time scales. The occurrence frequency is noticeably larger after 2003 than prior to 2003 for nodes 1 and 4, and vice versa for nodes 6 and 9, and the difference between the two periods is significant at 95% confidence level. Given the spatial patterns of these four nodes (Figure 1), this indicates that the warm Arctic-cold Eurasia pattern occurred more frequently after 2003. A linear trend analysis of the time series for each node (Table 2) reveals significant positive trends in occurrence frequency for nodes 1 and 4 and significant negative trends for nodes 6 and 9, which agree with the result from a previous study (Clark and Lee, 2019) that suggested an increasing trend of the warm Arctic and cold Eurasia pattern.

These trends in the occurrence frequency of the SOM nodes contribute to the trends in the total wintertime (DJF) surface temperature anomalies (Figure 8, top panel) that have significant positive trends over the Arctic Ocean and in regions of Northern and Southern Europe and negative trends in Central Siberia. The contribution, however, varies from node to node (Figure 9). Node 1 has the largest domain-averaged contribution of 18.7%, followed by its mirror node (node 9) at 10.1%. Nodes 4 and 6 account for 2.8% and 4.3% of the total trend, respectively. None of the remaining nodes explain more

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than 2%. All nodes together explain 39.5% of the total trend in wintertime surface air temperature. The spatial pattern of the SOM-explained trends (Figure 8, middle panel) is similar to the warm Arctic--cold continent pattern, whereas the residual trend resembles more the total trend (Figure 8 bottom panel).

3.6 Mechanisms

The results presented above indicate that the SOM patterns explain nearly 40% of the trend in wintertime surface air temperature anomalies and majority of the contributions (35 out of 40%) come from the two pairs of the nodes (nodes 1, 9, and 4, 6). The analyses hereafter will focus on these four nodes. Below we assess the atmospheric and oceanic conditions associated with the occurrences of the four nodes via regression analysis. Specifically, the anomalous seasonal SST and atmospheric circulation variables are regressed onto the normalized time series of the number of days when each of the four nodes occurs (Figures 10, 11, and 12).

For node 1, the SST regression pattern in the Pacific Ocean shows significant positive anomalies over the tropical western Pacific Ocean and central North Pacific Ocean. The positive SST anomalies also occur over most of the North Atlantic. Negative SST anomalies occur over the central tropical Pacific Ocean, though they are not significant at 95% confidence level. The SST regression pattern is reversed for node 9. The corresponding anomalous 500-hPa height regression shows two Rossby wavetrains: one is excited over the central Pacific Ocean and propagates northeastwards into North America and North Atlantic Ocean, and the other, which displays the stronger signal, originates from central North Atlantic and propagates northeastwards to the Arctic Ocean and southeastwards to the Eurasian continent and the western Pacific Ocean. The large SST anomalies over the Nordic Ocean augment the wave signal through local air-sea interaction. The wave activity flux and streamfunction

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exhibit well the horizontal propagating direction of the planetary wave. For node 9, the corresponding anomalous 500-hPa height and streamfunction show an opposite pattern, but the wave activity flux is similar to that of node 1.

For node 4, the SST anomalies over the tropical Pacific Ocean appear to be in a La Niña state, which shows stronger negative SST anomalies over the eastern tropical Pacific Ocean than those for node 1. The positive SST anomalies over the North Pacific shift more northwards relative to that of node 1. The positive SST anomalies over the North Atlantic are weaker than those for node 1. The corresponding wavetrain over the Pacific Ocean is stronger than that over the Atlantic Ocean, which can also be observed in the pattern of wave activity and streamfunction. The corresponding pattern for node 6 is nearly reversed, but there are some noticeable differences in the amplitude of the wavetrain and SST anomalies. For example, the magnitude of the anomalous SST and the 500-hPa height over the central North Pacific is larger for node 6 than that for node 4.

Besides the above-mentioned variables, similar regression analysis is also performed for the anomalous 850-hPa wind field and anomalous downward longwave radiation (Not shown). Their regression patterns, which are similar to those in Figures 3 and 4, explain well the decadal variability of the number of days for nodes 1, 4, 6, and 9. Together, these results indicate that the decadal variability of the occurrence frequency of the four nodes in recent decades is related to two wavetrains induced by SST anomalies over the central North Pacific Ocean and the North Atlantic Ocean. The aforementioned SST regression patterns over the Atlantic and Pacific Oceans also show features of the AMO and PDO (Figure 10). Since both the AMO and PDO exhibited a phase change in the late 1990s (Yu et al., 2017), the question is whether a similar change in the SOM frequency also appear in the late 1990s. A comparison of the averaged frequency before and after 1998 shows a significant drop in frequency for

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nodes 6 and 9 and an increase in frequency for node 1. This result suggests that the change in the AMO and PDO indices may contribute to the change in the frequencies of the warm Arctic-cold Eurasia continent pattern.

3.7 Interdecadal variability

The four-decade-long ERA-Interim reanalysis is not adequate for examining interdecadal to multi-decadal variations represented by the PDO and AMO indices. Further analysis is performed using the 20CR daily reanalysis data for the 1854-2014 period. Before applying the SOM technique to the 20CR data, we first remove the trend to eliminate the influence from the global warming. No low-pass filter is applied before SOM analysis in order to test the stability of the SOM results for the different periods. The spatial SOM patterns from the de-trended century-long 20CR data (Figure 13) are similar to those for the 1979-2019 period (Figure 1). Nodes 1, 4, and 7 correspond to the positive phase of the warm Arctic-cold Eurasia pattern and the negative phase can be observed in nodes 3, 6, and 9. The magnitude is smaller compared to the recent four decades. The occurrence frequencies of all the nodes (Figure 14) are close to those for the recent four decades. It indicates that the SOM method can obtain stably the main modes of wintertime surface air temperature variability. For the recent four decades, the time series of the number of days also displays a noticeable increasing (decreasing) trend for nodes 1 and 4 (6 and 9), suggesting that the trend in the recent four decades is a reflection of an interdecadal variability of wintertime surface air temperature.

Next, we apply a 40-year low-pass filter to the time series of the occurrence frequencies for nodes 1, 4, 6 and 9 and the AMO and PDO indices and calculate correlations. There is a significant correlation between the time series and the AMO index, with correlation coefficients of 0.36 for node 1, 0.27 for node 4, -0.37 for node 6, and -0.20 for node 9, all of which are at the 95% confidence level. No

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significant correlations, however, are found between the filtered time series and the PDO index. If we define an SST index to represent the variability of SST anomalies over the central North Pacific Ocean (20°N-40°N, 150°E-150°W), the 40-year low-pass filtered central North Pacific Ocean SST index is now significantly correlated with the filtered time series of occurrence frequencies for nodes 1 and 9 (0.55 for node 1 and -0.46 for node 9). The results are consistent with the SST regression map for the recent decades (Figure 10).

