Dynamic Arctic weather variability and connectivityJun Meng,1, 2 Jingfang Fan,3, 2, ∗Uma S Bhatt,4 and J¨urgen Kurths2, 4, 51School of Science, Beijing University of Posts and Telecommunications, Beijing 100876, China2Potsdam Institute for Climate Impact Research, Potsdam 14412, Germany3School of Systems Science/Institute of Nonequilibrium Systems,Beijing Normal University, Beijing 100875, China4Geophysical Institute, University of Alaska Fairbanks, Fairbanks, AK 99775, USA5Institute of Physics, Humboldt-University, Berlin 10099, Germany(Dated: February 7, 2023)AbstractThe rapidly shrinking Arctic sea ice is changing weather patterns and disrupting the balance of nature.Dynamics of Arctic weather variability (WV) plays a crucial role in weather forecasting and is closely re-lated to extreme weather events. Yet, assessing and quantifying the WV for both local Arctic regions andits planetary impacts under anthropogenic climate change is still unknown. Here, we develop a complexity-based approach to systematically evaluate and analyze the dynamic behaviour of WV. We reveal that theWV within and around the Arctic is statistically correlated to the Arctic Oscillation at the intraseasonal timescale. We further find that the variability of the daily Arctic sea ice is increasing due to its dramatic declineunder a warming climate. Unstable Arctic weather conditions can disturb regional weather patterns throughatmospheric teleconnection pathways, resulting in higher risk to human activities and greater weather fore-cast uncertainty. A multivariate climate network analysis reveals the existence of such teleconnections andimplies a positive feedback loop between the Arctic and global weather instabilities. This enhances themechanistic understanding of the influence of Arctic amplification on mid-latitude severe weather. Ourframework provides a fresh perspective on the linkage of complexity science, WV and the Arctic.∗jingfang@bnu.edu.cnarXiv:2302.01960v1 [physics.ao-ph] 3 Feb 2023Arctic sea ice is declining and thinning at an accelerating rate due to anthropogenic climatechange [1, 2]. The warming trend is more prominent in the Arctic and is double of the globalaverage or even greater regionally [3], a phenomenon known as Arctic amplification (AA) [4–6].The Arctic sea ice conditions can affect the Arctic ecosystem, wildlife, hunting and shipping, ex-ploration of nature resources and more [7–9]. As one crucial component of the complex Earthsystem [10, 11], changes in Arctic sea ice are found to have statistical and dynamical connec-tions with regional as well as remote climatic impacts [12–15] (as shown in Fig. 1) through bothlarge-scale atmospheric and oceanic circulations [16–20]. The rapid shrinking of the ice cover hasattracted much attention about the Arctic sea ice teleconnections and predictions from seasonal-to-decadal time scales in recent years [21–24]. However, the understanding about its variabilityon weather time scales is still in its infancy [25, 26], although it is crucial for weather forecasting,the safety of commercial and subsistence maritime activities, the survival of polar mammals andthe benefit of polar economics. The impact of day-to-day Arctic sea ice variations has been un-derestimated in most of the climate models [27]. To fill this gap, here we adopt complexity-basedapproaches and the climate network framework to investigate the daily WV of the Arctic sea iceand its connections to climate phenomena on different spatio-temporal scales, including the ArcticOscillation (AO), climate change and local weather conditions even in regions faraway.Complexity science employs the mathematical representation of network science and providesa powerful tool to study the structure, dynamics and function of complex systems [28]. The climatesystem is a typical complex adaptive system due to its nonlinear interactions and feedback loopsbetween and within different layers and components. In recent years, network science has beenimplemented to the climate system to construct the climate network (CN) [29]. The CN is a noveltool to unveil and predict various important climate mechanisms and phenomena [30], includingforecasting of the El Ni˜no Southern Oscillation [31, 32] and Indian summer monsoon rainfall [33,34], the global pattern of extreme-rainfall [35], the changes of global-scale tropical atmosphericcirculation under global warming [36], teleconnections among tipping elements in the Earth system[37], the Indian Ocean Dipole [38] and so on.The AO is one of