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Changes in the Frequency of Extreme Cooling Events in Winter over China and Their Relationship with Arctic Oscillation

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Abstract: Extreme weather and climate events are becoming increasingly frequent and have gained an increasing amount of attention. Extreme cooling (EC) events are a major challenge to socioeconomic sustainability and human health. Based on meteorological stations and NCEP/NCAR reanalysis data, this study analyzed the temporal and spatial distributions of EC events in winter in China by using the relative threshold and the relationship between EC events and the Arctic Oscillation (AO) index during the period of 1961–2017. The results show that the frequency of EC events in China decreased by 0.730 d in these 57 years, with a trend of -0.1 d/10 y. Northeast China had the highest frequency of EC events in winter, with an average of 4 d. In addition, EC events are significantly negatively correlated with the AO index in China, with a correlation coefficient of -0.5 , and the AO index accounts for approximately 21% of the EC event variance. The strongest correlations are mainly located in Northwest China. Our research shows that significant changes in the mid-high latitude atmospheric circulation anomalies, which are associated with the AO, are responsible for EC events. These findings provide theoretical guidance for the prediction and simulation of EC events.



Citation: Song, S.; Yan, X. Changes in the Frequency of Extreme Cooling Events in Winter over China and Their Relationship with Arctic Oscillation. *Sustainability* **2021**, *13*, 11491. <https://doi.org/10.3390/su132011491>

Academic Editor: Adriana Del Borghi

Received: 22 August 2021

Accepted: 13 October 2021

Published: 18 October 2021

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Keywords: extreme cooling events; Arctic Oscillation; winter in China; atmospheric circulation

1. Introduction

According to the sixth assessment report of the IPCC, the global surface temperature has shown an upward linear trend, increasing by 0.99 °C since the 21st century compared to the preindustrial period [1]. Changes in extreme weather and climate events, which have caused serious impacts on society, the ecological system, and public health [2–5], are more sensitive to global warming than the mean climate [6,7]. The frequency and intensity of extreme weather and climate events are also increasing [8,9]. However, the impact of these changes is directly felt by people in the form of day-to-day temperature changes. Extreme cooling (EC) events represent a sharp decrease in temperature between contiguous days, and such events may be a major challenge to socioeconomic sustainability and human health. Several studies have found that EC events can easily lead to the onset of disease [10]. EC events are strongly associated with nonaccidental deaths, cardiovascular deaths, and respiratory deaths, especially for elderly individuals [11,12]. For example, Guo et al. [11] showed that for every drop of 3 °C on two consecutive days, there was a 15.7% increase in nonaccidental deaths in the population. Furthermore, studies have shown that EC events are associated with the onset of infectious diseases. EC events can significantly increase the number of infectious diseases, such as hand, foot, and mouth disease [12,13], respiratory tract infections [14], and pneumonia [15]. In addition, EC events affect industrial and agricultural production and transportation conditions. In 2008, an extreme cold surge invaded central and southern China, causing economic losses of more than USD 22 billion, and 129 people lost their lives [16]. China has complex climatic conditions and a large population. Therefore, it is of great practical significance to clarify the spatial and temporal characteristics of EC events in China and their possible mechanisms and thereby improve the prediction of these events and reduce human casualties and property losses.

The spatial and temporal patterns of EC events in winter have become the focus for many researchers. Studies have shown that global cooling events above 10 °C are decreasing [17]. As one of the more influential EC events in winter in China, cold waves have also received widespread attention due to their temporal and spatial variability. In recent decades, the frequency of cold surges in China has shown a decreasing trend [18]. However, most definitions are based on absolute thresholds [19–21]. China is a vast country, and the climate varies greatly from region to region. Considering that people in different regions have different adaptive capacities and emergency measures for EC events, the definition of EC events for different regions should be defined by relative thresholds. Xu et al. [22] used daily minimum temperature data and the rotating empirical orthogonal function (REOF) method to divide China into seven regions, and different thresholds were attached to each region. The results showed that the frequency of EC events is higher in the north and lower in the south, and the overall trend of the change in the frequency of EC events is decreasing. Zhai et al. [23] proposed using a certain percentile value as the threshold for extreme weather events, and exceeding this threshold is considered to be the definition of an extreme weather event. Cai et al. [24] defined EC events in eastern China using the 90% quantile. The results showed that EC events are decreasing in eastern China. Therefore, most scholars have concluded that EC events have decreased in China using different definitions of EC events. However, the intensity and weakening trends of EC event reduction in different regions still need further attention.

