SOM-based synoptic analysis of atmospheric circulation patterns and temperature anomalies in China

Meng Gao^{a,*}, Ye Yang^{a,b}, Honghua Shi^{c,d}, Zhiqiang Gao^a

^a Chinese Academy of Sciences, Yantai Institute of Coastal Zone Research, Yantai 264003, China

^b University of Chinese Academy of Sciences, Beijing 100049, China

^c State Oceanic Administration, The First Institute of Oceanography, Qingdao 266061, China

^d Laboratory for Marine Geology, Qingdao National Laboratory for Marine Science and Technology, Qingdao 266061, China

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ABSTRACT

Anomalous atmospheric circulation patterns in relation to surface air temperature anomalies during 1979–2017 within China are investigated using the self-organizing map neural network. The SOM-based synoptic analysis begins with classifying the normalized daily anomalies of 500-hPa geopotential height, zonal and meridional winds fields into 4×4 SOM arrays in winter and summer, respectively. The synoptic analysis shows that the spatial distributions of anomalous geopotential height (anticyclones or cyclones) are highly consistent with that of surface air temperature anomalies within China. The influences of two teleconnections, the El Niño–Southern Oscillation and the Arctic Oscillation, on anomalous atmospheric circulation patterns and surface air temperature anomalies are also visually investigated based on the above SOM classification. Changes of node frequencies in winter and summer for the two periods 1979–1998 and 1999–2017 are also observed indicating the changes of regional atmospheric circulations. Our analysis also shows that the decrease of cold extreme and the increase of warm extreme in the two periods are mainly caused by the thermodynamics factor within China, while change in atmospheric circulation sometimes contributes negatively to temperature extreme changes.

1. Introduction

Temperature anomalies, especially temperature extremes, have already been extensively studied at global, regional, and local scales due to its severe impact on ecosystems, economy and human health (Aguilar et al., 2005; Alexander et al., 2006). During the past few decades, changes in temperature extremes have been identified in many parts of the world (Brown et al., 2008; You et al., 2011; Mika, 2013; Monier and Gao, 2015; Gao and Franzke, 2017). At regional and local scales, unlike the warming trend of global mean temperature, a wide variety of changes in temperature extremes is possible (Alexander et al., 2006; Brown et al., 2008). The changes in temperature extremes used to be primarily explained by the shift in the mean temperature (Robeson, 2002; Simolo et al., 2011; Donat and Alexander, 2012). Additionally, the natural variability and regional processes were also considered as the two factors leading to changes in temperature extremes (Ford and Quiring, 2014; Grotjahn et al., 2015; Schoof and Robeson, 2016; Ford and Schoof, 2017). At regional and local scales, the detection and attribution of changes in temperature extremes is a challengeable task (Horton et al., 2015).

In climatology, accurately extracting key features and characteristic patterns of climate variability from a large data set is crucial to correctly understand the atmospheric processes (Liu et al., 2006). By classifying atmospheric conditions into one of a number of different states, synoptic climatology provides a powerful method to directly link the atmospheric circulation and local environmental variables (Yarnal, 1993; Sheridan and Lee, 2011). One of the most commonly utilized methods in synoptic climatology is cluster analysis, which is usually preceded by a principal component analysis (PCA) (Yarnal, 1993; Barry and Perry, 2001). A general shortcoming of this traditional synoptic classification is that while they represent discrete realizations of an atmospheric system, they generally cannot be organized into a continuum (Hewitson and Crane, 2002; Sheridan and Lee, 2011).

The self-organizing map (SOM), an unsupervised neural network methodology, may solve the above-mentioned shortcoming (Hewitson and Crane, 2002). SOM projects high-dimensional input data onto a low dimensional (usually two-dimensional) space, with the aim of discovering patterns in the data (Kohonen, 1995). According to Hewitson and Crane (2002), the SOM can be used in synoptic climatological analysis, which is similar to most other clustering methods, such as the

* Corresponding author.

E-mail address: mgao@yic.ac.cn (M. Gao).

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PCA. Liu and Weisberg (2011) presented a review of SOM applications in meteorology and oceanography and concluded that the SOM has many advantages over conventional feature extraction methods i.e. empirical orthogonal function (EOF) or principal component analysis (PCA) method. SOM is also more flexible than traditional clustering method such as k-means (Solidoro et al., 2007). In addition, SOM method was effective in linking anomalous atmospheric circulations and temperature or precipitation extremes (Horton et al., 2015; Ohba et al., 2015; Loikith et al., 2017; Agel et al., 2018). Based on SOM clustering, Cassano et al. (2007) formulate a method that separates the factors contributing to changes in net precipitation. This method has been widely employed to the attribution of climate changes (Higgins and Cassano, 2009; Skific et al., 2009; Horton et al., 2015; Mioduszewski et al., 2016). Horton et al. (2015) adopted this SOM-based climate change partitioning methodology to the attribution of extreme temperature change in mid-latitude regions.