the major modes of atmospheric circulation over the mid-to-high latitudes ofthe Northern Hemisphere (NH) [39], which influences climate patterns in Eurasia, North Amer-ica, Eastern Canada, North Africa, and the Middle East, especially during boreal winter [40–42].2The AO index is defined as the leading empirical orthogonal function of NH sea level pressureanomalies from latitudes 20 ◦ N to 90 ◦ N and is characterized by the back-and-forth shifting ofatmospheric pressure between the Arctic and the mid-latitudes. During the positive AO phases,the surface pressure is lower-than-average in the Arctic region and the jet stream shifts northwardaccompanied by a poleward shift of the storm track [43]. Correspondingly, we find that both thesea ice and air temperature in mid-to-high latitudes of the NH changes more rapidly (i.e., withblueshifted frequency spectrum) paired with more stable weather conditions (i.e., redshifted) inregions further south during the AO positive phases, in contrast to the AO negative phases whenpressure north of the Arctic Circle is higher than normal. To quantify the blue/red-shift effectand its geographic distribution indicating increased/reduced WV, here we introduce two novelmathematical techniques: the advanced autocorrelation function method, i.e., WACF and the ad-vanced power spectrum method, i.e., WPS (see Methods). This way enables us to find that theday-to-day variability of ice cover for a large area of the Arctic is increasing due to the dramaticmelting of the sea ice [44], which indicates more enhanced risks for severe weather under climatechange [45–48]. This may also increase the probability of unstable weather conditions globallythrough atmospheric teleconnections between the Arctic and the global climate systems (see linksshown in Fig. 1). Finally, we statistically verify the existence of such teleconnections between theArctic sea ice and weather conditions in remote global regions via a multivariate climate networkframework. Such teleconnections can result in a positive feedback loop of WV between the Arcticand the rest (see Fig. 1) and contribute to understanding the mechanisms of linkage between theAA and mid-latitude weather [49]. The presented results and methodology not only facilitate aquantitative risk assessment of extreme weather events (see Fig. S1), but also reveal the existenceof interaction or synchronization paths among regional and global climate components.RESULTSLinkage of the weather variability and the AOThe WV refers to the irregularity/predictability of the climate data at weather time scales (i.e.,hours - days). There are various ways to evaluate the data variability/irregularity, such as the en-3tropy [50–52], the detrended fluctuation analysis [53, 54], the correlation dimension [55], thelyapunov exponents analysis [56], etc. However, most of them would be problematic, biased orinvalid when dealing with short and noisy data, such as the weather data. The standard devia-tion (SD) is an effective technique to quantify the dispersion of data, but not a good measure forirregularity, e.g., the SD of a randomly shuffled data is the same as the original. Besides, the auto-correlation function describes how fast the self-similarity of a variable decays with time [57] andthe power spectral analysis [58] allows us to discover periodicity in the data. Yet, a systematicevaluation of the auto-correlation and the power spectrum as well as their dynamic evolution fornon-stationary climate data are still lacking.Therefore, here we introduce two mathematical functions: WACF and WPS (see Methods fordetails) to quantify the WV in and around the Arctic in a given month, as well as its dynamicbehavior during the period from Jan. 1980 to Dec. 2019. For a given time series, the physicalmeanings of these metrics are: higher values of the WACF stands for weaker short-term mem-ory; while higher values of the WPS indicates faster changes. In particular, to better understandtheir physical meanings, we construct various nonlinear time series (as shown in Fig. 2a) via thefollowing dynamical equations,$x_t = \cos(2\pi t/20)$,(1)$y_t = \cos(2\pi t/10)$,(2)$zx_t = 0.2x_t + 0.8u_t$,(3)$zy_t = 0.2y_t + 0.8u_t$,(4)where $t \in [0, 1000]$, u_t is the nonlinear logistic function as: $u_{t+1} = \mu u_t(1 - u_t)$. Here we setthe parameter $\mu = 3.8$ and $u_0 = 0.01$, i.e., it generates a chaotic behavior [59]. Mathematically,Eqs. (1) and (2) are two periodic functions but with different periods 20 and 10, respectively; while,Eqs. (3) and (4) consist of a periodic term and a chaotic term (Fig. 2a). Therefore, strictly speaking,the value of WACF for zx_t (zy_t) is higher than x_t (y_t), i.e., weaker short-term memory, due to thechaotic term u_t; the value of WPS for y_t (zy_t) is higher than x_t (y_t), i.e., faster changes, due to theperiodic term with different periods. One should note that a segment of unstable data is usuallychanging faster, with both high WACF and WPS, e.g., Eqs. (3) and (4). While a segment of quicklychanging data is not necessarily irregular, such as high frequency periodic data, with high WPS4but low WACF, as Eq. (2). We extract 31 (i.e., the maximal length of one month in the climatedata) consecutive data points from each of the samples and perform WACF and WPS analysis onthe extracted subsets. All results presented in Fig. 2b and c, are consistent with our theory, whichindicates that our two functions can be used as effective tools to describe the variability (bothdisorder and frequency) for given time series.Next, we apply WACF and WPS to quantify the Arctic sea ice WV based on the sea ice coverdataset (daily, 1979-2019, see DATA for details). Our results are shown in Figs. 2d-h. A positivevalue of r denoted by blue in Figs. 2d or e, indicates positive correlation between the annualmean of WACF or WPS with the AO index. We observe that both WACF and WPS tend to behigher, i.e., indicating faster and more irregular day-to-day changes of ice cover, during the AOpositive phases than AO negative phases, in some parts of the Arctic region, such as, the CanadianArchipelago, Beaufort Sea, and the Central Arctic. To illustrate the effect of the AO on WPS, weshow that the power spectrum of Arctic sea ice during the AO positive phase, e.g., Jan. 1989,is significantly blueshifted comparing to that during the AO negative phase, e.g., Jan. 2010 (seeFig. 2f). To illustrate the effect of the AO on WACF, we show that the timeseries of AO index andWACF are significantly synchronized during the period 1980-2019 (as shown in Fig. 2g and h).Moreover, we uncover that the climatic effects of the AO are more prominent in winter-spring thanin summer-autumn (see Figs. S2 and S3).The underlying physical mechanism is related to the typical atmospheric character of the AO,as well as the close interactions between the Arctic sea ice and the surface atmosphere.

Duringthe positive phases of AO, the jet stream shifts northward and the storm tracks are located farthernorth than during the AO negative phases [60], see Fig. S4. This results in more unstable regionalweather in mid-to-high latitudes of the NH, and yields higher WACF and WPS of the air temper-ature data, see Fig. 3 and Figs. S5-S8. In contrast, the WACF and WPS of the air temperature inthe mid-latitudes of the NH increase with more outbreaks of significant weather events (e.g., coldevents, frozen precipitation and blocking days) [60] as the zonal wind weakens during the negativeAO phases, see Fig. 3 and Figs. S5-S8. In particular, as shown in Figs. S5-S8, there are evensignificant connections between the AO and the WV in some regions of the Southern Hemisphere.The WACF and WPS analysis provides an additional way to describe the quantitative responseof both the Arctic sea ice and the atmosphere to the AO, thus could be used to assess the risk of5extreme events in mid-to-high latitudes of the NH.Increased irregularity of Arctic sea ice coverIn the following, our results shown in Fig. 4 indicate that the sea ice cover in a large area of theArctic, including the East Siberian, the Beaufort Sea and the Central Arctic, where the ice thicknessdecrease is dramatic (as shown in Fig. S9), has changed more rapidly and irregularly over the past40 years (1980-2019). That is since both values of the WACF and WPS are significantly increasing.The observed enhancing trend of WV may be attributed to the following two reasons: One isrelated to the development of remote sensing and data analyzing technology, resulting in better dataresolution and accuracy over the data record; the other reason is the rapid decline of multi-year icecover, due to the dramatic increase of air temperature [61]. The multi-year sea ice has been definedas the ice that survives at least one summer melt and represents the thick sea ice cover, while thefirst-year ice refers to the ice that has no more than one-year's growth. As more of perennial icecover is replaced by younger and thinner ice cover, the regional ice cover becomes more fragile andvulnerable to fluctuations of air temperature or some other forces [44]. Therefore, local interactionsbetween the sea ice and atmosphere would be enhanced and the weather in the Arctic and remoteglobal regions may affect each other more easily through potential tele-connected pathways (e.g.,Fig. 5), which may increase the WV associated with the short-term weather predictability.In addition, we observe relatively more areas with a significant trend of enhanced instabilityin the melt season under global warming (see Fig. 4a). This is because during the melt season(Apr.