To confirm the effect of SST anomalies on the warm Arctic -cold Eurasia pattern, we also perform EOF analysis of wintertime detrended seasonal surface air temperature anomalies for the 1854-2014 period (Figure 15). The spatial patterns of the first and second EOF modes show the negative phase of the warm Arctic-cold Eurasia pattern and the 40-year low-pass filtered time series is inversely correlated with the 40-year low-pass filtered wintertime AMO index (-0.46 $p<0.05$ for mode 1 and -0.44 $p<0.05$ for mode 2). The 40-year low-pass filtered time series of the two EOF modes has a significant negative correlation with the 40-year low-pass filtered central North Pacific Ocean SST index, with correlation coefficients of -0.19 and -0.26 ($p<0.05$). Only PC1 has a significant correlation with the PDO index (0.38 $p<0.05$). Thus, the increase in the occurrence of the warm Arctic-cold Eurasia pattern in the recent decades is a part of the interdecadal variability of the pattern, which is influenced by the AMO index and the central North Pacific SST.

4 Conclusions and Discussions

In this study, we examine the variability of wintertime surface air temperature in the Arctic and the Eurasian continent (20°E-130°E) by applying the SOM method to daily temperature from the gridded ERA-Interim dataset for the period 1979-2019 and from the 20CR reanalysis for the period 1854-2014 and the EOF method to seasonal temperature from the 20CR reanalysis for the period 1854-2014.

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The spatial pattern in the surface temperature variations in the study region, as revealed by the nine SOM nodes, is dominated by concurrent warming in the Arctic and cooling in Eurasia, and vice versa. The nine SOM patterns explain nearly 40% of the trends in wintertime surface temperature and 88% of that are accounted for by only four nodes. Two of the four nodes (nodes 1 and 4) represent the warm Arctic-cold Eurasian pattern and the other two (nodes 6 and 9) depict the opposite cold Arctic-warm Eurasia pattern. There is a clear shift in the frequency of the occurrence of these patterns near the beginning of this century, with the warm Arctic – cold Eurasia pattern dominating since 2003, while the opposite pattern prevailing from the 1980s through the 1990s. The warm Arctic-cold Eurasia pattern is accompanied by an anomalous high pressure and anticyclonic circulation over the Eurasian continent. The anomalous winds and the associated temperature and moisture advection interact with local longwave radiative forcing and turbulence to produce positive (negative) temperature anomalies in the Arctic (Eurasian continent). The circulation is reversed for the cold Arctic-warm Eurasia pattern. The warm, moist air mass advected to the Arctic by the anomalous atmospheric circulations and the increased downward turbulent heat flux also explain sea ice melt in the Barents and Kara Seas. In other words, the sea ice loss in the Barents and Kara Seas and the cooling of the Eurasian continent can both be traced to anomalous atmospheric circulations.

Increasing occurrences of the warm Arctic-cold Eurasian continent pattern appear to relate to rising SST over the central North Pacific and North Atlantic Oceans (positive AMO phase). The SST anomalies trigger two Rossby wavetrains spanning from the North Pacific Ocean, North America, and the North Atlantic Ocean to the Eurasian continent. The two wavetrains are strengthened through local sea-atmosphere-ice interactions in mid-high latitudes, which influence the change in the occurrence frequency of the warm Arctic-cold Eurasian continent pattern. Our results agree with those of previous

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studies (Lee et al., 2011; Sato et al., 2014; Clark and Lee, 2019). But previous studies only focus on the effect of SST anomalies over either North Pacific or North Atlantic Oceans. We also note that the two wavetrains excited by SST anomalies over different oceans differ in amplitudes, leading to somewhat different warm Arctic-cold Eurasia patterns.

Using century-long data, we show that the warm Arctic-cold Eurasia pattern is an intrinsic climate mode, which has been stable since 1854. The recent increasing trend in its occurrence is a reflection of an interdecadal variability of the pattern resulting from the interdecadal variability of SST anomalies over the central Pacific Ocean and over the Atlantic Ocean represented by the AMO index. Sung et al. (2018) investigated interdecadal variability of the warm Arctic and cold Eurasia pattern and considered the variability of the SST over the North Atlantic as its origin. Our results suggest that the variability of the SST over the North Pacific also plays an important role. However, internal atmospheric variability remains another potential source. The Rossby wavetrains also lead to deepening of a trough in East Asia and generate an anomalous low and cold temperature in northern China, which further suggests that the relationship between a warmer Arctic, especially warmer Barents and Kara Seas, and the occurrence of cold spells in East Asia may not be as strong as previously thought (Kim et al., 2014; Mori et al., 2014; Kug et al., 2015; Overland et al., 2015).

Our results help broaden the current understanding of the formation mechanisms for the warm Arctic-cold Eurasia pattern. The SST anomalies over Northern Hemisphere oceans may offer a potential for predicting its occurrence.

Data Availability

All data used in the current analyses are publicly available. The monthly sea ice concentration data are available from the National Snow and Ice Data Center (NSIDC) (http://nsidc.org/data/NSIDC-0051), the ERA-Interim reanalysis data are available from the European Center for Mid-Range Weather

Forecasting (https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era-interim) and the sea surface temperature data are available from the Hadley Centre for Climate Prediction and Research (ftp://ftp.cdc.noaa.gov/Datasets/noaa.oisst.v2.highres/). The long-term SST data are derived from from the Twentieth Century Reanalysis project, version 2c (20CR) (https://climatedataguide.ucar.edu/climate-data/noaa-20th-century-reanalysis-version-2-and-2c).

Competing interests

The authors declare that they have no conflict of interest.

Author Contributions

L. Yu designed the study, with input from S. Zhong, and carried out the analyses. L. Yu and S. Zhong prepared the manuscript. C. Sui plotted a part of Figures.

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Table 1. Spatial correlations (Corrs) between the daily winter (DJF) surface air temperature and the corresponding SOM pattern for each day from 1979 to 2018.

	3×1	2×2	3×2	4×2	3×3	5×2	4×3	5×3	4×4
Corr	0.26	0.43	0.48	0.48	0.50	0.49	0.50	0.51	0.51

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Table 2. Averaged anomalous NAO and AO indices for all occurrences of each SOM node. Asterisks indicate the above 95% confidence level.

	Node1	Node2	Node3	Node4	Node5	Node6	Node7	Node8	Node9
NAO	0.38*	0.22*	0.12*	0.05	-0.22*	-0.02	-0.07	-0.31*	-0.32*
AO	0.44*	0.38*	1.03*	-0.42	-0.62*	0.22*	-0.44*	-1.11*	-0.41*

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Table 3. Trends in the frequency of occurrences for each SOM node (day yr^{-1}). Asterisks indicate the above 95% confidence level.

