

Change of probability density distributions of summer temperatures in different climate zones

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Abstract Extreme events have become increasingly frequent worldwide which are reflected in diverse changes in the shape of the temperature probability density function. However, few studies have paid attention to the heterogeneity of temperature at the scale of climate zones. Here, we use the ERA5-land data set to explore interdecadal summer temperature changes and the distribution across different climate zones from 1981 to 2019. Comparing the minimum ($T_{\min}$) and maximum ($T_{\max}$) temperature of 1982–1991 and 2010–2019, the results imply that $T_{\min}$ and $T_{\max}$ in summer maintained a notable upward trend over the past 40 years, especially $T_{\min}$. The effects of a simple shift toward a warmer climate contributed most to all climate zones, while the standard deviation, skewness and kurtosis had minor effects on extreme temperature except for tropics. Quantile analysis shows that the probability of extreme events in all climate zones is increasing in frequency and intensity, especially $T_{\min}$ and $T_{\max}$ in temperate climate zone. Understanding diverse reasons for climate change can assist us with taking different measures to address extreme climate in distinct climate zones.

Keywords Climate change, probability density function, extreme events

1 Introduction

Over the past decades, extreme events have become increasingly frequent globally. The Intergovernmental Panel on Climate Change (IPCC) reported that a changing climate leads to changes in the frequency, intensity, spatial extent, duration, and timing of extreme weather and climate events (IPCC, 2012). These changes are

closely related to changes in the shape of the temperature probability density function (PDF, i.e., its mean and variance). There are three hypotheses about the effect of changes in temperature distribution on extremes: 1) effects of a simple shift of the entire distribution toward a warmer climate; 2) effects of an increase in temperature variability with no shift in the mean; 3) effects of an altered shape of the distribution (IPCC, 2012). Therefore, it is vital to identify changes in temperature distribution characteristics to explain the probability of extreme events.

Numerous studies have shown that frequent extreme events are mainly caused by the moving of the mean toward the hotter part, but the impact of variance and shape parameters is not significant. For example, studies using simulation models (Wang et al., 2017; Ma et al., 2020) and observational data sets (Simolo et al., 2010; McKinnon and Deser, 2018) found that there was an obvious warming shift of PDFs of temperature anomalies, and this phenomenon in most regions of the world is significant, such as America, Italy and Europe. Furthermore, changes in the minimum temperature ($T_{\min}$) are greater than those of the maximum temperature ($T_{\max}$), but the variance changes in global day-time and night-time temperatures were not significant (Donat and Alexander, 2012). McKinnon et al. (2016) obtained similar conclusions using the quantile regression of the $T_{\max}$ and $T_{\min}$ of summer days in the Northern Hemisphere from 1980 to 2015. The author used principal component analysis to express the temperature distribution changes by four orthogonal basis functions, each of which corresponds to the mean, variance, skewness, and kurtosis change of temperature. Temperature fluctuation in most regions can be explained by a positive shift of the mean without any significant shape changes (McKinnon et al., 2016). Similar conclusions have been found when applied to smaller regions (Simolo et al., 2010). However, Schär et al. (2004) found

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that the above conclusions could not explain summer heatwaves in Switzerland in 2003. With increases in greenhouse gas concentrations, the temperature variance has doubled in Europe (Schär et al., 2004). It can be implied the temperature distribution influencing the increases of extreme events mainly focuses on the change in the mean and variance. This influence is more spatially heterogeneous in a changing climate weather in the past (Katz and Brown, 1992) or in the future (Carvalho et al., 2021). Climate characteristics, including temperature distribution of each grid is similar within a climate zone. Existing researches on drought often take the climate zone as the spatial scale (Ogunjo et al., 2019). However, few papers focus on the statistical characteristic differences for temperature on the scale of climate zone. It has been proved that there is heterogeneity in temperature changes in different regions (Davy et al., 2017; Guirguis et al., 2018).

An increasing number of studies had demonstrated the contribution of climate change to extreme events, including heatwaves (Stott, 2016; Vogel et al., 2019). The heatwave characteristics are related to temperature distribution (Anderson et al., 2018). The frequency of heatwaves in summer over the western part of Central Europe is increasing due to an obvious warming shift under global warming (Guirguis et al., 2018; Ma et al., 2020). A study using the Coupled Model Inter-comparison Project Phase 5 (CMIP5) daily data sets illustrated that extreme temperatures undergo asymmetrical changes under the Representative Concentration Pathways 8.5 (RCP 8.5) (Wang et al., 2017). Many scholars concerned about the climate change in summer, because it is the season with highest productivity it may have the greatest impact on humanity (Hansen et al., 2012) and the largest changes of standard deviation are in summer (Huntingford et al., 2013). Therefore, determining the contributions of distinct types in summer climate change is important to manage the extreme events.

At present, the papers researching the relationship between temperature distribution and extreme temperature are often based on the given threshold. The previous studies found that the probability of the extreme weather is influenced by the climate background (Liao et al., 2018; Luo and Lau, 2021), but few papers explore them by the shape of temperature distribution on the global climate zones. What's more, the hypothesis tests used in most of the previous studies are biased when the distribution of temperature is non-gauss. This paper uses a variety of nonparametric test methods to explore the relationship between climate change and extreme temperature in different climate zones around the world and clarify the role of climate background on temperature distribution and extreme events. Within this context, our work aims to explain the regional heterogeneity of global temperature changes under distinct climate backgrounds. This paper is organized as follows. In Section 2, we

describe the data sets and methods used. In Section 3, we compare the temperatures of 1982–1991 and 2010–2019 to analyze the statistical characteristics of temperature changes and extreme events in different climate zones. In Section 4, we discuss extreme event management and robust tests of time series. In Section 5, we present our conclusions and further work.

2 Data and methods

2.1 Data

Although the accuracy of observation data is higher, considering the better coverage of data worldwide, we used 2-m daily maximum temperature and daily minimum temperature from the ERA5-Land data set to assess global warming. This data set is the fifth-generation European Centre for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalysis of the global surface air temperature from 1981 to 2019 provided by the Copernicus Climate Change Service (C3S). For more details about the ERA5 data set, please refer to ECMWF website. The spatial resolution of the data used in our experiment was $1^\circ \times 0.994^\circ$. The data are more accurate for all types of land applications with the improvement of ERA5 climate reanalysis. It is a reliable data set to simulate and analyze climate change or extreme events (Sheridan et al., 2020; Liu et al., 2021). And the study had shown that the correlation between this data set and the observations at the station in China is 0.976, the RMSE is 2.717°C and the bias is -0.706°C in the recent three years (Huang et al., 2021). The RMSE in north-east Brazil is between 0.41°C and 1.11°C in the last ten years (Araújo et al., 2022). And the correlation is 0.94 in July of a city in Republic of Tyva in the past 13 years (Dergunov and Yakubailik, 2020).

Here, we used the Köppen-Geiger climate classification at 1-km resolution for the present-day (1980–2016) produced by Beck et al. (2018). The Köppen climate classification system has been used universally because of its application in climate change studies (Zhao et al., 2014; Li et al., 2019). It has been proved to be a useful tool for detecting the first-order bioclimate influence (Chan and Wu, 2015). According to the Köppen-Geiger climate classification, we identified five climate zones: tropical, arid, temperate, cold, and polar. To maintain consistency with the temperature data set, the majority interpolation method was used to unify the data of each climate zone into the temperature data resolution. The final climate classification is shown in Fig. 1.