-Aug.), the sea ice declines and fluctuates more dramatically than in other seasons when themonthly average ice cover extent (the area of ocean with at least 15% sea ice, marked by the bluecurve in Fig. 4a) reaches its maximum/minimum. An intensification of the summer Arctic stormactivity is also likely to happen as the land-sea thermal contrast increases under global warming[62–64], which can increase the WV both in the ocean and atmosphere.6Arctic-global teleconnection patternsNext, we propose the multivariate climate network approach to statistically reveal the poten-tial teleconnection patterns between the Arctic sea ice (Fig. S10a) and the global air temperaturefield (Fig. S10b), see more details in the Methods. Different from the classical climate networkapproach with only one climate variable, see Ref. [30, 65, 66] and references therein, we constructclimate networks where each link connects one node located in the Arctic (Fig. S10a) and the otherin the globe (Fig. S10b). In particular, the link weight quantifies the similarity of temporal evolu-tion between two different climate variables, i.e., the Arctic sea ice and the global air temperature.By comparing to a Null-model (see Methods), we observe the dynamic behavior of network con-nectivity (as shown in Fig. S11a), which is defined as the ratio of significant links for each month'snetwork. The statistical significance for each link is defined by comparing to the null-model, seedetails in Method section. A value of above 5% connectivity indicates statistically significant syn-chronization of weather between the Arctic and areas outside, such as Feb. 2010 (see Fig. S11band c), when the AO is in a strong negative phase and the cold polar air plunged into lower lat-itudes of the NH and result in extreme weather conditions in a large area of the globe [67, 68].We identify the significant Arctic-global teleconnection patterns by using climate network nodedegree fields, which are defined as the number of significant links that connect to the Arctic foreach global node, for two specific periods, Feb. 2010 (AO negative phase) and Mar. 2019 (AOpositive phase) in Fig. 5a and c, respectively.Moreover, two typical links presented in Fig. 5 indicate strong synchronizations between thedaily sea ice cover for one Arctic node and the air temperature for another remote global node(their time series are shown in Figs. S12 and S13). As shown in Fig. S12b, changes in the sea icefor node i (77.5 ∘ N, 160 ∘ E) in the Arctic are two days ahead of the air temperature variations fornode j (30 ∘ N, 105 ∘ E) in the Sichuan Province of Southwest China, i.e., evolution of the Arctic seaice could affect the anomalies of air temperature in Southwest China. To better understand howsea ice affects air temperature variability faraway, we identify the most probable teleconnectionpropagation path through the shortest path method (see Methods for more details). We show apotential propagation path for this teleconnection (marked by yellow in Fig. 5b) and find that itseems to be roughly a straight line from the Arctic to Southwest China through Eastern Russia and7Mongolia. The path length is close to 6400 km. From a meteorological perspective, this path canbe well explained by the main large-scale atmospheric circulation. A negative phase of the AOleads to a stronger Siberian High and extends farther southeastward. This results in repeated coldair outbreaks into South China [42]. Our analysis is highly consistent with the wind climatology,see the background information of Fig. 5b.In addition, its feedback is also considered. However, we observe a relatively weaker connectionin the opposite direction, i.e., from Southwest China to the Arctic. We find that changes in the airtemperature at the same location in Southwest China influence that of the sea ice for the sameArctic node 11 days later, as shown in Fig. S12c. Correspondingly, we identify its potentialpropagation path (marked by orange in Fig. 5b) and