	Node1	Node2	Node3	Node4	Node5	Node6	Node7	Node8	Node9
Trend	0.80*	0.10	-0.18	0.22*	-0.02	-0.39*	0.17	-0.17	-0.50*

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Table 4. Frequencies of occurrence (%) of wintertime surface air temperature patterns in Figure 1 for all winters before 1998 and after 1998 for the period 1979-2019. Values with Asterisks are significantly different from climatology above the 95% confidence level.

	Frequencies of occurrence		
SOM patterns	All winters	Winters before 1998	Winters after 1998
Node 1	17.1	7.4*	26.8
Node 2	4.4	3.3	5.4
Node 3	17.2	18.8	15.6
Node 4	8.6	5.4	11.7
Node 5	3.4	3.4	3.5
Node 6	10.2	15.2*	2.1*
Node 7	13.7	10.6	16.8
Node 8	10.1	12.1	8.0
Node 9	15.4	23.7*	7.1*

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Figure Captions

Figure 1. Spatial patterns of SOM nodes for daily wintertime (December, January, and February) surface air temperature anomalies (℃). The number in brackets denotes the frequency of the occurrence for each node.

Figure 2. Corresponding 500-hPa geopotential height anomalies (gpm) for each SOM node. Dotted regions indicate the above 95% confidence level.

Figure 3. The same as Figure 2, but for anomalous 850-hPa wind field (ms^{-1}).

Figure 4. The same as Figure 2, but for anomalous downward longwave radiation (10^5 W m^{-2}).

Figure 5. The same as Figure 2, but for anomalous turbulent heat flux (sensible and latent heat) (10^5 W m^{-2}). Positive values denote heat flux from atmosphere to ocean and land and vice versa.

Figure 6. The same as Figure 2, but for anomalous sea ice concentration.

Figure 7. Time series of the number of days for occurrence of each SOM node in Figure 1.

Figure 8. Total (top), SOM-explained (middle), and residual (bottom) trends in wintertime surface air temperature (^oC yr^{-1}). Dots in the top panel indicate above 95% confidence level.

Figure 9. Trends in surface air temperature explained by each SOM node (℃ yr^{-1}). The percentage in the upper of each panel indicates the fraction of the total trends represented by each node.

Figure 10. Anomalous SST (℃) regressed into the normalized time series of

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occurrence number for nodes 1, 4, 6, and 9.

Figure 11. As in Figure 10, but for the anomalous 500-hPa geopotential height (gpm).

Figure 12. The anomalous wave activity flux (vectors) and stream function (colors, 10^7 m^2/s) regressed onto the normalized time series of occurrence number for nodes 1, 4, 6, and 9.

Figure 13. Spatial patterns of the SOM nodes for daily wintertime (December, January, and February) surface air temperature anomalies (℃) for the 1851-2014 period. The number in brackets denotes the frequency of the occurrence for each node.

Figure 14. Time series of the number of days for occurrence of each SOM node in Figure 1.

Figure 15. The (a) leading pattern and (b) its time series (PC1 and PC2) of EOF analysis of wintertime surface air temperature anomalies. Prior to EOF analysis, surface air temperature data are detrended. A 40-yr low-pass filtered is applied to the time series of PC1, PC2, AMO and PDO indices.

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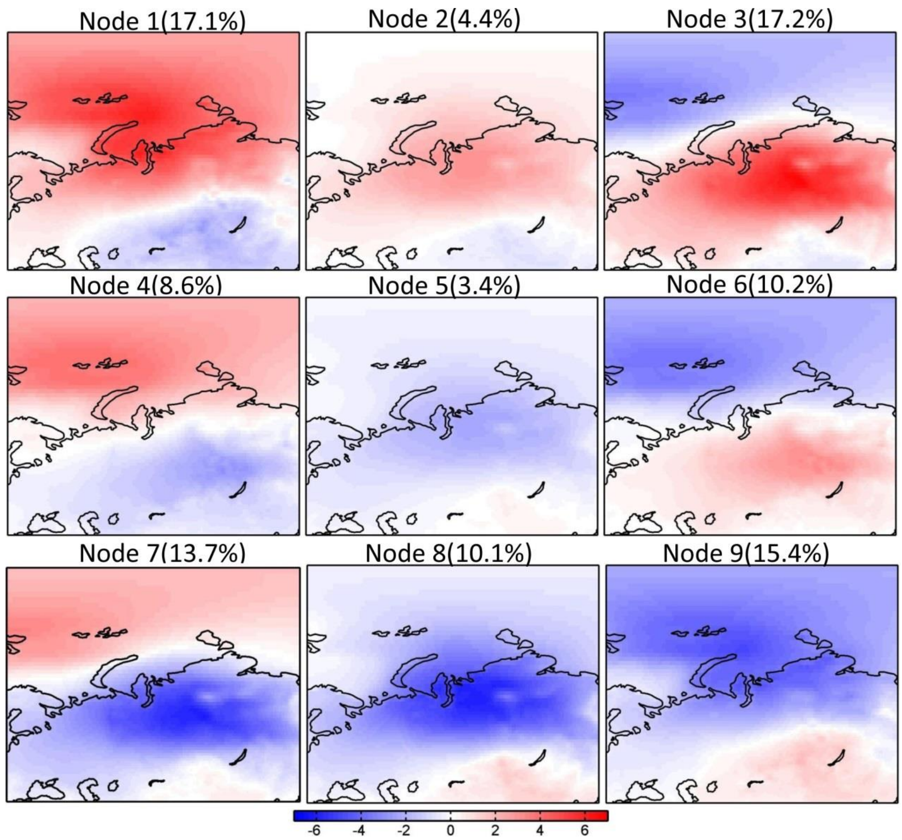

Figure 1. Spatial patterns of SOM nodes for daily wintertime (December, January, and February) surface air temperature anomalies (℃). The number in brackets denotes the frequency of the occurrence for each node.

