City-level resilience to extreme weather shocks revealed by Satellite nighttime lights in China

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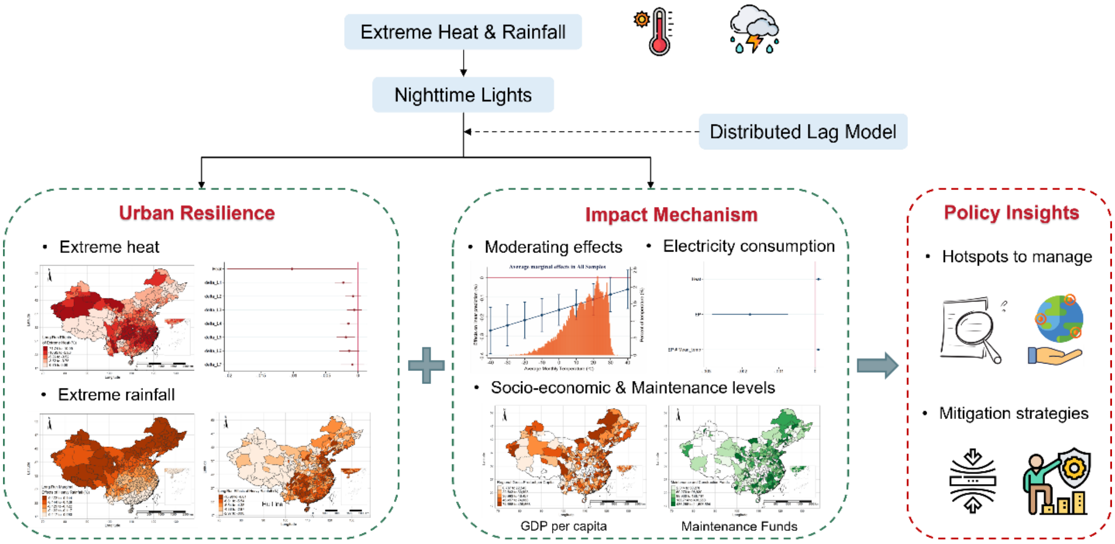
Abstract

Given the unprecedented climate change, extreme weathers have become more intense and frequent, causing severe socio-economic impacts. Urban resilience is vital for mitigating extreme events, but little is known about its city-level response to such shocks in China. Here, we aim to investigate the persistent effects of extreme heat and heavy rainfall on Chinese cities, ultimately revealing urban resilience. We use monthly nighttime lights from 2013-2019 as a proxy for urban functioning. Our results suggest that cities are less resilient to extreme heat than to heavy rainfall, yet the adverse effects of heavy rainfall can persist for up to seven months. Importantly, we reveal for the first time that areas near the Hu Line are vulnerable to heavy rainfall (e.g., Beijing, Tianjin and Chongqing), and cities in the Yangtze River basin are most affected by extreme heat (up to 24.8% loss of nighttime light intensity). There is an urgent need to address severe weather impacts in regions dominated by secondary sector, while developed economies are vulnerable to climate hazards, despite having high defense. Our findings identify urban climate risk hotspots and underlying impact mechanisms, providing valuable insights into climate mitigation policies and urban development strategies.

Keywords

Urban resilience; Extreme heat; Heavy rainfall; Nighttime lights; Empirical model.

Graphical Abstracts



1 Introduction

With continued climate change, extreme weathers have become more frequent and intense (Seneviratne et al., 2021), seriously threatening human well-being (Vicedo-Cabrera et al., 2021) and socioeconomic stability (Felbermayr et al., 2022; Palagi et al., 2022). Specifically, heightened intensity in extreme heat and heavy rainfall significantly decreases economic growth (Callahan and Mankin, 2022; Felbermayr et al., 2022), electricity system stability (Barreca et al., 2022; Longden et al., 2022), and leads to infrastructure damage (Zhang and Villarini, 2020), posing alarming risks to urban sustainable development. Urban resilience will be a critical contributor to mitigating the impacts of these severe extremes (Quesnel and Ajami, 2017; Mård et al., 2018). Highly resilient cities have a strong capacity to resist and/or adapt to hazards and can quickly return to normal function or equilibrium (Ribeiro and Gonçalves, 2019). Thus, understanding urban resilience is crucial for attenuating the climate risks (Barton-Henry and Wenz, 2022).

There has been a wealth of research exploring the urban resilience of climate risk (Kabisch et al., 2016; Li et al., 2020; Barton-Henry and Wenz, 2022). For example, Callahan and Mankin (2022) tracked the persistence of heatwaves and identified their potential to exert prolonged, multi-year effects on the global capital and productivity. In addition, extensive studies measure urban resilience to climate hazards in economic, social and environmental dimensions (Georgeson et al., 2016; Rus et al., 2018;

Feofilovs and Romagnoli, 2021) through exposure, sensitivity, adaptability and recovery (Wang et al., 2012; Sun et al., 2022). However, these quantitative assessment methods at the national scale, essential for effective and timely management, demand substantial datasets with refined spatial and temporal resolution. Therefore, a growing body of literature attempts to use satellite imagery (e.g., nighttime lights) to more accurately assess the impact of climate disasters (Ceola et al., 2014; Yu et al., 2023), ultimately revealing the resilience of cities (Qiang et al., 2020; Barton-Henry and Wenz, 2022).

