The impact of extreme heat climate on the sustainable development of urban economies

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Abstract

Purpose – Extreme heat (EH) occurs frequently in China, severely hindering the sustainable development of the urban economy. Improving green economic efficiency (GEE) is key for sustainable economic development. This study aims to explore the influence of EH on GEE.

Design/methodology/approach – This article measured the annual GEE level using the superefficiency slacks-based measure (Super-SBM) model, including undesired outputs. The number of EH days in each city was measured using the relative threshold method. The bidirectional fixed effects model was adopted to explore the impact of EH on GEE. The authors verified the mitigation mechanism of aggregated positive externalities and innovatively constructed a temperature-adjacency spatial matrix to confirm the spatial spillover effect of EH on GEE.

Findings – The results indicate that EH negatively influences GEE and has a more pronounced adverse impact on GEE in nonclimate-adaptive pilot cities and regions east of the Hu Huanyong Line. Innovative talent agglomeration and industrial collaborative agglomeration can mitigate this negative impact, and their coupled and coordinated development can reduce the adverse effects of EH on GEE. Concerning the spatial effect, local EH has a positive spillover effect on surrounding cities' GEE.

Originality/value – This study expands and supplements existing research and provides new insights for objectively assessing the economic consequences of EH. The authors offer scientific recommendations for cities to address extreme climates and enhance the economic green efficiency of Chinese cities.

Keywords EH, GEE, Spatial correlation, Innovation talent agglomeration, Industrial collaborative agglomeration

Paper type Research paper

1. Introduction

Recently, climate change has intensified, and extreme weather events occur frequently, which seriously threatens the sustainable economic and social development of humankind. China's diverse climates, combined with its aging population and other factors, makes it vulnerable to climate extremes (Zhang *et al.*, 2020).The China Blue Book on Climate

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Change (2023) indicates a marked increase in the frequency of extreme heat (EH) events since the late 1990s, accompanied by escalating climate risk levels, which poses significant challenges to China's ecological systems, socioeconomic development and other sectors. At present, China's economic development prioritizes economic growth and ecological protection equally. Within the context of global warming and with the increasing occurrence of extreme weather events, developing a green economy has become essential for effectively addressing climate change challenges in China.

The impact of EH is characterized by both economic disturbance and environmental shock (García-León *et al.*, 2021; Jin *et al.*, 2020). The existing studies have mainly defined extreme climate events based on the statistical distribution of climate variables and a fixed climate reference period (Smith, 2011). A fixed climate reference period usually refers to the historical climate records of a specific time and region. The identification of extreme climate events relies on the setting of extreme thresholds, which can be achieved via two main methods: absolute extremity and relative extremity. The absolute extreme threshold emphasizes predefined absolute extreme values. For example, some scholars have used the absolute threshold method to define a heat wave as occurring on at least three consecutive days with daily maximum temperatures ≥ 35°C (Niu *et al.*, 2025; Huang *et al.*, 2020). Relatively extreme thresholds are characterized by cross-temporal and spatial comparability, are mostly defined by percentiles and usually take 30 years as the climate base period (Jahn, 2015; Li *et al.*, 2025a). In this study, we adopt the relative threshold method to determine the threshold of EH events in sample cities. EH is defined as an event that occurs in a sample city if the highest temperature of a specific day exceeds the EH threshold of that day. The EH threshold is based on the climate reference period from 1973 to 2002. The daily maximum temperatures on the same day of each year are sorted from high to low, and the 90th percentile value is taken as the EH threshold. In the robustness test, we updated the climate baseline period (1983–2012) to increase the accuracy of the EH event quantification results.

According to the definition of the United Nations Environment Program (UNEP), a green economy is an economic development model that can not only reduce environmental risk and scarcity but also enhance human well-being and social equity (https://www.unep.org/zh-hans/node/19231). Green economic efficiency (GEE) is a comprehensive efficiency indicator that combines "sustainability," "greenness" and "economic efficiency" (Wang *et al.*, 2023). It emphasizes the maximization of expected economic outputs and the minimization of undesired environmental pollution outputs under stable inputs of resource elements and ecological constraints (Chen *et al.*, 2023c; Zhou *et al.*, 2025). It is an essential yardstick for measuring the development of a green economy. Enhancing the efficiency of the green economy is widely recognized as an essential path toward sustainable economic and social development and effectively respond to climate change (Ma *et al.*, 2024; Yan *et al.*, 2024; Ping *et al.*, 2025). In this study, GEE is defined as a climate-friendly efficiency indicator that comprehensively considers economic, ecological and environmental benefits. It is an input–output efficiency that includes the input of resource elements, actual economic output and pollution emissions.

Previous studies have systematically investigated the influence of EH events on socioeconomic systems at the macro scale and on corporate decision-making at the micro scale. Focusing on macro dimensions, EH, as a typical extreme climate event, can cause negative macroeconomic shocks and lead to slower economic growth (Sheng *et al.*, 2024), reduced agricultural and industrial output (Chen and Gong, 2021; Song *et al.*, 2022; Aragón *et al.*, 2021; Zhang *et al.*, 2025), supply chain disruptions (Li *et al.*, 2025b; Pankratz and Schiller, 2024), increased urban unemployment (Gray *et al.*, 2023), increased financial pressure on the government (Chen *et al.*, 2024d) and increased regional inequality (Yang and

Tang, 2022). However, the adverse effects of climate extremes on the real economy can further spill over into the financial system and contribute to a decline in financial stability (Battiston *et al.*, 2021). Focusing on the micro dimension, most studies note that EH has an impact on the economic behaviors of individuals at the microlevel, which not only leads to reduced labor productivity (Liu *et al.*, 2023), increased labor costs (Wang *et al.*, 2025) and increased enterprise earnings volatility (Wang *et al.*, 2023), inhibits green innovation (Su *et al.*, 2024) and exacerbates the financial distress of firms (Aguilar-Gomez *et al.*, 2024). Rising temperatures increase residential electricity consumption (Zhang *et al.*, 2022), which further increases household energy expenditures and can trigger energy poverty (Li *et al.*, 2023). In addition, EH can lead to a decline in social welfare, damage physical and mental health (Xiang *et al.*, 2024), reduce personal well-being and intensify environmental inequality (Chen *et al.*, 2024a).