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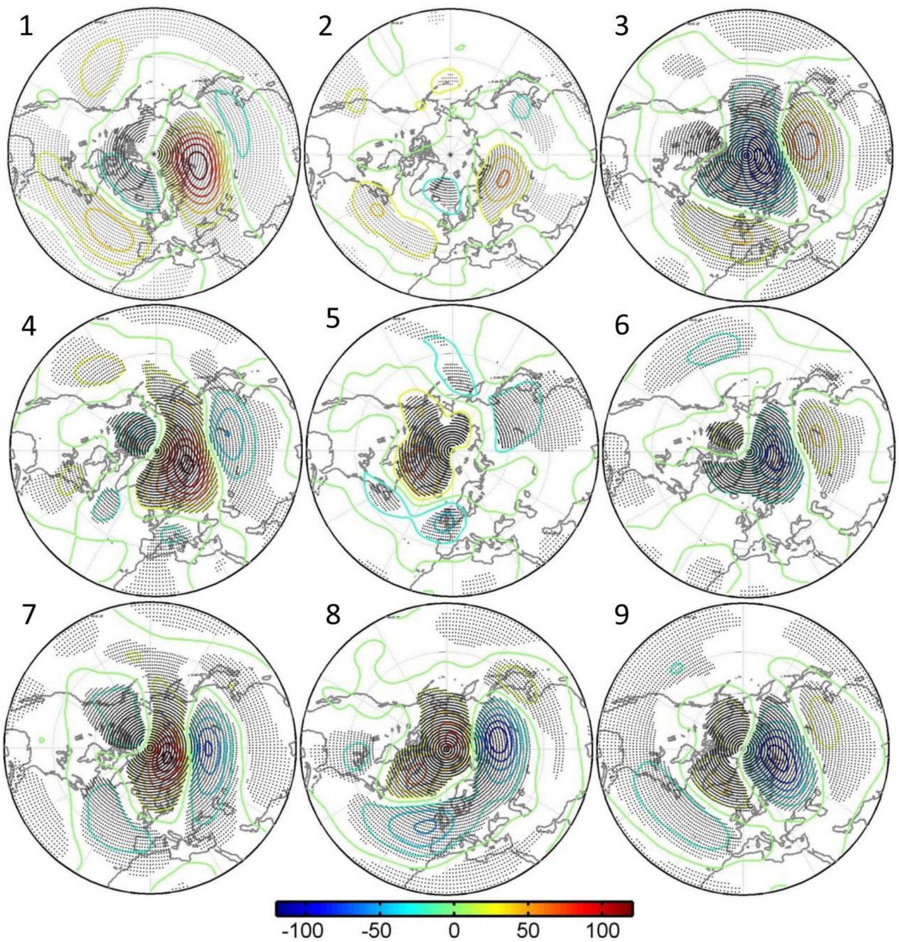

Figure 2. Corresponding 500-hPa geopotential height anomalies (gpm) for each node. Dotted regions indicate the above 95% confidence level.

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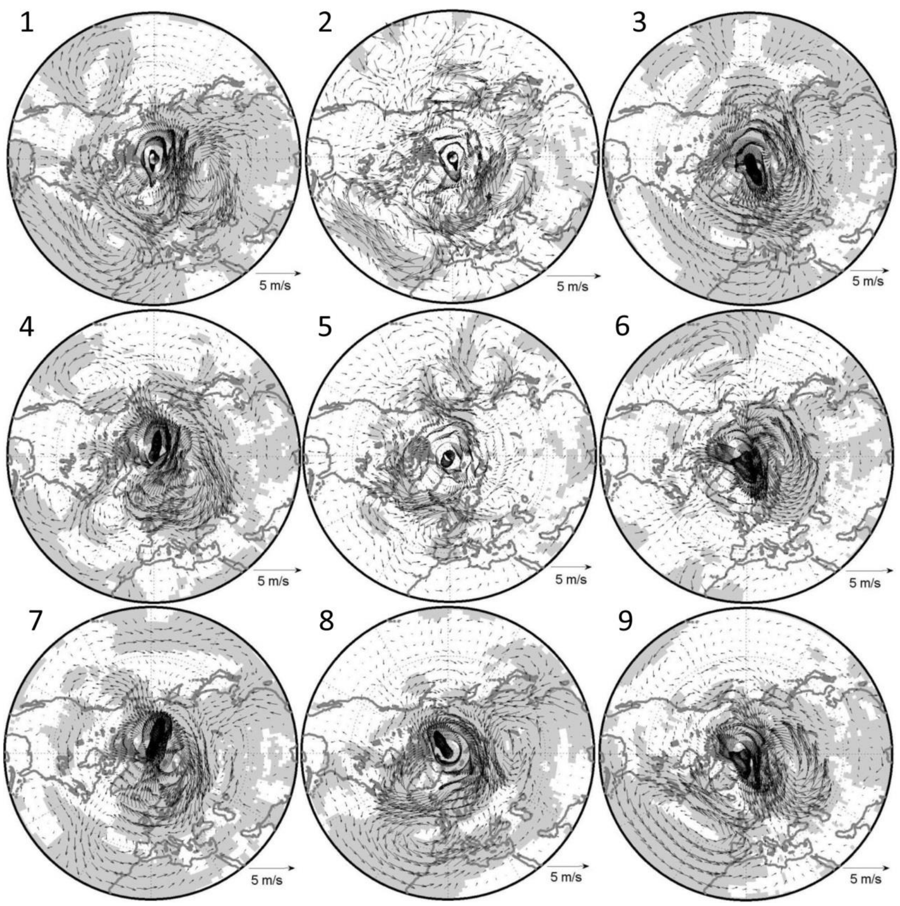

Figure 3. The same as Figure 2, but for anomalous 850-hPa wind field (ms^{-1}).

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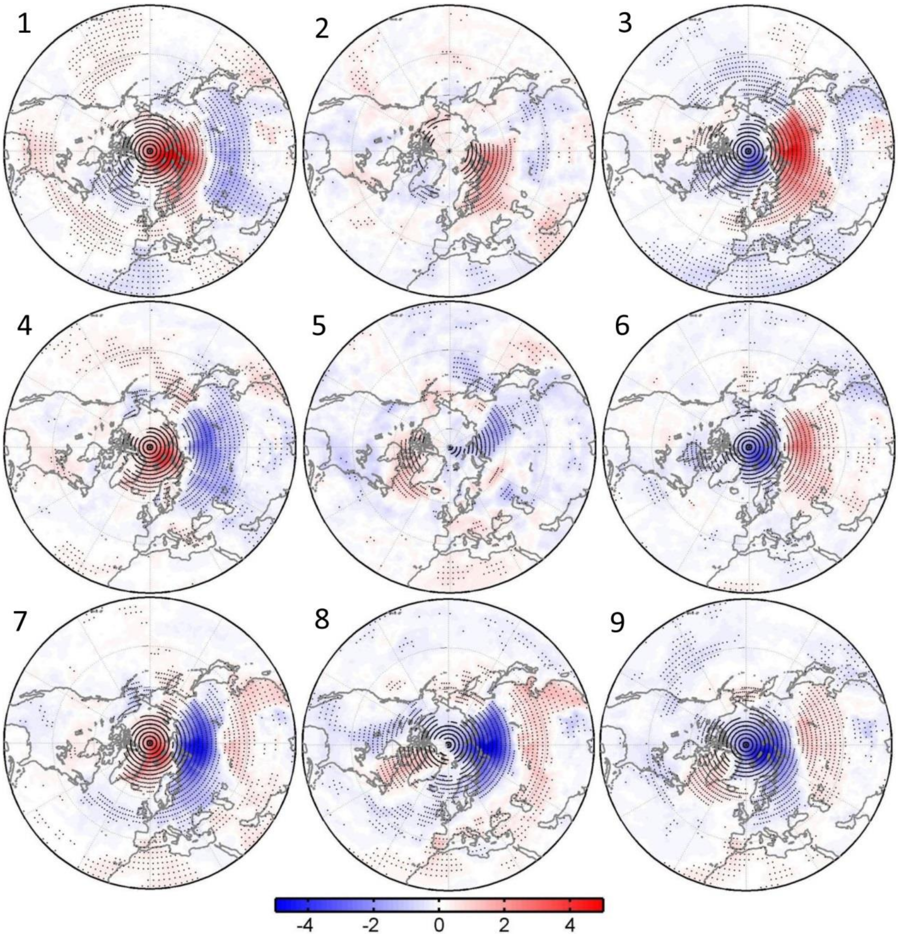

Figure 4. The same as Figure 2, but for anomalous downward longwave radiation (10^5 W m^{-2}).