Nighttime lights, a high-resolution global remote sensing data, can directly represent human activity intensity (Ma et al., 2012; Qiang et al., 2020) and urbanization levels (Zhao et al., 2019). Therefore, numerous studies have employed nighttime lights as a proxy for examining responses in socio-economic activity (Beyer et al., 2021; Felbermayr et al., 2022), thereby shedding light on urban resilience to extreme weather shocks (Qiang et al., 2020). This approach serves to mitigate the limitations arising from data scarcity and the inherent subjectivity of human statistics (Felbermayr et al., 2022). For example, Mård et al. (2018) employed nighttime lights to reveal human relocation activities during floods, establishing a significant correlation between urban resilience levels and light data. However, previous studies aggregate the impact of extreme weathers on nighttime lights to the annual level (Mård et al., 2018; Felbermayr et al., 2022), or small regional impacts of mega-hazards (Elliott et al., 2015; Barton-Henry and Wenz, 2022; Liu et al., 2023). In China, there is a lack of nationwide research on resilience to monthly extreme weather shocks at city level, challenging the effectiveness of climate policies to improve urban resilience and mitigate climate risks.

In this paper, we therefore investigate underlying relationships between extreme meteorological events (i.e., extreme heat and heavy rainfall) and their potential response as measured by nighttime lights in China cities, with the aim of revealing urban climate resilience levels. Based on preprocessed data of monthly nighttime light from Zhong et al. (2022), we use a distributed lag model to explore plausible causal effects of climate extremes in the short and long term. To investigate potential impact channels, we then assess the impact of extreme weathers on household electricity consumption (data collected from China Urban Statistics Yearbook), and further perform heterogeneity analysis through city types and dominant industry. Our empirical evidence thus provides a sound understanding of city-level climate resilience and a critical benchmark for estimating the socio-economic impacts of climate extremes.

2 Theoretical basis

The objectives of this study are to understand the extent, duration and potential mechanisms by which severe weathers affect nighttime lights, ultimately indicating the urban resilience. To enhance the theoretical foundation of our research, we elaborate on the rationale for utilizing nighttime lights as a representation of urban functionality. This allows us to investigate the assumption that extreme weather conditions can impact nighttime lights, ultimately revealing the overarching goal of urban resilience.

Nighttime lights strongly correlate with socio-economic development (Cui et al., 2020; Chen et al., 2023). For instance, nighttime light data is employed to revise GDP growth (Zhang et al., 2019), depict county-level economics (Ji et al., 2019), and exhibits a substantial correlation with population density ($r^2>0.8$) (Sarkar, 2021). Zhao et al. (2022) also use utilize nighttime light data to compile global annual urban extents and analyze the spatiotemporal patterns of urban dynamics. Therefore, nighttime light intensity can act as a proxy for economic activity, which we can utilize to evaluate the effects of natural disasters and aid in the development of mitigation measures for the Natural Response Community (Qiang et al., 2020). In a previous study, nighttime light emissions were employed to investigate the response of economic activity to weather anomalies, such as precipitation anomalies, droughts, cold spells, and storms (Felbermayr et al., 2022). The impacts of extreme weather conditions on urban socio-economic development can influence nighttime lights through both direct and indirect mechanisms (Qiang et al., 2020; Felbermayr et al., 2022). Consequently, the restoration of nighttime lights in the aftermath of natural disasters can serve as a proxy for urban functionality (Barton-Henry and Wenz, 2022).

In particular, extreme weather events can disrupt the electrical system, thereby affecting nighttime lights (Wang et al., 2018; Román et al., 2019). For example, extreme heat can lead to excessive electricity consumption (Auffhammer et al., 2017; Wang et al., 2023) and may even reduce hydropower generation due to droughts caused by prolonged high temperatures (Yalew et al., 2020). This was evident during the extreme heat and drought in the Yangtze River of China in 2022 (Mallapaty, 2022). Therefore, electrical systems may become overwhelmed and suffer from power shortages during extreme heat events (Li et al., 2019; Barreca et al., 2022), potentially leading to system failures and the implementation of electricity restriction policies. This, in turn, can result in reduced nighttime light intensity compared to normal conditions (Barton-Henry and Wenz, 2022; Liu et al., 2023). During intense precipitation, which can potentially lead to floods, there is a risk of damage to electricity infrastructure, ultimately resulting in the loss of nighttime lights (Zhao et al., 2018; Liu et al., 2023).

In addition, weather anomalies can diminish labor productivity (Parsons et al., 2021), influence enterprise performance (Zhang et al., 2018), and ultimately attenuate local economic activity (Dasgupta et al., 2021; Parsons et al., 2021). Individuals may migrate to areas with milder weather conditions, and investors tend to establish factories therein (Mueller et al., 2014; Zhang et al., 2018). Consequently, the adverse impacts on economic production caused by exogenous disasters can lead to positive spillover effects in neighboring regions (Felbermayr et al., 2022). Nighttime lights can serve as indicators of population density and economic activity, thereby encapsulating the dynamics of human migration aimed at alleviating adverse climate-related effects (Mård et al., 2018). As a result, regions susceptible to extreme hazards may witness adverse effects on nighttime lights, suggesting that economic production may struggle to recover in time.

Nevertheless, a higher intensity of nighttime lights implies long-term influential human activities such as increased urbanization (Zhao et al., 2019), which, in turn, could exacerbate heatwaves and heavy rainfall, rendering cities more vulnerable to the impacts of such climatic extremes (Zhong et al., 2017; Wang et al., 2021; Han et al., 2022; Huang et al., 2023). This introduces the potential for reverse causality when estimating the causal impact of extreme weather conditions on night-light emissions. This potential reverse causation could undermine causal inference and introduce biased assessments of effects (Leszczensky and Wolbring, 2022; Xu et al., 2022), making it challenging to identify the impact of extreme weather conditions on urban areas. To address this issue, we incorporate lagged terms of extreme weathers as independent variables (i.e., the extreme weathers in previous 1-7 months). Since extreme weather conditions in previous months are unaffected by human activities (with nighttime lights as a proxy variable) in the current month, this approach allows us to employ previous periods of extreme weather as exogenous shocks influencing the present intensity of nighttime lighting.