A dominant pattern of the Northern Hemisphere in winter is the Arctic Oscillation (AO) [25,26]. The AO has a significant effect on climate variability and air temperatures in the Northern Hemisphere at middle and high latitudes [27–29]. Therefore, quantifying the relationship between EC events and the AO index can effectively improve EC event prediction. Recent studies have shown a positive correlation between the AO and winter temperatures in most parts of China [30]. The AO phase shift usually leads to weather and climate anomalies at middle and high latitudes in the North Atlantic, North Africa, and East Asia [31–33]. In addition, cold events occur more frequently in East Asia during the negative phase of the AO, and the East Asian trough deepens with stronger East Asian winter winds [34]. When El Niño and the positive-phase AO, or La Niña and the negative-phase AO, are combined, the temperature anomaly in northern China accelerates [35].

Therefore, studies on the effects of the AO on winter temperatures in China have been more extensive. However, few studies have been conducted to investigate the relationship between the AO index and EC events in China; in particular, the effects of the AO index on EC events in different regions are unclear. Given this situation, this study defined EC events using observed and reanalyzed data, combined with the relative threshold method, and analyzed the relationships between EC events and the AO index. The spatial and temporal variation characteristics of EC events and the influencing mechanisms of the AO index in China were also examined. The results of this study deepen our understanding of cold-related extreme events and provide theoretical guidance for the prediction of EC events.

2. Materials and Methods

2.1. Data

Daily mean surface air temperature data were obtained from the National Meteorological Information Center of the China Meteorological Administration. We mainly considered the average state of the daily temperature cycle and variations as the condition of EC events, and the daily mean temperature was used instead of the maximum and minimum temperatures. These data were subjected to strict quality control, and a total of 1115 meteorological stations were finally selected. The winter months during the period of 1961–2017 were selected. To highlight the influence of different natural geographic conditions on EC events, China was divided into seven regions: Northeast China, Northwest China, North China, Central China, East China, South China, and Southwest China (Figure 1).

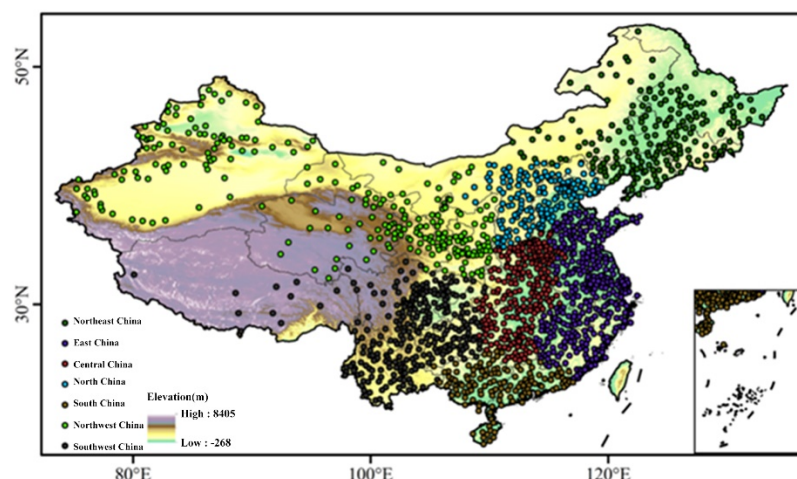


Figure 1. Spatial distribution of the 1115 meteorological stations and elevation of the topography over mainland China.

Monthly mean geopotential height, sea level pressure, and zonal and meridional wind speed data were obtained from the National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis product [36]. The spatial resolution was $2.5^\circ \times 2.5^\circ$, and a total of 144×73 grid points were obtained globally. This study applied AO index data from the Climate Prediction Center (CPC) of the National Oceanic and Atmospheric Administrator (NOAA); the data can be downloaded from https://www.cpc.ncep.noaa.gov/products/precip/CWlink/daily_ao_index/ao.shtml (accessed on 14 November 2020) [37,38]. The AO index was defined according to Thompson and Wallace [25].

