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# Pattern Variability in Arctic Air Temperature Records

**Cristian Suteanu**

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**Abstract** The goal of this paper is to provide an overview of recent progress regarding the acquisition and processing of surface air temperature data in the Arctic. It highlights potential methodological contributions to the identification and characterization of pattern change, focusing on spatial and temporal correlations and scale-symmetry properties of time series. The presented methods include L-moments, climate network analysis, detrended fluctuations analysis, and Haar wavelet analysis. New results concerning data from high-latitude Arctic stations illustrate some of the presented methodological aspects.

**Keywords** Arctic climate · Air temperature · Pattern analysis · Pattern change · Climate change

## 1 Introduction

### 1.1 Aim and Scope of the Paper

Due to the importance of the Arctic for climate from the regional to the global scale (Przybylak 2003; Serreze and Barry 2005), numerous in-depth studies have been performed on various aspects of change occurring in this region. Air temperature enjoys a privileged situation in terms of its relevance for climate studies and its availability in space and time. Even under such circumstances, in the Arctic information coverage concerning air temperature is affected by significant limitations. Ample research efforts using improved and novel means of investigation have led to better ways of acquiring data,

C. Suteanu (✉)
Department of Geography, Saint Mary's University, 923 Robie St., Halifax, NS B3H 3C3, Canada
e-mail: cristian.suteanu@smu.ca

C. Suteanu
Department of Environmental Science, Saint Mary's University, 923 Robie St., Halifax, NS B3H 3C3, Canada

analyzing patterns in space and in time, and understanding the mechanisms underlying the data.

The goal of this paper is to provide an overview of recent progress regarding the acquisition and processing of surface air temperature (SAT) patterns in the Arctic, and in particular to highlight potential contributions of several—to some extent newer—methodological approaches, which focus on spatial and temporal correlations and pattern symmetry properties, to the identification and characterization of pattern change in space and in time. The presented methods will be illustrated with new results concerning data from high-latitude Arctic stations.

The paper is structured as follows. The remaining section of Sect. 1 concerns the selection of spatial and temporal windows for Arctic climate studies and discusses some of the implications of such choices. Section 2 is devoted to air temperature observations, from studied processes to data sources. Section 3 focuses on the methodology applied to the analysis of temperature data and the interpretation of results. The last section is dedicated to conclusions.

### 1.2 Spatial and Temporal Delimitations: Implications

The spatial definition of the area to be studied can have significant implications for the outcomes of the analysis. This is particularly evident in the case of the Arctic, where climatic conditions vary considerably with location. Although there is general agreement with respect to broad aspects that should be considered in the process of region definition, a variety of choices can be found in Arctic research. Przybylak (2003) reviews three different categories of criteria: astronomical (given by the latitude of 66.5°N, therefore being simple and objective—Fig. 1), botanical (based on a natural boundary, the tree line, and thus integrating a number of factors that are relevant to climate studies, but suffering from ambiguities related to the definition of the boundary), and climatological (one based on a comprehensive set of meteorological elements, and not only on the 10 °C isotherm in the warmest month). In practice, other selection criteria are often applied. McBean et al. (2005) even argue against the specification of sharp boundaries for the Arctic; they decide upon a latitudinal limit of 60°N emphasizing, at the same time, the importance of interactions between this region and other areas south of that limit. In most studies, a latitudinal boundary is chosen, and the actual latitude differs among the various studies: it is often 60°N (e.g., Comiso 2003; ACIA 2005; Bekryaev et al. 2010), but it is also chosen at 64°N (Overland et al. 2004; Chylek et al. 2009, 2011), 62°N (Polyakov et al. 2003), or even 55°N (Walsh et al. 2005). Exceptions from such a net latitudinal delimitation and/or more detailed area specification can also be found. While Bekryaev et al. (2010) use the ACIA (2005) definition of the Northern Polar Area (NPA) as the area north of 60°N, they include selected data sources delimited by 59°N and even 57°N (long records from Scotland). Chylek et al. (2009) distinguish a low Arctic, from 64°N to 70°N, and a high Arctic, from 70°N northward. Focusing on the Arctic Ocean, Zygmuntowska et al. (2012) set the southern boundary of the Arctic at 68°N and exclude the zone from 30°W to 100°E south of 75°N. Overland et al. (2004) find that adding the larger number of stations south of 65°N tends to induce biases toward the subarctic, while locations north of 64°N, which are north of the Arctic front in winter, are still representative; they also include stations at lower latitude, where long records are available and for which the studied temperature trends point toward common patterns with stations located farther north. Scandinavian stations are excluded by Przybylak (2000), but those in the Scandinavian north subject to Arctic air masses are included by Overland et al. (2004).

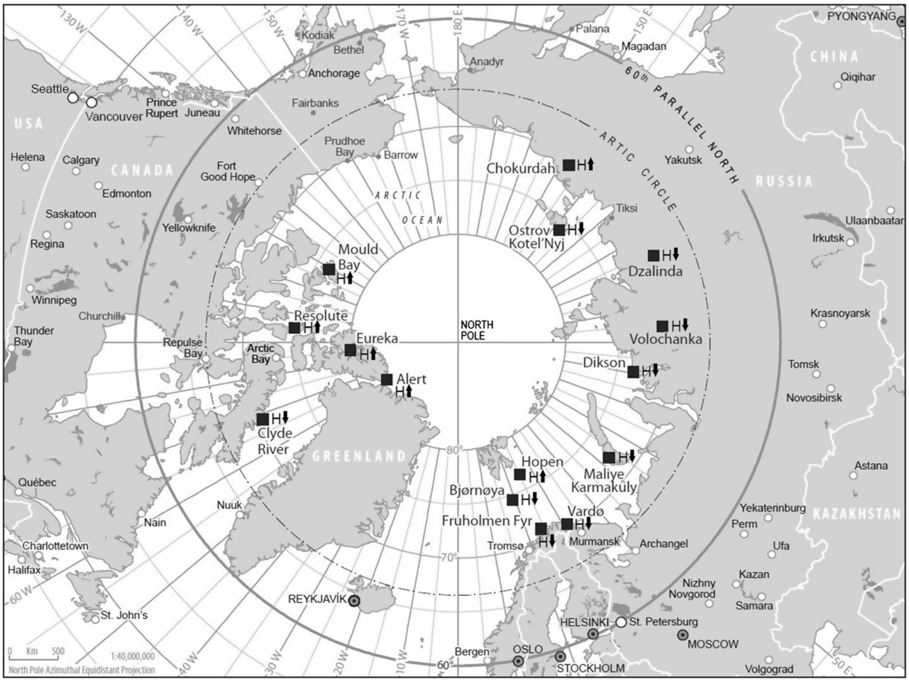


**Fig. 1** Stations located northward of 70° latitude, for which at least 60 years of daily minimum and maximum temperature records are available (*black squares*). *H* and *arrow symbols* refer to temporal change in temperature pattern properties shown in Table 1 and discussed in Sect. 3.2.3

Expectedly, the number of stations drops with increasing latitude. Based on the same source (KNMI 2013), Fig. 2 presents the number of available stations with record length of 10 years or more, taking into consideration the latitude dependence of the surface area (Rapp 1991). As latitude grows, the spectrum of geographical conditions covered by stations becomes narrower, with most stations beyond 70°N being located at low elevations (Fig. 3, data from KNMI (2013)) and in marine locations. Moreover, large land areas remain uncovered in terms of meteorological station data, which creates a significant gap in information acquisition. For instance, in order to obtain a station set that is less biased toward marine locations, Walsh et al. (2005) move the station boundary as far south as 55°N. Areal averages are significantly affected by the choice of the southern areal limit; this is especially true in the context in which climate patterns change considerably toward mid-latitudes: the results can be confusing when different patterns are evaluated together (Przybylak 2000, 2003). On the other hand, rigorous comparisons among studies referring to different definitions of the Arctic can become more complicated. The wide range of definitions for this region thus affects both the specialists and the public, with possible implications for decision makers.