Importantly, the lagged effects of extreme weather on nighttime lights can be an effective indicator of urban resilience under exogenous shocks (Barton-Henry and Wenz, 2022). While studies have shown that extreme weather events lead to a reduction in nighttime light intensity (Wang et al., 2018; Yu et al., 2023), the persistence of these effects remains uncertain. Thus, through an examination of the lagged repercussions of extreme shocks, we can determine the duration of climate-related impacts, which can serve as an indicator of a city's resilience (Qiang et al., 2020; Callahan and Mankin, 2023). For instance, urban infrastructure, including power networks, may suffer damage due to extreme precipitation (Ji et al., 2016; Dave et al., 2021). However, cities with low resilience may struggle to swiftly restore these facilities, resulting in a reduction in nighttime light intensity (Liu et al., 2023). Conversely, areas with high resilience may experience rapid technological advancements and potentially even an augmentation of nighttime lighting (Qiang et al., 2020). As a result, cities with diverse resilience levels exhibit distinct lag effects and magnitude variations in response to extreme weather events. These distinctions can be elucidated by employing distributed lag models (Callahan and Mankin, 2023), thereby yielding valuable insights into urban resilience.

Extreme weathers have distinct seasonal characteristics and could occur multiple times and exist for several months within the same year. However, by using annual data (Felbermayr et al., 2022), we may not capture the short- and long-term impacts of different seasonal hazards, which would ignore valuable insights, thus emphasizing the importance of this monthly impact study.

3 Material and Methods

In this section, we will provide an overview of the data collection, data processing, and methodologies employed in this study (***Fig. 1***). Our approach involved aggregating extreme temperatures and heavy rainfall data at the city and monthly levels, allowing us to apply a distributed lag model to assess the short- and long-term impacts of climate extremes. We also explore the hypothesized mechanisms of influence by investigating how extreme weather events influence household electricity consumption. In addition, we conduct heterogeneity analysis based on urban types and the dominant industry. Finally, we subject the main results to several robustness tests.

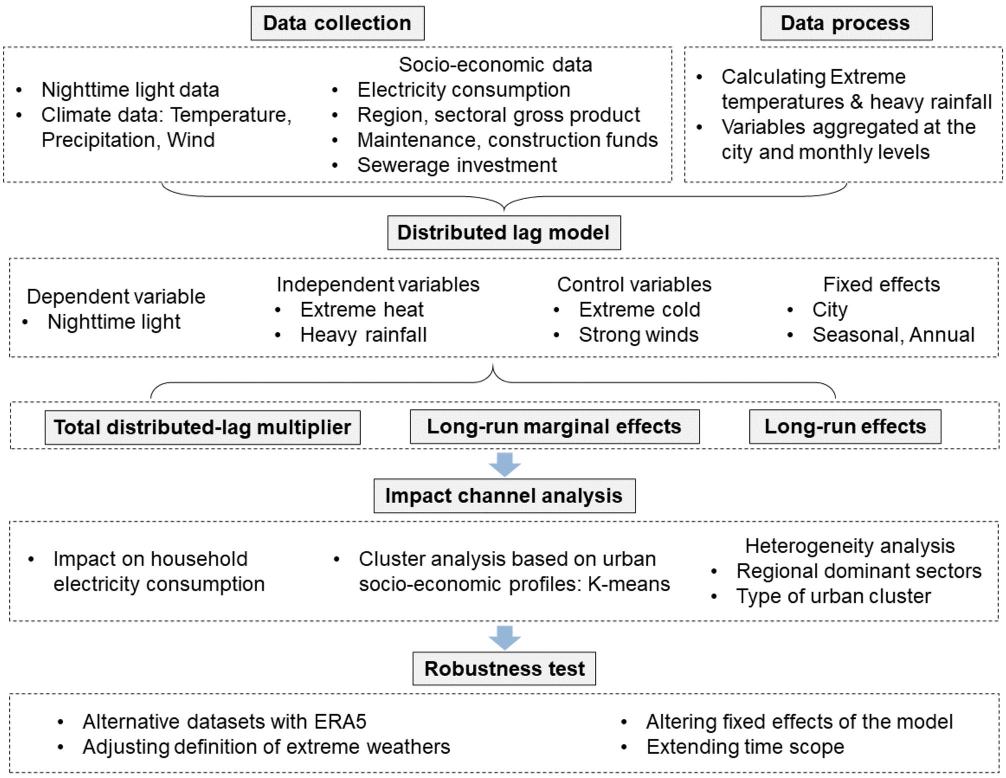


Fig. 1. Methodology flowchart.

3.1 Data

3.1.1 Nighttime lights

We utilize monthly nighttime light data, available at this Global Change Research Data (https://www.geodoi.ac.cn/edoi.aspx?DOI=10.3974/geodb.2022.06.01.V1), spanning from January 2013 to March 2019, as our dependent variable. As elucidated in the research conducted by (Zhong et al., 2022), the data has undergone a series of preprocessing, correction, and fusion procedures utilizing version 4 of the Suomi National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite (NPP-VIIRS) nighttime light data. Comprehensive information on the data preprocessing steps, which encompass any corrections or adjustments, is expounded in the research of Zhong et al. (2022). The monthly NPP-VIIRS nighttime light data, with a spatial resolution of 500 m, is aggregated to the prefecture level in China.

To assess the robustness of our model results, we have also employed an extended dataset of China's nighttime lights spanning from 2000 to 2018 on an annual basis (Zhang et al., 2021). This dataset is obtainable from A Big Earth Data Platform for Three Poles (https://poles.tpdc.ac.cn/en/data/e755f1ba-9cd1-4e43-98ca-cd081b5a0b3e/).