2.2. EC Event Definitions and Calculations

A day-to-day temperature change is estimated as the temperature change between neighboring days (TCN) [39]:

$$TCN = T_i - T_{i-1} \quad (i = 1, 2, 3, \dots, n) \quad (1)$$

where TCN denotes a change in the average daily temperature for day i , and T_i (T_{i-1}) denotes the average daily temperature for day i (the previous day is denoted as $i - 1$). The term n is the total number of days in winter. $TCN < 0$ indicates a cooling event.

The TCN data of a single station in winter were sorted from highest to lowest (except for the positive TCN values), and the value of the 90th percentile was taken as the threshold for EC events. Only TCN values exceeding this threshold were considered to be indicative of an EC event. According to this method, the cooling thresholds of 1115 stations in China were obtained as the criteria for EC events.

2.3. Correlation Analysis

The relationship between EC events and the AO index is calculated by correlation coefficients and is often expressed as R :

$$R = \frac{\sum_{i=1}^n (x_i - x_m)(y_i - y_m)}{\sqrt{\sum_{i=1}^n (x_i - x_m)^2} \cdot \sqrt{\sum_{i=1}^n (y_i - y_m)^2}} \quad (2)$$

where n denotes the number of years, and x_m and y_m are the average values of x and y , respectively. R assumes values in the range of $[-1, 1]$. Positive R values indicate a positive correlation between x and y ; negative R values indicate a negative correlation between x and y . Significance levels of the correlation coefficient were estimated according to the two-tailed Student t -test [40].

2.4. Synthetic Analysis

In this paper, the conventional synthetic analysis method was used to analyze the changes in each element when an AO event occurs. The results were tested for statistical significance, and t -tests were used for two overall means, x , y .

$$t = \frac{x_m - y_m}{\sqrt{\frac{(n_1-1)s_1^2 + (n_2-1)s_2^2}{n_1+n_2-2}} \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \quad (3)$$

where n_1 and n_2 denote the sequence lengths of samples x and y , respectively; x_m and y_m are the means; s_1 and s_2 are the variances; and $n_1 + n_2 - 2$ is the overall degree of freedom. The t -distribution table was queried to determine if the results were significant.

2.5. Linear Trend Analysis

The long-term trend of the air temperature time series data was analyzed using the linear tendency estimate method [41]. A simple linear regression was performed between the temperature variable (y) and the corresponding time (x):

$$y = ax + b \quad (4)$$

where a is a linear regression coefficient, which represents the rate of change in EC events. A positive or negative value indicates an increasing or decreasing trend of EC events, respectively. The trend results were tested for significance using the t -test at the 95% confidence level.

3. Results

3.1. Temporal Variation and Spatial Pattern of EC Events

Figure 2h shows the time series of EC events in China from 1961 to 2017. The EC events show an obvious interannual and interdecadal variability, but the trend is not significant, with a decline of 0.730 d in these 57 years, and a trend of -0.128 d/10 y ($p > 0.05$). The largest EC event occurred in 1965 at 7.803 d, and the smallest occurred in 2006 at 2.643 d, with an average of 4.265 d. The interdecadal variability shows that the EC events in China had a rapidly increasing trend from 1961 to 1970 and a decreasing trend from the 1970s to the present, with the fastest decreasing trend in the 1990s at -0.038 d/10 y ($p > 0.05$).

To facilitate the analysis of the regional characteristics of the EC events, we calculated the frequency and trend of winter EC events for each station in seven regions of China. The results show that the frequency of EC events displays a spatial pattern of more in the north and less in the south (Figure 3). Most EC events occurred in Northeast China, with an average of 4.373 d, followed by Southwest China and Northwest China, with average values of 4.335 d and 4.334 d, respectively. The lowest number of EC events occurred in South China, at 4.059 d (Table 1).

In terms of the trend of winter EC events, obvious decreases were observed (Figure 2). The statistical results of all meteorological stations show that 858 of the stations had a decreasing trend of winter EC events. Among them, the trend of 240 stations reached the 90% confidence level (Figure 4). The trends of the EC events in the seven regions show that the rate of decrease in Northeast China was the fastest, with an average of -0.196 d/10 y, and approximately 31.1% of the stations showed a significant change. The regional average trends of the frequency of EC events in North China, East China, and Northwest China had values of -0.194 d/10 y, -0.162 d/10 y, and -0.127 d/10 y, respectively. Central China, South China, and Southwest China had smaller decreasing rates, with averages of -0.115 d/10 y, -0.075 d/10 y, and -0.040 d/10 y, respectively, and these values did not pass the 90% confidence level. This result shows that Northeast China and North China are the regions with the most EC events and the fastest decreasing trends.

