Analysis of Spatiotemporal Variations and Influencing Factors of Extreme Temperature in Northern China over the Past 58 Years (Postprint)

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Abstract

Based on daily maximum and minimum temperature data from 404 meteorological stations in northern China during 1960–2017, this study analyzed the spatiotemporal variation characteristics of extreme temperatures and investigated the influencing factors of temperature indices using linear trend estimation, Mann-Kendall test, moving t-test, cumulative anomaly method, and correlation analysis. The results indicate that extreme temperature warm indices and extreme value indices exhibit an upward trend, while cold indices and diurnal temperature range show a downward trend. In terms of magnitude of change, cold indices are greater than warm indices, nighttime indices are greater than daytime indices, with the largest changes in extreme temperature indices occurring in Northwest China and the smallest in Northeast China. Regarding the timing of abrupt changes, mutations in extreme temperature indices mainly occurred in the 1980s and 1990s, with warm indices and extreme high value indices changing later than cold indices and extreme low value indices. The timing of abrupt changes in extreme temperature indices was earliest in Northeast China and latest in Northwest China. After the mutation, extreme warm events and temperature extreme value events entered a frequent occurrence stage, while extreme cold events entered a rare occurrence stage. The changes in extreme temperature indices from 1988 to 2012 responded to the global warming hiatus phenomenon. Most extreme temperature indices are significantly correlated with latitude, longitude, and altitude. The Arctic Oscillation (AO) index has the strongest influence on extreme temperatures, with the most pronounced effect on cold indices. Aerosol optical depth is negatively correlated with most cold indices and positively correlated with most warm indices.

Full Text

Temporal and Spatial Changes of Extreme Temperature and Its Influencing Factors in Northern China in Recent 58 Years

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Abstract

Based on daily maximum and minimum temperature data from 404 meteorological stations in northern China from 1960 to 2017, we analyzed the spatiotemporal variation characteristics of extreme temperature events and explored their influencing factors using linear trend estimation, sliding t-test, cumulative anomaly, and correlation analysis methods. The results show that: (1) Warm extreme indices and extreme value indices exhibited significant upward trends, while cold extreme indices and diurnal temperature range (DTR) showed downward trends. The magnitude of change was greater for cold indices than for warm indices, and greater for night indices than for day indices. The northwest region showed the largest magnitude of change in extreme temperature indices, while the northeast region showed the smallest. (2) The abrupt changes in extreme temperature indices mainly occurred during the 1980s–1990s. Cold indices and extreme low-value indices mutated earlier than warm indices and extreme high-value indices. After the mutation, extreme warm events and temperature extreme value events entered a phase of frequent occurrence, while extreme cold events became less frequent. The northeast region had the earliest mutation time, while the northwest region had the latest. (3) The changes in extreme temperature indices responded to the global warming hiatus phenomenon during 1998–2012. (4) Most extreme temperature indices were significantly correlated with longitude, latitude, and altitude. (5) The Arctic Oscillation (AO) index had the strongest influence on extreme temperatures, with the most significant impact on cold indices. (6) Aerosol Optical Depth (AOD) showed a decreasing trend from 2007 to 2016, during which extreme high temperature events increased while extreme low temperature events decreased. Most cold indices were negatively correlated with AOD, while most warm indices were positively correlated with AOD.

Keywords: extreme temperature; temporal and spatial variation; influencing factors; northern China

Introduction

Under the background of global warming, temperature increases directly affect the occurrence of extreme weather events and increase the frequency and intensity of natural disasters, posing serious threats to human safety, social construction, and ecosystems. The Coupled Model Intercomparison Project Phase 5 (CMIP5) predicts that by the end of the 21st century, the frequency and magnitude of warm events will increase globally while cold events will decrease. Numerous scholars have studied the variation characteristics and influencing factors of extreme temperature events both domestically and internationally. Research on Indonesia found that cold days (nights) decreased while warm days (nights) increased. Studies on extreme temperatures in the United States showed that extreme minimum temperatures have increased significantly over the past decades, with frost days decreasing noticeably. Many Chinese scholars have investigated extreme temperature changes in different regions of China, finding that cold events gradually decreased while warm events increased, with notable regional differences.

The influencing factors of extreme temperatures are complex, including geographical location, large-scale atmospheric circulation, greenhouse gas emissions, urban heat island effects, land cover changes, and cloud cover variations. This paper analyzes the impacts of geographical location, atmospheric circulation, and Aerosol Optical Depth (AOD) on extreme temperatures to provide a scientific basis for understanding the causes of extreme temperature events in northern China.

