Chinese Journal of Population, Resources and Environment 23 (2025) 62–74

Chinese Journal of Population, Resources and Environment

Comprehensive index of extreme climate risk in China and urban sustainable development

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ARTICLE INFO

Keywords:
Urban sustainable development
SDG 13
Comprehensive index of extreme climate risk
Climate change

ABSTRACT

Climate change severely challenges our ecosystem and society, affecting urban residents' socioeconomic activities. Thus, assessing severe weather risk is crucial for evaluating urban sustainability; understanding trends, causes, and impacts on socioeconomic development; and supporting the United Nations Sustainable Development Goal (SDG) 13. Using meteorological data from 1980 to 2020, we investigate five disaster-causing severe weather events in China and construct a comprehensive index of extreme climate risk (CIECR) at the county, city, province, and national levels. The CIECR can identify high-risk regions and primary severe weather events and provide early warnings. We empirically test the impact of extreme climate risks on agricultural production, industrial structure, and labor employment. The results show high risks in Xinjiang, northern Inner Mongolia, and southern regions, with high temperatures, low temperatures, and high winds as the leading risks. At the national level, the extreme climate risk fluctuates, indicating climate warming. While risks reduce agricultural production and employment, they promote modern agriculture, industrial production, and urbanization. The novelty of the study lies in its development of the county-level CIECR, which can capture heterogeneity characteristics and provide microdata support for urban climate change research and efforts toward SDG 13. This study aids in mitigating climate risks; responding to climate change; and comprehensively analyzing the causes, trends, and impacts of extreme climate risks.

1. Introduction

Climate change severely challenges our ecosystem and society (Walsh et al., 2020). Extreme climate risks are a significant global challenge caused by the increasing variability and intensity of climate change – related severe weather events. In recent years, severe weather, such as high temperatures and torrential rains, has become the focus of concerns among urban residents, profoundly affecting their social and economic activities and happiness. Severe climatic disasters such as rainstorms and typhoons have become frequent, causing heavy economic losses and casualties. Thus, comprehensively assessing severe weather risks is important for evaluating the sustainable development of cities and communities. Such assessment can evaluate the direct impact of climate change, help us understand the trends and causes of severe weather, and identify potential effects on economic and social development (Landrum and Holland, 2020). Additionally, it can help develop monitoring methods and tools to achieve the United Nations Sustainable Development Goal (SDG) 13, demanding urgent action to address climate change and its impacts. Such action requires reliable and comprehensive information on climate change, for which this paper provides data support.

Based on the characteristics of severe weather in various regions of China and the socioeconomic impacts of different types of severe weather events, we use monthly meteorological data from 1980 to 2020 to study five severe weather events that caused disasters in the country: high temperatures, low temperatures, heavy precipitation, high winds, and tropical cyclones. For each severe weather event, we use the traditional index to construct a single severe weather index and standardize it. We then build the comprehensive index of extreme climate risk (CIECR) based on each county's climatic characteristics and historical data. First, at the county level, Xinjiang and northern Inner Mongolia show the highest levels of extreme climate risk. Notably, extreme climate risk indexes have increased rapidly in northwest Xinjiang, Shaanxi, Jiangsu, and eastern Gansu. At the municipal and provincial levels, southern regions have recently experienced a significant increase in extreme climate risk and are in a high-risk

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https://doi.org/10.1016/j.cjpre.2025.01.006
Received 24 January 2024; Accepted 15 August 2024
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state. Second, high and low temperatures and high winds are the primary sources of risk in high-risk counties. High temperatures and heavy precipitation are the main extreme climate events in most high-risk provinces, consistent with Fischer and Knutti's (2015) results. Third, at the national level, the CIECR decreased in the last century but increased in recent years. Global warming is apparent based on the high- and low-temperature risk indexes. The CIECR can be used to obtain early warnings about global warming and climate change. Moreover, people are particularly perceptive to hot weather (Dai et al., 2015). Constructing a CIECR helps improve public adaptation after extreme weather events, especially heat waves. Finally, we use county-level economic panel data to empirically examine the impact of extreme climate risks on sustainable development. The CIECR signi ficantly reduces agricultural production, inhibits agricultural development, shrinks employment, and is inconducive to economic development. However, as extreme climate risks increase, they promote the development of modern agricultural and industrial production as well as the migration of the labor force from rural to urban areas, leading to urbanization.

Most research focuses on a single extreme climate event or extreme climate risk in a particular city or region of China (Ren et al., 2010a; Ren et al., 2010b; Wang et al., 2010; Yan et al., 2001; Zhai et al., 2005). Bucchignani et al. (2017) used the regional climate model COSMO-CLM to simulate extreme events in China but did not construct an early warning system for extreme climate risk. Only a few comprehensive indicators are available and only at the national level, making it difficult to conduct detailed county- or province-level analyses. In particular, there are significant differences in geographical characteristics and climate across provinces in China, which face vastly different extreme climate risks. This paper comprehensively assesses extreme climate risks in each county, city, province, and country using meteorological data and geographic grid points. It scientifi cally constructs comprehensive indexes of extreme climate risk to provide data support for research and analysis of climate change and sustainable urban development. This paper constructs a municipal extreme climate risk index, which it uses to systematically analyze the spatiotemporal changes in extreme climate risks in several of China's counties, provide climate risk warnings, empirically test the impact of extreme climate risks on urban sustainable development and comprehensively determine the reasons, development trends, and consequences of extreme climate risks.

The rest of the paper is organized as follows. Section 2 provides the data source and the methodology for constructing the CIECR. Section 3 shows the characteristics of the calculated CIECR at the county, city, province, and national levels. We test the CIECR's effects on economic development at the county level in Section 4. Section 5 concludes the paper.

2. Methodology and data

Attention to severe weather events varies significantly among regions within the same country. Based on local conditions in China and commonly used indicators in the literature, we selected fi ve severe weather events and their corresponding indicators: high temperatures (Htem), low temperatures (Ltem), heavy precipitation (rain), frequent tropical cyclones (typhoons, abbreviated as typh) and high winds (wind). The five selected severe weather events are common in China and can result in severe disasters. High temperatures can cause water and electricity shortages, heatstrokes, and even death. Frost, freezing, and cold during low temperatures can cause severe losses to agricultural production. Heavy precipitation events cause flood disasters, resulting in signi ficant economic losses and casualties. Tropical cyclones (typhoons) produce heavy rain and high winds, causing severe floods and windstorms. High-wind events other than typhoons also cause considerable local damage.

2.1. Data

Meteorological data from the China Meteorological Data Service Center (http://data.cma.cn/) comprise daily minimum and maximum temperatures, precipitation, and maximum wind speeds (m/s) recorded at 839 meteorological stations from 1980 to 2020. Given that the original data are measured at irregularly located stations, a direct regional aggregation would result in data gaps for certain districts or cities due to the absence of stations. To address this issue, we established grid data based on China's geographical divisions, interpolated the observational values onto these grids, constructed raster data, and then computed regional averages.

We created grid data using China's geographical vector data to create grid data with a resolution of 0.1° × 0.1° in both latitude and longitude. We then used the inverse distance weighting (IDW) method to interpolate the station data onto the grid. The IDW assigns weights to the sample points based on their distances from the interpolation point, with closer points carrying greater weights. Recognizing that a direct regional averaging of the grid data could result in missing values for small districts devoid of grid points, we further refi ned the raster data. Finally, we calculate regional averages of the raster data. Upon obtaining daily district-level data, we aggregated these values monthly. This approach ensures comprehensive coverage across all districts and counties while minimizing data gaps and facilitating more accurate and reliable regional meteorological analyses.