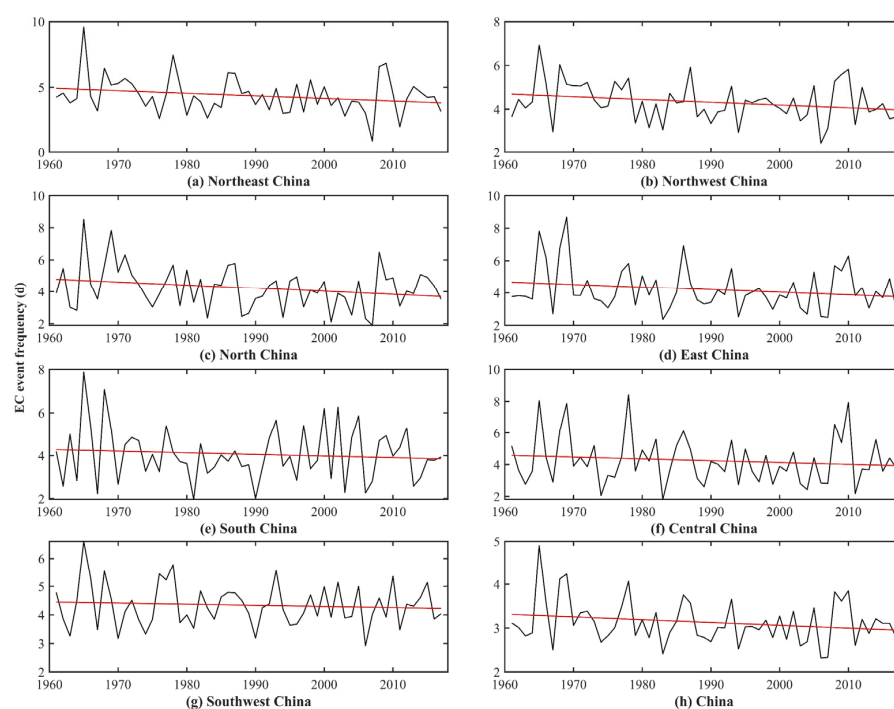


Figure 2. Time series changes of EC events in China and its subregions.

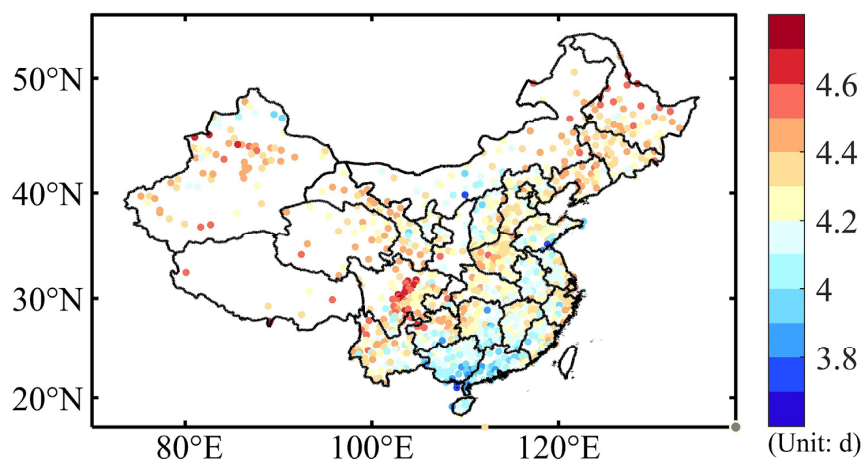


Figure 3. Climatological distribution of winter EC events in China.