3.1.2 Climate data

Climate data such as temperature, precipitation and wind are provided by the Resource and Environment Science and Data Center (https://www.resdc.cn/Default.aspx). The daily-scale dataset is derived from over 2400 meteorological observation stations across China, which are also aggregated to the monthly municipal level in China. We use absolute indices of monthly maximum or minimum values to measure temperature extremes (Alexander et al., 2006). The definitions of temperature and precipitation extremes in the model are detailed in ***Table 1***.

Table 1. Definitions of extreme weather variables.

Extreme weather variables	Definition	Variable types in the model	References
Extreme high temperature	Daily maximum temperature exceeding 35°C for at least three consecutive days	Independent variable	(Sachindra et al., 2016; Farah et al., 2019; Seneviratne et al., 2021)
Extreme precipitation	Days with more than 50 mm of daily total rainfall	Independent variable	(General Administration of Quality Supervision, Inspection and Quarantine of the People's Republic of China and Standardization Administration of the People's Republic of China, 2012)
Extreme low temperature	Daily maximum temperature below 0°C	Control variable	(Alexander et al., 2006; Xu et al., 2022)

Initially, we calculate the monthly averages for extreme heat, total rainfall, and extreme cold using the following formulas (***Eqs. (1-3)***).

$$\bar{T}_{heat(r,t)} = \begin{cases} \dfrac{\sum_{d=1}^{D_{heat(r,t)}} T_{\max(r,t,d)}}{D_{heat(r,t)}}, & T_{\max(r,t,d)} \geq 35°\mathrm{C}; \\ 0, & T_{\max(r,t,d)} < 35°\mathrm{C} \end{cases} \tag{1}$$

$$\bar{P}_{storm(r,t)} = \begin{cases} \dfrac{\sum_{d=1}^{D_{storm(r,t)}} P_{storm(r,t,d)}}{D_{storm(r,t)}}, & P_{storm(r,t,d)} \geq 50mm; \\ 0, & P_{storm(r,t,d)} < 50mm \end{cases} \tag{2}$$

$$\bar{T}_{cold(r,t)} = \begin{cases} \dfrac{\sum_{d=1}^{D_{cold(r,t)}} T_{\max(r,t,d)}}{D_{cold(r,t)}}, & T_{\max(r,t,d)} < 0°\mathrm{C}; \\ 0, & T_{\max(r,t,d)} \geq 0°\mathrm{C} \end{cases} \tag{3}$$

where $\bar{T}_{heat(r,t)}$, $\bar{P}_{storm(r,t)}$ and $\bar{T}_{cold(r,t)}$ represent the average extreme heat (°C), average total rainfall (mm) and average extreme cold (°C) for city r, and month t, respectively. $T_{\max(r,t,d)}$ and $P_{storm(r,t,d)}$ represent daily maximum temperature and daily total rainfall on day d of month t in city r, respectively. $D_{heat(r,t)}$, $D_{storm(r,t)}$ and $D_{cold(r,t)}$ represent the extreme heat, precipitation and cold days in city r, and month t, respectively.

We further define the intensity of extreme weathers as the difference between the monthly average of extreme weather events and the threshold value, multiplied by the number of days on which extreme weather occurs:

$$EH_{(r,t)} = \begin{cases} (\bar{T}_{heat(r,t)} - 35) \times D_{heat(r,t)}, & \bar{T}_{heat(r,t)} \geq 35℃; \\ 0, & \bar{T}_{heat(r,t)} < 35℃ \end{cases} \tag{4}$$

$$EP_{(r,t)} = \begin{cases} (\bar{P}_{storm(r,t)} - 50) \times D_{storm(r,t)}, & P_{storm(r,t)} \geq 50mm; \\ 0, & P_{storm(r,t)} < 50mm \end{cases} \tag{5}$$

$$EC_{(r,t)} = \begin{cases} (0 - \bar{T}_{cold(r,t)}) \times D_{cold(r,t)}, & \bar{T}_{cold(r,t)} < 0℃; \\ 0, & \bar{T}_{cold(r,t)} = 0℃ \end{cases} \tag{6}$$

where $EH_{(r,t)}$, $EP_{(r,t)}$ and $EC_{(r,t)}$ represent the intensity of extreme heat, precipitation and cold for city r, and month t, respectively.

3.1.3 Socio-economic data

We perform heterogeneity analysis using various data reflecting the socio-economic development of Chinese cities from 2013 to 2018. Total electricity consumption, household electricity consumption, regional gross product per capita and sectoral gross product, and maintenance and construction funds in urban areas are from China Urban

Statistics Yearbook (data covering the period from 2000 to 2018). Sewerage investment is from the China Stock Market & Accounting Research Database (CSMAR database). Dams and reservoirs are from Global Reservoir and Dam Database (https://www.globaldamwatch.org/database).

3.2 Empirical analysis

3.2.1 Main model

This study takes the duration and intensity of hazard impacts to represent the level of urban resilience (Barton-Henry and Wenz, 2022; Liu et al., 2023). Therefore, to account for the short- and long-term effects of extreme weathers on nighttime lights, we apply a distributed lag model as our main model (Kotz et al., 2021; Lai et al., 2022), as shown in ***Eq. (7)***. We then calculate the Akaike's information criterion (AIC), whose minimum values are determined as the lagged terms of the model. Based on the minimum AIC and significance level of the main model, a maximum lag of seven is used to track and measure the impact of events over a half-year period.

$$\begin{aligned} lnDN_{(r,t)} = & \sum_{l=0}^{7}\left(\alpha_{t-l}^{r} EH_{(r,t-l)}\right) + \sum_{l=0}^{7}\left(\gamma_{t-l}^{r} EP_{(r,t-l)}\right) + \eta_{t}^{r} EP_{(r,t)} \times \bar{T}_{(r,t)} \\ & + \sum_{l=0}^{7}\left(\beta_{t-l}^{r} EC_{(r,t-l)}\right) + \omega_{t}^{r} W_{(r,t)} + \mu_r + \pi_s + \pi_y + \mu_r * \pi_s \\ & + \mu_r * \pi_y + \varepsilon_{(r,s,y)} \end{aligned} \tag{7}$$

where $lnDN_{(r,t)}$ is the logarithm of the nighttime light intensity in city r at month t.