The temporal delimitation concerning analyzed temperature data represents another factor affecting observations in the Arctic. On the one hand, the longest direct observation series are based on meteorological stations. In their turn, station-based records are also severely limited in length. Time series examples referring to comparable temporal intervals are shown in Fig. 4. Setting up and maintaining stations in the harsh conditions of the

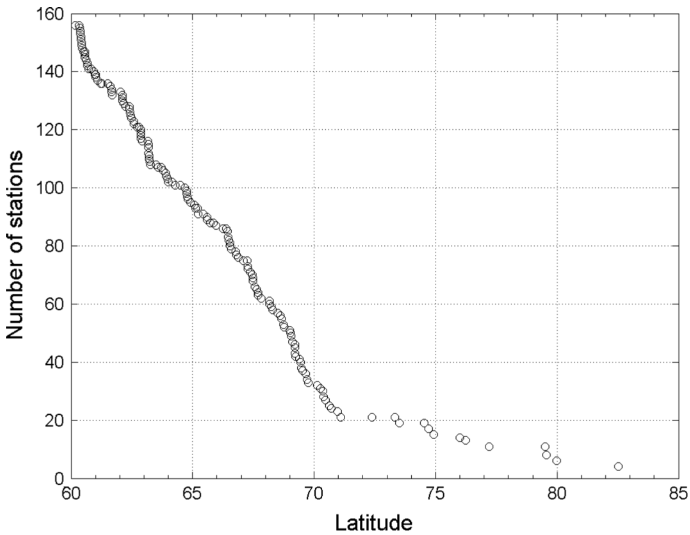


**Fig. 2** Number of available weather stations northward of a given latitude (data from KNMI 2013)

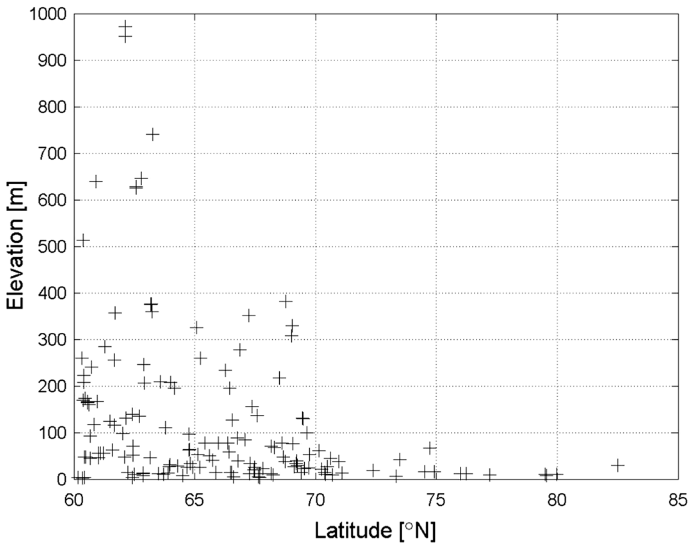


**Fig. 3** The range of station elevations is lower in the Arctic at high latitude, particularly beyond 70°N

northern regions have been accomplished with great effort, and the information collected with their help is particularly valuable. Interruptions or discontinued data acquisition drastically affect data availability, with often irreversible implications for our access to information.

Aspects of temporal window availability can be important because taking into consideration different time intervals can lead to distinct outcomes. Time series non-stationarity should be explicitly addressed (Kantz and Schreiber 2004). The selection of the

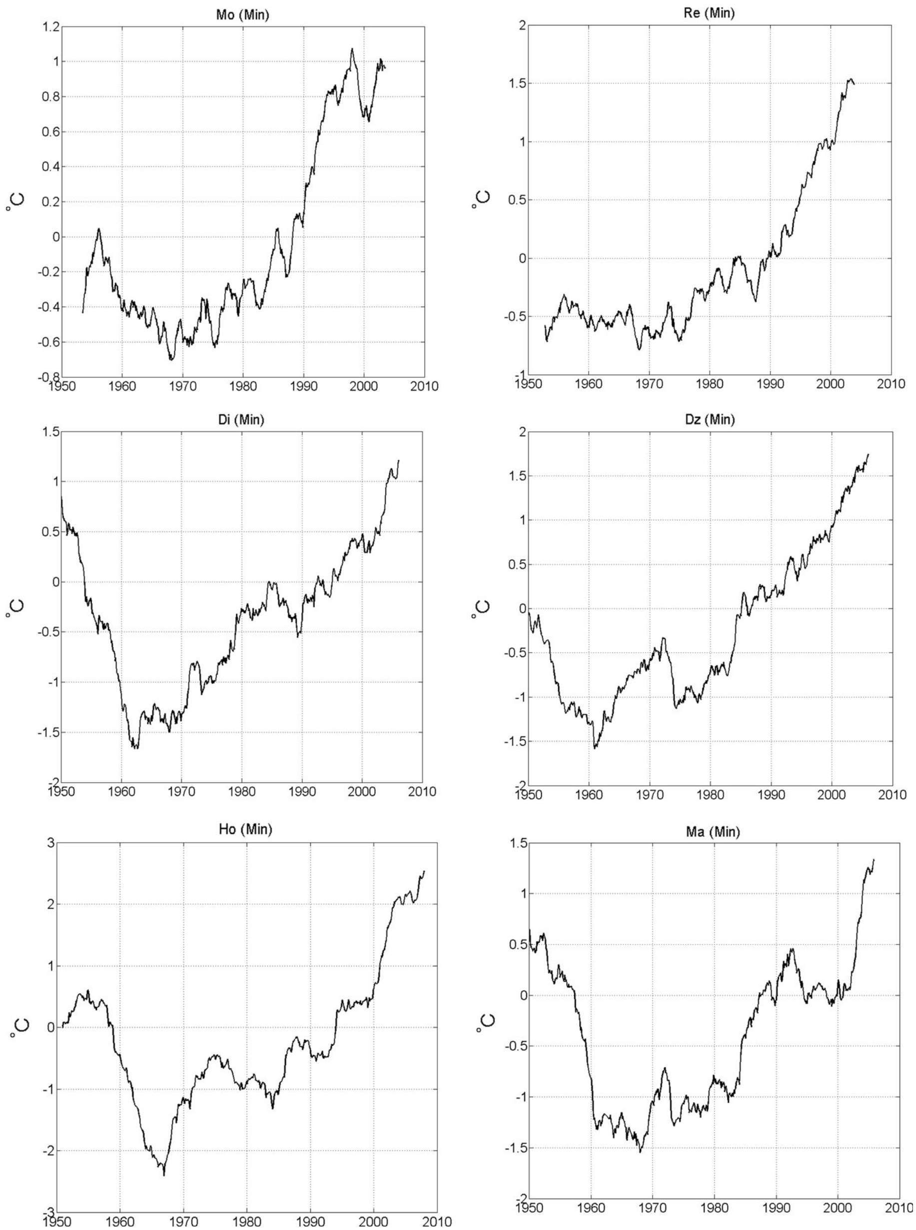


**Fig. 4** Examples of surface air temperature patterns (minimum temperature records): monthly averages and 10-year sliding means. From *left to right* and *top to bottom:* Mould Bay, Resolute, Dikson, Dzalinda, Hopen, Maliye Karmakuly

analyzed time window in terms of its length and position in the time series may lead to a broad spectrum of trend values—see, for example, Figure 11 in Comiso 2003, and Figure 1 in Hinzman et al. 2005. It is worth noting that while window selection is the researcher's responsibility, in some cases the analyzed window is simply based on data availability. However, the fact that the studied time interval is not the result of an actual (possibly subjective) choice—but rather a matter of data availability—does not enhance the validity of the analysis. Overall, information access is subject to major restrictions; long temperature records originate in a relatively low number of points, which are unevenly distributed in space. However, many other data sources than meteorological stations exist, and although they do not cover intervals of comparable length, they offer valuable insights into climate processes.

The conditions one would like to see fulfilled for Arctic studies are often difficult to address together in a convenient way, e.g., having data from climatologically relevant points in the Arctic, obtaining long records, including stations that cover a diversity of geographical conditions in terms of continentality/proximity to the coast, elevation, etc. Consistent and detailed long records (e.g., daily temperature values over intervals of decades, a century, or more) can be obtained from land-based meteorological stations. Figure 1 shows a map indicating the position of stations north of 70°N for which at least 60 years of daily temperature records are available from KNMI (2013).

## 2 Observations: From Processes to Data Sources

The data discussed here concern air temperature records obtained on the ground and from the air, based on a range of acquisition methods (proxy data and climate models, which involve different types of approach, are not included in this study). Informed choices concerning data acquisition and handling—from location selection to application of recording and processing techniques—take into consideration the climatic processes at work; the latter will thus be briefly discussed in the next section.

### 2.1 Processes Involved

Climate processes are particularly complex, characterized by nonlinear, time-varying relations and feedback loops on a wide range of temporal and spatial scales. Our understanding of critical linkages and the dynamics of interrelationships is still inadequate (Liston and Hiemstra 2011). Changes in some parts of the system may lead to different types of response in other subsystems: The same type of forcing may have different consequences as a function of the system's history and background state (Kern et al. 2010; Sedlacek et al. 2012). Only some of the (interconnected) processes will be discussed here in relation to patterns and pattern change.