Although many scholars have studied extreme temperatures in northern China, most research has focused on maximum and minimum temperatures rather than comprehensive analysis of extreme temperature indices. Previous studies have been limited by fewer stations, earlier data cutoff years, and fewer indices, resulting in an incomplete understanding of extreme temperature event characteristics across the entire northern China region. Building on previous research, this study utilizes the maximum possible number of meteorological stations with historical data covering the basic characteristics of the study area to conduct a comprehensive and in-depth analysis of the spatiemporal variations of extreme temperatures in northern China. This will help to deeply grasp the characteristics of extreme temperature changes, conduct meteorological disaster prediction and early warning research, reduce the adverse impacts of extreme temperature events on local production and life, and ensure agricultural production safety.

1 Data and Methods

1.1 Study Area Overview

Northern China covers a vast territory (Fig. 1), spanning longitudinally from 75.14°E to 132.58°E and latitudinally from 33.24°N to 53.28°N. The region includes Northeast China (Heilongjiang, Jilin, Liaoning, eastern Inner Mongolia), North China (Hebei, Beijing, Tianjin, Shanxi, Shandong, Henan, central Inner

Mongolia), and Northwest China (Xinjiang, Qinghai, Gansu, Ningxia, Shaanxi, western Inner Mongolia). The terrain shows large differences, crossing three topographic steps from west to east with complex and diverse landforms. The climate types are diverse, including monsoon climate, temperate continental climate, and plateau mountain climate.

1.2 Data

Daily maximum and minimum temperature data from 404 meteorological stations in northern China were selected, sourced from the China Meteorological Data Network (http://cdc.cma.gov.cn). Missing data from individual stations were interpolated using regression methods, and RClimDex was used to screen for outliers and erroneous values. The study period was 1960–2017.

Monthly data for three atmospheric circulation indices were used: Arctic Oscillation (AO), North Atlantic Oscillation (NAO), and El Niño-Southern Oscillation (ENSO), obtained from the NOAA Climate Prediction Center (http://www.cpc.noaa.gov/). The ENSO index was represented by the Nino3.4 sea surface temperature index (SOI) and the Multivariate ENSO Index (MEI). Aerosol Optical Depth (AOD) data were obtained from NASA (https://ladsweb.modaps.eosdis.nasa.gov/search/order). The ENVI/IDL function library was used for data reprojection, mosaicking, and clipping to extract AOD data for each station in northern China.

1.3 Methods

Sixteen extreme temperature indices were calculated using the RClimDex1.0 software package in R, following the definitions of the World Meteorological Organization (WMO). Linear regression was used to fit trends in extreme temperature indices, and the Mann-Kendall non-parametric test was applied for significance testing. Mutation analysis employed the Mann-Kendall test, sliding t-test, and cumulative anomaly method. Correlation analysis was completed using SPSS software.

2 Results

2.1 Temporal Variation of Extreme Temperature Indices

Table 2 shows the trends of extreme temperature indices in northern China and its subregions. Absolute indices FD and ID showed significant decreasing trends, while SU showed a significant increasing trend. Relative indices TR and TN90p showed significant increasing trends, while TX10p showed a significant decreasing trend. Extreme value indices TXx, TNn, TXn, and TNx all showed significant increasing trends. GSL and WSDI showed significant increasing trends, while DTR and CSDI showed significant decreasing trends.

The magnitudes of change in cold indices (FD, ID, TX10p, TN10p, CSDI) were greater than those in warm indices (TR, SU, TX90p, TN90p, WSDI), particularly in North and Northeast China, indicating that the temperature increase in the study area was mainly contributed by the rise in minimum temperature, consistent with the findings of Guo Zhimei et al. The changes in extreme temperature indices in each subregion were basically consistent with the entire study area, but differences existed among subregions: TXx and TXn changed significantly only in Northwest China; SU, TNn, TXn, and DTR had the largest change magnitude in Northeast China; TR had the largest change magnitude in North China; and the remaining indices had the largest change magnitude in Northwest China. This shows that the magnitude of change in extreme temperature indices was larger in Northwest China and smaller in Northeast China.

Compared with global and national extreme temperature index changes during the same period, the trends in northern China were consistent with global and national trends, but the magnitude of change for most indices was more pronounced in northern China than globally and nationally.