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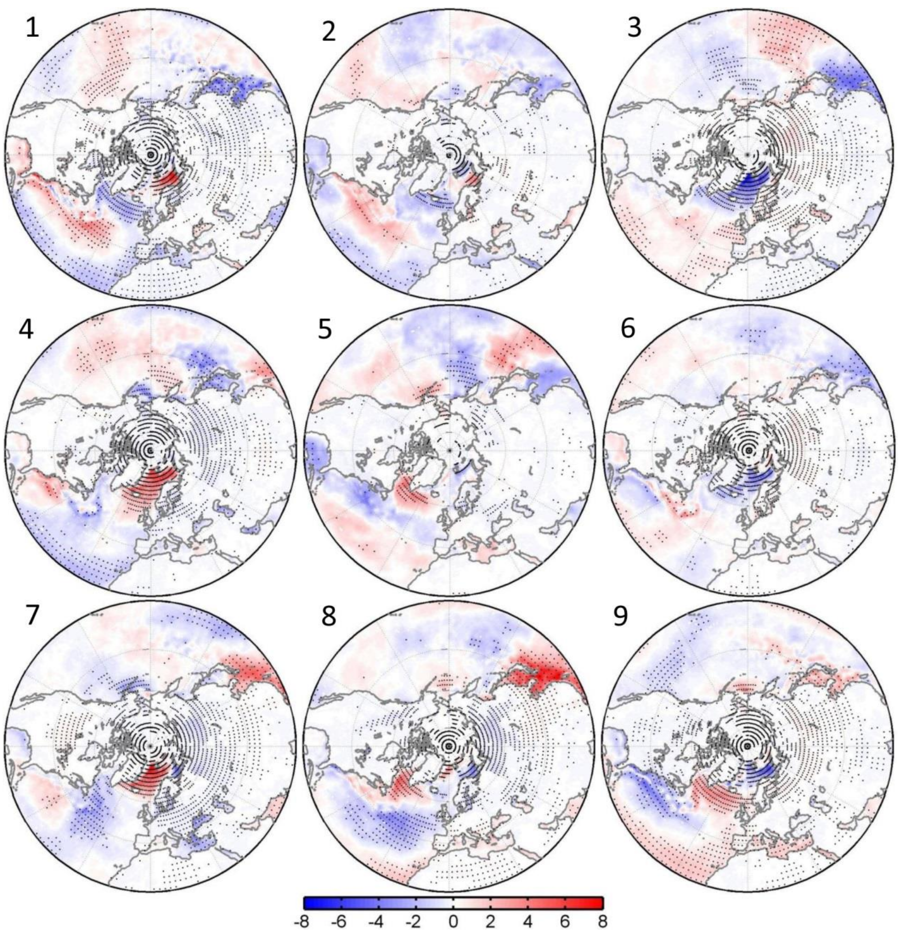

Figure 5. The same as Figure 2, but for anomalous turbulent heat flux (sensible and latent heat) (10^5W m^{-2}). Positive values denote heat flux from atmosphere to ocean and vice versa.

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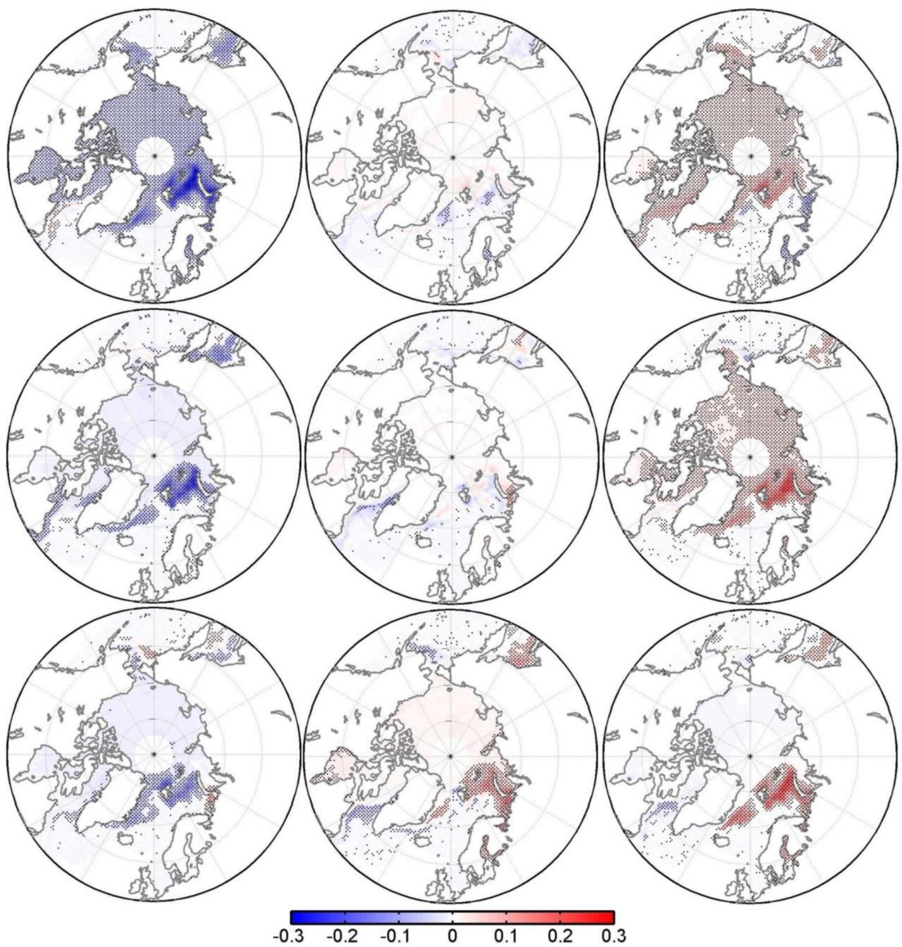

Figure 6. The same as Figure2, but for anomalous sea ice concentration.