Feedback mechanisms play a particularly important role in the Arctic, contributing to the polar amplification (PA)—the enhanced warming of the Arctic compared to the northern hemisphere or to the entire globe (Chylek et al. 2009; Miller et al. 2010; Chylek et al. 2011). The study of the vertical profile of Arctic air temperature supports insights into the mechanisms of warming, including sea ice loss and poleward heat transport (Graversen et al. 2008; Screen et al. 2012). The loss of sea ice, followed by heat transfer from the oceans to the atmosphere, stimulates the Arctic amplification in the fall and winter while, in the summer, earlier snowmelt and a drying soil enhance the warming (Francis and Vavrus 2012). Variations in ice thickness are involved in positive feedback loops, playing a significant role for climate change in the Arctic (Bekryaev et al. 2010). Ice-albedo and sea ice insulation feedback enhance the Arctic region's sensitivity to warming (Serreze and Francis 2006; Miller et al. 2010).

Ice loss processes are irregular in time. They involve rapid sea ice loss events, i.e., ensembles of events clustered in short time intervals, made possible by previous ice thinning occurring on longer timescales, and stimulated by changes in atmospheric circulation (Döscher and Koenigk 2012). However, estimating the actual feedback contribution to PA remains a delicate task (Bekryaev et al. 2010). Both natural and forced changes in atmospheric circulation occur in the Arctic, and attempts at delimiting causes associated with one factor or another have to consider the multiple nonlinear couplings at work. Döscher et al. (2010) distinguish between climate variability generated in the Arctic ("internal variability") and forcings occurring on a larger scale ("external variability"). They show that, while both may have similar magnitude, the external variability plays the key role for the predictability concerning the resulting interannual variation. Given the complexity of the interconnected processes affecting Arctic climate, it would be useful to have a better understanding of the existence of tipping points or thresholds able to trigger sudden and drastic changes; in the context of rapid sea ice loss, Semenov et al. (2010) found that, if such a threshold has already been reached, the internal fluctuations have been playing an essential role in the process.

One of the most important changes in terms of atmospheric circulation that have occurred in the last decades concerns the Arctic oscillation (AO). From its negative phase in 1970s, it switched to a positive phase in the 1990s, after which it varied more swiftly, and a new climate pattern was identified, called the Arctic Rapid-Change pattern by Zhang et al. (2008) and, more generally, the Arctic Dipole (AD) (Overland and Serreze 2012). An atmospheric pattern with an across-pole meridional character, AD brings warm air masses into the Arctic Ocean and also has an impact on sea ice transport—the removal of older, thick sea ice from the Arctic Ocean to the Atlantic Ocean (Walsh et al. 2011). Interrelationships between these changes in sea ice and atmospheric circulation were investigated by Francis et al. (2009) and Overland and Wang (2010).

Beyond the large natural variability that is typical for the atmospheric circulation in the Arctic, persistent changes are highlighted by Overland and Serreze (2012) in terms of sea ice cover, sea surface temperature (SST), as well as SAT, and associated with the large-scale warming of the Arctic related to anthropogenic climate change. Diurnal signals of ample (up to 4–5 K) SST warming events were found by Eastwood et al. (2011) both from satellite and buoy data in the Arctic up to 80°N. In the Canadian Arctic, a warming trend has been identified in all seasons in the last four decades, an interval over which summer total sea ice decrease has occurred at an area-dependent rate ranging between 3.6 and 17.3 % per decade (Derksen et al. 2012). Changes in Arctic sea ice have an impact on the general circulation of the atmosphere, with variable, region-dependent effects (Budikova 2009).

Sedlacek et al. (2012) find that sea ice anomalies have an ample impact both on the ocean (temperature and salinity are affected to a depth of about 200 m in the Arctic Basin) and on the atmosphere (temperature increases are found throughout the atmospheric column). They highlight the complexity of the studied processes, noting that the actual initial conditions play a role that is difficult to estimate. They caution against extrapolating findings based on short-term changes. In their turn, Wu et al. (2011) show that anomalies in autumn–winter Arctic sea ice content combined with SST anomalies influence air temperature patterns at mid-high latitudes in Eurasia and East Asia. Implications of atmospheric warming with respect to the ice sheets mass balance also include complex nonlinear processes covering a wide range of timescales (Winton 2008; Bengtsson et al. 2011) and have ample effects not only upon the larger-scale thermohaline circulation (Box et al. 2009), but also, more broadly, on the climate system (Callaghan et al. 2011). On the other hand, freshwater produced by the melting of polar ice is involved in feedback mechanisms affecting ocean–atmosphere interaction, with implications for surface air patterns (Stammer et al. 2011). Major changes in the precipitation fraction falling as snow were identified over the last decades, with snowfall quantities decreasing by 40 % between 1989 and 2009 (Screen and Simmonds 2012); the effects of these changes include a decreased snow-covered area, a corresponding decrease in albedo, and, consequently, changes in surface air patterns. Perhaps more surprising was the large-scale bathymetric control exerted on sea ice formation patterns in the Arctic, found by Nghiem et al. (2012); the importance of their results is enhanced by the fact that changes in bathymetry are insignificant over decades and centuries, and therefore, one could, in principle, make more reliable predictions regarding sea ice pattern recurrence. Tetzlaff et al. (2013) showed that heat transfer to the atmosphere is influenced not just by the size, but also by the orientation and spatial distribution of open water areas. By exerting control upon sea ice formation patterns, bathymetry thus has an impact on cloud cover, by influencing heat flux from ice-covered versus open water surfaces (Nghiem et al. 2012).

Cloud cover represents, in fact, not only a key element regarding climate processes, but also one that is difficult to estimate. Zygmuntowska et al. (2012) show that striking inconsistencies arise among reports with respect to cloud cover, starting with differences regarding cloud detection by various types of sensors, spatial and temporal sampling, and cloud definition. Clouds have variable boundaries and an irregular distribution in space: Cloud patterns have been found to enjoy self-affinity—they have no "characteristic size"—over a wide range of scales (Lovejoy et al. 2001), and such geometric properties can be applied in cloud detection algorithms.

The Arctic is a cloudy area, being characterized by an annual average of 70 % cloud cover, with clouds especially affecting oceanic regions. The fact that clouds are changing in the region is significant. Eastman and Warren (2010) identified in the last three decades an increase in precipitating clouds over land, and a decrease in precipitating clouds over the ocean, which is expected to contribute to the further warming of the Arctic. The tendency toward "global dimming" widely discussed decades ago (and attributed to enhanced cloud cover and/or aerosol presence) was reversed; although cloud formation and the clouds' radiative properties are very important, their relationship to changes in climate is not well understood (Trenberth and Fasullo 2009). While Trenberth and Fasullo (2009) found an increase of absorbed solar radiation during the last decade due to a decrease in cloud amount, Sugi (2012) obtained similar results due to increased short wave absorption based on higher water vapor content in the atmosphere; Sugi (2012) thereby shows that similar outcomes in terms of energy balance can be obtained through different scenarios.

Intriguing links between SAT and space weather were also suggested (Seppälä et al. 2009; Baumgaertner et al. 2011), although the detailed processes involved in such links have not been elucidated. Suggested mechanisms include energetic particle precipitation (EPP): charged particles from the solar wind initially trapped by the magnetosphere penetrate into the upper and middle atmosphere and contribute to an enhanced production of NOx. When they reach the stratosphere during the polar winter, EPP-NOx leads to ozone depletion and the cooling of the lower stratosphere, and thereby to the strengthening of the polar vortex. This produces positive North Annular Mode anomalies. The authors find significant correlations between an index of geomagnetic activity (Ap) and SAT, as well as between Ap and the North Atlantic Oscillation (NAO). Further studies are required to clarify the mechanisms involved.

Overall, surface air warming and cooling trends in the Arctic are variable in time and strongly region-dependent, with warming dominating especially during the last decades

(Comiso 2006; Overland et al. 2008; Førland et al. 2011), which is also the case for SST in the Arctic Ocean (Hansen et al. 2010). The interrelated processes at work cover a wide range of temporal scales. The scale dependence of the size of fluctuations in air temperature records will be investigated in Sect. 3.2.

## 2.2 Data Sources

Confronted with the richness and complexity of the processes involved in climate dynamics, sources of data seem modest. Nevertheless, numerous ways of acquiring information on air temperature have been applied in the Arctic, each with its strengths and limitations. While no source can compete with temperature records from meteorological stations in terms of their combination of record lengths and accuracy, useful insights from shorter-term records are also made possible by a combination of valuable research instruments and approaches, some of which will be addressed here.