α_{t-l}^{r}, β_{t-l}^{r} and γ_{t-l}^{r} are the elasticity coefficients of interest, describing the percentage impact of each unit increase in extreme weathers on the urban nighttime lights. $EH_{(r,t-l)}$, $EP_{(r,t-l)}$ and $EC_{(r,t-l)}$ are the extreme heat, precipitation and cold intensity in city r at month $t-l$. We also include the interaction term of extreme precipitation $EP_{(r,t)}$ and monthly mean temperature $\bar{T}_{r,t}$ to further investigate whether monthly conditions can moderate the effect of extreme precipitation on urban nighttime lights. $W_{(r,t)}$ is the extremely strong wind speed as the control variable of the model. μ_r, π_s and π_y are city, seasonal and annual fixed effects, respectively, as well as $\varepsilon_{(r,s,y)}$ is the city-season-annual error. The fixed effects of city and year allow us to account for omitted variable bias between cities and contemporaneous shocks to climate and urban development.

3.2.2 Total distributed-lag multiplier

To explore the eventual percentage change in urban nighttime lights given a permanent, one-unit increase in the extreme heat and rainfall, we calculate the total distributed-lag multiplier, referred to as the Long Run Propensity (LRP) (Li, 2020; Kotz et al., 2021):

$$LRP_{heat}^{r} = \sum_{l=0}^{7} \alpha_{t-l}^{r} \tag{8}$$

$$LRP_{EP}^{r} = \sum_{l=0}^{7} \gamma_{t-l}^{r} \tag{9}$$

where LRP_{heat}^{r} and LRP_{EP}^{r} are the cumulative effects of extreme heat and extreme precipitation in city r.

3.3 Impact channel

3.3.1 Impact on household electricity consumption

We first calculate the annual average of extreme weather and multiply it by the number of days that extreme weather occurs to obtain the intensity of the annual level of extreme weathers, as shown in ***Eqs. (1-6)***. Following the main model (***Eq. (7)***), we further examine the annual impact of extreme weathers on household electricity consumption $Elec_{(r,y)}$:

$$lnElec_{(r,y)} = \alpha_y^r EH_{(r,y)} + \beta_y^r EP_{(r,y)} + \gamma_y^r EP_{(r,y)} \times \bar{T}_{(r,y)} + \eta_y^r EC_{(r,y)} + \omega_t^r W_{(r,t)} + \mu_r + \pi_y + \varepsilon_{(r,y)} \tag{10}$$

where $lnElec_{(r,y)}$ is the logarithm of household electricity consumption in city r at year y.

3.3.2 Cluster classification and heterogeneity analysis

We conduct a cluster analysis of city classification using socio-economic variables including total electricity consumption, regional gross product per capita, maintenance and construction funds, sewerage investment, and number of dams and reservoirs. To standardize the variables with different units, we first rank their values and then calculate the percentage of their rank. As a result, the values of the clustering variables range from 0 to 1, eliminating the impact of unit differences. The K-means algorithm is then implemented to determine the number of city groups and the Kruskal-Wallis test is used to examine the significance of the differences in the data between groups (Shan et al., 2018). In this way, we cluster Chinese cities into five groups, representing the different levels of economic development and resistance to extreme weathers. We perform urban resilience heterogeneity analysis by five city groups, as well as sectoral heterogeneity analysis using gross sectoral product.

3.4 Robustness check

In our first robustness analysis, we assess the extreme weather variables by substituting the climate data collected from the individual Chinese stations with Medium-Range Weather Forecasts Reanalysis-5 (ERA5) dataset (Hersbach et al., 2018) from the European Centre. The reanalysis data is relatively less susceptible to station weather bias, although it may still be subject to biases introduced by the climate models utilized in generating gridded products (Auffhammer et al., 2013; Kalkuhl and Wenz, 2020). From the ERA5 dataset, we utilize daily 2 m air temperature and precipitation on a 0.25° grid to calculate extreme weather intensity. The alternative monthly average weather variables are spatially averaged for cities over the period 2013-2019.

The definitions of extreme weather events can have varying impacts on urban socio-economics, potentially introducing biases in the estimation results (Harrington, 2021). To avoid potential biases arising from the definitions of extreme weathers on the main results, we redefine extreme high temperature as a maximum temperature exceeding 35°C in a month, and extreme low temperature as a minimum temperature below 0°C. In addition, we use the monthly average extreme precipitation rather than the sums described in the climate data section. We further check the robustness of the redefinition of extreme weather variables in the main model. We also check the robustness of the results for the extreme temperature intensity variable by using the duration of the extreme temperatures without multiplying by the average extreme temperatures.

To account for monthly disturbances and not solely concentrate on seasonal and annual shocks to nighttime lights, we assess the robustness of the main results by altering the fixed effects of the main model to a monthly basis. The utilization of monthly fixed effects, more stringent than seasonal and annual fixed effects, enhances the robustness of the results and bolsters our main findings.

Finally, we average extreme weathers on an annual basis and extend the time series for 2000-2018, fixing both annual and provincial effects to further test the robustness of the long-term multiplier effect. This robustness test can help reduce the impact of sample selection bias, capture long-term effects, and enhance result consistency, ultimately rendering the findings more reliable.