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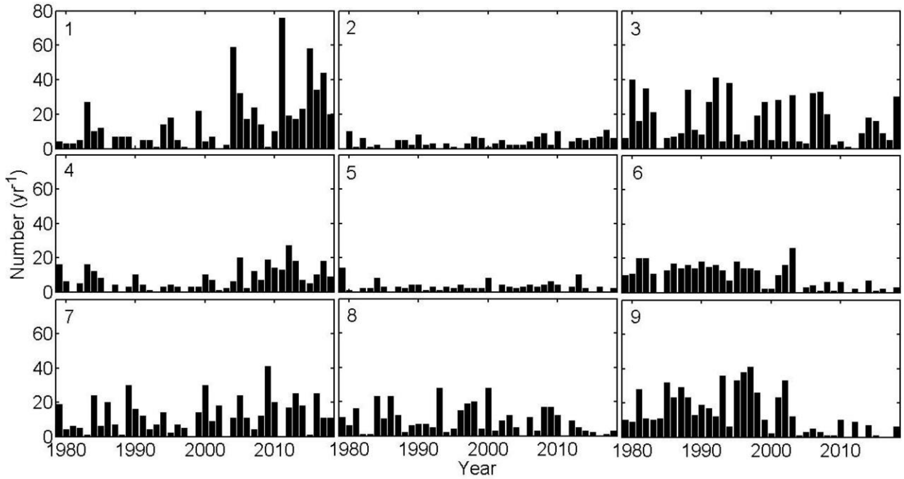

Figure 7. Time series of the number of days for occurrence of each SOM node in Figure 1.

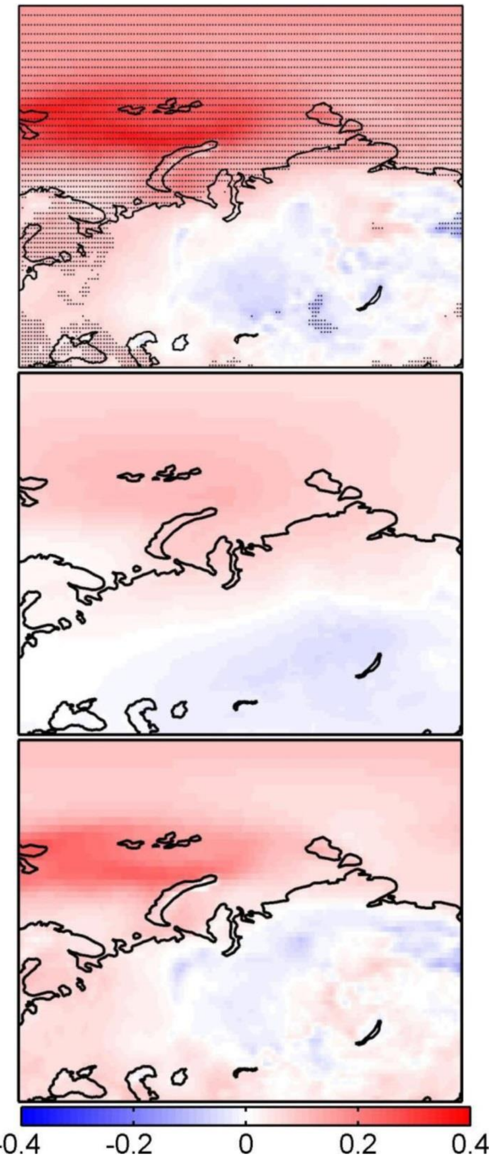

Figure 8. Total (top), SOM-explained (middle), and residual (bottom) trend in wintertime (DJF) surface air temperature (^{o} C yr^{-1}). Dots in the top panel indicate above 95% confidence level.

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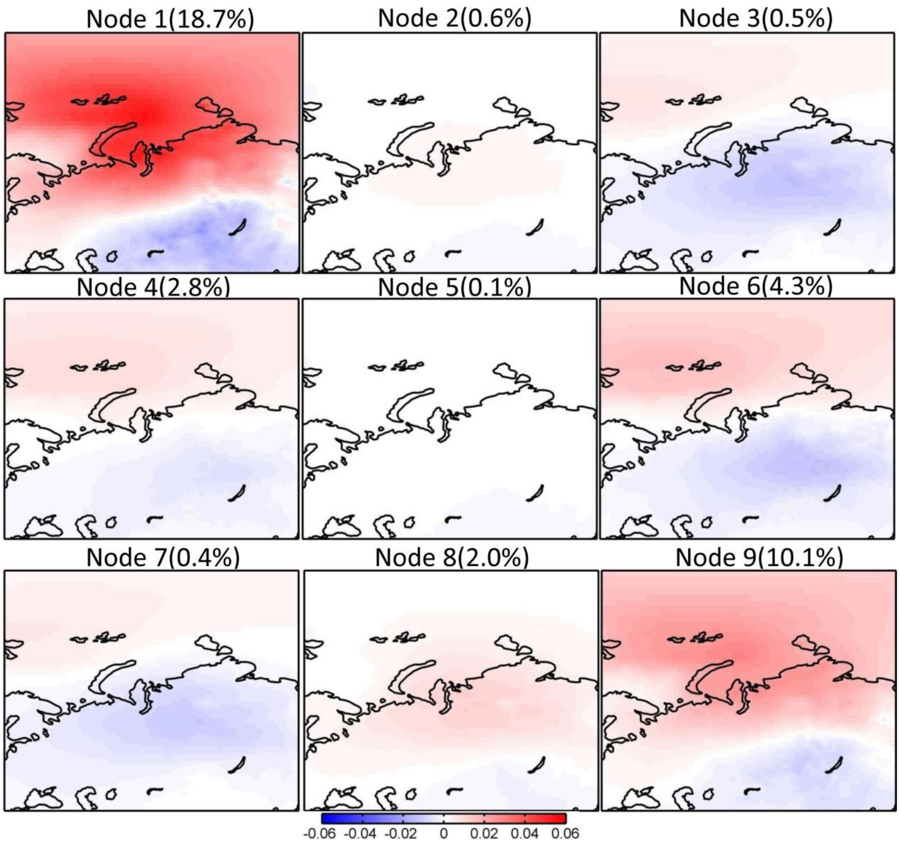

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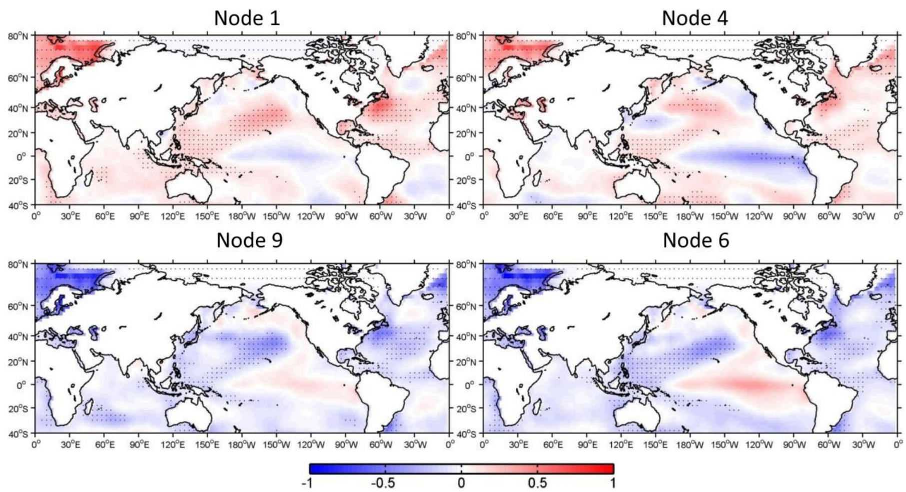