Air temperature data acquisition can be distinguished from many points of view, such as the location or trajectory of sensors, the covered spatial and temporal scales, the targeted atmosphere heights or height ranges, as well as sampling patterns and measurement principles. As pointed out above, land-based meteorological stations offer the longest direct temperature recordings. Numerous stations started their data records in the nineteenth century, but in the Arctic, many stations were established much later in the twentieth century. A historical overview of measurements and their outcomes is given by Serreze and Francis (2006). Certain information sources are still scattered among institutions from various countries, and thus difficult to find: Jones et al. (2012) highlight the role played by personal contacts in the process of obtaining data beyond those made available by World Meteorological Organization systems. Important additional sources of long-term data from the Russian Arctic have recently become available (Bekryaev et al. 2010; Jones et al. 2012). Notwithstanding the limitations implied by their sparse and non-uniform distribution in space—especially in the Arctic, land stations are a source of rich information, often recorded as daily minimum and maximum temperature values. Data are also provided as monthly or yearly averages.

Changes in instrument type or station features, sampling frequency, or station relocation occurring over time may lead to biases: the necessity of performing data homogenization (Vincent et al. 2002) depends on the recorded data as well as on the subsequently applied methodology for data analysis. Rust et al. (2008) provide evidence for the importance of homogenization in studies on long-range correlations analysis, while Box et al. (2009) report no significant change in time series stationarity due to inhomogeneity. Biases in air temperature measurement in the Arctic can also be produced by improper positioning of the sensors, such as too close to buildings or much above the standard 2 m height (Box 2002). Data smoothing is sometimes applied in time (e.g., using running means) and/or in space; representing temperature anomalies on a seasonal or annual scale rather than the temperature itself also leads to smoother fields (Hansen et al. 2010). Strong spatial variability in temperature patterns is typical for the Arctic (Overland 2006; Box et al. 2009). In this context, the uneven spatial distribution of stations must be taken into consideration, and bias-reduction techniques should be applied (Jones et al. 2012).

A distinct series of surface-based source of observations, stations drifting on ice floes in the Arctic Ocean, acquire valuable data concerning the ocean and the atmosphere, even if available records are not long, spanning intervals of years to decades at best (Morison et al. 2002). Data from autonomous buoys—a useful source of information from areas otherwise very difficult to reach—may suffer from measurement problems, e.g., the buoy may become covered by snow, and solar heating of the instrument housing may affect the data (Chen et al. 2002; Serreze and Francis 2006).

Koenig and Hall (2010) deployed thermochrons—button-sized temperature sensors—on ice surfaces in the Arctic. Compared to measurements using satellite instruments, thermochrons were found to be accurate within 0.1 ± 0.3 °C. While certain technical limitations must still be addressed (unattended thermochrons can be affected by rime ice, and radiation shields must be added for measurements during daylight), these sensors offer new opportunities to acquire precious information concerning surface temperature in the Arctic.

Other instruments use technology that is applied both from the ground and from the air—e.g., from aircraft and/or satellites. Infrared spectrometers, for instance, are particularly important for the study of the radiative balance and cloud properties. Mariani et al. (2012) report on results regarding the deployment of such an instrument at Eureka, Nunavut, where it collected data with a sampling rate of 7 min, for 1 year: among other outcomes, measurements showed that radiance increases over 400 % in the spectral range of 750–1,200 $cm^{-1}$ in the presence of clouds, highlighting the important role played by clouds in the radiative budget in the Arctic.

Measurements of a different type are offered by instruments that explore wider ranges of atmospheric elevation, providing information on air temperature and winds at higher altitude: lidar and radar. The objective of obtaining such data from high elevations can be addressed both through ground- and air-based instruments. Radar instruments offer access to elevations up to approximately 20 km and above 60 km, metal resonance lidars perform measurements between 80 and 110 km, while Rayleigh lidars can address the radar gap by making measurements up to 85 km (Hildebrand et al. 2012). Although lidars have been in use for over half a century (Nott and Duck 2011), implementations dedicated to the study of Arctic climate have been relatively slow and challenging. The first simultaneous temperature and wind measurements using a Rayleigh lidar was performed at the high latitude ALOMAR research station in Norway (69°N) (Baumgarten 2010), and the first simultaneous measurements using two different lidar instruments (including a common volume) was reported by Hildebrand et al. (2012). The ALOMAR station is equipped with multiple ground- and air-based facilities and offers researchers the opportunity to study profiles in the Arctic atmosphere over a long, uninterrupted range of altitudes, up to high elevations: While balloons cover heights up to 40 km, rockets provide data from that height up to 80–90 km, a height at which radar and Na-lidar devices start contributing information (going up to 100 km and beyond), while the Doppler Rayleigh lidar reaches up to the mesopause (Baumgarten 2010). Smaller instruments—micropulse lidars—have been successfully applied for the study of the troposphere in Arctic locations. Ground-based micropulse and Raman lidars have proven to offer, together, an effective way of studying mixed-phase multilayer clouds (Lampert et al. 2010). A comprehensive overview of lidar applications in the Arctic is provided by Nott and Duck (2011).

Satellite remote sensing systems are particularly useful in the Arctic—where the station distribution is so sparse—in spite of challenges implied by cloud masking, sensor calibration, etc. (Serreze and Francis 2006; Kristjánsson et al. 2011). These systems have been contributing important information regarding the atmosphere, the land surface, and the ocean. A review of programs dedicated to these applications can be found in Tomlinson et al. (2011).

Such information sources, designed to answer specific questions, have been increasingly available, providing valuable contributions to our understanding of Arctic processes. At the same time, the integrated use of information from multiple sources is providing new opportunities for climate studies. Concerted applications of ground-based, rocket, and satellite measurements regarding temperature and wind patterns in the stratosphere and the mesosphere are described by Goldberg et al. (2006). An example from a study in Ny-Ålesund (Spitsbergen, at 78.9°N)—based on continuous use of a radiometer (for temperature and humidity profiles), daily radiosonde launches, a tethered balloon carrying radiosondes in predefined altitudes, an eddy covariance system, and a Raman-lidar—is provided by Ritter et al. (2012). Enhanced attention is also dedicated to the study of multiple records collected by various organizations, which used different approaches to data acquisition (Lemke and Jacobi 2012; Perrie et al. 2012).

Finally, we must mention one more important source of data: reanalysis (NCEP/NCAR—Kalnay et al. 1996; ERA-40—Uppala et al. 2005; JRA-25—Onogi et al. 2007). Reanalysis is a powerful tool that assimilates observations from multiple sources and produces dynamical models able to offer estimates of the state of the atmosphere with a high resolution—higher than that provided by the initial datasets. A potential problem with reanalyses consists of the fact that changes in incorporated observations (in terms of quality and quantity) may lead to discontinuities and an incorrect evaluation of trends (Alexeev et al. 2009). Such changes may be particularly significant in the Arctic, where the observations database is sparser than in other regions. Screen and Simmonds (2011) point out a discontinuity in ERA-40, which occurs in 1997 due to changes in satellite data processing, and show that trends calculated over time intervals that include this year are incorrect. They discourage the application of ERA-40 for studies regarding Arctic climate, indicating that the results concerning temperature trends and vertical profiles can be distorted; they suggest that other reanalyses should be applied instead. Although they highlight the merits of ERA-40, Serreze et al. (2007) signal its deficiencies in terms of energy budget. It is important to be aware of such shortcomings, because the results of reanalyses represent the starting point for other data processing operations, which depend on the quality of reanalysis data.

## 3 Methods

Considering the remarkable variety and complexity of processes involved in climate dynamics on the one hand, and the wide spectrum of information sources on the other, it comes as no surprise that a very large number of approaches have been applied to the study of change in air temperature patterns in general and those in the Arctic region in particular. For a detailed presentation of certain quantitative methods, the reader is referred to comprehensive monographs (Von Storch and Zwiers 2003; Donner and Barbosa 2008; Mudelsee 2010).

This section focuses on a number of methodological approaches dedicated to the identification and characterization of SAT pattern variability in space and in time. New results obtained for records from Arctic stations will also be presented. The main aspects of pattern evaluation considered below include initially spatial, then spatial–temporal, and finally temporal correlations and temporal symmetry.

### 3.1 Climate Network Analysis

Comprehensive ways of assessing pattern structure, including trends and oscillations, are offered by a range of powerful, widely applied methods. For instance, changing patterns such as oscillations propagating in space can be captured with the help of Hilbert empirical orthogonal functions (HEOF) and principal oscillation patterns (POP) analysis (von Storch and Zwiers 2003; Jolliffe 2002; Kantz and Schreiber 2004).

A more recently developed tool specifically designed to address nonlinear dynamics, network analysis, is focusing on correlations among the components of the studied complex systems (Cohen and Havlin 2010). In fact, empirical orthogonal functions and coupled patterns analysis represent powerful statistical methods, capable of effectively reducing data dimensionality in climatology. In contrast, network analysis offers tools to address the complexity of the studied system, including high-dimensional data (Donges et al. 2013).