4 Results

4.1 Extreme high temperature effects

Our results reveal, for the first time, a noteworthy adverse time-lagged impact of extreme heat on urban nighttime lights (***Fig. 2a***). This effect implies a delayed negative consequence of prior extreme heat events on nighttime lights. Moreover, it persists for an extended period, exceeding five months, as illustrated in ***Fig. 2a***. This indicates that extreme heat experienced in previous months can continue to exert a negative influence on nighttime lights in subsequent months. These findings imply that extreme heat events may induce profound disturbances in urban development, necessitating the implementation of sustained mitigation strategies for extreme heat. As extreme heat has a significant time-lagged effect, we then examine the cumulative effect on the permanent change in nighttime lights (***Fig. S1***). We find that a permanent one-unit increase in extreme heat results in a final significant negative change in nighttime lights of 1.02%, further implying the importance of cities mitigating the long-term effects of extreme heat.

In addition, as shown in ***Fig. 2b***, the long-term impact of extreme hot days has a distinct geographic distribution profile, with areas severely affected located mainly in China's Yangtze River basin. These densely populated regions observe a significant reduction of up to 24.8% in nighttime lights. This vulnerability may be attributed to the region's heavy reliance on hydropower generation, making it more susceptible to power supply stress due to heat-induced drought-related disasters (Yalew et al., 2020; Mallapaty, 2022). Furthermore, cities situated within the Yangtze River Basin exhibit relatively higher levels of urbanization compared to other regions (Han et al., 2022), potentially rendering them more susceptible to pronounced consequences associated with extreme heat events. Notably, some areas in Inner Mongolia and Xinjiang are significantly affected as well, where intense extreme heat weather is also observed. These areas might be susceptible to severe heat events due to their geographical location. Nevertheless, the relatively underdeveloped infrastructure in these regions may result in diminished urban resilience (Zhao et al., 2020).

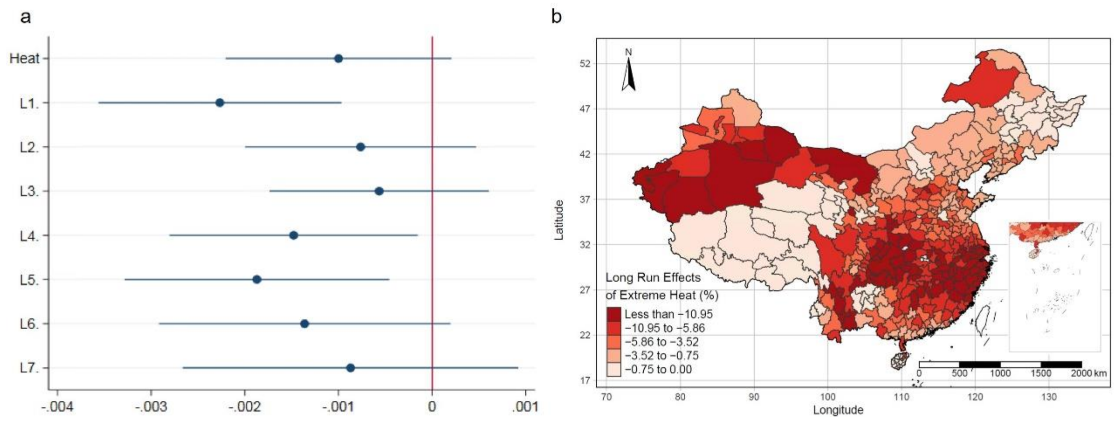


Fig. 2. Effects of extreme high temperatures on urban nighttime lights. (a) Solid dots represent coefficient values that measure a 100%-point change in nighttime lights with a 1°C-day increase in the intensity of extreme monthly high temperatures. The y-axis depicts the lags of extreme heat. 'Heat' represents the current extreme heat without lags, while 'L1' to 'L7' indicate lags of 1 to 7 months for extreme heat. The bars show the 90% confidence intervals. **(b)** Spatial distribution of the long-term impacts of monthly average extreme heat, showing changes in nighttime lights due to a long-term increase of one unit in extreme heat.

4.2 Extreme precipitation effects

As shown in ***Fig. 3***, we examine the effect of extreme precipitation on urban nighttime lights. The regression results indicate a notably strong negative impact of heavy rainfall during the month when the extreme weather event occurs (***Fig. 3a***) , especially within the entire sample group, as confirmed by the previous study (Felbermayr et al., 2022). In addition, our results are the first to reveal that Chinese cities generally fail to recover from heavy rainfall, with a lag of at least seven months in the full sample group. The explanation is that extreme precipitation can trigger cascading hazards such as flooding (Wang et al., 2020), which can devastate the lifelines of cities. For example, heavy rainfall can severely damage electrical system, disrupting power supplies for long periods (Cadini et al., 2017; Oh et al., 2021) and reducing the intensity of lighting at night.

We also identify that the response to extreme precipitation is significantly and positively moderated by monthly average temperature (***Fig. 3a-d***). This implies that areas with higher monthly average temperatures are more resilient to heavy rainfall (Kotz et al., 2022), whereas those with lower monthly average temperatures are less likely to mitigate the strong negative impact on nighttime lights. This effect may be due to the fact that cities with higher monthly average temperatures tend to experience more severe precipitation extremes (***Fig. S2***), and therefore, these cities may have relatively more advanced protection against extreme rainfall (***Table S1***).

We further select samples experiencing extreme hot weather into the "extreme heat" group (***Fig. 3a and b***). Surprisingly, we observe that in the extreme heat group, heavy rainfall has a long-term positive effect on nighttime lights, whereby a permanent increase of one unit will yield a 0.17% increase in nighttime lights (***Fig. 3b***). As shown in ***Fig. 3d***, the monthly average temperatures moderate positively in the effect of extreme precipitation on cities in the heat group. This phenomenon may be attributed to the fact that extreme precipitation can alleviate extreme heat-related drought conditions (Vogel et al., 2019), thereby providing valuable water resources to support urban industries and potentially fostering economic development. Therefore, the average marginal effects of extreme precipitation are negative in the full sample group, but positive in heat group (***Fig. 4a and b***). Our findings suggests that the impact of two weather hazards, extreme heat and heavy rainfall, for example, is not always negative when they occur simultaneously, with this conclusion holding for the full sample (not only for several typical cities) where heat occurs.