Figure 10. Anomalous SST (℃) regressed into the normalized time series of occurrence number for nodes 1, 4, 6, and 9.

https://doi.org/10.5194/acp-2020-413
Preprint. Discussion started: 28 July 2020

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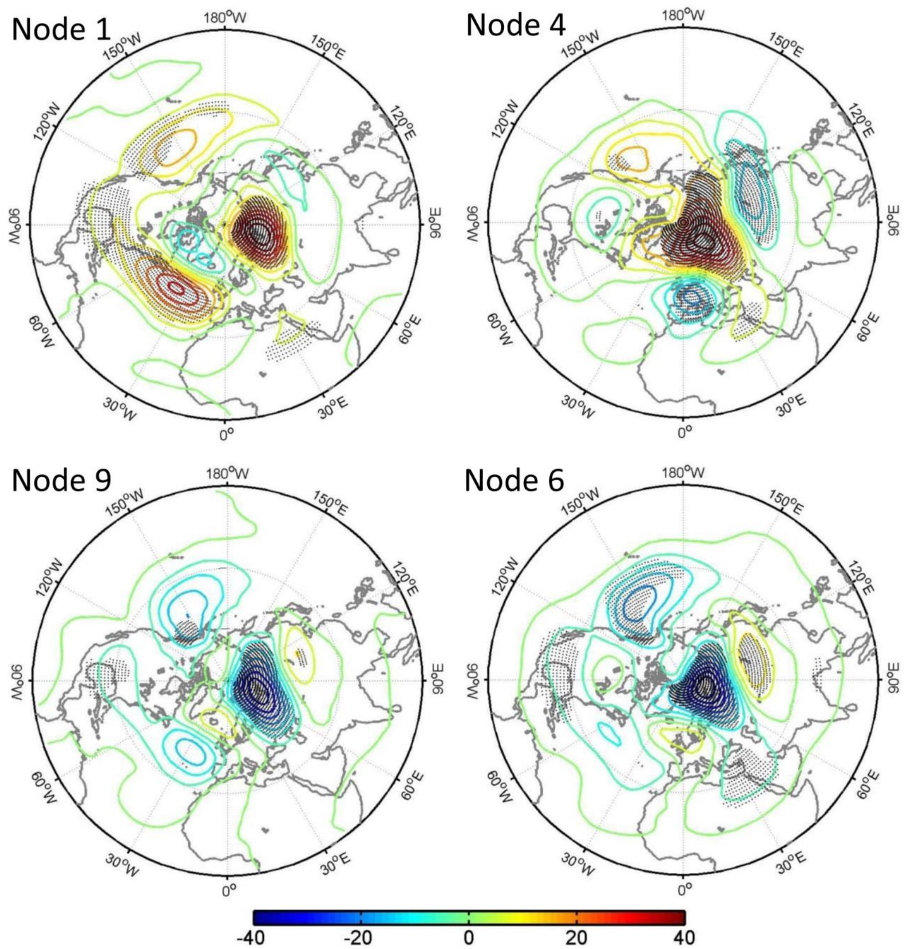

Figure 11. As in Fig. 10, but for the anomalous 500-hPa geopotential height (gpm).

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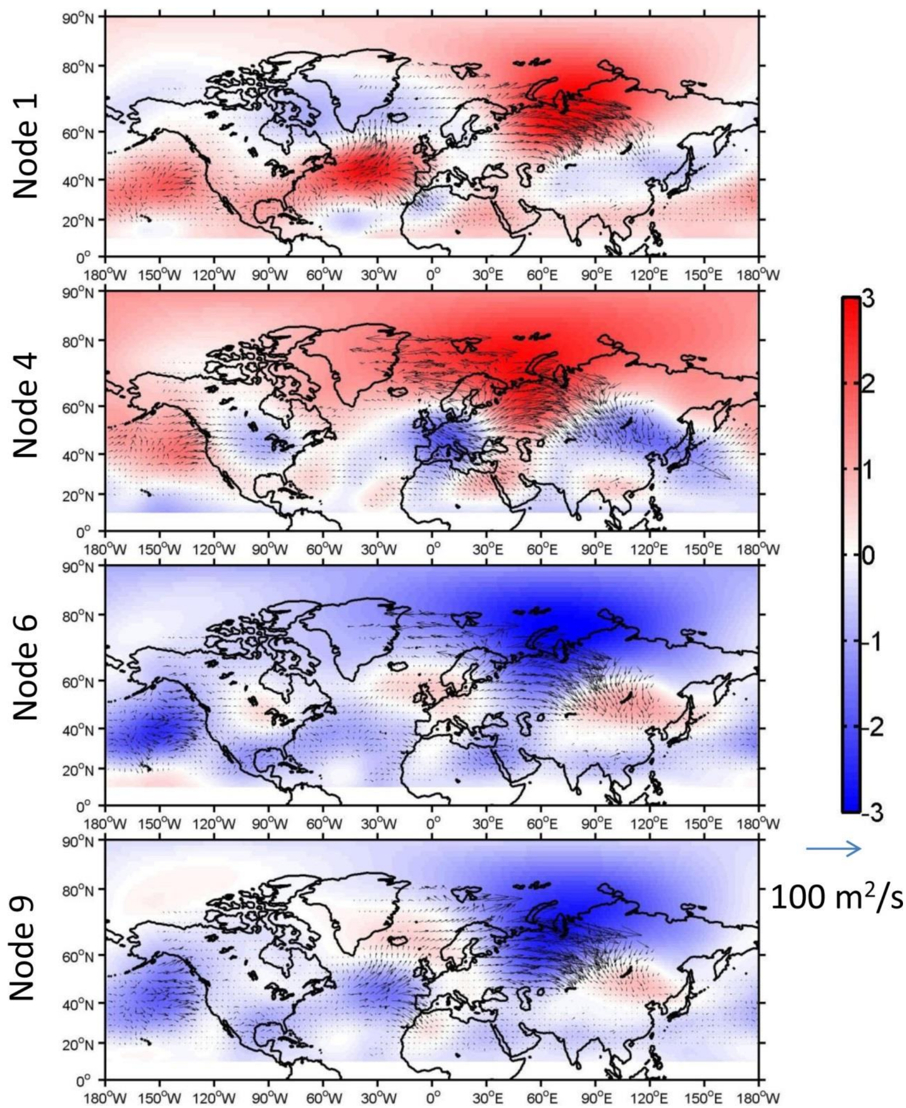

Figure 12. The anomalous wave activity flux (vectors) and stream function (colors, units: 10^7 m^2/s) regressed onto the normalized time series of occurrence number for nodes 1, 4, 6, and 9.