2.2 Methods

To analyze the changing trend of hydro-meteorological time series and diagnose mutations, we used the modified

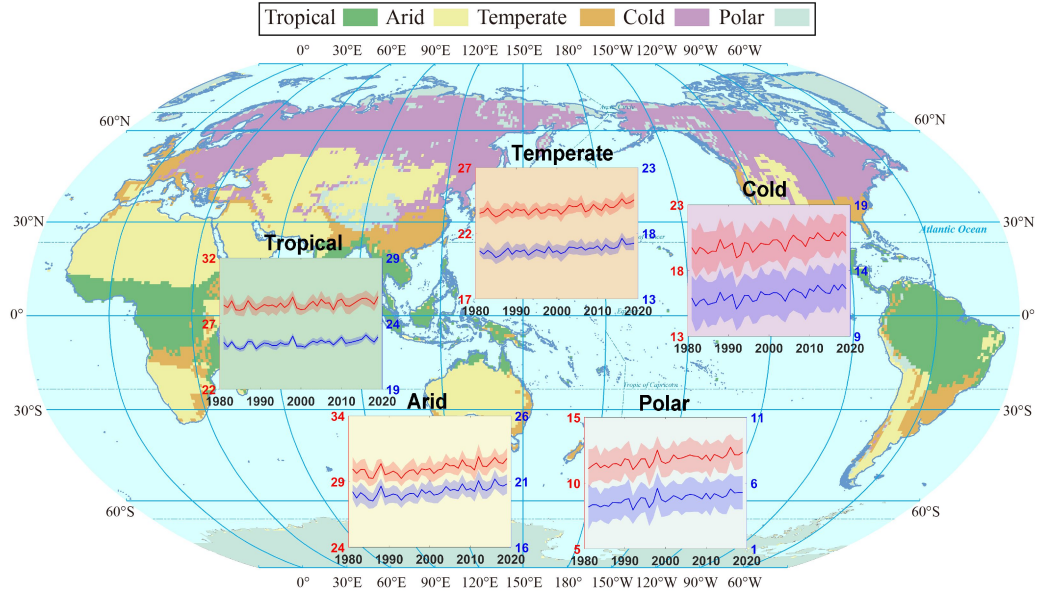


Fig. 1 Distribution of climate zones and their corresponding regional averaged temperature in summer during 1981–2019. The red curves denote the averaged $T_{\max}$ and the blue curves denote the averaged $T_{\min}$. The shadows denote temperature range within one standard deviation of each climate zone. 130 mm × 78.5 mm (600 dpi)

Mann–Kendall (mMK) test which is a nonparametric statistical climate prediction method (Mann, 1945; Hamed and Ramachandra Rao, 1998) based on the interannual changes of $T_{\min}$ and $T_{\max}$. Compared with the original MK version, the mMK method can even consider the autocorrelation in the time series, thereby providing an unbiased evaluation of the trend (Wang et al., 2019). The 95% confidence intervals are calculated as the middle 95% of the slopes of lines determined by pairs of points. Then two groups of summer temperature data were selected for analysis, 1982–1991 and 2010–2019, and the former was the based period. The study area was defined as 60°S–90°N and summer was defined as June to August in Northern Hemisphere and December to February in Southern Hemisphere. When calculating the global average temperature, we used the area-weighted method (Luo et al., 2022).

By analyzing the observed temperature data sets, non-Gaussian tails are common in different climate zones (Ruff and Neelin, 2012). Therefore, descriptive statistics including higher-order moments were used to examine the regularity of temperature change. It is superior to the Gaussian model in representing temperature PDFs, including the tails (Guirguis et al., 2018). The four moments include the mean, standard deviation, skewness, and kurtosis. The mean is the average temperature of the climate zone. The standard deviation represents the fluctuation in the temperature distribution. Skewness represents the dispersion degree of the temperature distribution. It implies the position of the relative modes of the average temperature with distinct lengths of cold tails and warm tails in the zones. Kurtosis represents the steepness of the temperature distribution and the

thickness of the tail, reflecting the temperature change of the extreme value. In this study, we use these parameters to calculate effects on heat wave probability arising from the rigid shift of the mean or the changes in scale or shape parameters. To be specific, an annual mean shift change was created by adding the mean temperature difference between the second period and the based period at each climate zone to the based period's daily temperatures (Saleem et al., 2021). When calculating the temperature distribution of each climate zone, the daily average temperature of each climate zone was used. The statistical characteristics of the distribution were calculated using the daily temperature of the climate zone (Huntingford et al., 2013).

To determine whether the data distribution conforms to the normal distribution, we used the Jarque–Bera test (Jarque and Bera, 1987; Tang et al., 2021). From the perspective of grids, it showed that the percentages of grids with non-normal distribution of $T_{\min}$ were 84.53% and 83.32% in 1982–1991 and 2010–2019, respectively. For the $T_{\max}$, these percentages were 86.84% and 88.98%, respectively (as shown in Fig. A1). From the perspective of climate zones, all of them are non-normally distributed, except for the arid and temperate climate zones for $T_{\max}$ during both periods. Consequently, we need to use nonparametric tests for statistical significance.

Corresponding to the mean and standard deviation, the nonparametric test methods were the Wilcoxon rank-sum test (Tingley and Huybers, 2015) and Levene homogeneity test (Conover et al., 1981), respectively. The Wilcoxon rank-sum test is a nonparametric procedure for testing differences between two populations. The null hypothesis tests whether the difference in the relevant

sample data comes from the population with a mean of 0. The Levene test was used to transform the data for one-way analysis of variance (ANOVA), which is used to test the homogeneity of variance of non-normal samples. A 90% confidence level was used in the above tests.

To explore the probability changes of extreme temperature, the climate percentile method was used to analyze the climate system in the designated area from the perspective of long-term probability statistics. According to the definition that extreme weather is a weather event with a small probability, the 95th percentile of $T_{\min}$ or $T_{\max}$ during the based period (1982–1991) was selected as the threshold value of extreme events, that is, a temperature above the threshold indicates extreme events (Anderson and Bell, 2011).

3 Results

3.1 Global climate changes

The mMK test showed that the annual mean $T_{\min}$ and $T_{\max}$ in summer increased in the past 40 years, with the mutation point appearing around 2005 (as shown in Fig. A2). The increasing trends of the global annual mean $T_{\min}$ and $T_{\max}$ were $0.232^{\circ}\text{C}/10\text{yr}$ and $0.227^{\circ}\text{C}/10\text{yr}$ in the summer of 1981–2019, respectively. Although it is slight compared with the weather fluctuation, the impact of warming is sufficiently large to draw extensive attention. The standard deviations of the global annual mean $T_{\min}$ and $T_{\max}$ were 0.324°C and 0.326°C in the past 40 years, respectively.

As shown in Fig. 2, we drew the temperature probability density distribution curves every ten years from 1981 to 2019 for comparison (Della-Marta et al., 2007). The trend over the past 40 years was consistent, only a few statistical characteristics had a slight reverse change. On the whole, the mean is moving to the hotter part, the standard deviation tends to increase and the shape parameters tend to decrease. It is similar to the research conducted by Hansen, which found that climate change of probability distribution shifted to the hotter part

and became wider in each successive decade from 1951 to 2011 (Hansen et al., 2012).