2.2 Spatial Variation of Extreme Temperature Indices

2.2.1 Absolute Indices As shown in Fig. 2, most stations showed significant decreasing trends in FD, with larger decreases in the eastern North China Plain, central Inner Mongolia Plateau, eastern Loess Plateau, eastern Tianshan Mountains, and Qinghai and Ningxia regions, averaging -3.5 d $\cdot$ (10 a)$^{-1}$. Most stations showed decreasing trends in ID, with about 60% of stations showing significant decreases, mainly distributed in the Loess Plateau region and Shandong and Qinghai regions, with larger decreases in the northeastern Loess Plateau and Qinghai region, averaging -2.0 d $\cdot$ (10 a)$^{-1}$. Most stations showed significant increasing trends in SU, with larger increases in the Loess Plateau, eastern Inner Mongolia Plateau, Qilian Mountains, Kunlun Mountains, and Greater Khingan Range, averaging 3.0 d $\cdot$ (10 a)$^{-1}$. The western and southern Northeast China Plain, North China Plain, Qinling Mountains, and Tianshan and Kunlun Mountains showed larger increases, averaging 2.0 d $\cdot$ (10 a)$^{-1}$. About 40% of stations showed decreasing trends in TR, concentrated in Qinghai region.

2.2.2 Relative Indices Fig. 3 shows that most stations had significant increasing trends in TN90p, with larger increases in the central and eastern North China Plain, western Northeast China Plain, Qilian Mountains, Qinling Mountains, Tianshan Mountains, and northern Xinjiang, averaging 3.5 d $\cdot$ (10 a)$^{-1}$. About 70% of stations showed significant increasing trends in TX90p, with larger increases in the Tianshan Mountains, Qilian Mountains, Inner Mongolia Plateau, and northern Xinjiang and Qinghai, averaging 3.0 d $\cdot$ (10 a)$^{-1}$. Most stations showed significant decreasing trends in TN10p and TX10p, with larger decreases in the Tianshan Mountains, Kunlun Mountains, Inner Mongolia Plateau, Greater Khingan Range, eastern North China Plain, eastern Loess Plateau, and northern Xinjiang and Qinghai, averaging -2.5 d $\cdot$ (10 a)$^{-1}$ for TN10p and -2.0 d $\cdot$ (10 a)$^{-1}$ for TX10p. Stations with decreasing trends in TN10p and TX10p were mainly distributed in southern Hebei and Henan.

2.2.3 Extreme Value Indices Fig. 4 indicates that most extreme value indices showed increasing trends. About 70% of stations showed significant increasing trends in TXx, with larger increases in the Loess Plateau, Qilian Mountains, Qinling Mountains, eastern Qinghai, and eastern Inner Mongolia, averaging 0.5 °C $\cdot$ (10 a)$^{-1}$. About 60% of stations showed significant increasing trends in TNx, mainly distributed in the Qinling Mountains and northern Qinghai, with larger increases in the northern and southern Northeast China Plain, central Inner Mongolia Plateau, Qinling Mountains, Tianshan Mountains, and northern Xinjiang and Qinghai, averaging 0.5 °C $\cdot$ (10 a)$^{-1}$. About 70% of stations showed significant increasing trends in TNn, with larger increases in the Northeast China Plain, central North China Plain, Tianshan Mountains, and northern Xinjiang, averaging 0.4 °C $\cdot$ (10 a)$^{-1}$. Stations with decreasing trends were mainly distributed in the central Loess Plateau. About 60% of stations showed significant increasing trends in TXn, with larger decreases in the western Northeast China Plain, western North China Plain, central Inner Mongolia Plateau, Qinling Mountains, Tianshan Mountains, and northern Qinghai, averaging -0.5 °C $\cdot$ (10 a)$^{-1}$.

2.2.4 Other Indices Fig. 5 shows that most stations had increasing trends in WSDI, with about 60% showing significant increases, mainly distributed in the Tianshan Mountains, Kunlun Mountains, Inner Mongolia Plateau, and northern Ningxia. The Tianshan Mountains, Kunlun Mountains, Loess Plateau, and eastern Qinghai showed larger increases, averaging 3.0 d $\cdot$ (10 a)$^{-1}$. Most stations showed decreasing trends in CSDI, with about 60% showing significant decreases. The distribution of significantly decreasing stations was basically consistent with that of significantly increasing WSDI stations, with larger decreases in the Tianshan Mountains, Kunlun Mountains, Inner Mongolia Plateau, northwestern Qinghai, northern Xinjiang, and southern Shanxi, averaging -2.5 d $\cdot$ (10 a)$^{-1}$. Most stations showed significant increasing trends in GSL, with larger increases in the Loess Plateau, Inner Mongolia Plateau, Qilian Mountains, Qinling Mountains, and Qinghai, averaging 5.0 d $\cdot$ (10 a)$^{-1}$. Most stations showed significant decreasing trends in DTR, particularly in the western Northeast China Plain, western North China Plain, and Inner Mongolia Plateau.