The methodology and its applications are developing fast and are increasingly capable of providing relevant information regarding, for instance, climate patterns and pattern change. A network is defined as a set of nodes potentially connected to each other by links or "edges." In some cases, it is considered that not all edges have the same strength, and edge weights are assigned to them. After applying network construction criteria to the system to be analyzed, the resulting network's characteristics are determined, such as the degree of each node (given by its total number of edges), or its equivalent in weighted networks, the strength or node-weighted connectivity (given by the sum of its edges' weights), the degree distribution (the probability for a node to be connected to other nodes), the network diameter (the maximum distance between any pair of its nodes), etc. (Boccaletti et al. 2006). Networks have been fruitfully applied to a variety of systems—biological, social, economic, etc.—in which numerous components are related to each other to different degrees. The discovery of relevant properties that characterize a wide range of real-world networks and the insights provided by this approach with respect to complex nonlinear systems (Albert and Barabasi 2002) have led to an intensification of network research in many fields. Some of the most interesting and widely identified real networks are the "scale-free" ones, which exhibit structural similarity on different scales (e.g., the node degree distribution is governed by a power law).

In climate applications, nodes are assigned to points corresponding to geographical locations (e.g., based on reanalysis grids), and time series of atmospheric variables in each location are considered; edges reflect relations or similarities between the time series corresponding to the nodes (Fig. 5). For example, Tsonis et al. (2006) use a 5° latitude × 5° longitude reanalysis grid with monthly values for 500-hPa pressure levels. Node similarity or interdependence can be assessed in various ways, such as determining the correlation coefficient between their corresponding time series (Tsonis et al. 2006), computing mutual information (Kantz and Schreiber 2004; Donges et al. 2009), etc. Interdependence strengths between the nodes are then examined, and those found higher than a certain threshold value are considered to represent network edges; threshold selection criteria must be applied for this purpose (Tsonis and Roebber 2003). The network structure is then analyzed and network properties (such as node connectivity) are assigned to each node. The outcome of this process leads to the emergence of a pattern that shows, for instance, the fraction of the analyzed area to which each node is connected. One can thus identify areas where the dynamics is comparatively more or less strongly related to those of other areas at shorter or larger distance, as well as zones that are particularly strongly connected to large sets of nodes. Tsonis et al. (2006) found in their analysis a scale-free signature of the network, which cannot be detected using linear approaches. As an interesting result, they show that more long-range correlations than short-range correlations emerge during the warming of the planet.

Network analysis provides powerful tools for studying the structure of correlations involved in climate dynamics. Correlations between climate oscillations—possibly including time lags of up to 30 years—and the role of the Arctic for relationships between

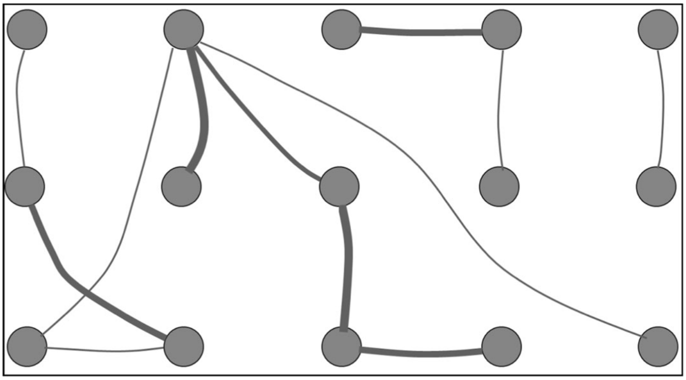

**Fig. 5** In a climate network, nodes are defined by a spatial grid, and time series of atmospheric variables are associated with each node. Edge weights (represented here by *line thickness*) are obtained based on the interdependence or "similarity" between the time series corresponding to the *nodes* connected by the edge

North Atlantic and North Pacific regions have been investigated by Heitzig et al. (2012); their study sheds light on the interaction among oceanic and atmospheric processes involved in Arctic climate.

Analyzing the SAT field, Donges et al. (2009) notice that mid-latitude and Arctic regions are characterized by fewer edges (more irregular dynamics) compared to tropical areas and point out the role of the contrast between the dynamics over land and over ocean; they also highlight the significant role played by ocean currents for the network structure. In their analysis based on temperatures and geopotential heights, Berezin et al. (2012) find that in spite of the strong local fluctuations and the instability of the climatological field, the network is remarkably stable; this stability is a consequence of both the two-dimensional embedding of the network, and of the physical coupling of climate dynamics among different locations in space.

Different solutions exist to approach the challenge of describing correlations both in space and in time: temporal networks (Holme and Saramäki 2012) and evolving networks based on static networks and sliding temporal windows (Radebach et al. 2013). Hlinka et al. (2014) successfully distinguish intra- and inter-regional effects in evolving climate networks; they identify the role of a region in the high-latitude Canadian Arctic in the way the global graph is evolving over time.

In Arctic regions, special attention must be paid to the spatial distribution associated with network nodes, since node density would artificially grow with increasing latitude, with effects becoming stronger for areas that are closer to the pole. The ensuing distortion in node proportionality with surface size can thus lead to biased results concerning the studied space–time connectivity. To avoid this type of bias, Heitzig et al. (2012) have introduced "node splitting invariant (n.s.i.) network measures," which support an effective and accurate approach to climate networks without the impact of geographically influenced node density. Their approach can also be applied to other situations marked by inhomogeneity in terms of node- or mesh cell distribution. Given the importance of studies regarding the role of connections between the Arctic and other regions in the framework of climate dynamics, network analysis presents itself as a particularly relevant methodological tool.

## 3.2 Temporal Variability Characterization

Temporal variability of air temperature represents a particularly important aspect of studies on climate and climate change. Like many other aspects of complex natural systems, variability can be evaluated in different ways, without exhausting the richness of the studied pattern. Due to the key role of the Arctic in the planetary climate system, studies on SAT variability in Arctic regions are important. In the following sections, two broad approaches will be reviewed: statistical methods, including L-moments, and methods focusing on scale symmetry. The latter represent an effective approach to pattern variability, which is valuable for studies on Arctic temperature also due to its capability of detecting and describing pattern change—both in time, and as a function of temporal scale.

### *3.2.1 Statistical Variability in Time Series*

Due to its importance for modeling and forecasting, multidecadal variability has captured the interest of researchers (Semenov et al. 2010; Chylek et al. 2011). In fact, variability evaluation applied to observations and model outputs represents a useful way of testing models' capabilities of producing reliable outputs (Fraedrich and Blender 2003; Vyushin et al. 2004; Rybski et al. 2008; Lennartz and Bunde 2010). Statistical evaluations have shown that although the mechanisms of change in SAT variability are not always clear, pattern variability fluctuates over time. For instance, standard deviation computed over 15-year running windows of annual temperature in Greenland changed by a factor of two to three during the twentieth century, with no clear "trend" or significant correlations with NAO or sunspot data (Box 2002). A clear season dependence of SAT pattern variability was found in numerous studies, with higher variability in the winter than in the summer (Timlin and Walsh 2007; Box et al. 2009). Summer melt sustained by unlimited day length dampens SAT variability by maintaining temperatures around the melting point, while winter is marked by more vigorous atmospheric circulation and thus by more pronounced temperature change due to the successive effect of cold and warm air masses (Box et al. 2009). On the other hand, maximum temperature records tend to be more variable, with the impact of clouds being considered significant (Timlin and Walsh 2007). As expected, the proximity of large water bodies tends to reduce variability.

Alarming increases in weather variability in the Arctic have been signaled based on human perception in the context of traditional ecological knowledge (Nakashima et al. 2012 and references therein). To test the contribution of changes in SAT pattern variability to the perception of enhanced variability, Walsh et al. (2005) analyzed minimum and maximum temperature records in terms of variance computed over running means and found no systematic increase over time, except in certain locations during certain seasons. They conclude that the reported decrease in weather predictability—based on long-term experience and knowledge of the Arctic environment—is probably a consequence of other changes than those captured by their statistical analysis applied to SAT: they hypothesize that the perceived changes may occur on different timescales than those analyzed (e.g., subdaily), or in terms of other variables, not air temperature (e.g., wind, precipitation, cloud cover, storms). On the other hand, Walsh et al. (2011) emphasize the potential contribution of extreme values (Alexander et al. 2006) to the pattern change perception, which may partly explain the lack of a signature of variability increase in SAT data.

Von Storch and Zwiers (2003) point out that L-moments can be more reliably estimated than central statistical moments. Introduced by Hosking (1990, 2006), L-moments are based on order statistics. The $r$-th L-moment for the random variable $X$ is defined by:

$$\lambda_r = r^{-1} \sum_{0}^{r-1} (-1)^k \binom{r-1}{k} EX_{r-k:r} \quad (1)$$

where $X_{k:n}$ represents the $k$th smallest value in an independent sample of size $n$ from $X$, and $E$ is the expected value. The first moment, $\lambda_1$, is the mean, while $\lambda_2$, also called L-scale, plays the role of standard deviation. Higher moments represent shape parameters: the ratio $\lambda_3/\lambda_2$ gives the L-skewness, and $\lambda_4/\lambda_2$ gives the L-kurtosis.