China has already experienced significant temperature changes during recent decades, and its increasing temperature trend is larger than the global trend and that of the Northern Hemisphere (Ding et al., 2007; Wang et al., 2010). The spatial and temporal characteristics of temperature anomalies within China have been extensively analyzed (You et al., 2013; Gao and Franzke, 2017; Zhang et al., 2017; Wu et al., 2018; Shi et al., 2018). It was estimated that the daily maximum and minimum surface air temperatures increased at rates of 0.13 and 0.32 °C/decade from 1955 to 2000, respectively (Wang and Gong, 2000). Previous studies showed that temperature changes for the cold and warm extremes predominantly occurred in winter and summer, respectively (You et al., 2013; Gao and Franzke, 2017). The change in large scale circulation was considered as one of possible causes besides global warming (You et al., 2011, 2013; Gao and Franzke, 2017; Gao and Zheng, 2018; Shi et al., 2018). To our best knowledge, the quantitative partitioning of temperature extreme changes within China has not been studied, although the potential causes have received wide attention.

The El Niño-Southern Oscillation (ENSO) is considered as an important factor for summer climate anomalies within China (Wang et al., 2008; Wu et al., 2010; Gao and Franzke, 2017). Additionally, it has been found that winter temperature extremes in Eastern China are also affected by the ENSO (Chen et al., 2012). ENSO cycle may influence the climate of China due to its effect on convection activity in the western Pacific Ocean, because this convection activity can change the atmospheric circulation in the East Asian region (Chen and Hu, 2003; Chen et al., 2012). The Arctic Oscillation (AO, also known as Northern Annular Mode) is one of the most dominant patterns of Northern Hemispheric climate variability (e.g. Feldstein and Franzke, 2017), and it is most prevalent in winter and in the mid and high latitudes (Ramos et al., 2010; You et al., 2013). Recent studies illustrated that the AO not only affects the cold extremes in northern and eastern China (Gong and Wang, 2003; You et al., 2013), but also affects summer warm extremes in northeastern and southern China (Gao and Franzke, 2017). Usually, correlation analysis or regression analysis were more used to investigate the impact of teleconnections the ENSO/AO on temperature extremes in China (Gong and Wang, 2003; Wu et al., 2010; You et al., 2013). As a matter of fact, SOM-based synoptic analysis could also be utilized to investigate the teleconnections such as the ENSO, NAO, and AO (Leloup et al., 2007; Reusch et al., 2007; Johnson et al., 2008; Ohba et al., 2015).

In this study, we first utilize the SOM method to represent a continuum of large scale anomalous atmospheric circulation patterns in winter and summer around China. The relationship between anomalous atmospheric circulation patterns and surface air temperature anomalies within China is investigated based on the classified SOM patterns. Then the features of anomalous atmospheric circulation patterns in different phases of the ENSO and AO are also analyzed and compared. Finally, change in anomalous atmospheric circulation patterns is detected and its contribution on temperature extreme change is quantified. This

paper is organized as follows. Section 2 contains a description of the data and methods utilized in the present study. The results are shown in sections 3, and finally discussed concluded in section 4.

2. Data and methodology

2.1. Data

The dataset used in the study spans 39 years, from 1979 to 2017. The four-times-daily geopotential and horizontal wind data at 500-hPa (0°–60°N, 40°–180°E) from the ECMWF interim reanalysis (ERA-Interim for 1979–2017) dataset are used for synoptic analysis (Dee et al., 2011, data accessed April 2018). The 500-hPa level has been chosen because it presents a strong relationship with surface variables (Tolika et al., 2007; Horton et al., 2015; Mioduszewski et al., 2016). Surface air temperature data are the homogenized daily mean temperature series of 808 meteorological stations in China. These selected stations cover a large part of China with relatively sparse coverage in western China. The datasets were accessed from the official website of Climate Data Center (CDC) of the China Meteorological Administration (CMA) (datasets accessed April 2018); and the RHTest software, developed at the Climate Research Branch of Meteorological Service of Canada (available at <http://etccdi.pacificclimate.org/software.shtml>), is applied to assess data homogeneity. In this study, only the reanalysis data and surface air temperature data in winter months (December, January and February, DJF) and summer months (June, July, and August, JJA) are used for synoptic analysis.