The increment of moments (i.e., mean, standard deviation, skewness, and kurtosis) for $T_{\min}$ and $T_{\max}$ in the two periods are shown in Fig. 3. The warming in the Arctic Circle was the most intense because of the amplification effect. The mean temperatures of the Eurasian continent and the Mediterranean generally showed a sharp increase because of the rapid human development. $T_{\min}$ in the Southern Hemisphere increased more intensely. To be specific, the increment of mean for $T_{\min}$ ($T_{\max}$) is 0.422°C (0.371°C) in the Southern Hemisphere while the increment is 0.810°C (0.773°C) in the Northern Hemisphere. The maximum warming for $T_{\min}$ ($T_{\max}$) is 3.434°C (2.695°C). Additionally, global warming was significant in most of the area. The area with significant increases of $T_{\min}$ was 89.35% of the global land, which was larger than that of $T_{\max}$ (77.3%). This is consistent with previous researches (Vose et al., 2005; Wang et al., 2017). However, some regions, such as western and northern Australia, South Africa, and the middle of the border area between the United States and Canada, show a cooling phenomenon.

The standard deviation also showed spatial heterogeneity. Regardless of $T_{\min}$ or $T_{\max}$, the fluctuation of the standard deviation exhibited trivial heterogeneity compared to the mean (Fig. 3(b)). And less significance was shown in standard deviation for $T_{\min}$ (73.59% of global land area) and $T_{\max}$ (70.44%) than the mean. The standard deviations of $T_{\min}$ and $T_{\max}$ in the same place exhibited the same change, but the extent of $T_{\max}$ was larger than that of $T_{\min}$. In the high-latitude region, except in Greenland, the standard deviation decreased significantly over a large area. In central and eastern Europe, South America, Oceania, and north of Greenland, the standard deviation significantly increased. The variation in the standard deviation was more significant in regions with substantial fluctuation.

The shape parameters, including skewness and kurtosis, performed differences geographically (Figs. 3(c) and 3(d)). The skewness of temperature increased in most regions but decreased in a few irregular regions. In other

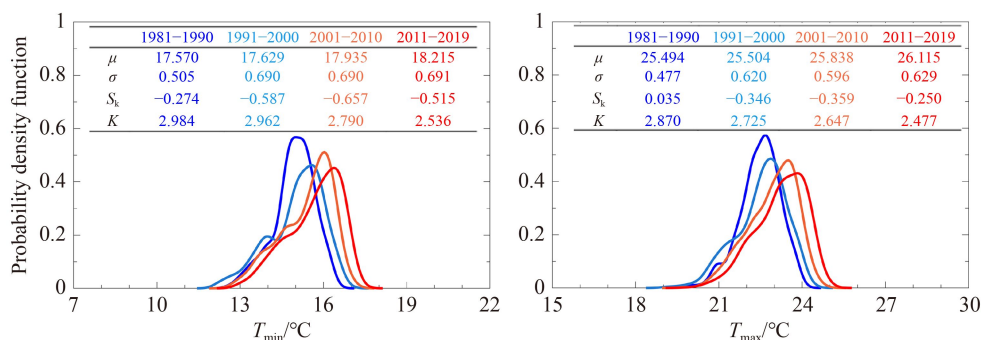


Fig. 2 Temperature probability density distribution curves of global. The left panel is for daily $T_{\min}$ and the right panel is for daily $T_{\max}$. μ denotes the mean, σ denotes the standard deviation, S_k denotes the skewness, K denotes the kurtosis. 125 mm × 44 mm (600 dpi)

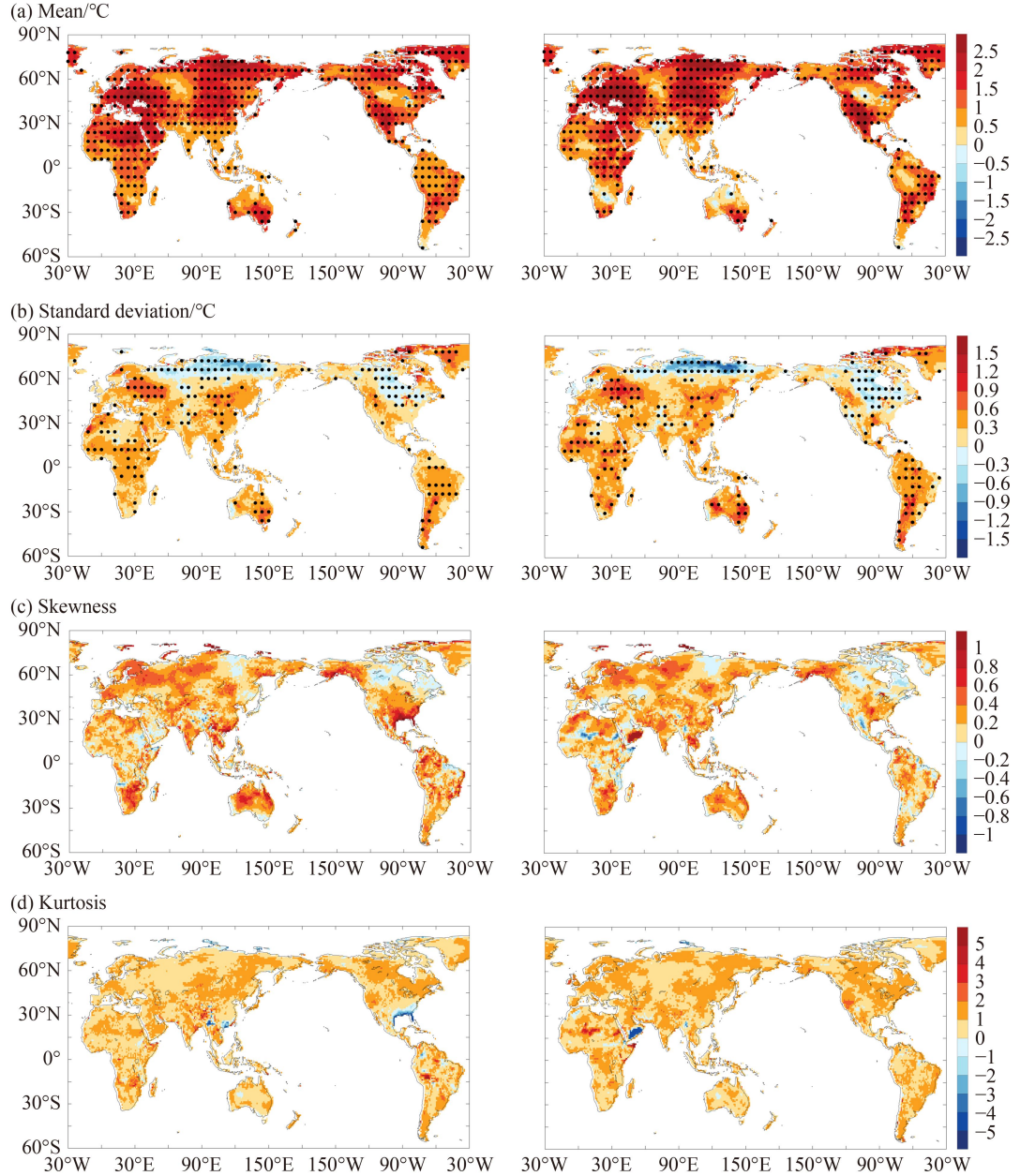


Fig. 3 The differences in moment statistics of (a) mean, (b) standard deviation, (c) skewness and (d) kurtosis between the two time periods of 1982–1991 and 2010–2019 for each grid box. The left panels for daily $T_{\min}$ and the right panels for daily $T_{\max}$. Hatching indicates the difference between the two periods that are significant at the 90% confidence level. Two figures in each row share the same legend. 125 mm $\times$ 152 mm (600 dpi)

words, the mode of temperature became higher than the mean in most regions. The regions with a large variation of skewness for $T_{\min}$ are relatively scattered, with the most intense increase on the south-east coast of the United States, South Africa, and northern Australia, and the largest variation in the Middle East for $T_{\max}$. With respect to the relatively small change in mode of temperature, the increase in skewness reflects that the mean increased rapidly and is more likely to have an extreme value. In most regions, except the south-east coastal areas of the United States and China for $T_{\min}$ and

the Middle East for $T_{\max}$, kurtosis increased by 0–2, which is about 15% of the difference between maximum kurtosis and minimum kurtosis. This implies that the shape near the peak of temperature distribution becomes steeper than the previous, and the thick tail phenomenon is more likely to occur, which leads to more extreme events.