The typhoon data come from Weather China (http://www.weather. com. cn/), including information on typhoon landing locations and dates from 1949 to 2021. We quantified each month's typhoon subindicator using the number of typhoons that made landfall in each district or county. By integrating the meteorological and typhoon data, our fi nal sample includes 2 878 counties in China from 1980 to 2020. Due to data availability, we only collected meteorological data up to 2020, leaving a gap in the past three years. Due to the slow pace of change in meteorological risks, we can draw insights from the trends observed over the past two decades and apply the methods above to process any newly acquired data as they become available. Furthermore, in Section 4, where we analyze the CIECR's impact on urban sustainable development, using data before 2020 mitigates the potential influence of the COVID-19 pandemic on our fi ndings. This approach allows us to focus on the long-term trends and effects of meteorological factors on urban sustainability, unencumbered by the pandemic's short-term disruptions.

2.2. Methodology

We define $X_{i,t}$ as the single index for each severe weather event in county *i* in year *t*. Specific indicators are described in Table 1.

Table 1
Description of each indicator of the CIECR

Index	Indicator	Description
Htem	High temperature	Frequency of maximum temperature > 90th percentile
Ltem	Low temperature	Frequency of minimum temperature < 90th percentile
rain	Heavy precipitation	Frequency of precipitation > 90th percentile
wind	High wind	Frequency of instantaneous average wind speed > 17 m/s
typhoon	Typhoon	Number of typhoons landing

For example, $\text{rain}_{i,t}$ is the heavy precipitation index, for which we first calculated the 90th percentile of precipitation in each county and then calculated the frequency of precipitation above the 90th percen-

tile in each county in year t. Therefore, using monthly data, we have $\text{rain}_{i,t} \in [0, 12]$. The high ($\text{Htem}_{i,t}$) and low temperatures ($\text{Ltem}_{i,t}$) are calculated similarly. For high winds, we calculated the frequency of the maximum wind speed above 17 m/s in each county in each year. Tropical cyclones ($\text{typhoon}_{i,t}$) are calculated as typhoon frequencies. We then normalized each single index as follows.

$$X_{i,t}^{Norm} = \frac{X_{i,t} - \min(X)}{\max(X) - \min(X)} \tag{1}$$

Therefore, each index is in [0, 1]. Finally, following Kim et al. (2022), we use arithmetic averaging to aggregate each index and obtain the CIECR.

$$\text{CIECR}_{i,t} = 1/5 \times \left(\text{Htem}_{i,t} + \text{Ltem}_{i,t} + \text{rain}_{i,t} + \text{wind}_{i,t} + \text{typhoon}_{i,t}\right) \tag{2}$$

By definition, the $\text{CIECR}_{i,t} \in [0, 1]$, and the higher the $\text{CIECR}_{i,t}$ is, the greater is the risk of extreme weather in the county.

3. CIECR characteristic

3.1. County-level estimation

The summary statistics of the normalized single indexes and the CIECR are presented in Table 2. The mean of low temperature (Ltem) and precipitation (rain) are the highest in five single indexes. As tropical cyclones are rare, the mean of typhoons is almost zero. There were 451 typhoons between 1980 and 2020, mainly in counties located along the coastline. For the CIECR, by definition, it lies in [0, 1]. However, the mean is only 0.093 and the maximum CIECR is only 0.475, indicating that the aggregate risk of severe weather is not high at the county level.

Table 2
Summary statistics of all indexes

Index	*N*	Mean	Std. Dev.	1st Perc.	99th Perc.	Min	Max
Htem	117 998	0.133	0.142	0	0.444	0	1
Ltem	117 998	0.150	0.237	0	0.750	0	1
wind	117 998	0.030	0.106	0	0.583	0	1
rain	117 998	0.150	0.179	0	0.625	0	1
typhoon	117 998	0.002	0.023	0	0	0	1
CIECR	117 998	0.093	0.054	0	0.250	0	0.475

Figure 1 presents the risk index for each county in China in 2020. We used the natural break method to classify each index into five groups to identify the counties with the highest risk①. Figure 1 (a) first shows the CIECR distribution, with the deeper the color, the higher the risk. Generally, extreme climate risk has regional characteristics, with higher risks in western regions of Xinjiang, Qinghai, and northern Xizang and in the north- and southeastern regions. Forty-two counties nationwide that fall into the highest group of extreme climate risk (CIECR > 0.197), mainly located in Inner Mongolia and Xinjiang (25 counties), with other individual counties distributed in Zhejiang, Fujian, Guangdong, Shandong, Shanxi, Anhui, Jiangxi, Guangxi, and other places.

Due to China's vast territory and significant regional differences, the regions' primary climate risks vary considerably. We further show the distribution of individual climate risk indicators in Figures 1 (b)–(f). Specifically, China's central and southeast regions and Xinjiang mainly face high-temperature risks (Figure 1 (b)). Most areas in Xinjiang have high-temperature risk, while individual counties in the southeast region face extremely high temperatures, especially Yunnan, Guangxi, Guangdong, Fujian. Counties in central China, such as Sichuan, Chongqing, Shaanxi, Shanxi, Henan, and Shandong, face significant high-temperature risks near the Qinling–Huaihe border. Additionally, the northern territories of Inner Mongolia, northern Hebei, western Liaoning, and western Jilin have high-temperature risks.

The areas in China with low-temperature risks are mainly concentrated in the northern regions (Figure 1 (c)). Xinjiang, Xizang, Qinghai, Gansu, Inner Mongolia, and the three northeastern provinces (Liaoning, Jilin, and Heilongjiang) face relatively high low-temperature risks. Among them, the counties with the highest low-temperature risks are in Heilongjiang, northeast Inner Mongolia, northern Xinjiang, and Qinghai. The distribution of high winds was relatively scattered (Figure 1 (d)), with the principal risk areas in northern Xinjiang and northern Inner Mongolia. Additionally, counties in Shanxi, Shandong, Sichuan, and Fujian provinces face extreme windy weather. Heavy precipitation is mainly concentrated in the southern regions of China, especially in Zhejiang, Anhui, Fujian, Jiangxi, Hunan, Guangdong, and Guangxi. Typhoon hazards are predominantly concentrated along the southeastern coastline, impacting a few counties (as depicted in Figure 1 (f)).

Figure 1 illustrates the recent distribution of extreme climate risks. We analyze the dynamic changes in the distribution of extreme climate risks in China by comparing the two periods. Based on data from 1980–2020, we divide the sample into 1980–1999 (Period 1) and 2000–2020 (Period 2). We calculate the CIECR average values for each period and then determine the change rate (defined as "diffper") by subtracting the average value of Period 1 from that of Period 2, dividing by the average value of Period 1, and then multiplying by 100 to analyze whether the extreme climate risks in each region have increased in recent years. Figure 2 illlustrates the corresponding results.

First, from the perspective of the CIECR (Figure 2 (a)), in the past two decades, some regions in China are located in the fifth group, where the growth rate of the index is above 45.6%. This indicates a significant increase in extreme climate risks. These regions are mainly located to the northwest of Xinjiang, Shaanxi, Jiangsu, and eastern Gansu, with some counties in Shanghai experiencing a climate risk increase of more than 70%. Overall, the climate risk index has increased in southern China.