The Southern Oscillation Index (SOI) has been used as the index for ENSO cycle, where a negative SOI corresponds to El Niño phase while positive value represents La Niña phase. SOI is a standardized index based on the observed sea level pressure differences between Tahiti and Darwin. The AO index is obtained by projecting the AO loading pattern to the daily anomaly 1000 millibar height field over 20°N–90°N latitude. Both the monthly time series of the SOI and AO index were accessed from the National Centers for Environmental Information, National Oceanic and Atmospheric Administration, USA (data accessed May 2018).

2.2. Self-organizing map methodology

In this study, SOM cluster analysis is employed to categorize large scale anomalous circulation conditions within the region 0°–60°N and 40°–180°E. SOMs are neural network algorithms that use unsupervised classification to perform nonlinear mapping of high-dimensional data sets onto regularly arranged two-dimensional arrays referred to as SOMs (Kohonen, 1995). Each of the elements in the SOM array is denoted as a node (or neuron). Because these nodes span the entire data space of the input data, the SOM methodology involves no a priori assumptions about the distribution of the data (Hewitson and Crane, 2002).

Several separate decisions are needed in implementing the SOM i.e. the choice of input variables and the determination of grid size of SOM (Sheridan and Lee, 2011). We selected three atmospheric variables as inputs for SOM: geopotential height, zonal and meridional winds at 500-hPa level. The winds were included because the enhanced or weakened winds associated with anticyclonic or cyclonic circulations might affect the eastern Asian monsoon (You et al., 2011, 2013; Gao and Franzke, 2017). Sub-daily datasets were firstly aggregated into daily datasets, and then daily anomalies were calculated by subtracting the seasonal cycles (calendar-day mean) for each grid cell. The seasonal cycle was defined from 1979 to 2017, and a 5-day running average was applied to reduce day to day variation. Then, all daily anomalies were normalized with respect to each variable so that each atmospheric variable receives equal weight in the SOM analysis (Ohba et al., 2015). Next, all daily anomaly fields were further weighted by the square root of the cosine of latitude to account for area differences across the grid

points. These daily anomaly fields were assigned to one of a pre-defined number of nodes, according to pattern similarity. The final SOM patterns were obtained by minimizing the Euclidian distance between iteratively updated nodes and their matching daily anomaly fields. Each SOM pattern can therefore be viewed as a representative composite of relatively similar anomalous atmospheric circulation patterns (Horton et al., 2015; Ohba et al., 2015).

The number of nodes is typically user-defined and a moderate-sized map is preferred. If the map size is too small, the diversity of highly generalized circulation patterns could not effectively captured; if it is too big, adjacent patterns will be too similar and visualization is unwieldy (Horton et al., 2015; Mioduszewski et al., 2016). We tested different grid sizes (3×3 , 4×4 , 5×5 , and 6×6) and found that 4×4 SOM appeared to capture and separate the important differences in large scale atmospheric circulation patterns in summer and winter, respectively. All following analyses were based on the 4×4 SOM classification results.

Using the created SOM, the associations between anomalous atmospheric circulation patterns and surface air temperature anomalies were studied. The surface air temperature anomalies were computed by removing the seasonal cycle from daily mean temperatures at each meteorological station, and then were interpolated into $0.5^\circ \times 0.5^\circ$ grid with Kriging technique according to the meteorological stations' latitude and longitude (Shi et al., 2018). In the created SOM, each date has been assigned a best matching node, and then the surface air temperature anomaly field from the same date can be composited over each node on the master map and displayed visually.

Also with the created SOM, change in node frequency and its significance over two periods of interest were calculated for these nodes (Cassano et al., 2007; Horton et al., 2015). In this study, this change was calculated by subtracting the averaged frequency over 1979–1998 from that of 1999–2017. Moreover, the statistical significance of differences in node frequency between the two time periods was calculated in a manner similar to that in Cassano et al. (2007). The null hypothesis states that the difference of the node frequencies between the two time periods is zero. The test statistic to test for change in this frequency is given by

$$\frac{p_1 - p_2}{\sqrt{\frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2}}} \quad (1)$$