From the changes of these parameters, it can be seen that the distribution characteristics of temperature function show spatial heterogeneity, which may be related to climate background. However, there are few

pieces of research identify the key controlling factors for the temperature probability density function in different climate zones, which motivates our analysis in the following section.

3.2 Regional climate changes in different climate zones

As shown in Fig. 1, in the past 40 years, the maximum increments of the mean and the maximum standard deviation for $T_{\min}$ were located in cold ($0.305^{\circ}\text{C}/10\text{yr}$, 0.508°C) and the minimum increment of the mean and the minimum standard deviation were in tropic ($0.137^{\circ}\text{C}/10\text{yr}$) and temperate (0.323°C). In terms of $T_{\max}$, the maximum increments of the mean and the maximum standard deviation were located in cold ($0.338^{\circ}\text{C}/10\text{yr}$) and polar (0.458°C) and the minimum standard deviation were in tropic ($0.133^{\circ}\text{C}/10\text{yr}$) and arid (0.259°C).

The changes in the moments for $T_{\min}$ and $T_{\max}$ in different climate zones are listed in Table 1. The mean and standard deviation increments of $T_{\min}$ and $T_{\max}$ in the same region were no more than 0.1°C . All the means increased significantly at the 90% confidence level.

By drawing the PDF curves, we can infer which parameter changes caused climate changes in each zone. The distribution shapes of each climate zone presented various patterns and characteristics, as shown in Fig. 4. The distribution of temperature is affected by many factors, including large-scale atmospheric circulation, local thermodynamics, radiation and small-scale effects (Linz et al., 2020). Complex physical mechanisms lead to diversified temperature changes on the earth.

From the PDF curves during the periods of 1982–1991 and 2010–2019, the distributions of $T_{\min}$ and $T_{\max}$ in tropic fluctuated in a small range. In particular, the probability distribution of $T_{\min}$ exhibited a typical thin and high shape. Since the tropic receives more radiation than middle and high latitudes, the mean daily minimum temperature and the mean daily maximum temperature

are above 20°C in summer. This is a typical characteristic of temperatures in low latitude and implies that the diurnal temperature range was small and $T_{\min}$ maintained stably in summer.

As the mean temperature of the tropical zone shifted to the warmer part, the standard deviation increased, and the shape of the distribution changed substantially (Fig. 4(a)). Concerning changes in the moment, the mean of $T_{\min}$ and $T_{\max}$ were increased by 0.436°C and 0.423°C during the study period, respectively. These changes were smaller than those in other climate zones. These changes are smaller than those in other climatic zones. The significant change in standard deviation has attracted our attention. The distribution tended to widen across the study period, implying that the temperature range increased. The change of standard deviation in tropic for $T_{\max}$ was 0.068°C in particular, which was the largest among the climate zones. The skewness was positive, whereas the change was slightly negative for $T_{\min}$. This suggests that the gap between mode and mean of $T_{\min}$ shrank during this period, although the former was lower than the latter all the time. Therefore, the warming trend can be observed for most daily night-time temperatures in summer. However, the skewness for $T_{\max}$ became larger than the previous period, it suggests that the mean move to the hotter part faster than the mode. The kurtosis of $T_{\min}$ and $T_{\max}$ increased, especially for $T_{\min}$. This means that thick tails become obvious and more extreme events are prone to occur in the tropics. Actually, the mechanism of ‘warmer and wetter’ in the tropics has played a key role in the context of global warming (Huang et al., 2013). The rising temperature lifts the wetter atmosphere, resulting in an increase in precipitation. And the increase in precipitation leads to wetter surface soil, resulting in a decrease in the minimum temperature fluctuation and a more leftward distribution.

Arid and temperate zones are present in most mid-latitude areas (Figs. 4(b) and 4(c)). The PDF curves of

Table 1 The differences of order moments between the time period of 1982–1991 and 2010–2019 for $T_{\min}$ and $T_{\max}$

T	Climate zone	$\Delta\text{mean}/^{\circ}\text{C}$	$\Delta\text{standard deviation}/^{\circ}\text{C}$	$\Delta\text{skewness}$	$\Delta\text{kurtosis}$
$T_{\min}$	Tropical	+ 0.436	+ 0.012	− 0.039	+ 0.323
	Arid	+ 0.678	− 0.014	+ 0.213	− 0.086
	Temperate	+ 0.543	− 0.005	+ 0.043	− 0.159
	Cold	+ 0.850	− 0.111	+ 0.033	− 0.041
	Polar	+ 0.676	− 0.002	+ 0.112	− 0.079
$T_{\max}$	Tropical	+ 0.423	+ 0.068	+ 0.002	+ 0.153
	Arid	+ 0.680	− 0.002	+ 0.063	+ 0.263
	Temperate	+ 0.535	+ 0.006	+ 0.197	− 0.900
	Cold	+ 0.918	− 0.179	+ 0.069	− 0.105
	Polar	+ 0.682	− 0.022	+ 0.184	− 0.111

Note: Bold text indicates the difference is significant at the 90% confidence level.