Previous studies have focused on the economic consequences of extreme weather and conducted extensive research, but relatively few studies have paid attention to the obstructive effect of EH on the GEE of cities. In fact, EH, as an external shock, can reduce urban economic output, damage social green welfare, and lead to the degradation of urban ecological functions, thereby hindering improvements in urban GEE. GEE not only enhances a city's climate and economic resilience but also provides an effective pathway for cities to achieve a win–win situation between economic growth and environmental protection in addressing climate change. At present, the Chinese government is comprehensively promoting the green transition of the economy and society, actively and effectively responding to global climate change. Against this backdrop, the scientific identification and estimation of the impact of EH on GEE provides new insights for responding to climate change and promoting GEE improvement, which has important theoretical and practical significance.

We focus on the adverse impact of EH on the efficiency of an urban green economy, taking 276 prefecture-level cities in China as the research sample and attempt to discusses and answers the following questions:

- Does EH inhibit the GEE? Are there differences in this effect on the basis of geographical location or policy pilot programs?
- Multiple studies have confirmed the positive externalities of innovative talent agglomeration and industrial collaborative agglomeration (Zhang and Guo, 2025; Zhang *et al.*, 2024b; Yan *et al.*, 2024). Do these agglomeration effects influence the relationship between EH and GEE? What role do the coupled and coordinated development of innovative talent agglomeration and industrial collaborative agglomeration play in the influence of EH on GEE?
- Does the inhibitory effect of EH on GEE vary due to differences in the distribution of GEE conditions?
- Multiple studies have confirmed that the economic impact of climate presents spatial correlation (Benhamed *et al.*, 2023; Liu *et al.*, 2025; Xie and Li, 2024; Felbermayr *et al.*, 2022). Considering spatial effects, how does EH affect GEE? Is there a spatial spillover effect?

Clarifying these issues can provide an essential reference for China to effectively address extreme climate risks, enhance urban climate adaptability and promote green development.

This study makes the following three possible contributions:

(1) Previous studies have paid less attention to the obstructive effect of EH on the development of urban green economy. This study delves deeply into the economic

consequences of EH from the perspective of GEE, as well as the heterogeneous impact of EH at different quantiles of GEE. This research enriches the existing literature on the economic consequences of EH climate.

(2) The results of this paper confirm the significant role of innovative talent, industrial collaborative agglomeration and the coupled and coordinated development of the two in weakening the negative impact of EH on GEE. These findings provide theoretical support for policymakers committed to enhancing urban climate resilience and promoting a green economic transformation.

(3) This study innovatively constructs a temperature adjacency spatial matrix to verify the spatial spillover effect of EH on GEE.

These findings provide theoretical support for the construction of a cross-regional collaborative climate governance system.

2. Literature review and hypotheses

2.1 Extreme heat and green economic efficiency

Unlike traditional economic growth, GEE covers the two core concepts of "green" and "economic efficiency" and has the dual characteristics of economic growth and eco-friendliness (Gao and Gao, 2024; Xu *et al.*, 2022). EH, as a physical climate risk, is characterized by unpredictability and destructiveness, poses a serious threat to the economy, society and ecology and directly affects a city's green development process. The negative impacts of EH on GEE are reflected mainly in urban output decline, social green welfare loss and ecological function degradation.

First, EH negatively impacts agriculture, industry and construction, which are key areas of the real economy. Specifically, EH causes crop damage (Wreford and Adger, 2010), reduced agricultural productivity (Ciais *et al.*, 2005; Aragón *et al.*, 2021; Lesk *et al.*, 2022), increased labor costs and decreased productivity (Wang *et al.*, 2025). These adverse effects are further transmitted to the financial sector (Peillex *et al.*, 2021; Schuster *et al.*, 2025), and ultimately affect both urban economic output and financial market stability (Chen *et al.*, 2024b; García-León *et al.*, 2021; Callahan and Mankin, 2022). This hinders the improvement in GEE.

Second, EH can damage the physical and mental health of urban residents. For example, the impairment of workers' intellectual productivity (Lai *et al.*, 2023) and the increase in the disease rate and mortality rate (Chen *et al.*, 2023a) not only increase healthcare costs for workers but also further increase their "degree of labor aversion" and aggravate the degree of income inequality among individuals, industries and groups (Chen *et al.*, 2023b), reducing the overall well-being of society. Moreover, EH accelerates the depreciation and damage of green public infrastructure, reduces the level of urban green public services and has an adverse impact on GEE.

Finally, EH accelerates the evaporation of surface soil moisture in urban areas, leading to a rising frequency of extreme weather events, including droughts and heat waves. EH exacerbates the shortage of urban water resources and urban heat islands, reduce biodiversity and undermines the stability of the urban eco-environmental system. This further hinders the improvement in GEE. Moreover, on the basis of the theory of climate change adaptability, the adaptive behaviors taken in response to climate change themselves involve nonproductive energy consumption and pollution emission costs (Jin *et al.*, 2020), which result in increased pollution emissions from urban production and life and damage GEE.

2.2 Theoretical analysis of the moderating *role*

2.2.1 Moderating role of innovative talent aggregation. Innovation plays an important role in addressing climate change (Adedoyin *et al.*, 2022). Innovative talent serves as an effective carrier for technological innovation, knowledge accumulation and information circulation. Its agglomeration within a given geographic space benefits specialized knowledge sharing and technology diffusion, promotes digital technologies in the development and application and provides both impetus and intellectual support for regional green development. These comprehensive benefits contribute positively to GEE.