find it corresponds to negative wind anomaliesfrom Southwest China to the Arctic. These two tele-connected paths form an interaction loop thatsuggests a large-scale atmospheric feedback of WV between the Arctic and Southwest China.In a contrast, during a positive phase of the AO, we show another teleconnection and its pathin Fig. 5c and d, which indicates that the fluctuations of air temperature in California can affectthe Arctic sea ice through the upper atmospheric circulations. Meanwhile, changes in the Arcticsea ice can also influence the temperature fluctuations in California along upper wind routes inan opposite direction, however, at a weaker strength (see more details in Fig. S13c). This isbecause during the positive phase of the AO, low pressure dominates the Arctic regions, leadingto a northward and intensified jet stream that blocks the outbreaks of frigid polar air into lowerlatitudes and reduces storm activity in California [69]. The uncovered teleconnection loop betweenthe Arctic and California suggests that Arctic sea ice decline may drive more California droughtsand wildfires [70].The synchronization of day-to-day weather between the Arctic and other regions can favorpositive feedbacks of WV, where increasing WV/instability of the Arctic sea ice may cause ahigher risk of extreme weather conditions in remote global regions. Meanwhile, impacts fromglobal regions may also induce unstable weather conditions in the Arctic.8DISCUSSIONIn summary, we have introduced the mathematical WACF and WPS functions to quantify theshort-term dynamic WV relating to the irregularity and frequency of the day-to-day changes ofclimate data. By adapting WACF and WPS, we are able to identify significant effects of the AOon day-to-day changes of the Arctic sea ice as well as the WV in mid-to-high latitudes of theNH. We attribute the physical mechanism to the shifts of north-to-south location of jet streamand storm-steering associated with different phases of the AO. Furthermore, we found that duringthe past 40 years, the Arctic sea ice variability on weather time scales is substantially increasingdue to the melting of the thick perennial sea ice. Finally, in order to analyze the dynamic Arcticweather connectivity, we have constructed multivariable climate networks, i.e., between the Arcticsea ice and the global air temperature field. By applying the shortest path method, we are ableto identify teleconnections paths as well as positive feedback loops of WV. We also proposed apossible physical mechanism underlying these paths. The reduction of Arctic sea ice stability mayincrease the risk of unstable weather conditions and lead to reduced skill of weather forecasts [71]globally through the Arctic-global teleconnected feedback loops. Our new findings can help tounderstand the physical mechanisms linking the AA and the global climate, and implies prominentglobal impacts of the Arctic WV on human and natural systems under climate change [6, 49].As the Arctic is considered to be a barometer of global climatic change, in particular, Arctic seaice loss is approaching a tipping point and is extremely crucial for the whole Earth's climate [72].Besides the immediate utility of being able to quantitatively analyze the dynamics of WV for localArctic regions and its global impacts, our framework would be also applied to study and revealthe short-term synchronizations of connectivity among remote global regions, sea ice forecasting,as well as systemic risk induced by the interdependency among other complex subsystems andcascading of adverse consequences, which is particularly important for a systemic risk-informedglobal governance.9Figure 1: The arctic system as a crucial component of the Earth climate system. a, Schematicview of a climate network. Links indicate interactions between different regional climate systemsin the globe. Golden links represent teleconnections between the Arctic and regions outside. b,Illustration of the complex Arctic system. It contains the cryosphere, biosphere, hydrosphere, andatmosphere as well as the interactions among them. A change in one component often triggerschanges and feedbacks in numerous interconnected processes (e.g., Arctic sea ice decline). Thecircular arrow suggests a positive feedback of the WV between the Arctic and the rest of theclimate system.10048121620242832t (days)0101-11-11ax = cos(2 t/20)y = cos(2 t/10)zx = 0.2 * x + 0.8uut + 1 = 3.8ut(1ut)zy = 0.2 * y + 0.8uut + 1 = 3.8ut(1ut)-8-4048 (days)00.800.90101Absolute Auto-correlationWACF = 1.2WACF = 1.2WACF = 2.4WACF = 2.4b30 10532Period (days)0.00.150.00.150.00.50.00.5Normalized PSDWPS = 0.04 day1WPS = 0.10 day1WPS = 0.26 day1WPS = 0.29