where $\frac{p_1(1-p_1)}{n_1}$ and $\frac{p_2(1-p_2)}{n_2}$ are variances of two independent, random, binomial processes, p_1 and p_2 are the expected proportions of frequency in the two time periods, n_1 is the number of samples in 1979–1998 (winter months or summer months), and n_2 is the number of samples in 1999–2017. If the test statistic exceeds 1.96, we reject the null hypothesis at the 95% confidence level and consider the change in node frequency between two periods to be significant. Because this statistical test does not account for the effects of serial correlation in the atmospheric circulation fields, and thus likely overestimates the degrees of freedom. Analogously, we also divide the number of samples of the two data sets by 5 resulting in fewer degrees of freedom and therefore a test statistic of greater magnitude and raising the threshold to achieve statistical significance (Mioduszewski et al., 2016). To illustrate the influences of the two teleconnections, ENSO and AO, on anomalous atmospheric circulation patterns and surface air temperature anomalies within China, the node frequencies in 5 winters/summers with highest/lowest SOI or AO indices (SOI+/SOI- and AO+/AO-) were shown as heat maps, respectively. Significant node frequency differences are more likely to be caused by the ENSO and AO, and the statistical significance is tested using Eq. (1).

Similar to previous studies, temperature extremes are calculated based on the statistical distribution of daily temperature anomalies in each interpolated grid cell ($0.5^\circ \times 0.5^\circ$) (Screen, 2014; Horton et al., 2015). Warm/cold extreme thresholds were defined as the 95th/5th percentile value of 1979–2017 daily surface air temperature anomaly

distribution in winter and summer, respectively. On each day, warm/cold extreme occurrence intensity (EOI) is defined as the ratio of weighted area of grid cells on which daily temperature anomalies are greater/less than (or equal to) the warm/cold extreme thresholds to the total area of all grid cells covering China's mainland. Following Cassano et al. (2007), the factors contributing to a temporal change in a climate variable can be separated into the portion caused by a change in daily frequency of a given SOM node (dynamic change), the portion due to a change in the node-averaged value of the physical variable (thermodynamic change), and a third due to a combination of the two effects. Specifically, the equation is as follows:

$$\Delta EOI = \sum_{i=1}^M (\Delta f_i EOI_{init,i} + f_{init,i} \Delta EOI + \Delta f_i \Delta EOI) \quad (2)$$

where ΔEOI is the total change in warm/cold extreme occurrence intensity in the period 1999–2017 vs. the initial period 1979–1998. Δf_i is the change in node frequency between two periods, f_{init} is the node frequency of occurrence in the initial period, EOI_{init} is the node averaged EOI in the initial period, i indicates the node, and M is the total number of nodes. The three terms in Eq. (2) correspond to dynamic, thermodynamic, and combination terms, respectively.

3. Results

3.1. Atmospheric circulation patterns and temperature anomaly

The master SOM with the associated node frequencies in winter months (DJF) is shown in Fig. 1. Red (blue) shaded contours indicate relatively high (low) normalized 500-hPa geopotential height (Z500) anomalies, and green vectors represent the normalized wind above the 0.75 quantile of all wind speeds. The percentages in the parentheses depict the node frequency in the entire period 1979–2017. The least frequent node is SOM-4 (4.68%), while the most frequent node is SOM-3 (7.97%). For SOM node 1–6, extended anticyclones and positive geopotential height anomalies are located around northern China. On the contrary, the nodes in the lower right side of the master SOM (node 7–8, 10–12, and 14–16) are characterized by negative geopotential height anomalies (cyclones). The average of surface air temperature anomaly fields associated with each master SOM node in winter months is shown in Fig. 2. Also the red (blue) shaded contours indicate relatively high (low) normalized surface air temperature anomalies. Nodes in the upper left of the master SOM tend to have positive temperature anomalies over China, while nodes at the opposite side are featured with negative temperature anomalies. It is concluded that the maps of node averaged daily surface air temperature anomalies show a close relationship to the anomalous atmospheric circulation patterns presented in the master SOM (Fig. 1).

Similarly, Figs. 3 and 4 show the master map of normalized atmospheric circulation anomalies and composites of surface air temperature anomalies in summer months (JJA). The least frequent node is SOM-14 (4.68%), while the most frequent node is SOM-16 (7.89%). In general, the intensity of geopotential height anomaly is weaker in summer months than that in winter months. So is the surface air temperature anomaly. Although the spatial patterns of surface air temperature anomaly are more diversified than those in winter months, the relationships between anomalous atmospheric circulation patterns and surface air temperature anomalies are also very close. The areas of positive/negative geopotential height anomalies (anticyclones and cyclones) are also consistent to the areas of positive/negative surface air temperature anomalies.