Second, we analyzed each risk indicator individually. For high temperatures (Figure 2 (b)), the group with the lightest color represents a decrease or a slight change in the high-temperature risk, with most regions in the west falling into this group. The northeast region, southern Inner Mongolia, Sichuan, Gansu, Ningxia, and coastal Jiangsu have experienced a significant increase in the high-temperature risk, exceeding twice the level at the end of the last century. Most regions in China have a significantly higher high-temperature risk than 20 years ago. For low temperatures (Figure 2 (c)), most regions in China have a significantly lower risk of low temperatures than before. Only some counties in Hebei, Shanxi, and Shandong have an increased risk of low temperatures. The increase in the high-temperature risk and the decrease in the low-temperature risk suggest that China is generally experiencing a warming trend.

The risk of high winds (Figure 2 (d)) has increased significantly in northern Xinjiang and southern Xizang; furthermore, some counties in southern China have experienced an increase. Although areas with increased high-wind risks are scattered, only 108 counties show a positive growth rate for this indicator. Most counties in China have experienced a decrease in the high-wind risk. Regarding heavy precipitation (Figure 2 (e)), northern Heilongjiang, Shanxi, Gansu, and Shandong have experienced a significant increase in recent years. In some counties, the risk of heavy rain has increased three to seven

①The natural break method uses an algorithm to minimize the difference in data values within the same category and maximize the difference in data values between categories. This classification method aims to minimize the average deviation from the group's mean and maximize the deviation from the mean of the other groups. This method reduces the within-group variance and maximizes the between-group variance.

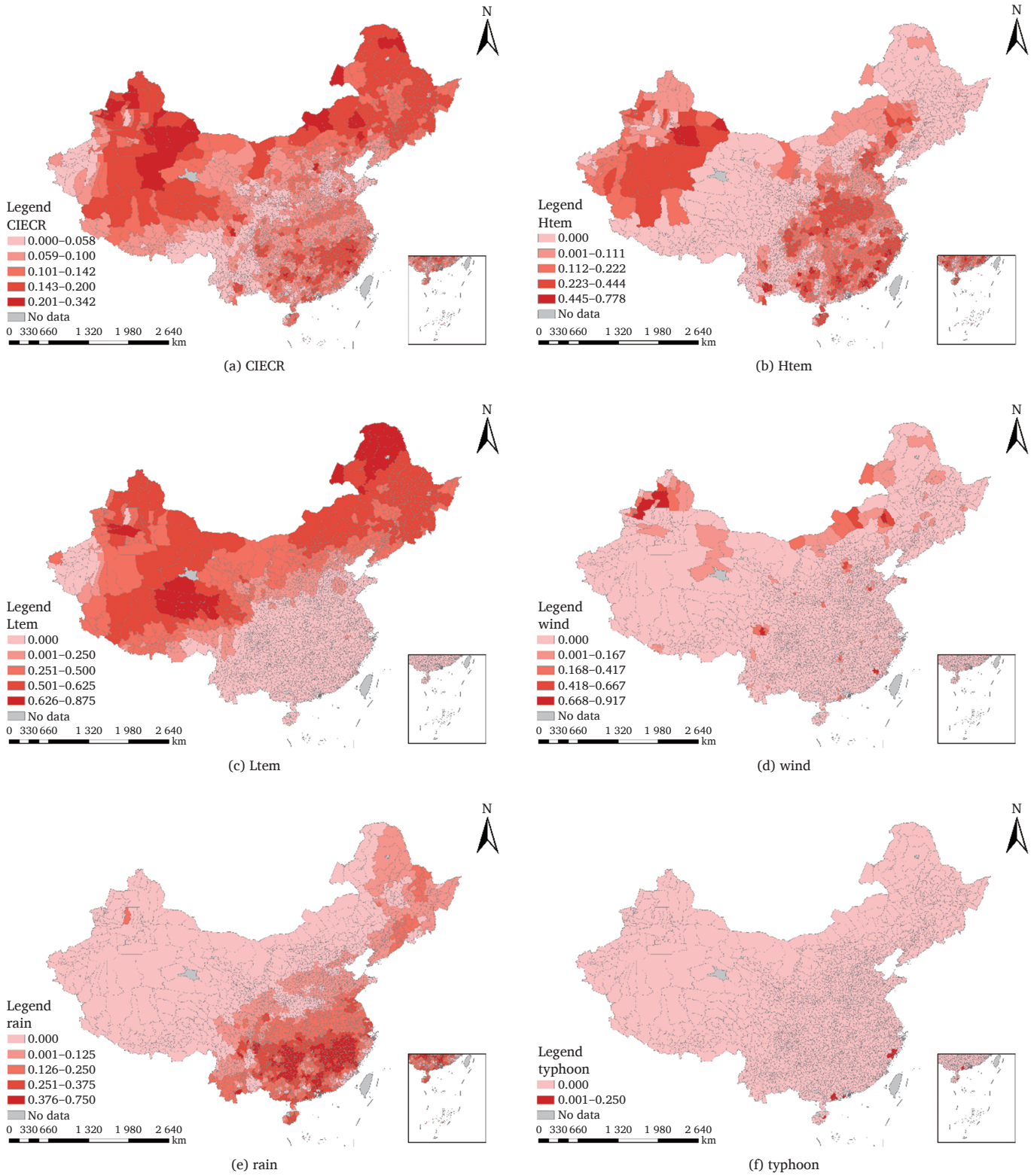


Figure 1. Distribution of CIECR and its components in 2020

Notes: This map is based on the standard map (approval number GS(2024)0650) downloaded from the standard map service website of the National Platform for Common GeoSpatial Information Services. The base map is not modified.

times, which can lead to severe flood disasters and endanger people's lives and property safety. Because typhoons mainly affect coastal regions, there has been no significant change in typhoon risk in most parts of China (Figure 2 (f)). While the risk of typhoons has decreased in the Bohai Sea region, it has both increased and decreased in different regions along the southeast coast. Parts of Shanghai and Fujian face a higher risk of typhoons.