Specifically, innovative talent aggregation can accelerate the diffusion and application of climate-friendly technologies in key fields, such as smart city construction, industrial production and environmental protection. The aggregation of innovative talent can help form a cooperative and shared regional innovation network, enhance carbon emission efficiency and green total factor productivity (Zhang *et al.*, 2024a; Yu *et al.*, 2023), alleviate the negative impacts of EH and improve GEE. In addition, by supporting the establishment of pre-event early warning mechanisms and post-event response mechanisms, the aggregation of innovative talent weakens the harmful effects of EH on a city's economic system; provides intellectual support for early warning of climate disasters, post-disaster relief and other aspects; and thereby enhances a city's ability to respond quickly and resist the risks of EH climates. This can alleviate EH's negative impact on GEE.

2.2.2 Moderating role of industrial co-agglomeration. The co-agglomeration of the manufacturing and productive service industries further deepens the division of industrial labor and generates the external benefits of knowledge and technology spillovers (Ding *et al.*, 2022). It also pushes the innovation of products, services and technologies; helps manufacturing achieve the green transformation of production processes and product supplies; and promotes the green transformation of city economies.

Industrial co-agglomeration can help manufacturing enterprises divest noncore businesses, focus more on technological innovation in production and the green transformation of processes, enhance the clean production capacity and pollution control level of enterprises, reduce greenhouse gas emissions (Liu *et al.*, 2024) and lower the probability of EH weather. This approach can also mitigate the unfavorable effects of EH on GEE. Industrial co-agglomeration entails advantages related to spatial proximity and information exchange. It can promote the flow, transformation and application of technology and talent for climate adaptation in agglomeration areas; improve a region's ability to withstand extreme climate risks; and promote total factor energy efficiency (Yang *et al.*, 2022). This can weaken EH's influence on GEE.

2.2.3 Moderating role of the coupled and coordinated development between innovative talent aggregation and industrial co-agglomeration. New economic geography holds that connections in the economic field and the knowledge field are the driving forces for the development of the spatial economy (Fujita, 2007). There is a dynamic interactive relationship of mutual support and reinforcement between innovative talent aggregation and industrial co-agglomeration. The coupled and coordinated development of the two within a geographical region strengthens economic and knowledge connections, which can effectively promote the deep integration of urban innovative elements, meet the demands for industrial transformation and development and enhance the economic and climatic resilience of the city, thereby providing a continuous impetus for the GEE growth of the city. According to the agglomeration externality theory, the coupling coordination of innovative talent aggregation and industrial co-agglomeration can produce an innovation multiplier effect. The collaborative innovation network is constructed through the dual impacts of Marshallian and Jacobs positive externalities, which effectively transform the external implications of the EH climate into the endogenous driving force of economic green transformation and green technology progress.

The positive externalities of agglomeration resulting from the coupling and coordination of innovative talent aggregation and industrial co-agglomeration contribute to the formation of close vertical upstream and downstream collaborative relationships between the urban manufacturing and production-oriented service industries (Cheng *et al.*, 2023). The labor pool effect and knowledge spillover effect can also promote the aggregation of professional talent and knowledge accumulation, and the exchange, absorption and application of climate-friendly technologies and experiences among industries and within departments. This positive externality of agglomeration can further deepen the cooperation and sharing of climate adaptability technological innovation achievements among industries (Wu and Xu, 2025), reduce the marginal cost of environmental pollution and technological research and development, enhance the climate adaptation and response capabilities of urban economic systems and alleviate the adverse impact of EH on GEE. In addition, the coupling coordination of innovative talent aggregation and industrial co-agglomeration can reduce the transformation costs of traditional industries through scale economy effects, promoting the transformation of traditional industries into intelligent, green and service-oriented industries. This effectively reduces their climate sensitivity and weakens the adverse impact of EH on GEE.

Therefore, we propose the following hypotheses:

H1. EH negatively affects GEE.

H2. Innovative talent agglomeration and industry co-agglomeration can reduce the negative influence of EH on GEE.

H3. The coupled and coordinated development between innovative talent aggregation and industrial co-agglomeration can alleviate EH's negative impact on GEE.

Furthermore, Figure 1 illustrates the theoretical framework of this study.

3. Model and data

3.1 Model construction

3.1.1 Empirical model. The benchmark model is established to verify the relationship between EH and GEE:

$$GEE_{it} = \alpha_0 + \alpha_1 EH_{it} + \alpha_2 X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{1}$$

where GEE_{it} reflects the GEE of city i in year t; EH_{it} is an indicator of EH, which indicates the quantity of EH days in city i in year t; X_{it} is the control variable sequence, λ_i and μ_t denote the city fixed and year fixed effects, respectively; and ε_{it} is a random disturbance term.

3.1.2 Moderation model. Extending Model (1), we use equations (2)–(4) to examine the moderating role of innovative talent agglomeration (*iita*) and manufacturing–producer services co-agglomeration (*coagg*) and the moderating effect of the degree of coupling coordination between innovative talent aggregation and industrial co-agglomeration (*ccd*):

$$GEE_{it} = \varphi_0 + \varphi_1 EH_{it} + \varphi_2 itta_{it} + \varphi_3 (EH_{it} \times itta_{it}) + \varphi_4 X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{2}$$

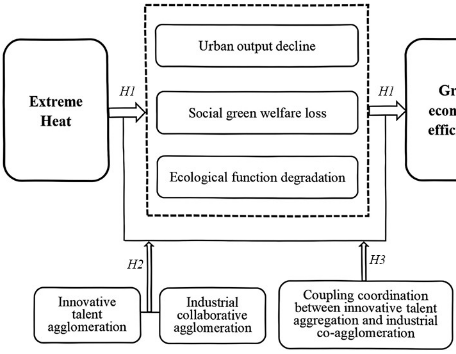

Figure 1. Analysis framework of the influence of EH on GEE
Source: Created by the authors

$$GEE_{it} = \theta_0 + \theta_1 EH_{it} + \theta_2 coagg_{it} + \theta_3 (EH_{it} \times coagg_{it}) + \theta_4 X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{3}$$

$$GEE_{it} = \gamma_0 + \gamma_1 EH_{it} + \gamma_2 ccd_{it} + \gamma_3 (EH_{it} \times ccd_{it}) + \gamma_4 X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{4}$$

where $itta_{it}$ and $coagg_{it}$ represent the moderating variables for innovative talent agglomeration and manufacturing–producer services co-agglomeration, respectively, and ccd_{it} represents the coupling coordination degree between $itta_{it}$ and $coagg_{it}$. Other variables are defined as before.