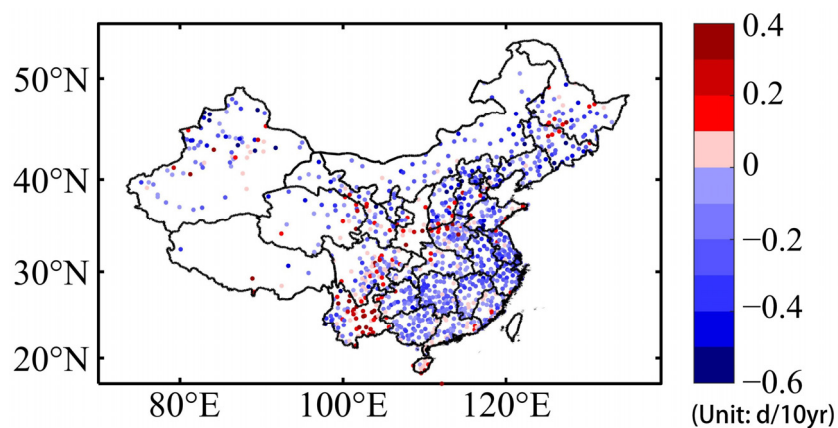


Figure 4. Same as Figure 3 but for the trend.

Table 1. Frequency and trends of EC events in different regions of China (Column 2 and Column 3 represent the range; in Column 4 and Column 5, the number in parentheses indicates the number of meteorological stations that passed the 90% significance test).

	Mean (d)	Trends (d/10 y)	Positive	Negative
Northeast China	4.373 (4.105~4.632)	−0.196 * (−0.720~0.354)	18 (1)	117 (42)
Northwest China	4.334 (3.930~4.667)	−0.127 * (−1.081~0.450)	48 (6)	120 (43)
North China	4.240 (3.719~4.456)	−0.194 * (−0.691~0.310)	19 (2)	94 (37)
East China	4.221 (3.789~4.579)	−0.162 (−0.544~0.231)	32 (0)	207 (64)
South China	4.059 (3.702~4.333)	−0.075 (−0.373~0.338)	30 (1)	81 (7)
Central China	4.250 (3.860~4.509)	−0.115 (−0.384~0.419)	26 (2)	130 (17)
Southwest China	4.335 (3.895~4.719)	−0.040 (−0.785~0.480)	82 (17)	109 (30)
China	4.265 (3.702~4.719)	−0.128 (−1.081~0.480)	255 (29)	858 (240)

* indicates significance at the 0.1 level.

3.2. Correlation between EC Events and the AO Index

As shown in Figure 5, the AO and EC events were significantly negatively correlated, with a correlation coefficient of -0.459 ($p < 0.01$). When the AO was strong, the number of EC events in China was low, and the AO can explain 21.1% of the variation in EC events in China. To detach EC events from the global warming environment, this study detrended EC events and the AO index. The results show that regardless of whether EC events and the AO index were detrended separately or simultaneously, EC events and the AO index in China still had a highly significant negative correlation (Table 2).

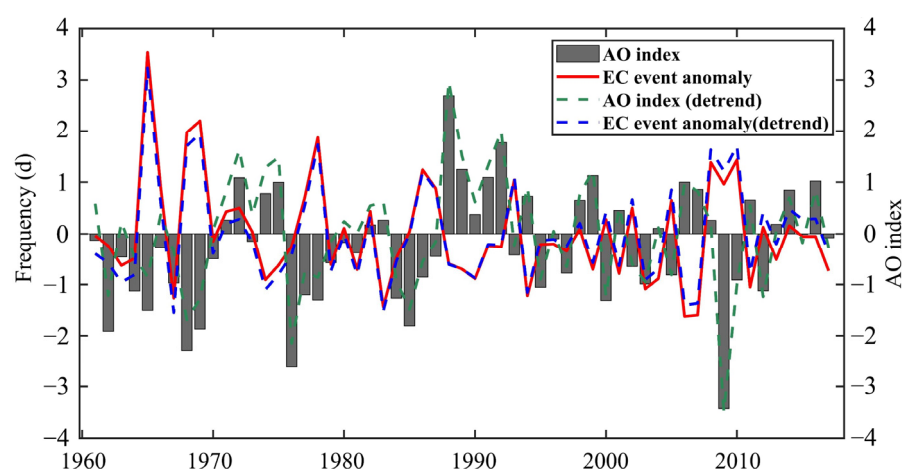


Figure 5. Time series of AO index changes and EC events in China.

Table 2. The correlation between EC events and the AO index in different regions.