Figure 6a, b illustrates the application of the L-scale determination for sliding 7-year long intervals of daily minimum temperature records from two stations in Norway (raw data from Klein Tank et al. 2002, KNMI 2013). One cannot distinguish an increase in variability as expressed by L-scale over the studied interval; variability oscillations seem to be superposed on a gradual decrease in L-scale, which might represent, in its turn, a fragment of an oscillation occurring on a longer timescale.

### *3.2.2 Autocorrelation and Scale Symmetry in Time Series: Detrended Fluctuation Analysis (DFA)*

Pattern variability has been assessed on various temporal scales and with a wide range of methods. Statistical moments only partially reflect SAT variability; for instance, the succession of the temperature values in time is not considered. Distinguishing "fluctuations" from "trends"—on different scales—is particularly challenging (Bekryaev et al. 2010). The characterization of temporal variability on multiple scales offers an effective approach to this challenge. In the Arctic, where SAT variability and its change over time is so important (Walsh et al. 2005, 2011), it is even more critical than elsewhere to properly address questions regarding pattern characterization from this point of view (Fig. 7).

The study of variability characterizing climate variables on a wide range of temporal scales, from days to decades and beyond, represents an important objective for climate research, in general, and for the study of Arctic climate, in particular. By applying a set of different methods, researchers have successfully assessed long-range correlations in temperature time series, i.e., the situation in which the signal's values at different moments are correlated with each other over long intervals of time, so that the autocorrelation function decays slowly, according to a power law rather than an exponential function. A power law scaling of the fluctuation function has been widely reported (Bunde and Havlin 2002; Fraedrich and Blender 2003). Most importantly, it was demonstrated that formerly used methods for time series analysis—such as fluctuations analysis and other comparable methods for determining the Hurst exponent as well as spectrum methods—may provide incorrect results in the presence of trends (Bunde and Havlin 2002). Newer methods such as detrended fluctuation analysis (DFA) and wavelets analysis were shown to effectively remove trends, scale by scale, and thus to provide results able to characterize the self-affine (or scale-symmetric) nature of time series, accurately characterizing patterns and pattern change. Methods capable of characterizing long-range correlations and distinguishing trends from fluctuations on different temporal scales have been successfully applied to atmospheric temperature time series. Patterns have been characterized over certain timescale ranges (weeks–years or decades) for the full length of the available datasets, as well as in temporally delimited windows. Region-specific patterns and pattern change could be distinguished, and links to factors acting on different spatial and temporal scales have been explored. In fact, cascade properties have been found to be abundant in weather and climate processes, and multiscale methods are particularly well suited for their

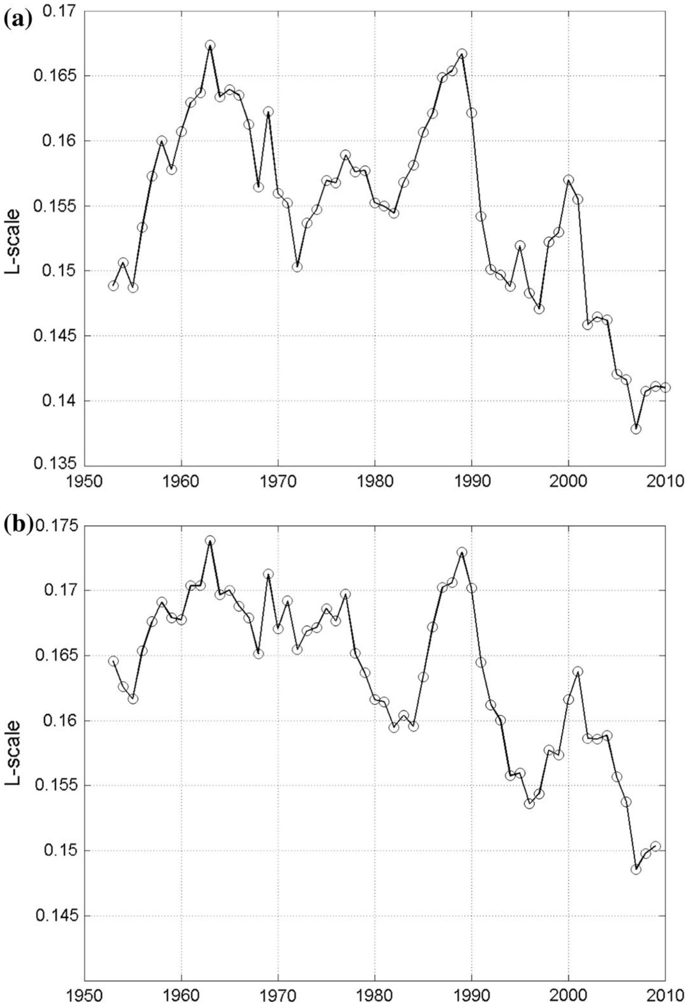


**Fig. 6** Statistical L-moment (L-scale) for daily minimum temperature records from **a** Fruholmen Fyr and **b** Vardø, from 1950 to 2012. The graph shows the midpoints of the sliding intervals

investigation (Lovejoy et al. 2009; Lovejoy and Schertzer 2013). Beyond the insights they provide with respect to the studied interrelated processes, these methods also have the valuable ability to shed light on important pattern properties, which can be used to check climate models. For example, it is essential to check whether model outputs have the long-range correlation properties found in patterns identified in observations (Bunde and Havlin 2002).

The number of multiscale pattern analysis methods based on the characterization of long-range correlations is large (Turcotte 1997; Malamud and Turcotte 1999). However, as mentioned above, natural complexity is such that no single method can capture the richness of its variability. It is not surprising that even methods considered mathematically "equivalent" may produce different results as a consequence of the fact that they address slightly different aspects of the pattern (Ioana et al. 1997). An important requirement of

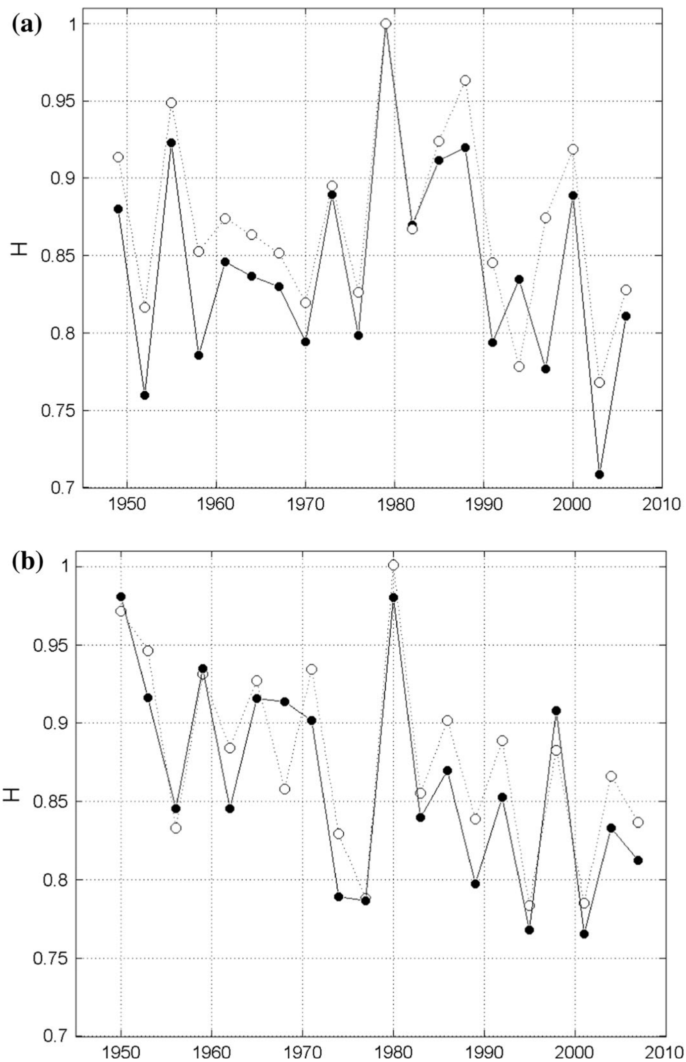


**Fig. 7** Temporal variation of the H exponent obtained with DFA3 for non-overlapping successive 3-year windows (based on data from Suteanu and Mandea 2012): minimum (*open symbols*) and maximum (*solid symbols*) daily temperature records: **a** Eureka, **b** Mould Bay. The graph shows the midpoints of the analysis windows

these methods is to effectively handle real-world time series without introducing biases, such as trend-induced overestimation of scaling exponents (Bashan et al. 2008; Eichner et al. 2003). One of the most successful methods in this category is DFA, initially introduced by Peng et al. (1994) in a different context (in biology), and then further developed (Kantelhardt et al. 2001). DFA avoids biases that affect other methods, such as the direct determination of autocorrelation and rescaled range analysis, which may overestimate exponents in the presence of trends (Eichner et al. 2003). DFA has proven to be effective in many different fields and has been widely used in applications concerning climate research