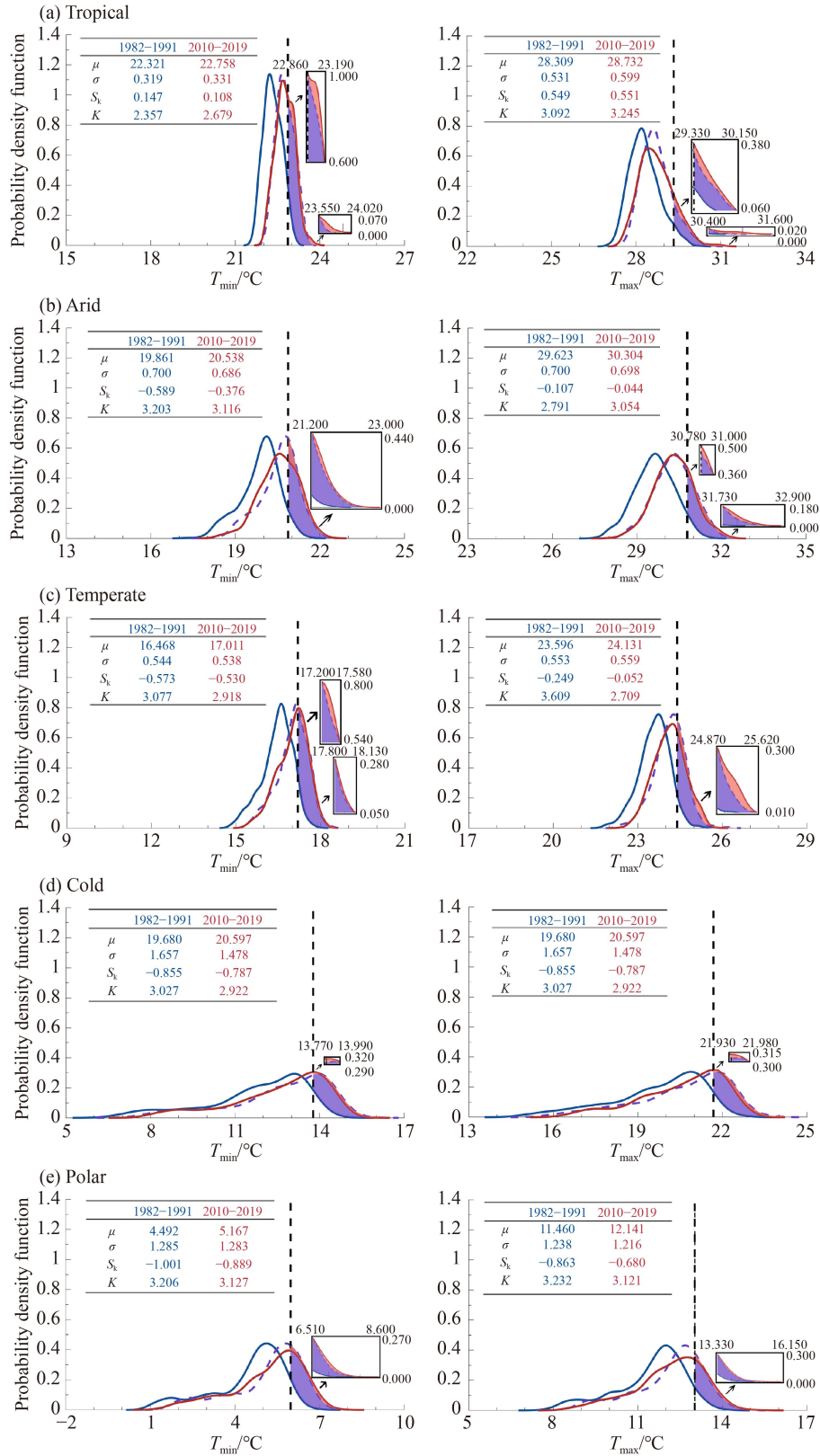


Fig. 4 Temperature probability density distribution of different climate zones. The left panels for daily $T_{\min}$ and the right panels for daily $T_{\max}$. μ denotes the mean, σ denotes the standard deviation, S_k denotes the skewness, K denotes the kurtosis. Bold indicates the change is significant. The dashed lines represent the 95th percentiles distribution of based period. The purple shadow indicates the changing probability of extreme events caused by the rigid shift, the blue shadow indicates the negative effects and the purple in the box represents the positive effect caused by other parameters.

these climate zones are more likely to be bell-shaped. This may be due to the lack of vapor and there is more evapotranspiration in the arid zone. This phenomenon is reflected in the daily temperature range between $T_{\min}$ and $T_{\max}$, as well as the standard deviation. The negative skewness was shown at mid-latitudes. The characteristic of the arid zone is that the precipitation is generally less than a monotonic increasing function of temperature. Precipitation is the main factor affecting the decadal variation of soil moisture. Soil moisture is an indicator of climate change, and its interaction with soil freezing and thawing state and underlying surface characteristics affects the energy balance (Wu et al., 2020). The climate in the arid zone is dry and the evapotranspiration is small. There are sparse vegetation and less heat consumption by photosynthesis. What's more, the surface albedo is large, and the energy of net solar radiation is mainly converted into sensible heat flux, which is reflected in the extreme temperature when the soil moisture is low. It shows in the distribution that the mode of temperature was hotter than the mean. The kurtosis in arid zone was larger than that in the temperate zone in the second period. It suggests that extreme events occur in arid zones with a higher probability in recent years.

The warming of $T_{\min}$ and $T_{\max}$ in mid-latitudes was approximately 0.6°C . It was higher than that in the tropical climate zone. Furthermore, the arid climate zone had a more intense warming trend than the temperate zone, owing to the low humidity and poor climate regulation ability. The increments of these zones were approximately 1.5 times of global change, which is in accordance with the IPCC AR6 report (Masson-Delmotte et al., 2021). The results show that the standard deviation was almost unchanged comparing 1982–1991, while the shape parameter in arid and temperate zones changed significantly. The skewness of $T_{\min}$ for arid and $T_{\max}$ for temperate increase steeply. This indicates that the change in the mode of temperature is slower than that of the mean and the mean plays a key role in climate change at mid-latitudes. The increase in kurtosis for $T_{\max}$ in the arid zone suggests that the temperature distribution tends to be steep and the tail of extreme hot becomes thickened. Therefore, changes in skewness and kurtosis make a substantial influence on changes of $T_{\max}$ in the arid climate zone compared with other zones. However, the change in kurtosis under other conditions was controlled in a retracted tail. This implies that the mean was the domain factor in the mid-latitude area.

The cold and polar zones are mostly located at high latitudes (Figs. 4(d) and 4(e)). In this area, the diurnal temperature ranges were similar, although the temperature of the polar was lower than that of the cold. Their PDF curves were flat, especially for the cold zone, reflected in a large standard deviation. The negative skewness and large absolute values were found in these areas suggest that there were several extreme cold

temperatures occurred than the extreme high temperature. For most of the conditions, the kurtosis was larger than 3. It represents the curve was steep around the peak.

The increment of the mean in the high-latitude zone was much higher than that in the mid-low latitudes. The $T_{\min}$ and $T_{\max}$ in both climate zones increased strikingly by about 0.7°C , which was almost twice than the global average. This finding agrees with the results of former studies (Screen, 2014; Routson et al., 2019). The standard deviation in the cold decreased significantly, whereas the shape parameter changed slightly. The distribution in the cold zone tended to narrow significantly and the temperature was more concentrated. Although the change rate of the mode of temperature in the cold zone was slower than the mean, the mode of temperature in the cold zone was also moving toward the hotter part because of the warming amplitude. Thus, the extreme temperature of this area was not caused by standard deviation. In contrast, the skewness of the polar increased relatively large, while the standard deviation and kurtosis changed slightly. For the polar zone, the variation in skewness for $T_{\min}$ was less than that of $T_{\max}$, but the changes in the mean were similar. The change in mode for $T_{\min}$ was faster than that of $T_{\max}$. It implies that the diurnal temperature range was likely to decrease. This phenomenon reveals that the mode of temperature shifts to the hotter part is slower than the mean, that is, the effect of the shape parameters was little. Taking the Qinghai-Tibet Plateau as an example, since the 21st century, the evapotranspiration of the underlying surface of the Qinghai-Tibet Plateau has been increased (Huang et al., 2016b). And the water vapor content has increased significantly, which may lead to a small fluctuation range of sensible heat flux and the changes in mode are not as large as the mean.

3.3 Changes in the probability of extreme events

Both the observed and simulated models have proven that location parameters (i.e., mean), scale parameters (i.e., standard deviation), and shape parameters (i.e., skewness and kurtosis) play a critical role in distinguishing the occurrence of extreme events. We wondered that what extent had changed for the probability of temperature extremes in different climate zones under global warming. The tail characteristics of PDF in climate zones can explain the changes of extremes under global warming. Taking the 95th percentile of the based period as the threshold, the changes in the occurrence probabilities of extreme events in each climate zone were calculated, as shown in Table 2. And we decomposed the changes into a rigid shift of mean, the positive and negative effects of other parameters (as shown in Table 3). The rigid shift implies that magnitude of warming. The other parameters suggest the scale and the shape of the tail.