3.2. Atmospheric circulation patterns and teleconnections

The node frequencies in 5 winters of strongest positive or negative AO and ENSO phases are shown in Fig. 5. In winter months of AO +

Fig. 1. The master 4×4 SOM of anomalous atmospheric circulation patterns around China (0° – 60° N, 40° – 180° E) in winter months (DJF) from 1979 to 2017. The SOM classification is based on the normalized daily geopotential height anomalies (red and blue shading) and zonal and meridional wind anomalies (green vectors) at 500-hPa level. Only wind speeds above the 0.75 quantile are indicated. The percentages in the parentheses depict the node frequency. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

phase (Fig. 5a), nodes SOM-1, SOM-2, SOM-3, and SOM-13 are the most frequent anomalous geopotential height patterns. The first three nodes correspond to anticyclones and positive geopotential height anomalies over northern China, while the last node corresponds to negative geopotential height anomalies over northwestern China. In winter months of AO- phase (Fig. 5b), nodes SOM-5, SOM-7, SOM-8, SOM-12, and SOM-15 account for 67% of all anomalous atmospheric circulation patterns. Except SOM-5, other nodes represent negative geopotential height anomalies and surface air temperature anomalies over northern China. Fig. 5c shows the difference of node frequency in winter months between AO+ phase and AO- phase. In total, 8 nodes exhibit statistically significant difference at a 95% confidence level. In winter months of SOI+ phase (Fig. 5d), nodes SOM-8, SOM-10, SOM-13 and SOM-14 are the most frequent anomalous geopotential height patterns. In winter months of SOI- phase (Fig. 5e), the most frequent nodes are SOM-2, SOM-3, SOM-13, and SOM-16. Fig. 5f shows the difference of node frequency in winter months between SOI+ phase and SOI- phase, and there are 4 nodes exhibit statistically significant difference at a 95% confidence level. The node frequency difference in different phases will be discussed in the next section.

Fig. 6 shows the node frequencies in 5 summers of strongest positive or negative AO and ENSO phases as well as the node frequency differences. In summer months of AO+ phase (Fig. 6a), nodes SOM-1, SOM-13, and SOM-16 are the most frequent anomalous geopotential height patterns. On the contrary, the frequent nodes in summer months

of AO- phase are SOM-7, SOM-13, and SOM-16 (Fig. 6b). Only the differences of node frequency in node SOM-7 and SOM-13 are statistically significant at a 95% confidence level (Fig. 6c). Moreover, the associated surface air temperature anomalies for node SOM-7 and SOM-13 are in exactly opposite states (Fig. 4). In summer months of SOI+ phases (Fig. 6d), the most frequent anomalous geopotential height patterns are presented in nodes SOM-3, SOM-9, and SOM-14. In summer months of SOI- phases (Fig. 6e), anomalous geopotential height patterns for nodes SOM-2, SOM-6, and SOM-8 occur more frequently. By comparing Fig. 6d and e, it is observed that the differences of node frequency for node SOM-3 and SOM-8 are statistically significant at a 95% confidence level (Fig. 6f).

3.3. Attribution of temperature extreme change

To assess the temporal change of SOM node frequency, the entire period 1979–2017 is split into two periods, 1979–1998 and 1999–2017. The change in node frequency is obtained by subtracting the former from the latter (new minus old) in summer and winter, respectively. For winter SOM (Fig. 7a), there is no node exhibits statistically significant changes at a 95% confidence level. Nodes SOM-2 and SOM-6 show decreases in frequency respectively corresponding to strong positive geopotential height anomalies over northeastern China. Node SOM-8 and SOM-15 show increases in frequency corresponding to strong negative geopotential height anomalies over northern China. For summer

Fig. 2. The average of surface air temperature anomalies within China for each node presented in Fig. 1 in winter months (DJF) from 1979 to 2017.

SOM (Fig. 7b), two nodes (SOM-5 and SOM-13) exhibit statistically significant change at a 95% confidence level (indicated in bold and italic). These two nodes correspond to negative and positive geopotential height anomalies over northern China. Several others changes are at a similar magnitude but without statistical significance (SOM-4, SOM-9, and SOM-14).

Next, we calculate the warm/cold EOI in winter and summer for the two periods 1979–1998 and 1999–2017, respectively. Fig. 8 shows all warm/cold EOI values for all 16 nodes in the two periods. Moreover, the percentages of total change in warm/cold EOIs are shown in Table 1. In winter months, cold EOI decrease for 11 nodes but increase for other 5 nodes (SOM-3, SOM-5, SOM-8, SOM-10 and SOM-14) in the two periods (Fig. 8a). The percentage of total change of cold EOI is -24.12% (Table 1). For warm EOI in winter months, there is an average increase of 28.87% , and 14 nodes contribute positively to this increase but the other two nodes (SOM-4 and SOM-10) contribute negatively (Fig. 8b). In summer months, cold EOI decrease for 15 nodes resulting in a 30.24% decrease of total cold extremes (Fig. 8c). On the contrary, the warm extremes increase 57.17% , which is due to wide increases of warm EOI for 15 nodes in summer months (Fig. 8d).