(Tsonis et al. 1999; Bunde and Havlin 2003; Kiraly et al. 2006; 2008; Varotsos et al. 2009; Fraedrich et al. 2009; Efstathiou and Varotsos 2010; Hsu et al. 2011). The DFA method involves several steps, which will be briefly specified here. For further explanations concerning the motivation and effects of the operations that are part of the procedure, as well as for application details, the reader is referred to explanatory papers (e.g., Kantelhardt et al. 2001; Bunde and Havlin 2003). We will assume that a time series consisting of daily temperature values will be analyzed. As a first step, seasonal detrending is performed. One calculates the mean temperature of each day of the year based on the whole dataset (the "average year" is established). The average temperature for every day of the year is then subtracted from all the corresponding values in the time series. A time series $U(i)$ with zero average is then produced by subtracting the mean temperature from all data. One then constructs the profile of the time series, which is equal to the cumulative sum of $U(i)$, a time series of length $M$:

$$Q(i) = \sum_{j=1}^{i} U(j) \quad i = 1, 2, \ldots, M \tag{2}$$

Following these preparatory stages, the profile $Q(i)$ is analyzed. The profile is divided in segments of size $s$, with $s$ taking a series of values that correspond to the timescales over which long-range correlations are investigated. The method may be numerically unstable for low values of $s$ ($s < n$, $n = 10,\ldots, 30$), and results should be considered with care for such short time intervals.

For every size of $s$ and for each segment $m$ of length $s$, the best fit polynomial of degree $N$ is found, its values are subtracted from the actual segment of $Q(i)$:

$$W_{s,m} = Q_m(i) - p_{m,N}(i) \tag{3}$$

and the mean square of the difference between the original segment and the polynomial fit is calculated for every segment $m$:

$$F_s^2(m) = \left\langle W_{s,m}^2(i) \right\rangle \tag{4}$$

Then, the average $F(s)$, for all $r$ segments of size $s$, is found:

$$F(s) = \left[ \frac{1}{r} \sum_{m=1}^{r} F_s^2(m) \right]^{\frac{1}{2}} \tag{5}$$

If $F(s)$ depends on segment length $s$ according to a power law:

$$F^{(N)}(s) \propto s^H \tag{6}$$

the exponent $H$ characterizes the long-range correlations over the scale range spanned by $s$ for which this power law is valid. Different degrees $N$ can be used for the polynomial fit, and the applied method is denoted by DFA$N$ (e.g., DFA1, DFA2). If $H > 0.5$, the pattern is *persistent*, i.e., increases (decreases) in the time series tend to be followed by further increases (decreases), whereas when $H < 0.5$, the pattern is *antipersistent*, and tendencies of growth or decrease tend to be reversed more promptly.

The results of this analysis provide information about pattern properties on a wide range of temporal scales, indicating with high accuracy the degree of persistence as well as the limits of the scale ranges. They reveal the fact that the analyzed profile looks similar—or has the "same pattern"—when considered at any of the scales in the established scale range, over which it is thus "self-affine." In the case of SAT time series, long-range correlation encompassing intervals from weeks to years were established (Eichner et al. 2003; Fraedrich et al. 2009; Pattantyus-Abraham et al. 2004). Maraun et al. (2004) point out the importance of establishing the power law nature of the fluctuation function, rather than assuming it a priori, and provide efficient tests for this purpose, such as the study of local slopes in the scale versus fluctuation-size graphs.

Scaling signatures from different locations are compared, and their relation to various factors is studied (station distance from the ocean, elevation, latitude, etc.—Kiraly et al. 2006); however, patterns are outcomes of time-varying nonlinear interactions among different factors.

Even if exceptions exist, minimum temperature time series are generally more persistent than those of maximum temperature (Kiraly et al. 2006; Suteanu 2011). The influence of the distance from the coast has not been clearly established: stations located far from oceans are not significantly discernible from those that are closer to the coast. However, by their higher persistence, stations on islands can be distinguished from those on land (Eichner et al. 2003). A relationship between persistence and station distance from the coast could be identified, however, over a shorter range of distances—up to around 10 km (Suteanu 2011).

Eichner et al. (2003) found exponents close to 0.65 in several Arctic stations. Suteanu and Mandea (2012) analyzed minimum and maximum daily SAT time series from the Canadian Arctic north of the Arctic Circle and found most H exponents in the interval $0.70 \pm 0.05$, over a temporal scale interval reaching from at least 1–2 months up to 5–8 years. In all stations, minimum temperature patterns were typically more persistent than those of maximum temperature. Suteanu and Mandea (2012) have also applied the SAT pattern analysis based on DFA to successive, non-overlapping temporal windows, to explore changes in pattern persistence. Persistence turned out to vary significantly over time (Figs. 7, 8). Minimum and maximum temperature pattern changes in persistence were found to be strongly correlated with each other. Moreover, local factors did not prove to play an important role in pattern persistence: stations located thousands of kilometers away from each other emphasized similar changes in terms of pattern variability. Based on the temporal change in variability as reflected in long-range correlation exponents, the studied stations could be divided in groups characterized by common patterns of change. The authors note that while it might be possible to delimit regions characterized by similar pattern change over time, such regions may have boundaries that shift over time.

Since SAT pattern persistence is variable in time, the actual selection of temporal window widths and position in the time series may influence the result. Tests involving window lengths of 3–5 years showed that the size of the window does not play an important role for the resulting exponents (Suteanu and Mandea 2012).

### *3.2.3 DFA Application Example*

To illustrate the capability of the methodology to identify and describe pattern change, we apply here the DFA method described above to the daily SAT records from the stations shown in Fig. 1. We divide up each daily minimum temperature time series in two segments, I and II, which we distinguish from each other by using as a threshold the minimum value in the smoothened records—like those shown in Fig. 4. We analyze therefore, in each case, two regimes: one of cooling (I) and one of warming (II). Using DFA3, we consistently find scaling from 60 to 3,000 days, with the exponents specified in Table 1. *H*-

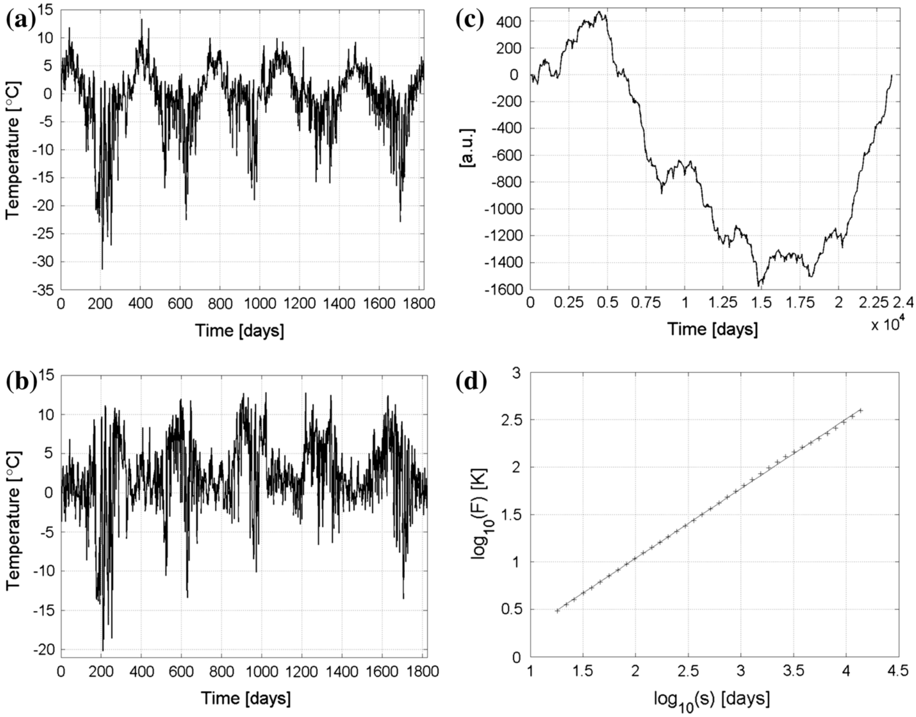


**Fig. 8** Haar wavelet analysis applied to daily maximum temperature data from Hopen: **a** fragment of raw data; **b** the same fragment after seasonal detrending; **c** profile of the time series obtained according to Eq. (2); **d** determination of the H exponent ($H = 0.73$, scaling over an interval from 20 days to 55 years)

value uncertainties based on the standard error of the slope are low (typically lower than 0.01).