	Northeast China	Northwest China	North China	East China	South China	Central China	Southwest China	China
$R(AOI_{detrend}, EC)$	−0.237	−0.471 ***	−0.374 ***	−0.390 ***	−0.285 **	−0.389 ***	−0.302 **	−0.421 ***
$R(AOI, EC_{detrend})$	−0.237	−0.471 ***	−0.374 ***	−0.386 ***	−0.278 **	−0.381 ***	−0.295 **	−0.418 ***
$R(AOI_{detrend}, EC_{detrend})$	−0.244	−0.485 ***	−0.385 ***	−0.398 ***	−0.286 **	−0.392 ***	−0.303 **	−0.431 ***
$R(AOI, EC)$	−0.286 **	−0.514 ***	−0.421 ***	−0.427 ***	−0.301 **	−0.408 ***	−0.315 **	−0.459 ***

** and *** indicate significance at the 0.05 and 0.01 levels, respectively.

Spatially, the correlation coefficient between EC events and the simultaneous AO index was mainly negative, and the correlation was positive only in Southwest China (Figure 6). From the regional perspective, the frequency of EC events in the seven regions was significantly negatively correlated with the AO index. The Northwest China region had the strongest correlation, and the correlation coefficient exceeded -0.5 .

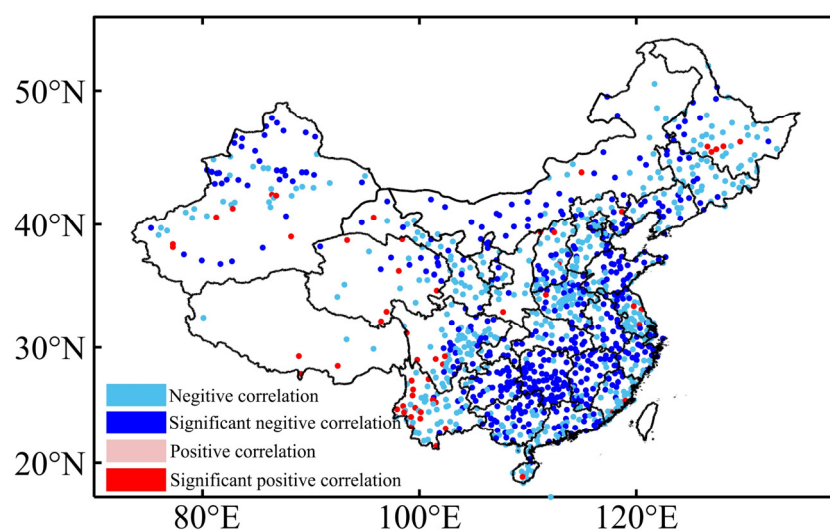


Figure 6. Climatological distribution of the correlation coefficient between EC events and the simultaneous AO index.

In addition, the relationship between the AO and EC events was closely related to the variation in atmospheric circulation anomalies associated with the AO in different climate contexts. Therefore, further analysis of the variability of atmospheric circulation anomalies associated with the AO is needed.

3.3. Possible Mechanisms of AO Affecting EC Events

The above results illustrate that EC events in China have a significant negative correlation with the AO. To further study the mechanisms by which the AO influences EC events in China, we selected the first eight years with the highest and lowest anomaly values from the winter AO index change series from 1961 to 2017 to define strong and weak AO index years, respectively. Among them, the strong AO index years were 2006, 2016, 1972, 1991, 1999, 1989, 1992, and 1988, and the weak AO index years were 2009, 1976, 1968, 1962, 1969, 1985, 1965, and 2000. As shown in Figure 7, the frequency of EC events was consistently lower when the AO index was strong, except for the southwestern station and some other stations. A total of 24.9% of these meteorological stations passed the 0.05 significance test, indicating that the typical years selected were representative of the anomalies of EC events in China.

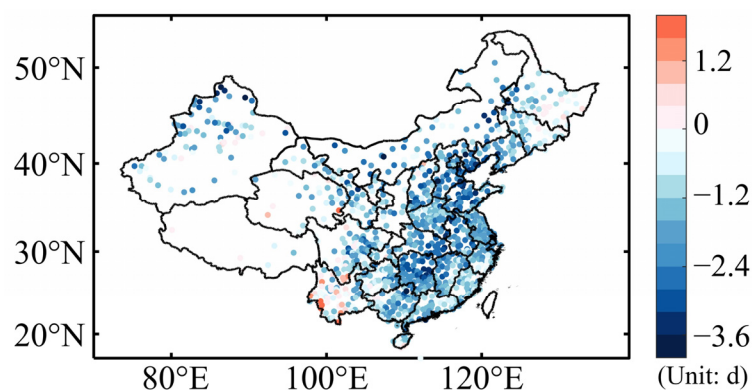


Figure 7. Climatological distribution of winter EC events in China during AO index anomaly years (AO-strong minus AO-weak years).