day1crdWACF0.500.250.000.250.50reWPS0.500.250.000.250.503010532Period (days)0.00.20.40.6Normalized PSDJan. 1989, AO = 3.1Jan. 2010, AO =2.6f1980198419881992199620002004200820122016year1.82.43.0WACF-4-202AOg-1.00.01.0AO2.22.42.6WACFr = 0.65hFigure 2: Blueshift effect of the Arctic Oscillation on the Arctic weather variability. a,Sample nonlinear time series generated based on Eqs. (1-4). b, The auto-correlation functionsand values WACF of each sample time series shown in a. c, The power spectrum density andvalues WPS of each sample time series shown in a. d, The correlations between the annual meanof the AO index and the WACF for the Arctic sea ice. The “x” marks represent the nodes withcorrelations significant at the 95% confidence level (Student’s t test). e, The same as d for WPS. f,The power spectrum of the sea ice for all nodes marked by symbol “x” in e in Jan. 1989 with apositive AO phase comparing to that in Jan. 2010 with a negative AO phase. g, The AO index(pink solid line for monthly and pink dashed line for annual) versus the WACF index (dark bluesolid line for monthly and dark blue dashed for annual) averaged over all nodes marked bysymbol “x” in d. h, The scatter plots of annual indexes (dashed lines in g) of the AO versusWACF, the r value between these two indexes is 0.65, with a p value of 5.5 × 10−6.11aWACFbWACFcWPSdWPS0.500.250.000.250.50rFigure 3: The relationships between the AO and weather variability. a,b, The correlationmaps between the annual mean of the AO index and WACF of the air temperature at 850hPapressure level during the period of 1980–2019. c,d, The same as a and b, but for WPS. Thesymbol “x” in each panel represents the region with correlation significant at the 95% confidencelevel (Student’s t-test).12bWACFcWPS0.60.40.20.00.20.40.6changes per decade ( )JanMar MayJulSep Nov0.00.20.4Ratio68101214Ice Index (106km2)aWPSWACFIce IndexFigure 4: The dynamic weather variability of the Arctic daily sea ice cover during June. a,The ratio of nodes that has statistically significant increasing trend for the WACF (gray) and WPS(purple); the Sea Ice Index, i.e. the area with at least 15% ice cover (blue) for the same monthsduring 1980–2019. b, Changes per decade as multiple of one standard deviation (σ), for eachArctic node’s WACF during June. c, the same as b for WPS. The symbol “x” in panels b and crepresents the region with trend significant at the 95% confidence level (Student’s t-test).13aFebruary 2010 AO=-4.2660306090120150Node DegreecMarch 2019 AO=2.1160306090120150Node Degreeb(77.5 N, 160 E) (30 N, 105 E)0306090120150Wind 850hPa(km/h)d(77.5 N, 140 W) (35 N, 115 W)04896144192240Wind 500hPa (km/h)Figure 5: Diagram of climate network teleconnection paths. a, Heatmap of the node degreedefined as the number of significant links for each node (see Methods) in the climate network ofFeb. 2010. The blue line indicates the teleconnection between one Arctic node and one nodelocated in Sichuan province of China. b, The propagation pathway of the teleconnection markedby blue in a. c, the same as a for Mar. 2019. The blue line indicates the teleconnection linkbetween one Arctic node and one node in California of United States. d, The propagationpathway of the teleconnection marked by blue in c. The colors and white arrows depict themagnitudes and directions of the 850 (500)-hPa winds in b (d).14DATA AND METHODSDataThe data used in the current work is the 0 hr (UTC) daily sea ice cover and the air temperatureat 850hPa pressure level from the ERA5 [73] (https://apps.ecmwf.int/datasets/)reanalysis, with a

spatial (zonal and meridional) resolution of $2.5^\circ \times 2.5^\circ$. The searching principlefor 850hPa pressure level is, since it is just above the boundary layer to avoid direct interactionsbetween the sea ice and surface atmosphere [24]. We select 8040 grids from the dataset of airtemperature which approximately equally cover the globe (see Fig. S10b). There are 377 gridslocated in the ocean of the Arctic region that with non-zero sea ice cover at least for one day (seeFig. S10a). Then, for each calendar year y and for each node, we calculate the anomalous value foreach calendar day t by using the original value minus the climatological average, then divided bythe climatological standard deviation. The calculations of the climatological average and standarddeviation are based on data from the year of 1979 to 2019. For simplicity, leap days are excluded.The AO index was downloaded from:
https://www.cpc.ncep.noaa.gov/products/precip/CWlink/dailyaoindex/monthly.ao.index.b50.current.ascii. [Ac-cessed in Sep. 2021].The Arctic Sea Ice Extent was downloaded from : https://nsidc.org/data/g02135/versions/3. [Accessed in Jan. 2021].Assessing Weather Variability FunctionsAdvanced autocorrelation function methodThe autocorrelation function (ACF) is widely used to measure the memory of a time series andreveals how the correlation between any two values of the signal changes as their time-lag [57].Generally, for a given time series, x_t, the ACF is defined as,$C(\tau) = \frac{\mathrm{Cov}(x_t, x_{t+\tau})}{\sqrt{\mathrm{Var}(x_t)\,\mathrm{Var}(x_{t+\tau})}}$,(5)15where $\mathrm{Cov}(X, Y) = E[(X - E[X])(Y - E[Y])]$ and $\mathrm{Var}(X) = E[X^2] - E[X]^2$. If the x_t arecompletely uncorrelated, for example, a white noise process, $C(\tau)$ is zero at all lags except avalue of unity at lag zero ($\tau = 0$). A correlated process on the other hand, has non-zero values atlags other than zero to indicate a correlation between different lagged observations. In particular,short-range memory of the x_t are described by $C(\tau)$ declining exponentially$C(\tau) \sim \exp(-\tau/\tau^*)$,(6)with a characteristic time scale, τ^*. For long-range memory, $C(\tau)$ declines as a power-law$C(\tau) \propto \tau^{-\gamma}$,(7)with an exponent $0 < \gamma < 1$. However, a direct calculation of $C(\tau)$, $\tau^*$and γ is usually notappropriate due to noise superimposed on the collected data x_t and due to underlying trends ofunknown origin [74]. In order to overcome the problems described above, here, we develop anadvanced autocorrelation function method to quantify the memory (both short and long range)strength W_{ACF} of a time series as,$W_{ACF} = \frac{\max(|C(\tau)|) - \mathrm{mean}(|C(\tau)|)}{\sqrt{\mathrm{Var}(|C(\tau)|)}} \equiv \frac{1 - \mathrm{mean}(|C(\tau)|)}{\sqrt{\mathrm{Var}(|C(\tau)|)}}$,(8)where 'max' and 'mean' are the maximum and mean values of the absolute ACF, i.e., $|C(\tau)|$,respectively. $\tau \in [-\tau_{max}, \tau_{max}]$ is the time lag. In the present work, we take $\tau_{max} = 10$ days,since we are considering the day-to-day changes of data at the time scale of weather forecasting,i.e., within two weeks. Equation (8) describes the fluctuations of the ACF and its values revealthe strength of memory, i.e., higher (smaller) W_{ACF} indicates a weaker (stronger) correlation andresults in a low (strong) memory. For example, white noise has a maximum value $W_{ACF} = (2\tau_{max} + 1)\sqrt{\frac{2\tau_{max}}{2\tau_{max}+1}}$. Other examples are described in Fig. 2. Another big advancement of ourmethod is eliminating the problematic nonstationarities.Advanced power spectrum methodThe advanced autocorrelation function W_{ACF} quantify well the strength of memory for an ar-bitrary time series, but does not reveal any information about the frequency content. For example,16Eqs. (1) and (2) are two functions with different periods. Their W_{ACF} values are almost the same,as shown in Fig. 2. To fill this gap, we further develop an advanced power spectrum (PS) method.Based on the

Welch’s method [75] we define the advanced power spectral density WPS as,WPS =ZfP(f) × fdf,(9)where P(f) is the normalized spectral density and f stands for the corresponding frequency, whichcan be obtained by Fourier transform. WPS is indeed the weighted mean of f, thus has the sameunit as frequency. Notably, a relatively higher value of the WPS indicates a larger ratio of the highfrequency components (i.e., blueshift), see examples shown in Fig. 2.Climate NetworksNodesDifferent from the classical climate network with only one node classification, see Ref. [30, 66]and references therein, here, we define two types of nodes: globe nodes i with air temperaturevariable Ti(t); Arctic nodes j with Arctic sea ice cover variable Ij(t). We thus have 8040 globenodes (as shown in Fig. S10b) and 377 Arctic nodes (as shown in Fig. S10a).LinksWe construct a sequence of multivariate climate networks. For obtaining the strength of thelinks between each pair of nodes i and j, we compute, for each month m, the time-delayed, cross-correlation functionCmi,j(τ) =T mi (t)Imj (t −τ)−⟨T mi (t)⟩Imj (t −τ)qVar(T mi (t)) Var(Imj (t −τ)),(10)andCmi,j(−τ) =T mi (t −τ)Imj (t)−⟨T mi (t −τ)⟩Imj (t)qVar(T mi (t −τ)) Var(Imj (t)),(11)17where the bracket ⟨⟩denotes an average over consecutive