2.3 Mutation Analysis of Extreme Temperature Indices

Mutation analysis was conducted for extreme temperature indices in northern China and its subregions. Due to space limitations, only the mutation analysis for extreme value indices in northern China is shown (Fig. 6), with mutation years for other indices summarized in Table 3.

The extreme value indices in northern China showed fluctuating upward trends. The Mann-Kendall mutation test indicated multiple intersection points between UF and UB curves within the confidence interval, making the mutation points uncertain. However, the cumulative anomaly values for TXx showed a decreasing trend before 1994 and an increasing trend thereafter, indicating a mutation in 1994. Combined with the Mann-Kendall test, cumulative anomaly, and sliding t-test, the comprehensive judgment shows that TXn, TNn, and TNx mutated in 1990, 1988, and 1990, respectively.

The mutation results for subregions were similar to those for northern China as a whole, but with temporal differences: SU, ID, FD, and CSDI mutated earlier in North China; TNn and DTR mutated earlier in Northwest China; and other indices mutated earlier in Northeast China. Therefore, Northeast China had the earliest mutation time, followed by North China, and Northwest China had the latest mutation time. After mutation, cold indices transitioned from frequent to less frequent occurrence, while warm indices and extreme value indices transitioned from less frequent to more frequent occurrence.

2.4 Changes in Extreme Temperature Indices During the Global Warming Hiatus Period

The global warming hiatus during 1998–2012 has received widespread attention. If this phenomenon indeed exists, how do extreme temperature indices respond? Table 4 shows that during 1988–1998, cold indices showed decreasing trends while warm indices and extreme value indices (except TXx) showed increasing trends, indicating a warming trend. After 2012, the changes in extreme temperature indices were similar to those during 1988–1998, also showing a warming trend. However, during the 1998–2012 hiatus period, cold indices showed increasing trends while warm indices (except TR) and extreme value indices showed decreasing trends, indicating a cooling trend. This demonstrates that the changes in extreme temperature indices responded to the global warming hiatus phenomenon.

2.5 Analysis of Influencing Factors

2.5.1 Geographical Location Table 5 shows that most extreme temperature indices were significantly correlated with longitude, latitude, and altitude, with particularly high correlations with altitude. FD and CSDI were significantly negatively correlated with altitude and significantly positively correlated with longitude and latitude, indicating that higher altitude and more western locations had greater decreases in FD and CSDI and smaller increases in SU. ID was significantly negatively correlated with altitude and significantly positively correlated with longitude and latitude, indicating that higher altitude and more southwestern locations had greater decreases in ID. TN10p was significantly negatively correlated with altitude and latitude and positively correlated with longitude, indicating that higher altitude and more northwestern locations had greater decreases in TN10p. TX10p was significantly positively correlated with altitude and significantly negatively correlated with longitude and latitude, indicating that higher altitude and more southwestern locations had greater increases in TX10p. TNx was significantly positively correlated with altitude and latitude and negatively correlated with longitude, indicating that higher altitude and more northwestern locations had greater increases in

TNx. GSL was significantly positively correlated with altitude and negatively correlated with latitude, indicating that low-latitude, high-altitude regions had greater increases in GSL. In summary, most indices showed larger change magnitudes in high-altitude western regions, further confirming that changes were more pronounced in Northwest China.

2.5.2 Atmospheric Circulation Indices The results (Table 6) show that cold indices, extreme low-value indices, DTR, and GSL were significantly correlated with the AO index; extreme low-value indices were significantly correlated with the NAO index. The SOI index had low and non-significant correlations with all extreme temperature indices, while the MEI index was significantly correlated with ID, CSDI, and WSDI. Since both SOI and MEI represent ENSO indices, ENSO had greater influence on ID, CSDI, and WSDI but smaller influence on other temperature indices, possibly because ENSO' s lagged characteristics make its impact on regional interannual temperature variations less significant in long-term studies. In conclusion, the AO index had the strongest influence on extreme temperature indices in the study area, followed by the NAO and ENSO indices. These three indices had greater influence on cold indices, with the AO index having the most obvious impact on cold indices.