The results of all quantitative partitioning of the total change in warm/cold EOI are presented in Table 1. Generally, the decrease of cold

extreme and the increase of warm extreme are mainly caused by the thermodynamics factor. However, the contribution to warm/cold extreme changes from the shifting of atmospheric circulation patterns is either negative or relatively small. Particularly, the percentages of thermodynamic contributions to warm/cold extreme in winter months exceed 100% , while atmospheric circulation patterns provide negative contributions (Table 1). We also show the mean probability density functions (PDFs) of temperature anomaly for the two periods in Fig. 9. In winter months, a little rightward shift of location of the mean PDF has been observed, while the scale and shape are nearly unchanged. This finding is consistent with the total change of EOI, since the percentage of cold EOI decrease (-24.12%) is equivalent to that of warm EOI increase (28.87%). In summer months, both the location and the scale of the mean PDF of normalized temperature anomaly have changed. The rightward shift of location of the mean PDF is also consistent with the decrease of cold EOI and the increase of warm EOI, while the increase of the scale is due to the difference of decrease and increase of cold or warm EOI (30.24% vs. 57.17%).

4. Discussion and conclusions

In this study, we have firstly applied SOM to represent a continuum

Fig. 3. The master 4×4 SOM of anomalous atmospheric circulation patterns around China (0° – 60° N, 40° – 180° E) in summer months (JJA) from 1979 to 2017. The legends are same to that in Fig. 1.

of anomalous large-scale atmospheric circulation patterns around China and as a basis for linking large-scale meteorological mechanisms with temperature extremes within China. As stated in the introduction, the SOM approach offers many advantages over conventional data analysis method. The anomalous atmospheric circulation patterns in summer and winter have been successfully discerned using the 4×4 SOM with three atmospheric variables (geopotential height, zonal and meridional winds at 500-hPa level) as input variables. Based on the SOM classification, the associations between synoptic patterns and surface air temperature anomalies within China in winter and summer months were compactly visualized. We found that the spatial distribution of anomalous geopotential height was almost consistent with that of surface air temperature anomalies. Actually, the influence of the vertical wind at 500 hPa was also considered by adding the vertical wind velocity as the fourth input variable of SOM. However, the vertical wind velocity anomalies were not very consistent with the spatial distribution of temperature anomalies (not illustrated as figures here).

The influences of two teleconnections, the ENSO and the AO, on anomalous atmospheric circulation patterns and surface air temperature anomalies were also investigated based on the SOM classification. Atmospheric and oceanic circulation is one of the basic reasons for the formation and evolution of climate extremes. Chen (2002) showed that a positive winter temperature anomaly usually was associated with a weak East Asian winter monsoon (EAWM) in El Niño years, while a negative winter temperature anomaly was associated with a strong EAWM in La Niña years in the vast area of China. In this study, by

comparing the winter node frequencies in El Niño or La Niña phases (Fig. 5d–f), we found that the SOM-8 was the only node with statistical frequency difference in El Niño and La Niña phases. Specifically, SOM-8 was prone to occur in La Niña years with a negative Z500 anomaly centered at northwest Pacific and extending to the eastern China (Fig. 1). Accordingly, the winter temperature was lower than the climatological averages in the vast area of China except for the north-eastern corner (Fig. 2). Alternatively, nodes SOM-2 and SOM-3 were prone to occur in El Niño years with positive geopotential height and winter temperature anomalies in northern China (Figs. 1 and 2). This finding partly verified the different influence of El Niño and La Niña on winter temperature anomalies in China. However, the associations between ENSO and atmospheric circulation patterns are not absolutely solid. SOM-13 occurs frequently in both El Niño and La Niña phases (Fig. 5). The other exception is SOM-16 with enhanced cyclones over Mongolia resulting in negative winter temperature anomaly in western China (Figs. 1 and 2). The feature of anomalous atmospheric circulation in summer of different phases was not obvious, and the influence of the ENSO cycle on surface air temperature anomalies was different at different parts of China. Nodes SOM-3 and SOM-8 represent opposite atmospheric circulation patterns in La Niña and El Niño phases, respectively (Fig. 2 and Fig. 6f). The SOM approach has revealed consistent associations between anomalous atmospheric circulation patterns and temperature anomalies; however, the presented relationships between ENSO and anomalous atmospheric circulation patterns are not definitive. Actually, this inconsistency has already been revealed in some