Figure 8 shows the spatial distribution of the difference between the sea level pressure, 850 hPa and 500 hPa geopotential heights, and wind fields in the strong and weak years. From the spatial distribution of the sea level pressure and wind fields (Figure 8a), the air

pressure was significantly lower at high latitudes and higher in China, indicating that the Siberian high and Aleutian low were weak at this time, and that the near-surface northerly wind became weaker, which was not conducive to the occurrence of EC events in China. The 850 hPa geopotential height and wind field in the positive anomaly year (Figure 8b) were further analyzed. When the AO index was strong, the geopotential height in the high-latitude region was higher, and the geopotential height in the middle- and low-latitude regions was lower. The colder airflow activity range was limited to the polar region, and China was affected by warm airflow from the Pacific Ocean in the south. From the 500 hPa geopotential height and wind field (Figure 8c), the geopotential height was significantly higher in China when the AO index was strong. At this time, the East Asian trough was weak, and China was controlled by anomalous anticyclonic circulation. Therefore, there were fewer EC events in China. Significant changes in the mid–high latitude atmospheric circulation anomalies associated with the AO led to the occurrence of the EC events.

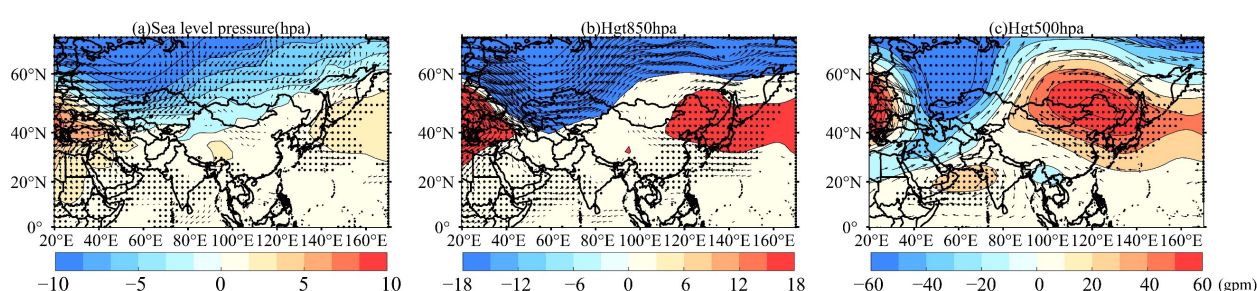


Figure 8. The difference in (a) sea level pressure, (b) 850 hPa and (c) 500 hPa geopotential heights, and wind fields between strong and weak AO index years (dotted areas indicate the areas that passed the 0.05 significance test; the wind field grid passes the significance test when u , v , and w pass 0.05).

4. Discussion

The purpose of this study was to use observational data to calculate the temporal and spatial variation in EC events in China under the 90th percentile threshold and to determine the relationship between EC events and the AO index in different regions. To assess the consistency of different EC event definitions with the conclusions of this study, the following discussion is presented.

EC events are defined using three relative threshold methods (90th, 95th, and 99th percentiles) and an absolute threshold (cold surge) method. A cold surge is defined as a temperature decrease within a 24-h period greater than 8 °C, a 48-h period greater than 10 °C, or a 72-h period greater than 12 °C, where the minimum temperature is less than 4 °C [42]. The results show that the frequency of EC events in China based on all four methods from 1961 to 2017 showed a decreasing trend of -0.128 d/10 y (90th percentile), -0.089 d/10 y (95th percentile), -0.028 d/10 y (99th percentile), and -0.132 d/10 y (cold surge) (Figure 9). Both the relative and absolute threshold methods using different percentile definitions showed a decreasing trend of EC events in China, which is in line with the findings of most studies [21]. In addition, the decreasing trend in the frequency of EC events is defined using the 90th percentile, and the cold surge is the closest.

To test the consistency of the correlation between different EC event definitions and the AO index, the correlation between the AO index and EC events before and after detrending was calculated. The results show that EC events, as defined by all four methods, were highly significantly correlated with the AO index, regardless of the detrending treatment. Among them, the EC events defined according to the 90th percentile were above the highest correlation coefficient of -0.459 to -0.418 (Figure 10).