The enhancing occurrence of the extreme event caused by the increase for $T_{\min}$ was larger than that of $T_{\max}$,

Table 2 The probability changes of $T_{\min}$ and $T_{\max}$ extreme value in different climate zones

T	Climate zone	Threshold/(°C)	1982–1991	2010–2019	Probability changes
$T_{\min}$	Tropical	22.86	4.89%	38.37%	33.48%
	Arid	20.87	4.78%	33.48%	28.70%
	Temperate	17.20	5.00%	40.98%	35.98%
	Cold	13.77	4.67%	27.83%	23.16%
	Polar	5.98	4.89%	31.30%	25.33%
$T_{\max}$	Tropical	29.34	4.89%	16.30%	11.41%
	Arid	30.78	4.89%	24.67%	19.78%
	Temperate	24.39	4.89%	31.74%	26.85%
	Cold	21.68	4.78%	28.15%	23.37%
	Polar	13.03	4.89%	25.65%	20.76%

Table 3 The probability changes decomposition in different climate zones

T	Climate zone	Probability changes	Changes caused by the mean*	Other parameters' effects	
				Positive	Negative
$T_{\min}$	Tropical	33.48%	32.50% (97.07%)	3.80%	− 2.82%
	Arid	28.70%	29.57% (103.03%)	2.18%	− 3.05%
	Temperate	35.98%	35.00% (97.28%)	3.60%	− 2.62%
	Cold	23.16%	27.72% (119.69%)	0.22%	− 4.78%
	Polar	25.33%	23.70% (93.56%)	1.80%	− 0.17%
$T_{\max}$	Tropical	11.41%	8.48% (74.32%)	3.37%	− 0.44%
	Arid	19.78%	20.54% (103.84%)	2.18%	− 2.94%
	Temperate	26.85%	27.28% (101.60%)	3.91%	− 4.34%
	Cold	23.37%	26.74% (114.42%)	1.85%	− 5.22%
	Polar	20.76%	19.35% (93.21%)	2.18%	− 0.77%

Note: *: the proportion in brackets indicates the proportion of right shift change in the total change.

which is consistent with findings of Zhang et al. (2019). For all climate zones, simple warming caused most of the changes in the probability of extreme events as Fig. 4 showed. And the rigid shift of $T_{\min}$ is more likely to experience the extremes than that of $T_{\max}$. $T_{\min}$ in the tropic zone, increased by 33.48%. It almost six times of the first stage. Among them, about 32.50% were caused by simple shift increases, the effects of other parameters caused 2.93% including 3.80% positive effects. In contrast, the change of extreme value for $T_{\max}$ in the tropical zone only increased by 11.41%, which was smaller than that in the other climate zones. With a slight kurtosis increasing, the standard deviation change in this climate zone was significant and intensive compared with other climate zones. From the PDF curves, the warming effect caused by the standard deviation was small, while the shape changes of the temperature distribution played an important role in the probability change. These parameters lead to 3.37% positive effects and − 0.44% negative effects. Additionally, kurtosis change leads to an obvious probability change, which is 0.76%. The longer warm tails and the shorter cold tails appear in $T_{\max}$ more obviously than that in $T_{\min}$.

In the arid climate zone, mean and skewness are the dominant factors driving the heat events. And the kurtosis for $T_{\max}$ also contributed to the extreme events a lot. It implied by the tail becoming thickened under global warming, resulting in 1.52% increase in extremes. The positive shift of skewness implies that the mode of temperature did not rapidly increase to the extreme part yet. Moreover, the occurrence of hot extremes for $T_{\max}$ increased by 20.54% in the arid zone. Combined with PDF curves shown above, there are only −0.002 changes in standard deviation. So, the change caused by skewness almost contributes −2.94% negative effects on the extremes. According to the analysis of the statistical characteristics in climate zones, the temperate zone is the region with the largest increase in extreme values for $T_{\min}$, about 35.98%. The mean has a strong impact on extreme events and contributed almost 97.28% of the whole increment. Both $T_{\min}$ and $T_{\max}$ in arid and temperate climate zones experienced changes of longer warm tails and shorter cold tails. The probabilities of extreme temperatures for $T_{\min}$ and $T_{\max}$ in the arid and temperate zones increased by about 30% and 20%. Under the background of climate change, the extreme weather in

the temperate zone is indirectly affected by large-scale circulation. Previous studies found that, with the disappearance of Arctic sea ice, the propagation speed of Rossby wave in the upper troposphere slows down and the descending motion in the middle latitude is significantly enhanced, which will result in the increase of the extreme heat in the East Asian monsoon region in the temperate zone of the northern hemisphere (Tang et al., 2014). Furthermore, the cold anomalies in the Arctic becomes more frequent in summer since 2005 (Luo et al., 2020). With the enhancement of tropospheric westerly wind in the Arctic and the weakening of the westerly wind in the middle and low latitudes of Asia, these weather conditions are conducive to the emergence of the thermal extreme in East Asia.

Although the increment of extremes in high latitude areas are similar, the negative effect caused by the shape parameter in the cold area is greater than the positive effect while the polar is the opposite. It proved that shape changes can buffer the warming because of the negative effects. Moreover, it also shows that a longer warm tail and a shorter cold tail in the polar due to the increase of skewness. But the contribution of shape parameters in the cold zone is about 15%, which is greater than that in the polar which is about 7%. Comparing the $T_{\max}$ and $T_{\min}$, the shape parameters play a more significant role in $T_{\max}$. In summary, the extremes of each zone increased, but the parameters led to different positive and negative effects on the more extreme parts.

4 Discussion

4.1 Adapt to the climate changes and extreme events

According to our results, in the past 40 years, climate zones have warmed by from 0.4°C to 1°C. Based on this trend, it will be challenging to keep global warming within 2°C of pre-industrialisation levels as recommended in the Paris Agreement, which has also been found in former studies (Tollefson, 2015; Raftery et al., 2017). Climate change can be attributed to historical greenhouse gases, historical anthropogenic aerosols and historical natural forcing (Hu and Sun, 2021).

The warming on the large scale is linked to the expected increase in greenhouse gas while the localized cooling results from the radiative effect of the aerosol (Schneider and Held, 2001). Understanding the physical mechanism of climate is helpful to explain the asymmetry of regional PDF (Ruff and Neelin, 2012). As for the distinct warming trend in five climate zones, the most significant natural forcing may be the complex and diverse land surface and subsurface characteristics. The surface characteristics will affect the balance of the energy budget, and then the advection from land, the sea breeze, and ocean air temperatures changed (Ruff and

Neelin, 2012). As a result, climate zones with different air temperature regulation capacities performed various shapes of tail. For example, the Arctic is covered with glaciers and snow and the underground contains greenhouse gases. The decreasing variance and retracted tails are related to the reduction of snow cover, which affects the local temperature change through the changes of surface heat flux and albedo feedback in large-scale circulation patterns (Screen, 2014). While land-air interaction is an important factor of climate change in arid areas. The reduction of convective latent heat heating on the surface of the desert strengthens the convective subsidence movement, the corresponding monsoon circulation weakens and the precipitation decreases (Xue and Shukla, 1996). What's more, the extremes can be driven by the atmospheric environment, such as interactions between atmospheric blocking and local feedbacks (Miralles et al., 2014). And it may also relate to abnormal climatic phenomena, including El Niños, La Niña, caused by distinct atmospheric circulation (Grotjahn et al., 2016; Gao et al., 2020; Luo and Lau, 2020).

More importantly, most studies have confirmed that the anthropogenic forcing contributed the most to the extreme events (Mitchell et al., 2016; Wang et al., 2017; Ma et al., 2020), especially for summer heat stress (Knutson and Ploshay, 2016). The level of social development varies in different climate zones, which may be a factor leads to the different performance of PDF changes. It is urgent that we take various measures to deal with the risk of climate change by considering the differential causes of parameters.

First of all, the mean temperature move to a warmer climate is inevitable. We must improve technology to reduce the emission of carbon dioxide and other greenhouse gases and enhance the resilience of infrastructures to adapt to high temperatures. We should notice that the social impact caused by unbalanced changes of extreme during the day ($T_{\max}$) and night ($T_{\min}$). The extremes of $T_{\max}$ may increase the consumption of water and energy while the extremes of $T_{\min}$ may prevent people from recovering from rest and affect human health (Guirguis et al., 2018).