The results in Table 1 show that when the pattern switches from overall cooling to warming, persistence is growing in some cases, and is decreasing in others. By showing these results on a map (Fig. 1), we can notice a consistent tendency for stations at high latitudes to be characterized by increasing persistence. All the Canadian stations, except Clyde River (which is located at a lower latitude), as well as Hopen, have increasing persistence when the pattern switches to warming. Most other stations have a lowering persistence. Chokurdah and Ostrov Kotel'Nyj are exceptions from this rule. Repeating DFA3 with another polynomial order (e.g., with DFA1) does not change these results; very similar results are obtained for daily maximum temperature records.

Table 1 and Fig. 3 show that, with the help of DFA, temporal variability can be characterized with precision, and pattern change can be identified from one interval to the next. By analyzing the results in a spatial context, we can also detect spatial correlations among stations for which similar temporal pattern change is identified. Extending this approach to a spatially denser set of stations or to time series associated with denser sets of points obtained through reanalysis would thus lead to new maps, in which certain areas characterized by the same types of pattern change can be delimited, supporting the study of SAT variability in space and in time.

**Table 1** Example of pattern change detection using DFA

| Station name | Latitude | Longitude | $H$(I) | $H$(II) |
|---|---|---|---|---|
| Alert | 82.52 | −62.28 | 0.65 | 0.75 |
| Eureka | 79.98 | −85.93 | 0.71 | 0.74 |
| Hopen | 76.50 | 25.07 | 0.83 | 0.84 |
| Mould Bay | 76.23 | −119.35 | 0.67 | 0.70 |
| Ostrov Kotel'Nyj | 76.00 | 137.87 | 0.79 | 0.73 |
| Resolute | 74.72 | −94.98 | 0.64 | 0.71 |
| Bjoernoeya | 74.52 | 19.02 | 0.85 | 0.79 |
| Dikson | 73.50 | 80.40 | 0.78 | 0.73 |
| Maliye Karmakuly | 72.38 | 52.73 | 0.78 | 0.76 |
| Fruholmen Fyr | 71.09 | 24.00 | 0.71 | 0.68 |
| Volochanka | 70.97 | 94.50 | 0.68 | 0.67 |
| Chokurdah | 70.62 | 147.88 | 0.63 | 0.65 |
| Clyde river | 70.48 | −68.52 | 0.74 | 0.67 |
| Vardo | 70.37 | 31.08 | 0.72 | 0.68 |
| Dzalinda | 70.13 | 113.97 | 0.74 | 0.68 |

$H$ exponents obtained for daily minimum SAT, for the two segments of the record (I cooling, II warming), using DFA3. Arrows in Fig. 1 point up if $H(\mathrm{II}) > H(\mathrm{I})$ and down otherwise

### *3.2.4 Haar Wavelets*

Detrended fluctuation analysis (DFA) is comparable to another broad category of analysis methods, involving wavelets. Among the latter, Haar wavelet analysis was found to be particularly effective for the study of natural time series like those corresponding to SAT patterns (Lovejoy et al. 2012). To apply this wavelet approach, one prepares the time series in a similar way with the one presented above for the DFA method, by starting with the seasonal detrending. In contrast to DFA, the Haar wavelet analysis can be applied not only to the time series integral $Q$, but also to the time series $U$ itself. If applied to the actual time series U, the method offers results that are more intuitive and easy to interpret than DFA; on the other hand, when applied to the signal integral, the method leads to results characterized by lower uncertainty intervals.

According to this method, one evaluates again the way the size of the fluctuation $F$ is scaling with the timescale or "lag" $s$. In fact, for this purpose, it is possible to choose from a variety of "mother" wavelets: the Haar wavelet, proposed as early as 1910 (Haar 1910), is shown to be both easy to implement and to interpret and leads to accurate results (see Lovejoy and Schertzer 2013 for details). The wavelet is defined by:

$$\Psi(i) = \begin{cases} 1; & 0 \le i \le 1/2 \\ -1; & -1/2 \le i \le 0 \\ 0; & \text{otherwise} \end{cases} \tag{7}$$

Similarly with the case of DFA, one divides the time series in sections of length $s$ and finds the fluctuation size $F$. The latter is given by the mean square difference between the values in the time series segments $(x(i) + s/2)$ and $(x(i) - s/2)$. The exponent $H$ is then determined from the power law obtained for the relation between the lag $s$ and the fluctuation size $F$, as in Eq. (6). The steps of the analysis method are illustrated in Fig. 8, with

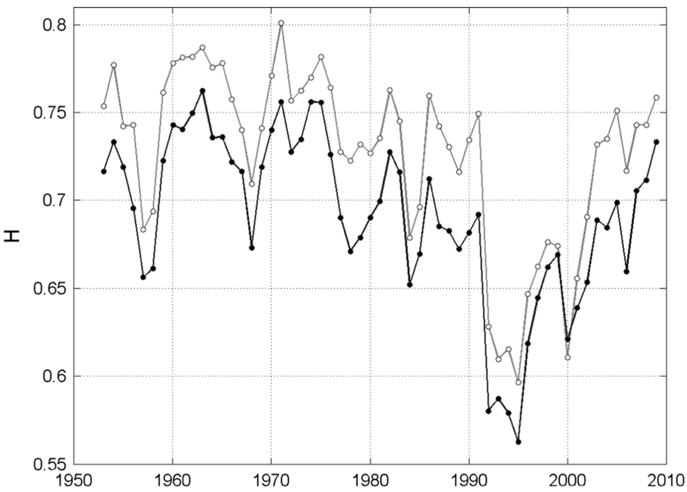


**Fig. 9** Haar analysis performed on overlapping running windows (7 year long, shifted by 1 year). Bjørnøya, minimum (*open symbols*) and maximum (*solid symbols*) daily temperature records, 1950–2012. The graph shows the midpoints of the analysis windows

data from Hopen. Figure 8d shows that the scaling is strong over an interval of around three orders of magnitude. Overall, the Haar analysis method proves to be easier to implement, faster to run, and more robust than DFA.

In order to follow the changes in persistence occurring over time, one can apply this method to sliding windows. Figure 9 presents the outcome of an analysis concerning daily SAT data from Bjørnøya. Again, the higher persistence of minimum temperature time series compared to maximum temperature stands out, as does the correlation between minimum and maximum temperature data. One can notice that beyond decade-long fluctuations around values that were found in other studies, as shown above ($H = 0.70,\ldots, 0.75$), strong changes also occur, with persistence decreasing below $H = 0.6$ in this case. As was the case with the large temporal fluctuations in variability highlighted in the study of Box (2002), one cannot point toward one particular factor that would be, for instance, responsible for the major drop in $H$ in the early 1990s.

As highlighted at the beginning of this section, a variety of methods can be applied for the characterization of air temperature patterns and their temporal change. None of them, however, can exhaust the task of characterizing the patterns. The methodological choice depends on the objectives of the studies, the type of data to be analyzed, the context in which the analysis is performed, etc.

## 4 Conclusions

The Arctic region is both particularly sensitive to global changes in climate and important in terms of its impact on climate from the regional to the global scale. Arctic SATs have been changing in the last decades, with warming being reported for most locations. While the witnessed sea ice loss is more dramatic than the changes in air temperature patterns, these and other important processes are coupled, and, despite our improved understanding of climate, their nonlinear interrelationships can still be a source for surprises.

Climate processes in this region are complex and characterized by high spatial and temporal variability. A range of powerful, relatively recently developed methodological approaches can be applied to characterize the features of SAT patterns. If one's goal is the evaluation of correlations between the Arctic and other different regions, climate network analysis offers rich and effective instruments; moreover, evolving networks enable one to monitor the change of such correlations over time. This approach is, however, quite data intensive: time series are necessary for each node included in the analysis. To characterize individual time series and the change in variability occurring over time, one can simply apply statistical measures of variability, with L-moments offering superior reliability. On the other hand, to capture scale-related pattern change and assess scaling properties over different intervals of the temporal scale, more powerful methods are available, such as DFA and Haar wavelets: both offer sensitive instruments for comparisons among patterns from different locations or pattern segments for different intervals of time. These two methods require time series of at least several hundred samples, which are not necessary for the application of statistical L-moments. The results of such studies support climate research by providing a more comprehensive picture regarding evolving temperature patterns, as well as an effective guide to regional comparisons; they can be applied to temperature records, reanalysis data, and model outputs.

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