In general, the CIECR has decreased in most regions compared to

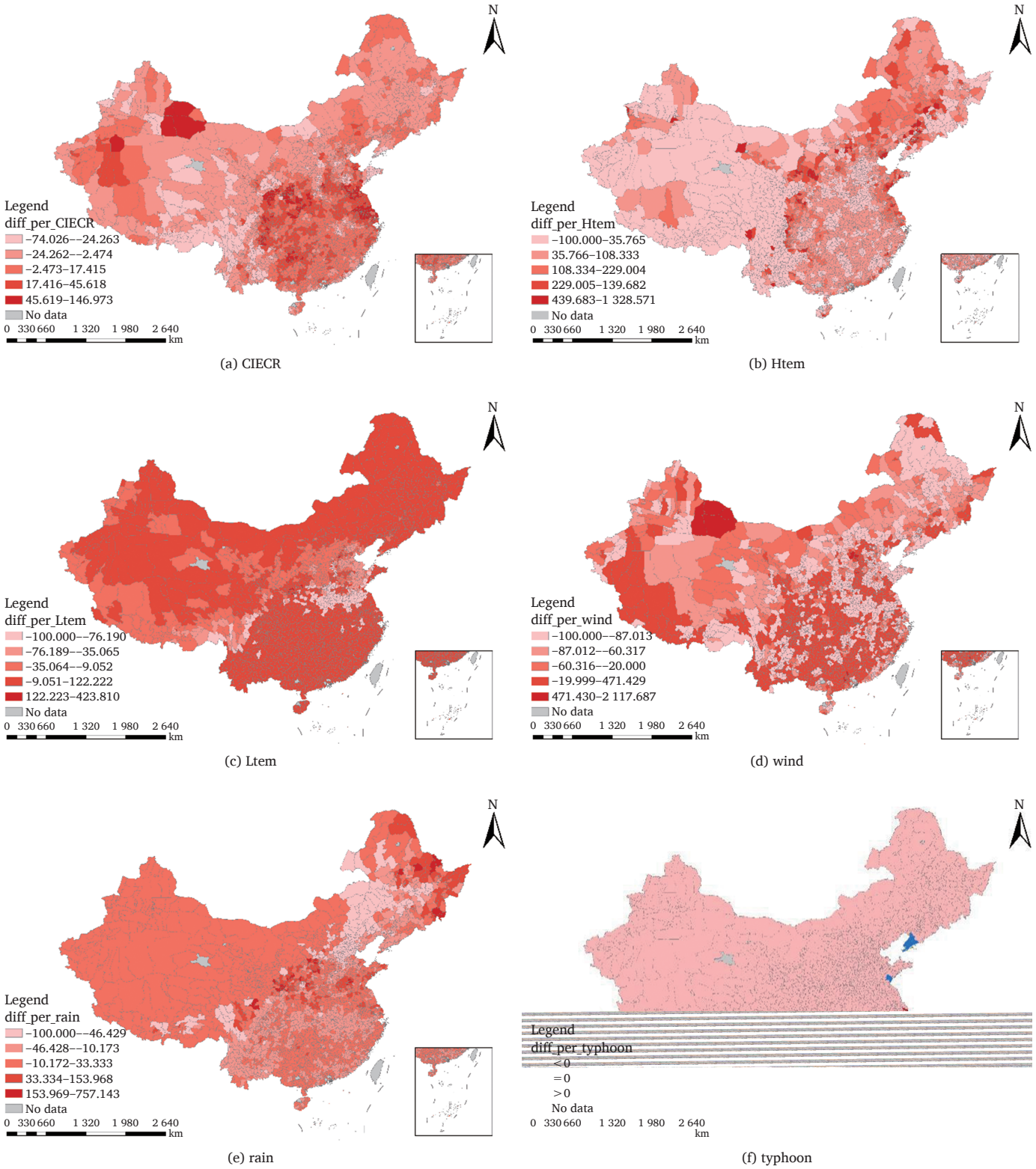


Figure 2. Change in CIECR and its components between 1980–1999 and 2000–2020
Notes: This map is based on the standard map (approval number GS(2024)0650) downloaded from the standard map service website of the National Platform for Common GeoSpatial Information Services. The base map is not modified.

the end of the last century, although some counties are facing increasingly extreme conditions. For example, the growth rate of the high-temperature and high-wind indexes exceeds 1 000%, reaching up to 20 times higher than before. This indicates that extreme climate is still a rare tail risk event; however, its negative impact on society and the economy cannot be ignored. Therefore, there is an urgent need to build efficient early warning systems. The CIECR we constructed can provide preliminary data support for this purpose.

For instance, in those cities prone to intense precipitation risks, reducing the population density in areas adjacent to rivers and lakes can mitigate potential hazards. Furthermore, refining the microlevel disaster prevention and mitigation measures is necessary. Governments must tailor disaster prevention policies according to specific climate risk characteristics, such as low temperatures, high winds, and intense precipitation, clarify departmental responsibilities, and ensure efficient resource allocation. Establishing long-term climate adaptation plans that integrate climate resilience into urban development frameworks, particularly for cities with extreme climate risks, is crucial for ensuring sustainable development in the face of climate change.

Second, enhancing green infrastructure investments can further mitigate extreme climate risks. In regions with escalating extreme climate risks such as Xinjiang and northern Inner Mongolia, prioritizing ecological restoration projects is imperative. For example, afforestation can increase green vegetation cover, inhibit soil erosion and desertification, reduce wind risks, and bolster ecological resilience, laying a solid foundation for regional ecological security and sustainable development. In response to climate warming and rising extreme climate risks, green concepts should be incorporated in urban planning. Energy-efficient and environmentally friendly materials and technologies should be embraced, and infrastructure that is resilient to extreme climate changes should be promoted. Renewable energy development and utilization should be vigorously promoted and adopted.

Third, optimizing urban transportation systems while considering the distribution of extreme climate risks is imperative to develop transportation facilities that are more resilient to extreme climatic conditions. For instance, in the southern regions prone to heavy rainfall, strengthening the design and construction of flood prevention and drainage systems should be prioritized. Protective measures such as the construction of windbreak barriers should also be implemented in areas where wind disasters frequently occur to ensure traffic safety.

3.3. Provincial estimation

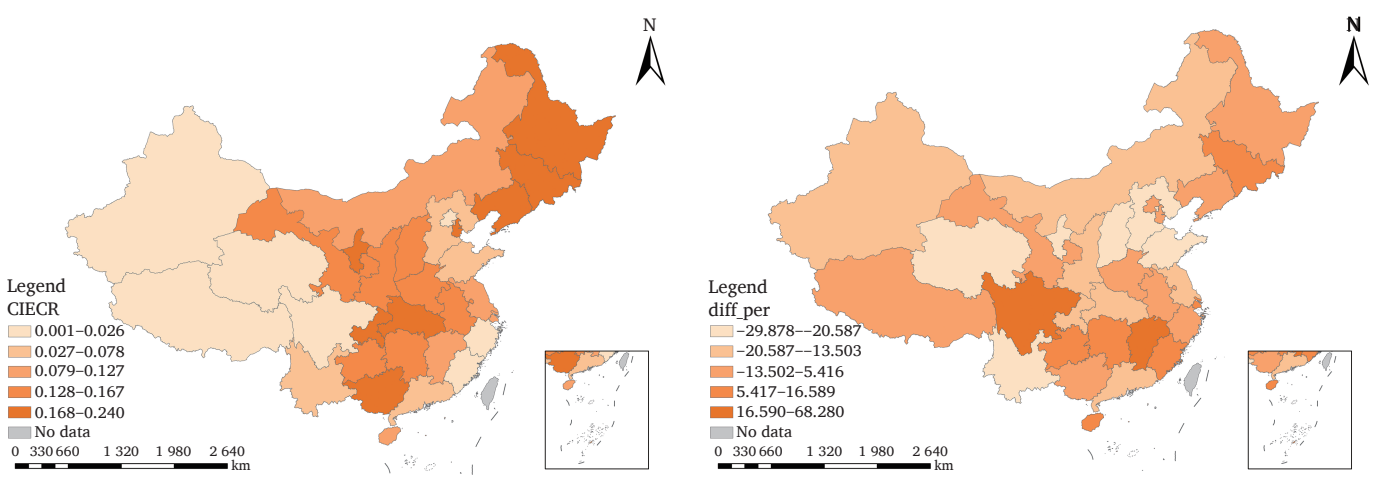
We next analyze extreme climate risks at the provincial level. Figure 4 shows the provincial CIECR's distribution in 2020 and the changes between 1980–1999 and 2000–2020. For the CIECR, Guangdong, Zhejiang, Heilongjiang, Xinjiang, and Sichuan were in a high-risk condition in 2020, while Beijing, Tianjin, Shanghai, and other regions were considered low risk. A comparison of the means of the two different periods shows extreme climate risks in China's central regions have increased. The CIECR in Shanghai and Jiangsu had increased by more than 50% at the end of the last century. Extreme climate risks in Zhejiang, Hunan, Chongqing, Shanxi, and Guangxi increased by more than 10%. In contrast, the CIECR in Qinghai, Ningxia, Xizang, Hainan, Inner Mongolia, and Shandong has decreased by more than 20%, while other regions have experienced relatively small changes in extreme climate risks. In general, Zhejiang has experienced a rapid increase in extreme climate risks in recent years and is currently at a high-risk status.