Considering the distribution and probability change of temperature, the temperature increases in the tropics are mainly controlled by increasing $T_{\min}$. Therefore, the environment is stable in a high temperature. At present, several studies have shown that limiting global warming to below 1.5°C could prevent most of the tropical climate zones from reaching the critical threshold (Zhang et al., 2021). And the relationship between CO₂ emissions and temperatures are significantly positive (Gil-Alana and Monge, 2020). Therefore, afforestation is required to increase carbon sequestration to prevent warming. And the increasing of interday-interday temperature variability which is revealed by the increment of the standard deviation, can increase the probability of people suffering

from diseases, such as chronic obstructive pulmonary disease (Tian et al., 2021). A little increment of standard deviation caused large changes in the probability of extreme events. Therefore, it is necessary to strengthen the health care and build the temporary shelters to prevent the loss of heat waves.

The increment of $T_{\min}$ extreme events in the temperate zone follows the tropic, while the increment of $T_{\max}$ is the highest. The highest degree of overall urbanization occurred in this zone and urbanization plays a key role in climate change (Sun et al., 2014). This suggests that people living in temperate zone are more likely to suffer from heatwaves. We can strengthen the resilience of buildings to protect people in a safe shelter and improve medical treatment to reduce death from heatwaves. In arid zones, the temperature is most affected by the shape and location parameters. Strengthening ecological restoration may be an effective means for this zone to prevent increases in mean and mode of temperature.

In high latitudes climate zones, increases in temperature are mainly caused by simple shifts of the entire distribution. The increase in the extreme value of $T_{\max}$ was large, especially for the polar climate zone. Methane released from melting glaciers induced the Arctic amplification effect, aggravating extreme high temperatures. Hence, it is necessary to improve the response capacity by protecting marine resources and glaciers and increasing the coverage of snow to address climate change in this zone. The probability changes in the cold cannot be neglected. Although fewer people live in high latitudes, human impacts are still existing (Qian and Zhang, 2015). Human intervention could adjust the expected climate change. It can be further studied to better quantify the change of extreme event risk probability and intensity caused by anthropogenic and natural forcing (Zhai et al., 2018).

4.2 Robust tests of time series

Geospatial differences in the probability of extremes are due to the shape of PDF across the climate zones. It may be discrepant in the uncertainty of probability change caused by different samples. Therefore, we conducted several experiments to determine whether our conclusions were affected by the based period, duration. The following experiments showed that the characteristics of climate change determined in this study were robust and effective.

Taking the duration into account, it may impact the number of samples and cause different distribution of PDF curves. We used five-year data of 1982–1986 and 2015–2019 to verify the impact of duration. The spatial distribution of the statistics was almost the same while the results were more intense and significant than those of our previous experiments. To be specific, the mean for $T_{\min}$ and $T_{\max}$ have been increased by 0.94°C and 0.93°C on global scale. And the area with a significant mean is

92.08% and 78.75% of the global land area for $T_{\min}$ and $T_{\max}$, respectively. As for the standard deviation, they are 68.31% and 62.83% of the global land area for $T_{\min}$ and $T_{\max}$, respectively. There are slight differences in the shape parameters only in North Africa, Central South America, and Central North America (as shown in Fig. A3).

Considering the impact of the based period selected for the threshold of extreme events, it may cause changes in the probability of events. We changed the based period from 1982 to 1991 to 1982–1996. The difference between the 15-year threshold and the 10-year threshold was no more than 0.07°C. The difference in probability between this experiment and the previous one is no more than 2.10%. And the increment of probability is also mainly caused by the mean (as shown in Table A1).

Therefore, the conclusions in our previous experiments are robust to the replacement of threshold and based period.

4.3 Limitations of the study

There are several limitations of this study. Although the consistent conclusions can be summarized by various global climate models, however, there is also uncertainty in the amount of warming expected (Guirguis et al., 2018). Therefore, integrating multiple observation data sets (Huang et al., 2016a) and extending the length of the time series (Hansen et al., 2012; Johnson et al., 2018) are the possible ways to avoid uncertainty. Furthermore, the simulation results from different global climate models in the CMIP6 can be used to predict and analyze future climate change in different scenarios (King et al., 2017; Wang et al., 2017). The factors which influenced temperature distribution in different climate zones are various, resulting in diverse changes.

5 Conclusions

Using ERA-5 land daily temperature data set, we show different changes of order moment characteristics for temperature distribution over the globe. Summer temperature and extreme heat events had been focused. It helps us to understand regional differences in global warming. We present how the global daily temperature of both $T_{\max}$ and $T_{\min}$ have experienced changes in different climate zones from 1982 to 2019. Furthermore, the analysis of percentile changes in different climate zones helps us understand the frequent occurrence of extreme weather.

$T_{\min}$ and $T_{\max}$ in summer maintained a notable upward trend over the past 40 years. Moreover, these increases in $T_{\min}$ were considerably greater than those in $T_{\max}$. The changes in standard deviation and its significance are spatially heterogeneous. The regions with large temperature variations are more likely to be changed

significantly. The temperature fluctuation in the central and eastern Europe, North Asia and Western North America is more significant than the changes in South Asia, Central North America and South Africa. Spatial heterogeneity also exists in skewness and kurtosis. The most intense increase of skewness for $T_{\min}$ is scattered, and the largest variation for $T_{\max}$ is in the Middle East. Kurtosis increased by 0–2 in most regions, which is about 15% of the difference between the maximum and minimum kurtosis.

The effects of a simple shift toward a warmer climate contributed to all climate zones, while the changes of the extreme temperature caused by standard deviation, skewness and kurtosis are small except for the tropic for $T_{\max}$. Specifically, the tropical zone is a typical climate zone that combines changes of all parameters. The extreme temperature in arid zone is associated with changes in the location and shape parameters, and the location parameter (i.e., the mean value) leads to the majority of extreme events while moving to the warmer part. Except for $T_{\max}$ in the polar zone, the climate changes in cold and polar zones and $T_{\min}$ in temperate zone are intensively influenced by the mean. Thick tailed distribution is common in the middle and low latitudes while thin tails are occurred in the high latitudes.

Quantile analysis shows that global extreme events are increasing in frequency and intensity. The $T_{\min}$ of the temperate zone rose by 35.98%, whereas that of the cold climate zone rose only by 23.16%. With respect to $T_{\max}$, the greatest increase was 26.85% in the temperate zone and the smallest was 11.41% in the tropical zone. The rigid shift of mean contributes most to the changes of extremes in the cold for $T_{\max}$ and $T_{\min}$. The scale and shape parameters in the tropic for $T_{\max}$ result in the largest proportion of change of extremes among all the climate zones. When we changed the duration and period of time series, we had the similar conclusions.