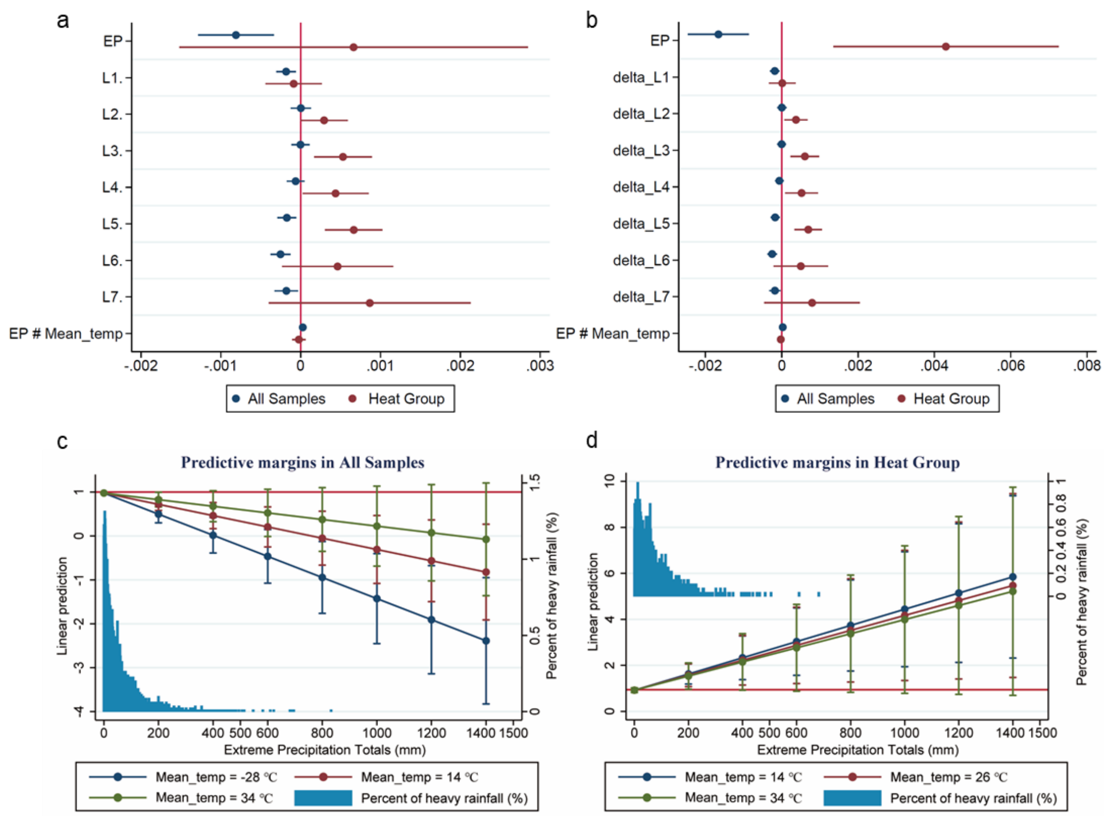


Fig. 3. Regression results for heavy rainfall in the main model. The solid dots represent the coefficient values of the main model, which measure the 100%-point change in nighttime lights for **(a)** a 1 mm-day increase in extreme monthly precipitation and **(b)** a permanent 1 mm-day increase in the full sample group and the heat group. The y-axis depicts the lags of extreme precipitation. 'EP' represents the current extreme precipitation without lags, while 'L1' to 'L7' indicate lags of 1 to 7 months for extreme precipitation. 'delta_L1' represents the difference between L1 and EP, while the same interpretation holds for 'delta_L2' to 'delta_L7'. Predicted margins of nighttime lights for a given heavy rainfall and monthly mean temperature in **(c)** full sample group and **(d)** heat group. The bars show the 90% confidence intervals.

In addition, the dependence of extreme precipitation has strong implication for its geographical distribution (*Fig. 4c*). The long-term negative propensity in the marginal effect of extreme precipitation is lowest in the south but highest in the north. This is consistent with previous results indicating that regions with higher monthly mean temperatures exhibit increased resilience under similarly severe storms (Kotz et al., 2022). This may be due to the fact that cities experiencing both extreme heat and precipitation may have relatively advanced protective measures. To further validate this inference, we provide cluster analysis results that align with our analysis, especially in Cluster 2 and 5, which exhibit the same characteristics as described (***Table S1***). However, despite the high adaptive capacity in the south, the adverse effects remain severe due to the exceptionally heavy precipitation (***Fig. 4d***). We reveal that the largest long-term negative impacts of heavy rainfall are in the coastal regions of China (e.g. Guangdong, Jiangsu and Shandong), and on both sides of the Hu Line (including the agglomerations of Sichuan-Chongqing-Guizhou, Beijing-Tianjin-Hebei). Although the relatively low average temperatures and less precipitation in some of these areas compared to coastal areas, the negative effects of heavy rainfall are extremely severe. This may be due to the concentration of generally underdeveloped (e.g. Sichuan-Chongqing-Guizhou) or densely populated (e.g. Beijing-Tianjin-Hebei) cities in these areas, where the urgency of mitigating extreme precipitation is likewise highlighted.