days during a given month m, and τ ∈[0, τmax] is the time lag. Since we mainly focus on the dynamic Arctic WV, here we chose themaximal time lag τmax = 20 days for Eqs. (10) and (11).We identify the time lag θ at which the absolute value of the cross-correlation function |Cmi,j(τ)|reaches its maximum. The weight of link (i, j)m is defined as the corresponding value of the cross-correlation function, i.e. Cmi,j = Cmi,j(τ = θ). Therefore, the weight of each link could be eitherpositive or negative, but with the maximum absolute value. The sign of θ indicates the direction ofeach link; that is, when the time lag is positive (θ > 0), the direction of this link is from j to i, andvice versa [76].Null-modelNext, we investigate the statistical significance of the link weights in the real networks bycomparing to the shuffled surrogate network. In the surrogate network, to calculate link weightfor each pair of nodes, we use two segment of data, each is corresponding to 30 consecutive daysstarting from the first day of a month that is randomly selected from the period Jan. 1980-Dec.2019, so that to destroy real correlations between two nodes in the temporal dimension. Then wedefine the significant threshold q as the 95% highest value of the absolute weights for all links inthe surrogate network. The link (i, j)m in the real network for a specific month m is defined assignificant if it is higher than q or lower than −q, i.e., |Cmi,j| > q. We find that the number ofsignificant links for each month’s network are dynamically changing with time as shown in Fig.S11.Node degreesWe define the degree for each global node as the number of significant links that connect to theArctic nodes. We show heatmaps of node degrees for two specific months, i.e., the Feb. 2010 (Fig.5a) and the Mar. 2019 (Fig. 5b). We observe higher node degrees in many regions, even in lowlatitudes, of the NH for Feb. 2010, comparing to that for Mar. 2019. We suppose it is related tothe different phases of the AO.18Teleconnection path miningTo identify the teleconnection path, we perform the shortest path method of complex networksto find the optimal paths in our climate networks. A path is a sequence of nodes in which each nodeis adjacent to the next one, especially, in a directed network, the path can follow only the directionof an arrow. Here, our climate network is based on only one climate variable–air temperature at850hPa pressure level, and we select 726 nodes from the 10512 nodes [34, 37]. For each climatenetwork link (i, j)m, we define its cost function value asEmi,j =1|Cmi,j|.(12)The

Dijkstra algorithm [77] was used to determine the directed optimal path between a sourcenode i and a sink node j with the following constraints [37, 78]: (i) the distance for every stepis shorter than 1000km; (ii) link time delay $\theta \geq 0$; (iii) the sum cost function value for all col-lection of links through path $i \longrightarrow j$ is minimal. In this way, we identify the optimal paths forinformation/energy/matter spreading in the two-dimensional space.DATA AVAILABILITYThe data represented in Figs. 2–5 are available as Source Data. All other data that support theplots within this paper and other findings of this study are available from the corresponding authorupon reasonable request.CODE AVAILABILITYThe C++ and Python codes used for the analysis are available on GitHub: (https://github.com/fanjingfang/DAWV).19ACKNOWLEDGMENTSThe authors wish to thank T. Liu for his helpful suggestions. We acknowledge the support bythe National Natural Science Foundation of China (Grant No. 12205025, 12275020, 12135003).AUTHOR CONTRIBUTIONSJ.M and J.F designed the research. J.M performed the analysis, J.M, J.F, U.S.B and J.K gener-ated research ideas and discussed results, and contributed to writing the manuscript.ADDITIONAL INFORMATIONSupplementary Information is available in the online version of the paper.COMPETING INTERESTSThe authors declare no competing interests.[1] Rothrock, D. A., Yu, Y. & Maykut, G. A. Thinning of the Arctic sea-ice cover. Geophysical ResearchLetters 26, 3469–3472 (1999).[2] Comiso, J. C., Parkinson, C. L., Gersten, R. & Stock, L. Accelerated decline in the Arctic sea icecover. Geophysical Research Letters 35 (2008).[3] Rantanen, M. et al. The Arctic has warmed nearly four times faster than the globe since 1979. Com-munications Earth & Environment 3, 1–10 (2022).[4] Miller, G. H. et al. Arctic amplification: can the past constrain the future? 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