2.5.3 Aerosol Optical Depth (AOD) Fig. 7 shows that AOD in northern China decreased from 2007 to 2016. During the same period, extreme temperature indices changed as shown in Table 7. The annual mean correlation indicates that AOD was negatively correlated with most cold indices and positively correlated with most warm indices, but the correlations were low and not significant. Research shows that the correlation between AOD and extreme temperature has strong regional variability, so regional averages cannot represent the entire northern China region. Future studies should further explore the regional characteristics of the correlation between AOD and extreme temperature.

3 Discussion

Regarding the variation characteristics of extreme temperature, previous studies have shown that extreme cold events gradually decreased while extreme warm events gradually increased. Our results corroborate these findings. Building on previous research, this study utilized more meteorological stations, adopted more extreme temperature indices, and applied more statistical methods to investigate extreme temperature changes in northern China, making the results more explicit, more detailed, and more comprehensive in reflecting the variation characteristics of extreme temperatures in northern China. This also helps describe the changes in extreme temperatures in specific subregions and provides a basis for formulating climate change response strategies, thereby mitigating the adverse impacts of extreme temperature events on local production and life and ensuring agricultural production safety.

The factors influencing extreme temperature changes are complex. Extreme temperature index changes are affected not only by geographical location but also by topography. The above research also shows that extreme temperature changes vary across different topographic regions. Northern China has complex terrain, and future studies should investigate different topographic regions to explore the impact of topography on extreme temperatures in northern China. Regional climate change is influenced by atmospheric circulation, which has important effects on the occurrence of extreme climate events. Wang Ziqi et al. pointed out that El Niño events cause lower winter daily average temperatures and more frequent extreme low temperature events in northeastern China, while La Niña events have weaker impacts on extreme low temperatures. Since different regional climates respond differently to various circulation indices, future research should investigate the mechanisms by which circulation indices affect extreme temperatures in different regions of northern China.

The correlation analysis results between AOD and extreme temperature indices corroborate Hu Ting’ s research. This study adopted more indices to better understand the relationship between AOD and extreme temperature events. Hu Ting’s research also showed that AOD has a certain cooling effect on temperature with seasonal differences, and the impact of AOD on extreme temperature is complex. In this study, the correlations between AOD and extreme temperature indices were not significant, so longer time series of AOD data are needed in the future to deeply explore the impact of AOD on extreme temperatures in northern China.

4 Conclusions

This study employed 16 extreme temperature indices to investigate the spatiotemporal variation characteristics and influencing factors of extreme temperature events in northern China, yielding the following main conclusions:

(1) The variation trends of extreme temperature indices in northern China and its subregions were consistent: warm indices and extreme value indices showed upward trends, while cold indices and DTR showed downward trends. In terms of magnitude, cold indices were greater than warm indices, and night indices were greater than day indices, indicating that the temperature increase in the study area was mainly contributed by the rise in minimum temperature. Regional differences existed: the northwest region showed the largest magnitude of change in extreme temperature indices, while the northeast region showed the smallest.

(2) The abrupt changes in extreme temperature indices in northern China and its subregions mainly occurred in the 1980s–1990s. The mutation time of warm indices and extreme high-value indices was later than that of cold indices and extreme low-value indices. After mutation, extreme warm events and temperature extreme value events entered a frequent occurrence phase, while extreme cold events became less frequent. Regional differences in mutation time also existed: the northeast region had the

earliest mutation time, while the northwest region had the latest.

(3) During the 1998–2012 global warming hiatus period, cold indices showed increasing trends while warm indices (except TR) and extreme value indices showed decreasing trends, indicating a cooling trend. This demonstrates that the changes in extreme temperature indices responded to the global warming hiatus phenomenon.

(4) In the analysis of influencing factors on extreme temperatures, most extreme temperature indices were significantly correlated with longitude, latitude, and altitude, with particularly high correlations with altitude. The AO index had the most obvious influence on extreme temperatures in northern China, followed by the NAO and ENSO indices. These three indices had greater influence on cold indices, with the AO index having the most significant impact on cold indices. From 2007 to 2016, AOD showed a decreasing trend, extreme high temperature events increased, and extreme low temperature events decreased. AOD was negatively correlated with most cold indices and positively correlated with most warm indices, but the correlations were not significant.

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Note: Figure translations are in progress. See original paper for figures.