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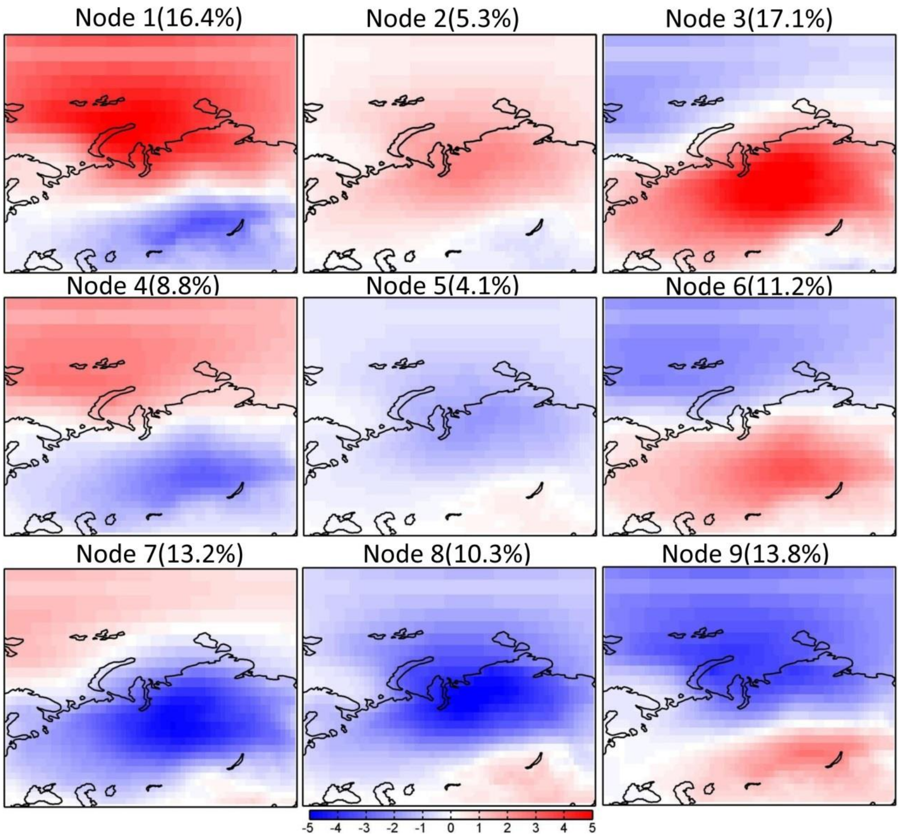

Figure 13. Spatial patterns of SOM nodes for daily wintertime (December, January, and February) surface air temperature anomalies (℃) for the 1851-2014. The number in brackets denotes the frequency of the occurrence for each node.

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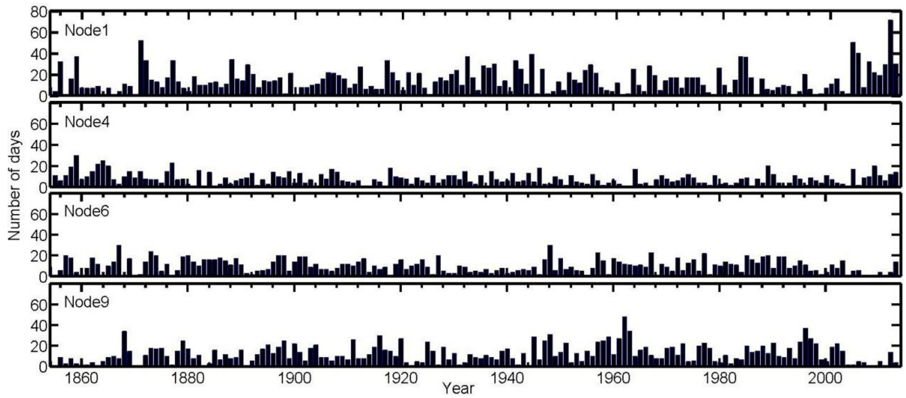

Figure 14. Time series of the number of days for occurrence of each SOM node in Figure 13.

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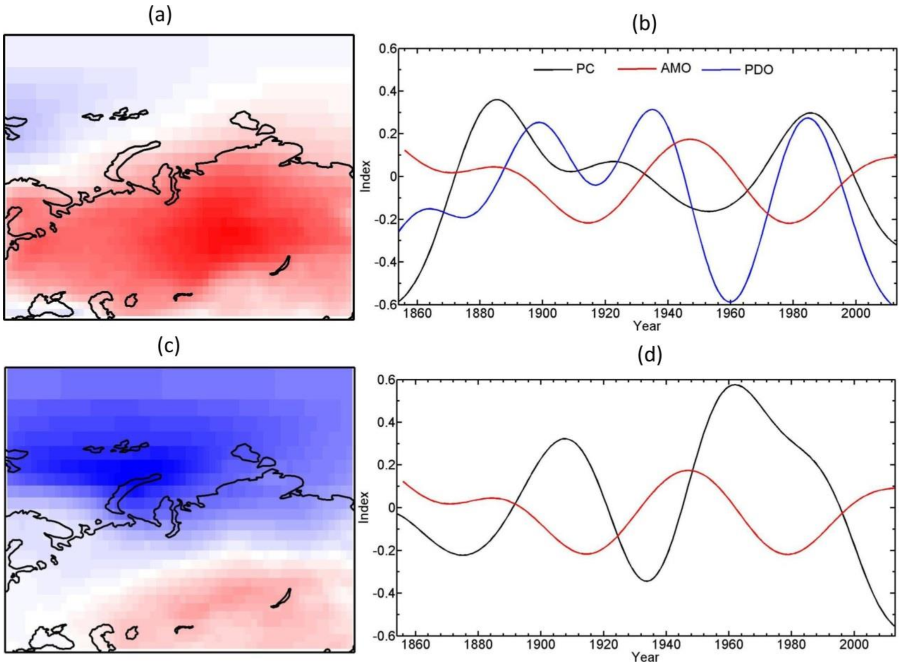

1045

1046 Figure 15. The (a) leading pattern and (b) its time series (PC1 and PC2) of EOF analysis of
1047 wintertime surface air temperature anomalies. Prior to EOF analysis, surface sir temperature data
1048 are detrended. A 40-yr low-pass filtered is applied to the time series of PC1, PC2, AMO and PDO
1049 indices.

1050