We also analyzed the sources of extreme climate risks in the provinces. Table 5 shows the provincial CIECR in 2020. Guangdong, Zhejiang, Heilongjiang, Xinjiang, and Sichuan rank among China's top fi ve high-risk regions. The primary sources of risk for Guangdong and Zhejiang are high temperatures, heavy precipitation, and typhoons. The core factor that contributes to the high risk of extreme climate in Heilongjiang is the low temperature. Xinjiang is affected by the combined impact of high temperature, low temperature, and high winds. The primary sources of risk of Sichuan are high temperatures and heavy precipitation. Although the leading sources of risk vary across provinces, high temperatures and heavy precipitation are the main extreme climate events in most high-risk regions. Regarding individual climate risk indicators, high temperatures pose the greatest risk to Henan, followed by Zhejiang and Guangdong. The northern regions of Heilongjiang, Inner Mongolia, Xinjiang, Liaoning, and Jilin are most affected by low temperatures. High winds mainly affect Xinjiang, Inner Mongolia, and Shandong. The central and southern regions of China are most affected by heavy precipitation, while typhoons mainly strike the coastal areas of Zhejiang, Guangdong, and Hainan.

3.4. National estimations

Figure 5 shows the CIECR of the whole country and the five corresponding standardized components for China. Panel (a) shows the aggregate CIECR from 1980 to 2020. The risk of severe weather initially decreased and then increased in recent years. The extraordinary increasing trend in high temperatures and the decrease in low temperatures in Panels (b) and (c) indicate a warning of global warming. Due to continuous afforestation in recent years, the risk of high wind in China has decreased significantly year by year, as shown in Panel (d). Panel (e) shows that the risk of heavy precipitation has recently increased, and there is noticeably higher volatility in the risk of typhoons in Panel (f).

Nationally, China has witnessed a significant decline in wind-



(a) CIECR in 2020 (b) Changes in CIECR

Figure 4. Distribution and changes in the provincial CIECR

Notes: This map is based on the standard map (approval number GS(2024)0650) downloaded from the standard map service website of the National Platform for Common GeoSpatial Information Services. The base map is not modified.

Table 5
Provincial CIECR in 2020

No.	Province	Htem	Ltem	wind	rain	typhoon	CIECR
1	Guangdong	0.417	0.000	0.033	0.532	0.219	0.240
2	Zhejiang	0.453	0.000	0.018	0.305	0.375	0.230
3	Heilongjiang	0.002	0.898	0.036	0.161	0.000	0.219
4	Xinjiang	0.327	0.508	0.215	0.000	0.000	0.210
5	Sichuan	0.403	0.095	0.066	0.480	0.000	0.209
6	Inner Mongolia	0.092	0.710	0.206	0.009	0.000	0.203
7	Hunan	0.367	0.000	0.087	0.541	0.000	0.199
8	Jiangxi	0.371	0.000	0.015	0.608	0.000	0.199
9	Henan	0.746	0.000	0.000	0.186	0.000	0.187
10	Hebei	0.372	0.282	0.036	0.147	0.000	0.167
11	Shanxi	0.279	0.360	0.060	0.108	0.000	0.161
12	Anhui	0.362	0.006	0.003	0.375	0.000	0.149
13	Guangxi	0.302	0.000	0.000	0.443	0.000	0.149
14	Shandong	0.272	0.055	0.116	0.257	0.000	0.140
15	Fujian	0.345	0.003	0.081	0.261	0.000	0.138
16	Hubei	0.331	0.000	0.000	0.344	0.000	0.135
17	Liaoning	0.068	0.430	0.009	0.129	0.000	0.127
18	Jiangsu	0.268	0.000	0.000	0.324	0.000	0.118
19	Jilin	0.018	0.413	0.027	0.119	0.000	0.115
20	Guizhou	0.115	0.000	0.000	0.399	0.000	0.103
21	Shaanxi	0.281	0.111	0.039	0.078	0.000	0.102
22	Yunnan	0.113	0.002	0.009	0.267	0.000	0.078
23	Gansu	0.007	0.305	0.018	0.041	0.000	0.074
24	Xizang	0.013	0.317	0.006	0.000	0.000	0.067
25	Chongqing	0.174	0.000	0.000	0.126	0.000	0.060
26	Qinghai	0.000	0.258	0.003	0.000	0.000	0.052
27	Hainan	0.122	0.000	0.000	0.095	0.031	0.050
28	Ningxia	0.036	0.073	0.015	0.005	0.000	0.026
29	Shanghai	0.052	0.000	0.000	0.071	0.000	0.025
30	Beijing	0.076	0.027	0.000	0.000	0.000	0.021
31	Tianjin	0.067	0.011	0.003	0.021	0.000	0.020

storm risks and a marked increase in heatwave risks, consistent with the previous analysis results at the county and city levels. However, national estimations only offer a temporal trend of a particular risk or the CIECR; they cannot provide a more detailed spatial distribution. Given China's vast territory and significant variations in geographical environments and social developments across regions, national-level results alone cannot yield targeted planning recommendations.

Specifically, the municipal-level analysis (Subsection 3.2) reveals a nuanced picture of extreme climate risk, with considerable variations within and across cities. For example, cities located in the northern latitudes—particularly in Heilongjiang, eastern and central Inner Mongolia, and Hebei—and those situated between 23.5°N and 30°N (e. g., Chongqing, Guizhou, Hunan, Jiangxi, Fujian, Guangdong, Guangxi) exhibit distinct risk profiles primarily driven by either low temperatures and strong winds (northern cities) or heavy precipitation (southern cities). Conversely, the national-level estimates (Figure 5) provide an aggregated view of trends, obscuring the intricate spatial variations observed at the municipal and regional levels.

At the municipal level, low temperatures and strong winds were the primary risk drivers in the 1980s. However, in recent decades, risks associated with high temperatures and heavy precipitation are greater, particularly in southern cities such as Chongqing. This shift is consistent with national-level trends, where an increasing trend in high-temperature risks (Figure 5(b)) and a decreasing trend in low-temperature risks (Figure 5(c)) indicate overall climate warming. However, the municipal analysis provides a more granular understanding of how these trends manifest in particular cities and regions.

Both municipal and national estimates confirm that the wind risk has significantly reduced over time, which is attributed to afforestation efforts and changing weather patterns. However, the municipal analysis allows for a more localized assessment of the effectiveness of these measures and their impact on specific urban areas.