3.1.3 Panel quantile regression model. The benchmark regression Model (1) explores the influence of EH on the conditional expectations of GEE, but fails to fully capture the impact of EH on GEE under different conditional distributions. We further explore whether the influence of EH on GEE is conditionally dependent by using the panel quantile regression model [equation (5)]:

$$GEE_{it(\tau)} = \beta_{0(\tau)} + \beta_{1(\tau)} EH_{it} + \beta_{2(\tau)} X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{5}$$

where $\tau(0<\tau < 1)$ represents different quantiles of the conditional distribution, i.e. 0.1, 0.25, 0.5, 0.75 and 0.9. Other variables are defined as before.

3.1.4 Spatial econometric model. EH is a physical climate risk with spatial spillover effects (Wu, 2025), and economic and social activities have certain geospatial dependencies. We use the spatial Durbin model to further explore whether there is spatial dependence in the impact of EH on GEE. The spatial Durbin model is constructed via equation (6) as follows:

$$GEE_{it} = \omega_0 + \rho WGee_{it} + \omega_1 EH_{it} + \omega_2 WEH_{it} + \omega_3 X_{it} + \omega_4 WX_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{6}$$

where ρ represents the coefficient for spatial autoregression, ω_{it} represents the EH spatial spillover effect and W is the spatial weight matrix (including the adjacency matrix and the temperature-adjacency matrix). The construction formula of the temperature-adjacency matrix is given in equation (7):

$$W_{ij} = \begin{cases} 1/|\overline{Temp_i} - \overline{Temp_j}|, & i \neq j \\ 0, & i = j \end{cases} \tag{7}$$

where W_{ij} denotes the degree of temperature correlation between regions i and j, and $(\overline{Temp_i})$ and $(\overline{Temp_j})$ denote the mean annual average temperature from 2011 to 2022 for regions i and j, respectively.

3.2 *Variable description*

3.2.1 Dependent variables. GEE. We adopt the approach of including undesired outputs in the Super-SBM model to assess the GEE on an urban scale (Zhou *et al.*, 2025; Zhang and Wei, 2024; Chen *et al.*, 2024c). In addition, we refer to Fang *et al.* (2019), who considered in depth the importance of science and technology (S&T) expenditure and education expenditure in the economic development of modern cities by adding S&T investment to the input variables. The specific indicators are shown in Table 1.

3.2.2 Independent variables. EH. The relative threshold method is used as a proxy variable of EH (Alexander *et al.*, 2006; Zhao *et al.*, 2024; Zeng *et al.*, 2025; Pan *et al.*, 2022). The climate reference period from 1973 to 2002 is selected. The daily maximum temperatures within the climate reference period are ranked from high to low, and the 90th percentile value is taken as the threshold of EH to calculate the total number of days of EH events each year from 2011 to 2022.

3.2.3 Moderation variables. Innovative talent agglomeration (*itta*). With reference to Ye *et al.* (2022), who consider the number of innovative, talented individuals and geographical location factors, the adopted location entropy measures the degree of innovative talent agglomeration. The specific formula is shown in equation (8) as follows:

$$itta_{it} = (p_{it}/p_t)/(e_{it}/E_t) \tag{8}$$

where p_{it} and e_{it} are the total employees in S&T and the overall count of employees in city i at time t; P_t and E_t are the total number of S&T employees and the overall count of employees in the country.

Table 1. Indicator system for measuring GEE

Type	Variables	Measure
Inputs	Labor inputs	Number of employees in the city's year-end units
	Capital inputs	Total investment in fixed assets of the whole society
	Energy inputs	Total water consumption and electricity consumption of the whole society
	Science and technology inputs	Sum of expenditure on science and technology and education
Outputs	Desired outputs	Real GDP of each city (Based on 2005, the calculated results were obtained)
	Undesired outputs	Industrial wastewater emissions Industrial sulfur dioxide emissions Industrial soot emissions

Source(s): Fang *et al.* (2019)

Manufacturing industry and producer service industry co-agglomeration (*coagg*). Referring to Liu and He (2024) and Ding *et al.* (2022). Location entropy is used to calculate the degree of agglomeration of the two industries. The specific formula is shown in equation (9):

$$coagg_{it} = \left(1 - \frac{|agg_{mi} - agg_{apsi}|}{|agg_{mi} + agg_{apsi}|}\right) + (agg_{mi} + agg_{apsi}) \tag{9}$$

where agg_{mi} denotes the degree of manufacturing agglomeration and agg_{apsi} is the degree of productive services agglomeration.