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Appendices

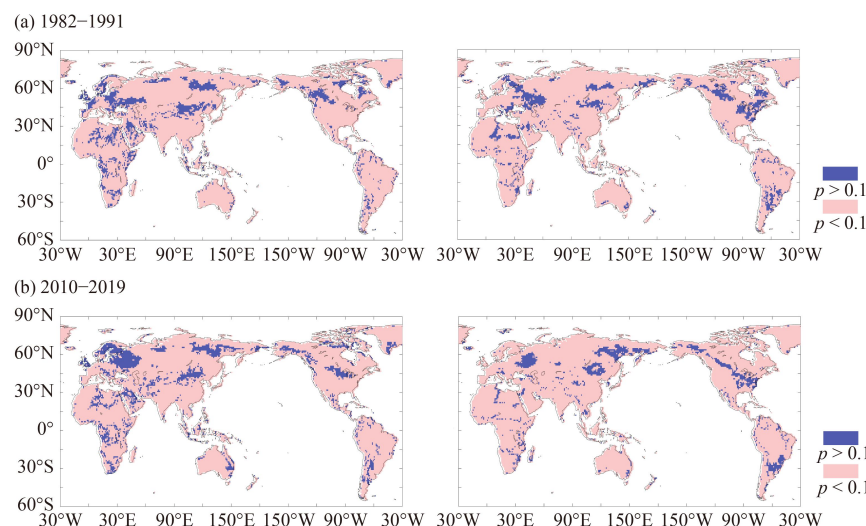


Fig. A1 P value of Jarque-Bera test for raster distribution in 1982–1991 and 2010–2019. The left panels for daily $T_{\min}$ and the right panels for daily $T_{\max}$. 122 mm × 80 mm (600 dpi)

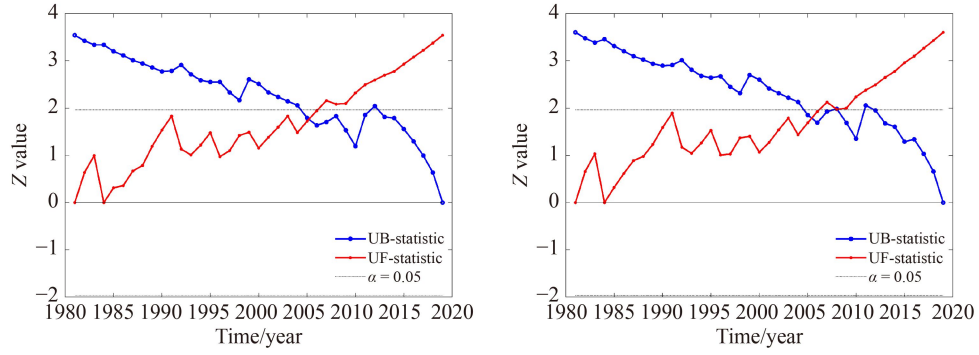


Fig. A2 The mMK test for global annual $T_{\min}$ and $T_{\max}$ in the past 40 years. The left panel is for daily $T_{\min}$ and the right panel is for daily $T_{\max}$. 130 mm $\times$ 50 mm (600 dpi)

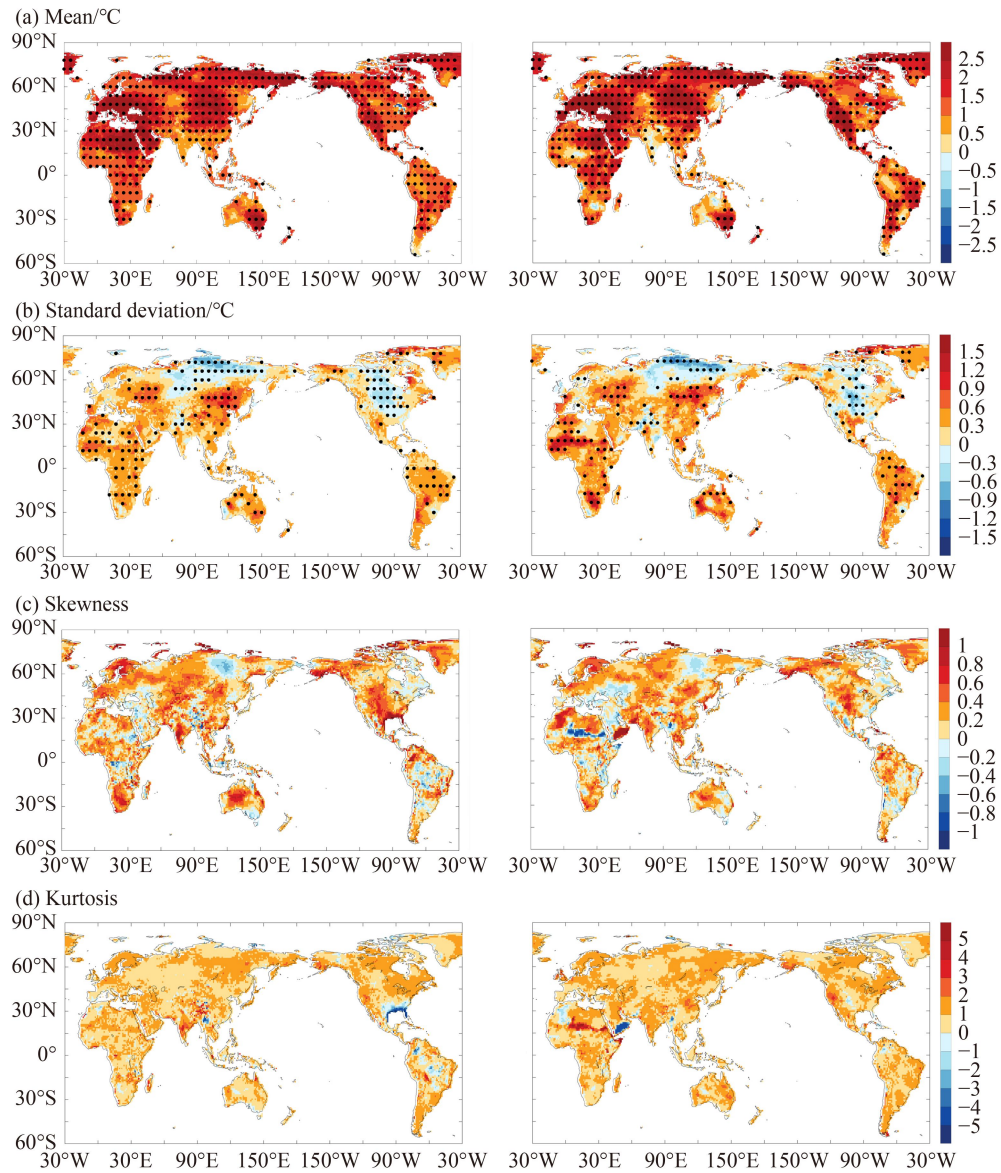


Fig. A3 The differences in moment statistics of (a) mean, (b) standard deviation, (c) skewness and (d) kurtosis between the two time periods of 1982–1986 and 2015–2019 for each grid box. The left panels for daily $T_{\min}$ and the right panels for daily $T_{\max}$. Hatching indicates the difference between the two periods that are significant at the 90% confidence level. Two figures in each row share the same legend. 140 mm $\times$ 170 mm (600 dpi)

Table A1 The probability changes of $T_{\min}$ and $T_{\max}$ extreme value in different climate zones

T	Climate zone	Threshold/°C	1982–1991	2010–2019	Probability changes	Changes caused by the mean
$T_{\min}$	Tropical	22.87	4.57%	37.50%	32.93%	32.06%
	Arid	20.80	6.20%	36.74%	30.54%	32.28%
	Temperate	17.19	5.00%	41.63%	36.63%	35.11%
	Cold	13.74	5.33%	29.24%	23.91%	27.93%
	Polar	5.99	4.67%	29.67%	25.00%	23.16%
$T_{\max}$	Tropical	29.40	3.70%	13.80%	10.10%	7.93%
	Arid	30.73	5.76%	26.63%	20.87%	21.74%
	Temperate	24.43	4.57%	29.35%	24.78%	24.45%
	Cold	21.66	5.22%	29.35%	24.13%	26.63%
	Polar	13.06	4.78%	24.78%	20.00%	18.48%