Fig. 4. The average of surface air temperature anomalies within China for each node presented in Fig. 3 in summer months (JJA) from 1979 to 2017.

previous studies. Wu et al. (2010) found that the relationship between Northeast China summer temperature and ENSO had changed in 1970s. Chen et al. (2013) showed that the influence of ENSO on winter temperature extremes in different parts of China was different in El Niño or La Niña phases. Han et al. (2014) showed that there was an interannual change in the response of winter temperature in China to ENSO due to the weakened meridional Hadley circulation in the western Pacific. Shi et al. (2018) also verified the interannual variation of relationship between ENSO and temperature extremes in China. The above interannual variation was one of the possible reasons why opposite atmospheric circulation patterns were not classified into opposite phases of ENSO.

The AO has an important influence on the climate of the northern hemisphere, especially the Eurasian continent. Some studies showed that the AO had a significant influence on the winter temperature in northern China, frequent cold air activities were closely linked to the continuously negative phase of AO (Wu and Wang, 2002; Gong and Wang, 2003; Wang and Chen, 2010; Chen et al., 2013; You et al., 2013; Gao and Zheng, 2018). In negative AO phase, the westerly circulation was weakened, and the East Asian trough (EAT) and Siberian High (SH) were enhanced, accordingly, the EAWM was strengthened in its lower layers and cold air burst resulting in negative temperature anomalies in many parts of China (Wei and Lin, 2009; Ding et al., 2014). In positive

AO phase, the circulation situation was opposite. In this study, the SOM approach identified 4 nodes (SOM-1, SOM-2, SOM-3 and SOM-13) associated with positive AO and 4 nodes associated with negative AO (SOM-8, SOM-10, SOM-12 and SOM-15) in winter months (Fig. 5a-c). We found that positive/negative geopotential height (anticyclones/cyclones) and surface air temperature anomalies frequently occurred in winter months of AO+/AO- phases (SOM-1 vs. SOM-8, SOM-2 and SOM-3 vs. SOM-12 and SOM-15) (Fig. 1). The above results were consistent with that in previous research. However, the atmospheric circulation patterns presented in SOM-10 and SOM-13 were not consistent with the above feature. In summer, SOM identified two opposite atmospheric circulation patterns shown in SOM-7 and SOM-13 in AO+ and AO- phases (Fig. 3). Accordingly, the summer temperature anomaly patterns were also opposite for these two nodes (Fig. 4). That means the AO also affects the atmospheric circulation pattern and temperature anomalies in summer months within China, which is consistent with the finding of our previous study (Gao and Franzke, 2017).

Changes in atmospheric circulation patterns in winter and summer have also been detected by comparing the SOM node frequencies in the two periods 1979–1998 and 1999–2017. Although the changes of temperature extremes under different atmospheric circulation patterns are different, the total changes of temperature extremes were definitive.

Fig. 5. Node frequencies in 5 winters of strongest positive or negative AO and ENSO phases. (a) AO+ phase, (b) AO- phase, (c) differences of node frequency AO+ phase vs. AO- phase; (d) SOI+ phase, (e) SOI- phase, (f) differences of node frequency SOI+ phase vs. SOI- phase.

The cold extremes decrease but warm extremes increase, which is consistent with many previous findings (You et al., 2013; Gao and Franzke, 2017; Zhang et al., 2017; Wu et al., 2018; Shi et al., 2018). As a matter of fact, the trends of changes in temperature extremes based on different indices were different (Shi et al., 2018). Xu et al. (2011) showed that the increase of daily minimum temperature was more notable than that of daily maximum temperature. In this study, the temperature extremes were not calculated based on daily minimum or maximum temperature. Since our primary objective was to evaluate the relationship between anomalous atmospheric circulation patterns and temperature anomalies, instead, daily mean temperatures were used. Next, the mean probability density functions of temperature anomaly in the two periods 1979–1998 and 1999–2017 were also presented to show the changes of temperature anomalies and extremes (Fig. 9). We found that temperature anomaly in winter was wider dispersed than that in summer. This finding could be explained by the larger spatial variability of cold extremes than warm extreme over China (Wen et al., 2016). Unsurprisingly, the 5th and 95th percentiles of temperature anomaly also became larger in the past 39 years (Fig. 9). This is in line with a general warming trend in China (Shi et al., 2018). Moreover, the changes in PDFs of temperature anomaly and the total changes in cold/warm EOs were also successfully explained by the changes of EOs for