Coupling coordination between innovative talent aggregation and industrial co-agglomeration (*ccd*). The coupled coordination degree model can quantify the level of synergy between different elements and is often applied to the coordinated development between systems. There is a dynamic interaction between innovative talent aggregation and industrial co-agglomeration, where each factor influences the other. To further examine the moderating role of the coupled synergies of innovative talent aggregation and industrial co-agglomeration in the impact of EH on GEE, we construct a coupled coordination degree model to quantify the coupled synergies of innovative talent aggregation and industrial co-agglomeration. Before conducting the coupling coordination measure, we normalize innovative talent aggregation and industrial co-agglomeration using the extreme value method. Equations (10) and (11) show the normalization process. Equations (12)–(14) illustrate the calculation of the coupling coordination degree:

$$itta_{new} = \frac{itta_{it} - \min(itta_{it})}{max(itta_{it}) - \min(itta_{it})} \tag{10}$$

$$coagg_{new} = \frac{coagg_{it} - \min(coagg_{it})}{max(coagg_{it}) - \min(coagg_{it})} \tag{11}$$

$$C = 2\sqrt{\frac{itta_{new} \times coagg_{new}}{(itta_{new} + coagg_{new})^2}} \tag{12}$$

$$T = \alpha itta_{new} + \beta coagg_{new},\ T \in [0,\ 1] \tag{13}$$

$$ccd = \sqrt{C \times T},\ D \in [0,\ 1] \tag{14}$$

where *ccd* is the degree of coupling coordination of innovative talent aggregation and industrial co-agglomeration. The larger the *ccd* value is, the greater the synergistic development of innovative talent aggregation and industrial co-agglomeration, and the more benign the interaction. The elements of innovative talent and industrial development show a state of deep integration. In addition, α and β are coefficients to be determined. In this work, we consider innovative talent agglomeration to be equally as essential as industrial synergistic agglomeration; thus, α and β each take a value of 0.5.

3.2.4 Control variables. In this study, we control for various factors that may influence the variables. With reference to previous research on GEE (Hu *et al.*, 2023; Zheng *et al.*, 2024; Wang *et al.*, 2023), we select the following variables:

Degree of population agglomeration (lnPD). Population agglomeration reflects urbanization intensity, driving increased resource demand and labor supply while exerting significant impacts on regional economic development. We use population density.

Economic development level (lnGDP). This reflects economic prosperity and can establish a strong basis for a low-carbon economy transformation. We measure it using the natural logarithm of regional GDP.

Industrial structure (IS). This is commonly used as a control variable. The contributions of the secondary and tertiary industries to the national economy can drive regional economic growth. We use the secondary and tertiary sectors' share of GDP as a measure.

Financial development level (Fin). It is calculated by the year-end balance ratio of financial institutions' deposits and loans to the regional GDP.

Economic development squared ($lnGDP^2$). The squared term of economic development is introduced to account for potential nonlinear effects of economic development on GEE.

3.3 Data sources

We analyze 276 prefecture-level cities in China between 2011 and 2022. Considering the data availability, continuity and other characteristics, we supplemented and deleted observations with missing values and outliers. We excluded certain city samples, including Shuangyashan, Bijie and Lhasa. Moreover, we used linear interpolation to complete the city samples with a few missing variables.

Data on the EH variables were derived from the National Meteorological Science Data Center of China (NMSDC) (http://data.cma.cn/). Original data for the remaining variables were extracted from the China City Statistical Yearbook (https://data.cnki.net/), the CNRDS database (https://www.cnrds.com[Link to the homepage of unep) and various municipal statistical yearbooks (https://www.shujuku.org/). Table 2 shows the variables' descriptive statistics.

4. Does extreme heat inhibit green economic efficiency?

4.1 Baseline regression analysis

Table 3 displays the stepwise regression analysis results. Column (1) is the result that does not include control variables, whereas Columns (2) through (6) illustrate the results with stepwise added control variables. The results demonstrate that the coefficient of EH is significantly negative, which indicates that EH adversely affects GEE. This finding confirms *H1*.

4.2 Robustness test

Five methods for robustness checks were used to test the results' stability, and the results are displayed in Tables 4 and 5.

Table 2. Descriptive statistics of the variables

Variables	Observation	Mean	SD	Min.	Max.
GEE	3,312	0.5198	0.2706	0.1454	1.3269
EH	3,312	24.8895	33.7564	0.0000	267.0000
lnGDP	3,312	16.6874	0.9391	14.1063	19.9169
$lnGDP^2$	3,312	279.3500	31.7489	198.9871	396.6849
lnPD	3,312	5.7331	1.0054	−3.8918	7.8816
IC	3,312	0.8820	0.0759	0.5011	1.0592
Fin	3,312	2.5806	1.2292	0.5879	21.3017

Source(s): Created by the authors

Table 3. Baseline regression results

Variables	(1) GEE	(2) GEE	(3) GEE	(4) GEE	(5) GEE	(6) GEE
EH	−0.001*** (−4.22)	−0.001*** (−2.96)	−0.001*** (−3.17)	−0.001*** (−3.22)	−0.001*** (−3.41)	−0.001*** (−3.37)
lnGDP		−0.169*** (−3.98)	−0.877** (−2.26)	−0.868** (−2.24)	−0.985** (−2.53)	−0.910** (−2.29)
lnGDP^2			0.021* (1.86)	0.021* (1.84)	0.023** (2.00)	0.022* (1.86)
lnPD				0.007 (0.69)	0.006 (0.62)	0.005 (0.49)
IS					0.816*** (3.11)	0.796*** (3.06)
Fin						0.017 (1.32)
_cons	0.516*** (52.75)	3.254*** (4.73)	9.125*** (2.76)	9.015*** (2.73)	9.720*** (2.93)	8.839** (2.59)
City-fixed	YES	YES	YES	YES	YES	YES
Year-fixed	YES	YES	YES	YES	YES	YES
N	3,312	3,312	3,312	3,312	3,312	3,312
R-square	0.069	0.100	0.106	0.106	0.115	0.117

Note(s): ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; *t*-values corresponding to robust standard errors are in parentheses, or *z*-statistics, as follows
Source(s): Created by the authors