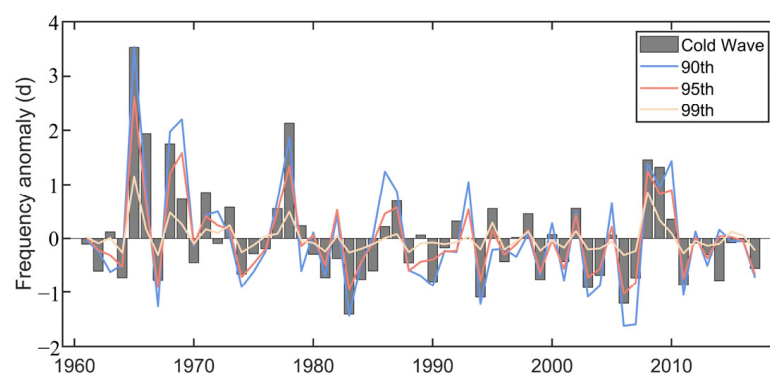


Figure 9. Time series of winter EC events with different definitions in China from 1961 to 2017.

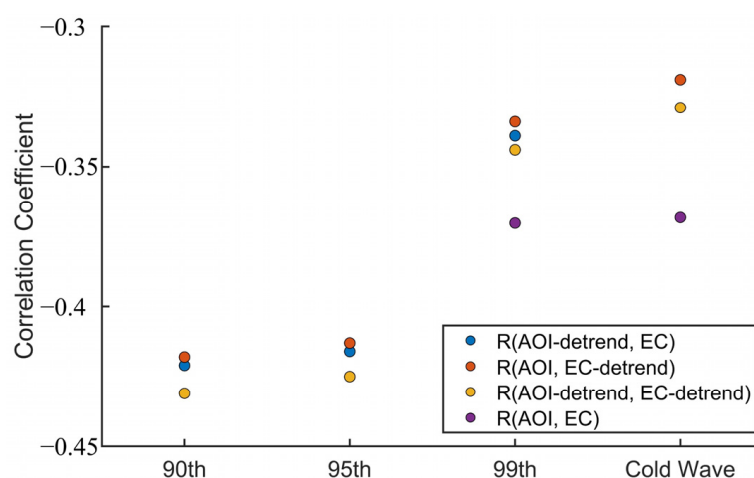


Figure 10. The correlation between winter EC events with different definitions and the AO index (AOI) in China.

It should be noted that the analysis of the AO mechanisms influencing EC events mainly began when the AO in the main circulation systems affected the winter temperature in China. However, the entire weather process by which the AO affects EC events in China is not discussed in detail here. Furthermore, in addition to the AO, the factors affecting the average winter temperature in China include ENSO [43], Arctic sea ice [44], and the East Asian winter monsoon [45]. The relationship between these factors and EC events and their mechanisms will be the focus of our future work.

5. Conclusions

The results of this study show that EC events in China exhibit an obvious interannual and interdecadal variability. EC events decreased by 0.730 d in the 57 years from 1961 to 2017, with a rate of -0.128 d/10 y. Most winter EC events occurred in Northeast China, with an average of 4.373 d.

The AO was significantly negatively correlated with EC events, with a correlation coefficient of -0.459 . After detrending EC events and the AO index, EC events still had a highly significant negative correlation with the AO index in China.

When the AO was strong, the Siberian high and Aleutian low were weak, and the near-surface northerly winds became weaker. The East Asian trough in the middle troposphere obviously weakened. Thus, the propagation of cold polar air was limited by the atmospheric circulation situation in the middle and high latitudes. China has had fewer EC events influenced by warmer Pacific Ocean currents. In addition, the occurrence of EC events due to other factors should be considered in future research.

Author Contributions: Conceptualization, resources, methodology, writing—review and editing, project administration, and funding acquisition, X.Y.; software, formal analysis, data curation, writing—original draft preparation, and investigation, S.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Key R&D Program of China, grant numbers 2018YFC509003 and 2019YFA0606904.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data are not publicly available due to the confidentiality of the research projects.

Acknowledgments: We would like to thank Daoyi Gong for help in this study. We also acknowledge the China Meteorological Administration for temperature data and information.

Conflicts of Interest: The authors declare no conflict of interest.

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