The municipal-level analysis highlights the importance of geographical and socioeconomic factors in shaping resilience to extreme climate events. For example, the broader geographical extent of some cities can dilute risk at the city level compared with more concentrated risks at the county or district level. Additionally, differences in infrastructure, economic activity, and population density across cities can significantly influence their ability to withstand and recover from extreme climate events.

This comparison underscores the need for policy interventions tailored to individual cities and regions' specific vulnerabilities and resilience factors. While national-level strategies set broad guidelines, municipal-level assessments enable targeted policies and planning initiatives to be developed, addressing the unique challenges each administrative unit faces. For instance, those cities with high heat risks may prioritize expanding green spaces, adopting innovative roof technologies, and enhancing heat warning systems. In contrast, regions prone to heavy precipitation may upgrade drainage systems, promote water-sensitive urban designs, and strengthen floodplain management.

Therefore, using the county-level or city-level estimation of the CIECR to study extreme climate risk is helpful. Developing integrated strategies that effectively mitigate and adapt to the impacts of extreme climate events is crucial.

4. Effects of CIECR on urban sustainable development

4.1. Data and empirical model

We calculated the CIECR at the county level to test the effects of severe weather risk on urban sustainable development. We used the *China Statistical Yearbook* of Counties data and merged them with the CIECR data. Due to data availability, the economic data sample is from 2000 to 2020. We investigate the CIECR's impact on agricultural production, industrial structure, and employment in urban sustainable development. Data descriptions and summary statistics of the variables are presented in Table 6.

Using county-level data, we ran the following county-level panel regression.

$$Y_{i,t} = \alpha + \beta \times \mathrm{CIECR}_{i,t} + \mathrm{controls}_{i,t} + \gamma_t + \eta_i + e_{i,t} \tag{3}$$

Where, $Y_{i,t}$ includes different dependent variables in county i in year t. $\mathrm{CIECR}_{i,t}$ is the calculated CIECR. $\mathrm{controls}_{i,t}$ includes control variables. γ_t controls the time fixed effect, η_i is the county fixed effect, and $e_{i,t}$ is the error term.

4.2. CIECR and agricultural production

We first used agricultural production–related indicators as the explained variable to examine the impact of extreme climate risks on this production. Extreme climate events, such as floods, high and low temperatures, and storms, can cause crop damage or even complete destruction, affecting crop quality and yield. We considered the production of three major crops—grain, cotton, and oil—as the dependent variables. Table 7 reports the regression results. When we only considered the CIECR and fixed effects, extreme climate risks significantly negatively impacted crop production, with the regression coefficient significant at the 99% level. This finding indicates that ex-

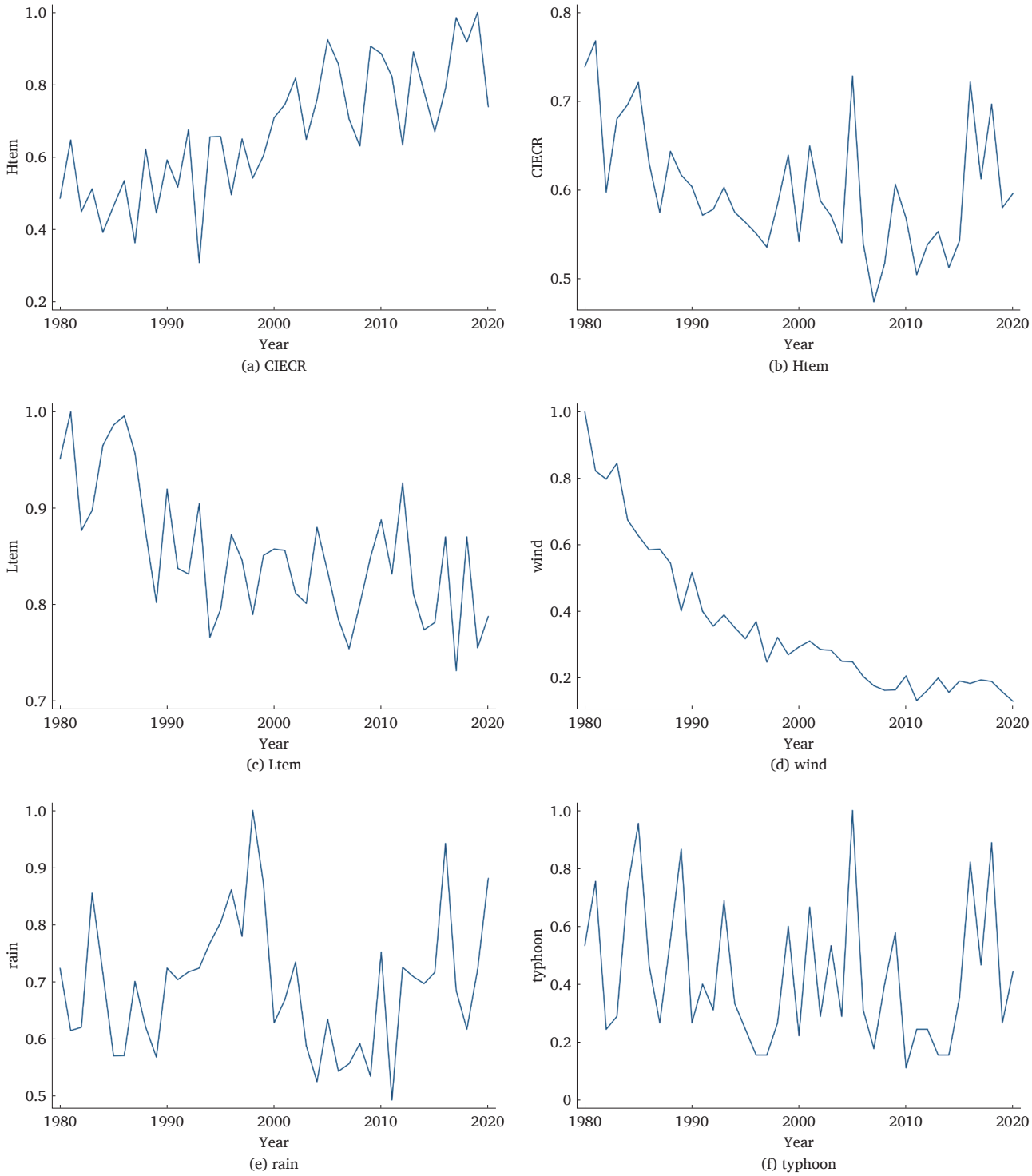


Figure 5. National CIECR in 1980–2020

treme climate risks constitute a non-negligible threat to crop production, regardless of crop type. We added several control variables closely related to crop production to better understand this impact: population, land area, and total power of agricultural machinery. These variables represent the key factors affecting crop production: labor, land, and machinery. In Column (2) of Table 7, the coefficient of CIECR decreased after adding these control variables; however, the coefficient remained signi fi cantly negative, suggesting that extreme climate risks drive the decrease in grain production even after considering other factors. We also considered cotton and oil crop production. Columns (4) and (6) show the negative impact of extreme climate risks on these two crops is more significant than grain production, with a coefficient approximately twice that of grain production. This may be because cotton and oil crops are more sensitive to climate conditions and, therefore, more vulnerable to damage when facing extreme climate risks.