Table 4. Robustness test results

Variables	(1) NewGEE	(2) GEE	(3) GEE	(4) GEE
EH	−0.0006*** (−2.94)		−0.0009*** (−3.53)	−0.0008*** (−4.48)
NewEH		−0.0009*** (−3.30)		
lnGDP	−0.4180 (−1.20)	−0.9106** (−2.28)	−1.0711** (−2.04)	−0.9103*** (−5.76)
lnGDP²	0.0105 (1.04)	0.0216* (1.86)	0.0267* (1.69)	0.0216*** (4.62)
lnPD	−0.0028 (−0.73)	0.0050 (0.50)	0.0035 (0.27)	0.0050 (0.62)
IC	0.6014*** (3.01)	0.7965*** (3.06)	0.7963*** (2.92)	0.7963*** (5.53)
Fin	0.0024 (0.28)	0.0165 (1.32)	0.0156 (1.14)	0.0165*** (3.27)
_cons	3.9672 (1.34)	8.8397** (2.59)	10.0912** (2.29)	9.6106*** (7.23)
City-fixed	YES	YES	YES	YES
Year-fixed	YES	YES	YES	YES
N	3,312	3,312	2,952	3,312
R-square	0.058	0.117	0.111	

Source(s): Created by the authors

Table 5. Endogeneity test results

Variables	(1) EH	(2) GEE	(3) EH	(4) GEE
IV1	−0.2637*** (–12.18)			
EH		−0.0033*** (−2.74)		
IV2			0.9326*** (21.73)	
EH				−0.0012*** (−2.82)
Control variables	YES	YES	YES	YES
City-fixed	YES	YES	YES	YES
Year-fixed	YES	YES	YES	YES
N	3,312	3,312	3,312	3,312
R^2	0.8994	0.7645	0.9521	0.7754
Kleibergen-Paap rk LM statistic	228.409***		347.429***	
Kleibergen-Paap rk Wald F statistic	302.614 [16.38]		1,199.767 [16.38]	

Source(s): Created by the authors

First, we substitute the dependent variable. Considering the close relationship between the selection of different indicators and the research results, we adopt input indicators, including capital (capital stock estimated using the sustainable inventory method), labor (total number of employees at year’s end), land (built-up area), energy (electricity consumption by society) and water resources (water consumption by society). Real GDP is used as the anticipated output indicator. The three industrial wastes are unexpected output indicators, and the regression is carried out after recalculating the explanatory variables. Table 4 Column (1) presents the regression results. The coefficient of EH remains significantly negative.

Second, we substitute the independent variable. Considering that the baseline period selection impacts the regression results, we adopt an alternative baseline period for assessing EH events. Using the climate baseline period of 1983–2012, we redefine the EH threshold, calculate the yearly count of EH days during the research period and reevaluate the results, as illustrated in Table 4, Column (2). The regression results remain robust.

Table 6. Heterogeneity analysis results

Variables	(1) East of "Hu Huanyong Line"	(2) West of "Hu Huanyong Line"	(3) Nonclimate-adaptive pilot cities	(4) Climate-adaptive pilot cities
EH	−0.0009*** (−3.74)	0.0009 (0.36)	−0.0010*** (−3.82)	0.0009** (2.16)
lnGDP	−0.9190** (−2.10)	1.6174 (0.72)	−1.0257** (−2.33)	−1.0147 (−1.14)
lnGDP^2	0.0221* (1.75)	−0.0608 (−0.85)	0.0253* (1.96)	0.0153 (0.75)
lnPD	−0.0342 (−0.66)	−0.0015 (−0.11)	0.0050 (0.49)	−0.7357* (−1.94)
IC	0.6854** (2.50)	1.2308* (1.85)	0.8755*** (3.04)	−0.5584 (−0.97)
Fin	0.0155 (1.24)	0.0522 (0.72)	0.0172 (1.28)	−0.0087 (−0.27)
_cons	9.1815** (2.45)	−11.1155 (−0.62)	9.6757** (2.58)	17.6373 (1.69)
City-fixed	YES	YES	YES	YES
Year-fixed	YES	YES	YES	YES
N	3,048	264	3,048	264
R-square	0.1270	0.1423	0.1155	0.3239

Source(s): Created by the authors

Third, we change the sample range. Given the distinct administrative status and socioeconomic advantages (e.g. larger economic scale and better infrastructure) of centrally administered municipalities and provincial capitals compared with other prefecture-level unit cities, our estimates may be biased. After these 30 regions are excluded, the results are shown in Table 4, Column (3). The EH coefficient still has a significantly negative value.

Fourth, we replace the estimation method. The re-estimation model's empirical results, using the generalized least squares (GLS) method, are shown in Column (4) of Table 4. EH and GEE present a negative correlation, which suggests that the results remain robust.

Fifth, we address endogeneity concerns. In this study, we use city latitude (IV1) and the mean EH days of other cities in the same province (IV2) as instrumental variables. Latitude objectively determines temperature (lower latitudes correspond to higher temperatures) and temperatures are correlated across cities within the same province. Neither variable directly affects GEE, which satisfies the instrumental variable assumption. The results are shown Columns (1)–(4) of Table 5. Both pass the underidentification and weak identification tests, confirming EH's significant negative impact on GEE and supporting our baseline results' robustness.

4.3 Heterogeneity analysis

To analyze the heterogeneous impacts of EH on GEE, we categorize cities according to two criteria: the Hu Huanyong Line and participation in climate-adaptive pilot city programs. The detailed regression results are shown in Table 6. The results indicate that in the cities east of the Hu Huanyong line and in nonclimate-adaptive pilot cities, EH substantially inhibits GEE. In climate-adaptive pilot cities, EH positively impacts GEE. The urbanization and industrialization levels, as well as the degree of industrial pollution in the region east of the Hu Huanyong Line, are greater than those in the western region. The high-density population concentration and concentrated industrial production activities further intensify the heat island effect in urban areas, thereby increasing the frequency and intensity of EH events. The climate-adaptive pilot cites initiative serves as a critical policy instrument that systematically advances institutionalized climate adaptation governance to effectively facilitate the urban low-carbon economic transition.