each node (Fig. 8). In future, the relationship between anomalous atmospheric circulation patterns and other percentile-based extreme temperature indices (i.e. cold/warm days, cold/warm night) will be studied in details in another paper. From Fig. 7a, we found that there was no winter node exhibits statistically significant changes at a 95% confidence level. Node SOM-2, showing a nonsignificant decreasing trend in frequency, was prone to occur in negative phase of ENSO and positive phase of AO (Fig. 5d, e). The other two nodes, SOM-8 and SOM-15, have increased and usually occur in positive phase of ENSO and negative phase of AO (Fig. 5a, b). The changes in node frequencies and the associations between nodes and different phases of the two teleconnections implied the roles of ENSO and AO in influencing the changes of winter temperature extremes. Analogously, the role of AO in influencing summer temperature anomalies could be revealed by the association between SOM-13 and AO (Fig. 6c). Recent studies showed that both ENSO and AO will likely be much more intense under the background of global warming (Givati and Rosenfeld, 2013; Graeme et al., 2018). Thus, the direct and indirect impacts of global warming on changes of regional climate extremes will also continue.

Based on the SOM classification, the attribution of temperature extreme change in China was also investigated. The total change in warm/cold extreme occurrence intensity was quantitatively partitioned

Fig. 6. Node frequencies in 5 summers of strongest positive or negative AO and ENSO phases. The subplots are similar to that in Fig. 5.

Fig. 7. Difference of node frequencies between the two periods 1979–1998 and 1999–2017. Significant differences at a 95% confidence level are indicated in bold and italic font. (a) winter months (DJF); (b) summer months (JJA).

into thermodynamic, dynamic and combined components. We found that the decrease of cold extreme and the increase of warm extreme are mainly caused by the thermodynamics factor. This verifies the important effect of global warming on regional climate change (Skific et al., 2009; Higgins and Cassano, 2009). Like Horton et al. (2015), there was also negative contribution from atmospheric circulation change to temperature extreme changes. We note that the change of

node frequencies is not equivalent to that of temperature extremes. For example, from Fig. 7a we see that the frequencies of nodes SOM-12, SOM-14 and SOM 15 all increase. These three nodes all correspond to negative temperature anomalies shown in Fig. 2. However, the corresponding cold EOs in Fig. 8a decrease and the corresponding warm EOs in Fig. 8b increase. This inconsistency partly verifies the negative contribution from atmospheric circulation change to temperature

Fig. 8. Warm/cold EOI values in winter months (DJF) and summer (JJA) for the two periods 1979–1998 and 1999–2017.

Table 1
Total change in warm/cold extreme occurrence intensity (EOI) within China and contributions to the total change in EOI from the thermodynamic, dynamic and combined terms.

Season	Temperature anomalies	Total change (%)	Quantitative partitioning		
			Thermodynamic (%)	Dynamic (%)	Combined (%)
Winter	Cold extreme	−24.12	117.00	−18.84	2.26
	Warm extreme	28.87	107.01	−5.49	−1.53
Summer	Cold extreme	−30.24	93.54	−7.79	14.25
	Warm extreme	57.14	99.03	2.21	−1.34

Fig. 9. The mean probability density functions (PDFs) of temperature anomaly for the two periods 1979–1998 and 1999–2017. The curves are the average of the PDFs from all 808 stations over China, while the shaded region surrounding each curve gives the ± 1 standard deviation within each temperature anomaly bin computed from the set of PDFs over all 808 stations. The dashed and dash-dotted lines indicated the 5th and 95th percentiles of temperature anomaly, respectively.

extreme changes.

Although the associations between anomalous atmospheric patterns and temperature extremes have been generally revealed by the SOM approach, the differences of anomalous atmospheric circulation patterns were not fully discriminated in warm/cold phases of the ENSO and the AO (Figs. 5 and 6). This might due to the inherent limitations of the SOM approach. Loikith et al. (2017) also found that the robustness of the associations between SOM nodes and climate extremes revealed varied in different regions. It is possible that a smaller SOM array can lead to opposite node frequency patterns in warm or cold phases of the

ENSO and the AO; however, decreasing the number of nodes comes at the expense of aggregating distinctive atmospheric circulation patterns into bigger group. Moreover, other combinations of atmospheric variables could be used as the potential input variables of the SOM, so that the synoptic regimes related to more local-scale climate extremes such as precipitation extremes could be interpreted. In addition, the SOM approach could be used evaluate the ability of climate models in predicting regional climate extremes. In future, we will extend the current SOM analysis to climate anomalies at regional scales.

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