Therefore, while extreme climate risks have different impacts on the production of various types of crops, the risks lead to reduced agricultural production. This affects agricultural development and may also threaten food security. Recognizing the situation's severity and

Table 6
Data descriptions and summary statistics of the variables

Variables	Descriptions	*N*	Mean	Std.	Min	Max
CIECR	Index of extreme climate risk	53 088	0.092	0.051	0	0.475
grain	Grain production	45 306	11.714	1.434	0.693	15.108
cotton	Cotton production	19 174	5.972	2.852	0	12.874
oil	Oil crop production	45 787	8.238	1.94	0	13.706
agr_s	Contribution of agriculture to GDP	46 463	−1.001	0.485	−10.491	−0.032
ind_s	Contribution of industry to GDP	46 197	−1.79	1.024	−14.148	0
service_s	Contribution of service to GDP	46 509	−1.053	0.335	−4.87	1.64
agr_e	Employment in agriculture	30 335	11.276	1.041	5.024	13.415
ind_e	Employment in industry	22 360	10.246	1.721	1.386	14.444
service_e	Employment in service	22 433	10.655	1.245	4.043	14.157
village_e	Proportion of rural employment	35 204	11.787	1.094	5.024	13.96
urban_e	Proportion of urban employment	23 827	9.873	0.865	4.111	13.757
pop	Total population	47 609	3.566	0.885	−1.514	6.322
land	Land area	46 987	7.591	1.109	2.079	12.246
machine	Total power of agricultural machinery	40 476	3.01	1.091	0	5.817
pgdp	GDP per capita	34 472	9.636	1.021	6.091	12.804
pgdp2	Square of pgdp	34 472	93.899	19.666	37.104	163.943
urban	Urbanization rate	30 856	−1.726	0.706	−6.337	0
inv	Investment in fixed assets	31 168	12.545	1.578	6.72	17.873
edu	Education	43 681	16.363	0.322	13.935	18.783

Notes: All variables, except CIECR, are logarithmic. The urbanization rate is calculated as the proportion of the urban population in the total population. Education is calculated as the proportion of primary and secondary school students in the total population.

Table 7
CIECR and agricultural production

Variables	(1) Grain	(2) Grain	(3) Cotton	(4) Cotton	(5) Oil	(6) Oil
CIECR	−1.470***	−1.102***	−4.697***	−2.540***	−2.287***	−2.160***
	(0.350)	(0.202)	(0.904)	(0.879)	(0.466)	(0.354)
pop		0.749***		−0.783***		0.821***
		(0.038)		(0.040)		(0.018)
land		0.156***		0.609***		0.163***
		(0.006)		(0.042)		(0.011)
machine		0.521***		1.882***		0.480***
		(0.042)		(0.056)		(0.014)
Constant	11.848***	6.485***	6.386***	−1.842***	8.446***	2.826***
	(0.032)	(0.047)	(0.080)	(0.279)	(0.042)	(0.097)
Obs	45 306	36 846	19 174	16 514	45 787	36 330
R^2	0.003	0.691	0.006	0.232	0.004	0.337
Double FE	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors are reported in parentheses. *** $P < 0.01$. Grain, cotton, and oil denote grain production, cotton production, and oil crop production, respectively. Furthermore, pop is the population, land is the land area, and machine is the total power of agricultural machinery. All the above variables are in logarithmic form. CIECR is the calculated comprehensive index of extreme climate risk.

taking appropriate measures to address extreme climate risks will contribute to ensuring the sustainable development of agriculture.

4.3. CIECR and industrial structure

Extreme climate risks directly impact on agricultural production and indirectly affect the industrial structure. We use the proportion of the primary industry's added value (agr_s), the secondary industry (ind_s), and the tertiary industry in GDP (service_s) as the explained variables to analyze the CIECR's impact on the industrial structure. Table 8 reports the regression results. Similarly, we first consider only the CIECR's effect and find that extreme climate risks significantly reduce the primary industry's proportion while increasing the that of the secondary industry; however, they do not significantly impact the proportion of the tertiary industry. A scholarly consensus confirms an inverted "U" relationship between the industrial structure and per capita real GDP. According to the Petty–Clark law, labor first shifts from the primary industry to the secondary industry as per capita income levels increase. When the per capita income levels increase, labor shifts to the tertiary industry. Therefore, following the research by Rodrik (2016), we add per capita GDP, the square of per capita GDP, and urbanization rate as control variables.

Column (2) reports the results for the contribution of agriculture to GDP. After adding the control variables, the extreme climate risk index coefficient continues to be significant at the 99% level, and its absolute value is higher than that in Column (1). This finding suggests that extreme climate events significantly reduce the contribution of agriculture to GDP, consistent with the results of Wei et al. (2017). A possible reason is that extreme climate events cause direct damage to crops and other agricultural products, reducing their quantity and quality and thereby affecting the share of agriculture.

In contrast, extreme climate risks increase the secondary industry proportion (Column (4)) because, when faced with extreme climate risks, more industrial products are required to prevent and respond to them. These include equipment and tools to directly address extreme weather events, including flood prevention equipment, drought-resistant machinery, and hail netting, and technical products that can improve agricultural adaptability and resilience, such as efficient irrigation systems and intelligent agricultural equipment. The increased demand for these products will drive up the industry share. After adding control variables, the CIECR significantly increased the proportion of the service industry. Still, its significance was not high enough to pass the 95% test, and its absolute value was relatively close to 0.

Table 8
CIECR and industrial structure

Variables	(1) agr_s	(2) agr_s	(3) ind_s	(4) ind_s	(5) service_s	(6) service_s
CIECR	−0.901***	−1.451***	1.569***	2.655***	−0.099	0.115*
	(0.114)	(0.076)	(0.131)	(0.283)	(0.075)	(0.060)
pgdp		1.070***		1.662***		0.190
		(0.145)		(0.147)		(0.119)
pgdp2		−0.032***		−0.125***		−0.017***
		(0.007)		(0.008)		(0.006)
urban		−0.092***		−0.114***		0.083***
		(0.010)		(0.016)		(0.004)
Constant	−0.917***	−8.243***	−1.936***	−6.455***	−1.044***	−1.223*
	(0.011)	(0.747)	(0.012)	(0.690)	(0.007)	(0.607)
Obs	46 463	25 147	46 197	25 149	46 509	25 147
R^2	0.010	0.395	0.007	0.500	0.000	0.088
Double FE	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors are reported in parentheses. * $P < 0.10$, *** $P < 0.01$. agr_s, ind_s, and service_s denote the contributions of agriculture, industry, and service, respectively, to GDP. pgdp is the per capita GDP, pgdp2 is the square of the per capita GDP, and urban is the urbanization rate. All the above variables are in logarithmic form. CIECR is the calculated comprehensive index of extreme climate risk.

This may be because the service industry's development is more influenced by other factors, such as the policy environment and technological development, and has a relatively weak direct correlation with extreme climate risks.

Therefore, extreme climate risks reduce the share of agriculture and promote the industry's development. First, agricultural production's high dependence on climate means it is highly vulnerable to the impact of extreme climate events, affecting farmers' income and posing a threat to national food security. Faced with insufficient agricultural production caused by extreme climate events, increasing the production of food processing and storage equipment may be necessary. Additionally, to improve the adaptability and resilience of agriculture, there may be a push for developing and producing intelligent agricultural equipment and efficient irrigation systems, which will promote industrial development, especially in agricultural areas. The 20th CPC National Congress report states that China should fully consolidate its foundation of food security, strengthen support for agricultural science and technology equipment, ensure that the food sector is under public control, establish a view of food from all sources, develop facility agriculture, and build a diversified food supply system. These measures can actively respond to the negative impact of extreme climate risks on agriculture, ensuring the stability and sustainability of agricultural production. They can also contribute to the two-way sustainable development of agriculture and industry. Facility agriculture, diversified food supply systems, and agricultural science and technology equipment can drive agricultural economic growth and industrial development while increasing farmers' income and living standards, thereby promoting positive interactions and coordinated development between agriculture and industry.