4.4 Moderation discussion

The results of the modulation effects of innovative talent aggregation, industrial co-agglomeration and the coupling coordination degree are shown in Table 7. Column (1) shows the moderating influence of innovative talent aggregation. The interaction term between EH and innovative talent aggregation (c_itta) indicates a significant positive coefficient at the 1% level. This finding demonstrates that innovative talent aggregation effectively mitigates EH's negative impact on GEE. Column (2) shows the results regarding the moderating effect of industrial co-agglomeration. The interaction term between EH and industrial co-agglomeration (c_coagg) has a statistically significant positive coefficient at the 10% level, indicating that industrial co-agglomeration effectively reduces the adverse impact of EH on GEE. Column (3) shows the moderating effect of the coupling coordination degree. The interaction term between EH and the coupling coordination degree (c_ccd) is positively significant at the 5% level, indicating that the coupled and coordinated development of innovative talent aggregation and industrial co-agglomeration can effectively mitigate the negative effects of EH on GEE. Theoretical analysis shows that innovative talent agglomeration and industrial co-agglomeration generate knowledge spillover effects and technological externalities. Their coordinated development is conducive to further exerting the multiplier effect of innovation, promoting the establishment of an urban green technology innovation system, forming a favorable urban innovation ecosystem and enhancing the efficiency of resource utilization, climate adaptability and sustainable development capabilities. These factors help reduce the adverse effects of EH on GEE.

5. Further research

5.1 Panel quantile regression analysis

Table 8 shows the panel quantile regression results. EH has a negative impact on GEE at different quantiles and shows structural characteristics. Specifically, EH has a significant negative impact on cities with medium-low and medium levels of GEE, while the impact on cities with low and high levels of GEE is negative but insignificant. This is mainly because

Table 7. Moderated effects test results

Variables	GEE	GEE	GEE
EH	−0.0010*** (−3.74)	−0.0027*** (−2.59)	−0.003*** (−3.14)
Itta	−0.0007 (−1.01)		
c_itta	0.0002*** (2.87)		
coagg		−0.0284 (−1.46)	
c_coagg		0.0008* (1.91)	
Ccd			−0.379** (−2.04)
c_ccd			0.012** (2.47)
lnGDP	−0.8816** (−2.23)	−0.7937** (−2.13)	−0.809** (−2.15)
lnGDP^2	0.0206* (1.80)	0.0181* (1.66)	0.018* (1.68)
lnPD	0.0050 (0.49)	0.0050 (0.50)	0.006 (0.56)
IC	0.7980*** (3.06)	0.8004*** (3.06)	0.818*** (3.13)
Fin	0.0164 (1.31)	0.0154 (1.26)	0.015 (1.25)
_cons	8.6195** (2.54)	7.9357** (2.47)	8.082** (2.49)
City-fixed	YES	YES	YES
Year-fixed	YES	YES	YES
N	3,312	3,312	3,312
R-square	0.1192	0.1212	0.1268

Source(s): Created by the authors

Table 8. Panel quantile regression results

Variables	(1) Q10	(2) Q25	(3) Q50	(4) Q75	(5) Q90
EH	−0.0006 (−1.31)	−0.0007** (−2.20)	−0.0008* (−1.66)	−0.0010 (−1.02)	−0.0012 (−0.84)
lnGDP	−0.7043* (−1.66)	−0.7755*** (−2.65)	−0.8977* (−1.86)	−1.0498 (−1.07)	−1.1586 (−0.85)
$lnGDP^2$	0.0159 (1.31)	0.0179** (2.13)	0.0212 (1.54)	0.0254 (0.91)	0.0284 (0.73)
lnPD	0.0050 (0.18)	0.0050 (0.26)	0.0050 (0.16)	0.0050 (0.08)	0.0050 (0.06)
IC	0.6598* (1.84)	0.7069*** (2.85)	0.7880* (1.93)	0.8888 (1.07)	0.9609 (0.84)
Fin	0.0091 (0.48)	0.0117 (0.90)	0.0161 (0.75)	0.0216 (0.50)	0.0255 (0.42)
City-fixed	YES	YES	YES	YES	YES
Year-fixed	YES	YES	YES	YES	YES
N	3,312	3,312	3,312	3,312	3,312

Source(s): Created by the authors

cities with medium to low and medium levels of GEE levels are in an economic transformation period. The transitional period of IS adjustment makes the industries in these cities show high climate sensitivity. Coupled with multiple risks such as industrial chain reconstruction and uncertainty in the institutional environment, these cities have a relatively weak ability to resist extreme climate risks.

5.2 Spatial spillover effects discussion

5.2.1 Spatial correlation test. The findings from the spatial correlation test presented in Table 9 show that, under the setting of an adjacency matrix and a temperature-adjacency matrix, GEE and EH have an obvious positive spatial correlation.

5.2.2 Spatial spillover effects test. The spatial spillover results in Table 10 show that EH has a positive spatial spillover effect, inhibiting local GEE while promoting it in neighboring regions. This occurs mainly because EH reduces urban livability and drives the flow of innovative talent and capital to neighboring areas. Moreover, owing to the heuristic effect between cities, frequent EH exposes local deficiencies in public infrastructure and emergency

Table 9. The results of Moran’s I index results

	GEE		EH	
Year	Adjacency matrix	Temperature-adjacency matrix	Adjacency matrix	Temperature-adjacency matrix
2011	0.162***	0.184***	0.792***	0.886***
2012	0.213***	0.243***	0.751***	0.859***
2013	0.230***	0.251***	0.786***	0.869***
2014	0.113**	0.107*	0.787***	0.852***
2015	0.111***	0.136**	0.698***	0.787***
2016	0.123***	0.173***	0.720***	0.842***
2017	0.164***	0.210***	0.768***	0.850***
2018	0.175***	0.201***	0.706***	0.793***
2019	0.212***	0.226***	0.760***	0.821***
2020	0.223***	0.224***	0.776***	0.828***
2021	0.241***	0.263***	0.858***	0.885***
2022	0.200***	0.214***	0.844***	0.890***

Source(s): Created by the authors

Table 10. The results of spatial spillover effects test results

Variables	Main	EH	Direct	Indirect	Total
Adjacency matrix					
EH	−0.001*** (−4.14)	0.001** (2.01)	−0.001*** (−4.19)	0.001* (1.84)	−0.001*** (−2.73)
lnGDP	−0.634*** (−3.73)	−0.422 (−1.52)	−0.668*** (−4.73)	−0.546** (−2.12)	−1.214*** (−5.05)
lnGDP^2	0.016*** (3.27)	0.010 (1.18)	0.017*** (4.12)	0.013* (1.76)	0.030*** (4.36)
lnPD	0.001 (0.07)	−0.023 (−1.05)	0.0004 (0.05)	−0.024 (−1.08)	−0.024 (−0.93)
IC	0.582*** (3.83)	0.382* (1.81)	0.568*** (3.33)	0.487** (2.08)	1.055*** (4.53)
Fin	0.010** (2.01)	0.034*** (4.00)	0.011** (2.31)	0.036*** (4.01)	0.047*** (4.39)
City-fixed	YES	YES	YES	YES	YES
Year-fixed	YES	YES	YES	YES	YES
N	3,312				
rho	0.122*** (5.17)				
R-square	0.0157				
Temperature-adjacency matrix					
EH	−0.001*** (−3.82)	0.001* (1.78)	−0.001*** (−3.86)	0.001 (1.49)	−0.001*** (−3.26)
lnGDP	−0.594*** (−3.45)	−0.545** (−2.16)	−0.626*** (−4.35)	−0.592*** (−2.64)	−1.218*** (−5.93)
lnGDP2	0.015*** (2.95)	0.013* (1.76)	0.016*** (3.71)	0.015** (2.25)	0.030*** (5.14)
lnPD	0.0001 (0.01)	−0.050* (−1.82)	−0.0004 (−0.05)	−0.049* (−1.89)	−0.050* (−1.75)
IC	0.539*** (3.55)	0.594*** (3.17)	0.525*** (3.07)	0.630*** (3.13)	1.156*** (5.70)
Fin	0.010* (1.94)	0.037*** (4.84)	0.011** (2.19)	0.036*** (4.75)	0.047*** (4.99)
City-fixed	YES	YES	YES	YES	YES
Year-fixed	YES	YES	YES	YES	YES
N	3,312				
R-square	0.0168				
Rho	0.065*** (3.27)				

Source(s): Created by the authors

management, offering lessons and insights useful for neighboring regions seeking to cope with EH risks. This encourages neighboring regions to adopt more proactive green development strategies, build more climate-resilient economic systems and enhance their GEE.

6. Conclusion and policy implications

6.1 Conclusion

We took 276 prefecture-level cities in China from 2011 to 2022 as research samples to explore the impact of EH on GEE. The primary conclusions are as follows:

- EH significantly inhibits the improvement in GEE.
- Heterogeneity analysis reveals that EH significantly inhibits GEE in the areas east of the Hu Huanyong Line and in nonclimate-adaptive pilot cities.
- Moderating effect analysis reveals that innovation talent agglomeration and industrial co-agglomeration effectively mitigate the negative influence of EH on GEE and that the coupled and coordinated development of the two likewise contributes to the mitigation of EH's negative impact on GEE.
- Further analysis indicates that the influence of EH on GEE varies across different conditional distributions of GEE. In the mid-low quantiles and the median quantile of GEE, the negative impact of EH on GEE is significant. The influence of EH on GEE has a positive spatial spillover effect and can enhance GEE in neighboring regions.

6.2 Policy implications

Based on the above conclusions, the following policy recommendations are proposed to promote the improvement of urban GEE and better address climate change:

Local governments should actively promote the digital and intelligent as well as green transformation of traditional industries that are vulnerable to EH (such as agriculture and manufacturing). Government departments should integrate concepts such as climate adaptation, energy conservation and emission reduction into local social norms while increasing public awareness of ecological and climate issues, thereby advancing the green transition in urban residents' living and consumption patterns.

Policies must be adapted to local circumstances. Regions east of the Hu Huanyong Line should actively cultivate new productive forces, incorporate climate adaptation and green economy development principles into urban planning strategies, actively alleviate "urban diseases" and improve both GEE and climate resilience.

For nonclimate-adaptive pilot cities, it is essential to scientifically identify vulnerabilities in infrastructure, ecosystems and socioeconomic systems under EH risk conditions on the basis of each city's climatic features, resource endowments and industrial conditions and selectively adopt successful practices from other pilot cities to formulate localized development strategies that effectively prevent EH climate risk.

Urban development must be enhanced through innovation empowerment. Local governments should scientifically assess the development of the local green economy and strive to attract talented individuals proficient in green/low-carbon technologies and climate adaptation solutions. Policies should promote the precise alignment between the supply of innovative talent and the demand for urban industrial development, and proactively integrate into the regional climate governance system.

7. Limitations and future research

This study has several limitations. Although it focuses on EH climate and has certain value, its scope is relatively limited. Specifically, the model adopted in this paper is used to examine the linear effect of a single extreme climate variable on the efficiency of the urban green economy. By contrast, in the actual climate system, nonlinear superimposed effects of compound extreme events may exist. Future research should conduct comparative analysis of various extreme climates to obtain a more comprehensive understanding of their differential impacts on the economic sustainability of cities. Other studies can examine the impacts under the interaction of extreme climate events, as well as the responses of cities with different economic and ecological resilience to extreme climates, which can more comprehensively reveal the complexity of the climate system's impact on the economy.

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