4.4. CIECR and employment

Finally, we analyze the impact of extreme climate risks on labor employment. We use the number of people employed in the primary industry (agr_e), secondary industry (ind_e),and tertiary industry (service_e) as the variables to analyze the impact of CIECR on labor employment. Table 9 presents the regression results. Similarly, we first consider only the fixed effects and find that the extreme climate risk index significantly reduces the proportion of employed people in all three industries. After adding per capita GDP, the square of per capita GDP, and urbanization rate as control variables, despite the absolute value of the CIECR's coefficient having decreased, it is still significantly negative. This indicates that even after considering the impact of economic development and urbanization on employment, extreme climate risks still harm employment. This may be due to economic growth and urbanization improving people's resilience to climate risks, even though their negative impact cannot be eliminated en-

Table 9
CIECR and employment

Variables	(1) agr_e	(2) agr_e	(3) ind_e	(4) ind_e	(5) service_e	(6) service_e	(7) village_e	(8) urban_e
CIECR	−3.773***	−1.494***	−6.222***	−7.765***	−3.977***	−5.033***	−1.870***	0.887***
	(0.263)	(0.256)	(1.453)	(0.820)	(1.000)	(0.547)	(0.141)	(0.136)
pgdp		2.368***		4.854***		1.646**	−0.926***	−0.093***
		(0.148)		(0.843)		(0.585)	(0.026)	(0.028)
pgdp2		−0.126***		−0.194***		−0.061**		
		(0.008)		(0.041)		(0.029)		
urban		−0.693***		−0.448***		−0.179		
		(0.023)		(0.143)		(0.110)		
inv							0.852***	0.606***
							(0.022)	(0.020)
edu							0.005	0.185***
							(0.049)	(0.043)
Cons	11.616***	−0.689	10.839***	−18.704***	11.034***	0.556	10.263***	0.266
	(0.024)	(0.674)	(0.138)	(4.309)	(0.095)	(2.930)	(0.836)	(0.785)
Obs	30 335	21 971	22 360	10 459	22 433	10 483	20 975	16 653
R^2	0.036	0.306	0.037	0.201	0.029	0.106	0.561	0.505
FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors are reported in parentheses. * $P < 0.10$, ** $P < 0.05$, *** $P < 0.01$. agr_e, ind_e, and service_e represent employment in agriculture, industry, and services, respectively. village_e and urban_e represent employment in rural and urban areas, respectively. Furthermore, pgdp is the per capita GDP, pgdp2 is the square of the per capita GDP, urban is the urbanization rate, inv denotes investment, and edu denotes education. All the above variables are in logarithmic form. CIECR is the calculated comprehensive index of extreme climate risk.

tirely. Extreme climate events may affect population migration, employment choices, and career development. For example, people may move away from regions easily affected by extreme climate events. Owing to geographic restrictions on agricultural employment, it is difficult to transfer to other regions; therefore, the CIECR's impact on the number of people employed in agriculture is less than that of the secondary and tertiary industries (Column (2)).

We take rural employment (village_e) and urban employment (urban_e) as the dependent variables to further verify this conjecture, and the results are reported in Columns (7) and (8) of Table 9. It can be seen that the increase in CIECR has a significant negative impact on rural employment and a positive impact on urban employment, suggesting that extreme climate risks contribute to urbanization.

First, rural areas are typically more vulnerable to extreme climate events. Rural residents are often more exposed to the impacts of floods, high temperatures, or typhoons because of their geographical location and limited infrastructure. When faced with such risks, rural residents may choose to migrate to urban areas for their safety and livelihood. At the same time, owing to their agglomeration effects and relatively well-developed infrastructure, cities and towns can often better cope with and adapt to the challenges of climate change. Thus, cities and towns provide incoming residents with more employment opportunities and better living conditions. Moreover, as cities and towns develop and expand, their demand for labor increases, leading to increased migration of rural residents to urban areas.

The urban – rural gap is also an essential factor contributing to this phenomenon. Rural residents often face more development constraints and have fewer opportunities. Therefore, when faced with extreme climate risks, rural residents tend to migrate to urban areas. Consequently, extreme climate risks directly impact rural areas and indirectly change the urban – rural population structure by driving population flows and urbanization.

5. Conclusion

We used monthly meteorological data from 1980 to 2020 to study five severe weather events that cause disasters in China: high temperatures, low temperatures, heavy precipitation, high winds, and tropical cyclones. We constructed the CIECR according to the climatic characteristics and historical data of each county. At the county level, Xinjiang and northern Inner Mongolia were found to have the highest levels of extreme climate risk, and extreme climate risk indexes increased rapidly in northwestern Xinjiang, Shaanxi, Jiangsu, and eastern Gansu. These findings provide vital insights for regional climate resilience planning. The steep increase in extreme climate risks in the southern regions underscores the urgency for coastal and economically developed regions to address climate change.

High temperatures, low temperatures, and high winds were identified as the main sources of risk in high-risk counties. High temperatures and heavy precipitation were the main extreme climate events in most high-risk provinces, highlighting the need for policymakers to prioritize climate resilience enhancement in these regions, including by reinforcing infrastructure, optimizing agricultural cropping patterns, and improving disaster warning and emergency response capabilities. Additionally, comprehensive climate adaptation measures are recommended, such as promoting water-saving irrigation techniques, strengthening urban drainage systems, and optimizing energy structures to mitigate heat island effects. The CIECR decreased at the national level in the last century; however, it has increased in recent years. Global warming is apparent based on the high- and low-temperature risk indexes.

Finally, we used county-level economic panel data to empirically assess the impact of extreme climate risks on sustainable development. Results showed that CIECR significantly reduces agricultural production, inhibits agricultural development, reduces employment, and is inconducive to economic development. However, as extreme climate risks increase, they promote the development of modern agriculture and industrial production as well as the migration of labor force from rural to urban areas, thus boosting urbanization. These findings indicate that policymakers should balance short-term emergency responses and long-term development planning, emphasizing the transformation and upgrading of economic and social structures in addressing climate change.

Despite the preliminary achievements in assessing extreme climate risks and their implications for sustainable urban development, our study has certain limitations. First, constrained by data availability and processing capabilities, the current study only encompasses five major extreme climate events; future research could investigate a broader range of events to develop a more comprehensive risk assessment framework. Second, the construction of the CIECR primarily relied on historical data and internationally recognized indicators; future endeavors could integrate regional specifics to create more tailored risk assessment models and indicators. Finally, fostering interdisciplinary collaboration and incorporating theories and methodologies from economics, sociology, geography, and other disciplines could enhance the depth and breadth of future research endeavors.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

The paper is supported by the National Key Research and Development Program of China under the theme "Construction of a data representation framework for sustainable development indicators" [Grant No. 2022YFC3802903-01]; the National Natural Science Foundation of China "An economic theory based on the new production function in carbon neutrality" [Grant No. 72250064]; the National Natural Science Foundation of China "Macroeconomics" [Grant No. 72122011].

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