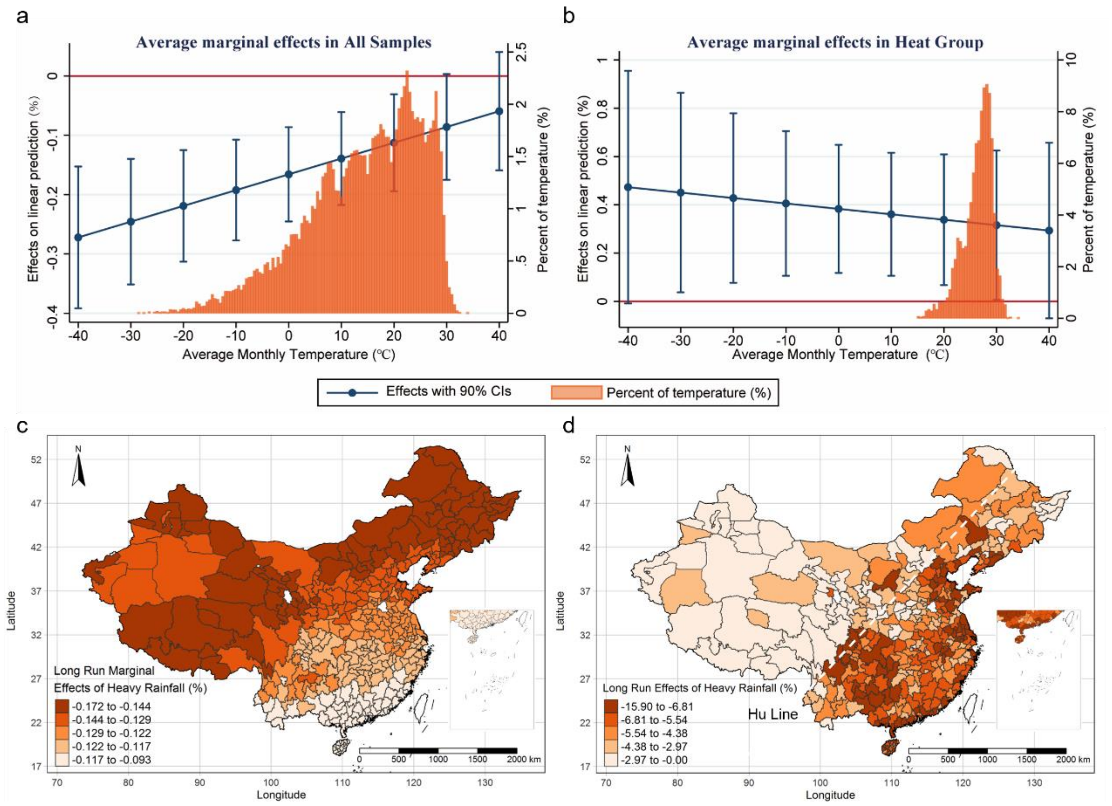


Fig. 4. Effects of heavy rainfall on nighttime lights. Average marginal effect of heavy rainfall on nighttime lights for a given monthly mean temperature in **(a)** full sample group and **(b)** heat group. The bars show the 90% confidence intervals. **(c)** Changes in nighttime lights due to long-term one-unit increase in monthly average extreme precipitation for the full sample group. **(d)** The historical average effects of extreme precipitation on nighttime lights in the full sample group.

4.3 Impact channel analysis

4.3.1 Household electricity consumption under extreme weathers

To verify that the negative long-term effects of extreme high temperatures on urban nighttime lights represents a stronger pressure on electricity supply, as analyzed in section 4.1, we further analyze the effect of extreme hot weather on household electricity consumption (***Fig. S3***). Our findings show that extreme hot weather has a positive impact on household electricity consumption, implying that households will spend more on electricity when extreme temperatures occur, which is consistent with the previous study (Auffhammer et al., 2017). Based on our findings, we can further elaborate on one of the potential mechanisms for the impact of high temperatures on nighttime lights. This hypothesized mechanism is associated to elevated electricity demands due to increased consumption, potentially coupled with a reduction in hydropower generation triggered by heat-induced drought conditions (Yalew et al., 2020). This situation could lead to disruptions in the power system during periods of extreme heat, although this may require further research to confirm.

As shown in ***Fig. S3***, we find that extreme precipitation negatively affects household electricity consumption, confirming our previous speculation that heavy rainfall interrupts the electricity supply and reduces the intensity of lights at night.

4.3.2 Cluster analysis

To capture the channels through which extreme weather affects urban nighttime lights, we divide cities into five classifications by their economic level and resilience (***Figs. S4-7, and Table S1***). Cluster 1 and 4, with less developed economies and less funding for maintenance and construction, have different numbers of dams and reservoirs. Cluster 2 has the most developed economy, the most maintenance and construction funding and relatively more dams and reservoirs. Cluster 3 has a relatively developed economy, more funding for maintenance and construction, and fewer dams and reservoirs. Cluster 5 has a relatively underdeveloped economy, relatively high maintenance and construction funding and has the most dams and reservoirs.

Our findings reveal that cities with lower levels of economic development exhibit reduced resilience to extreme heat, while most economically developed cities exhibit the least resilience to heavy rainfall. This disparity in the adverse effects of extreme weather events necessitates distinct mitigation measures for extreme heat and heavy rainfall. Specifically, our study reveals that extreme heat significantly and persistently affects nighttime lights in various regions, encompassing Clusters 1, 2, and 5 (***Fig. 5***). Specifically, Cluster 5 experiences the most pronounced negative impact, while Cluster 3 is not significantly affected by extreme heat in either the current or lagging months. This suggests that areas in Cluster 3 have mitigated the effects of extreme heat well over the last few years, with relatively developed economies and high maintenance funding. Compared to Cluster 3, areas in Cluster 5 are exposed to more severe heat, but have lower economic level and less effort invested in maintaining urban facilities to mitigate the negative effects of extreme heat (***Table S1***). This implies that relatively high economic levels and robust urban maintenance are crucial for mitigating the effects of extreme heat, while the role of reservoirs is comparatively less significant.

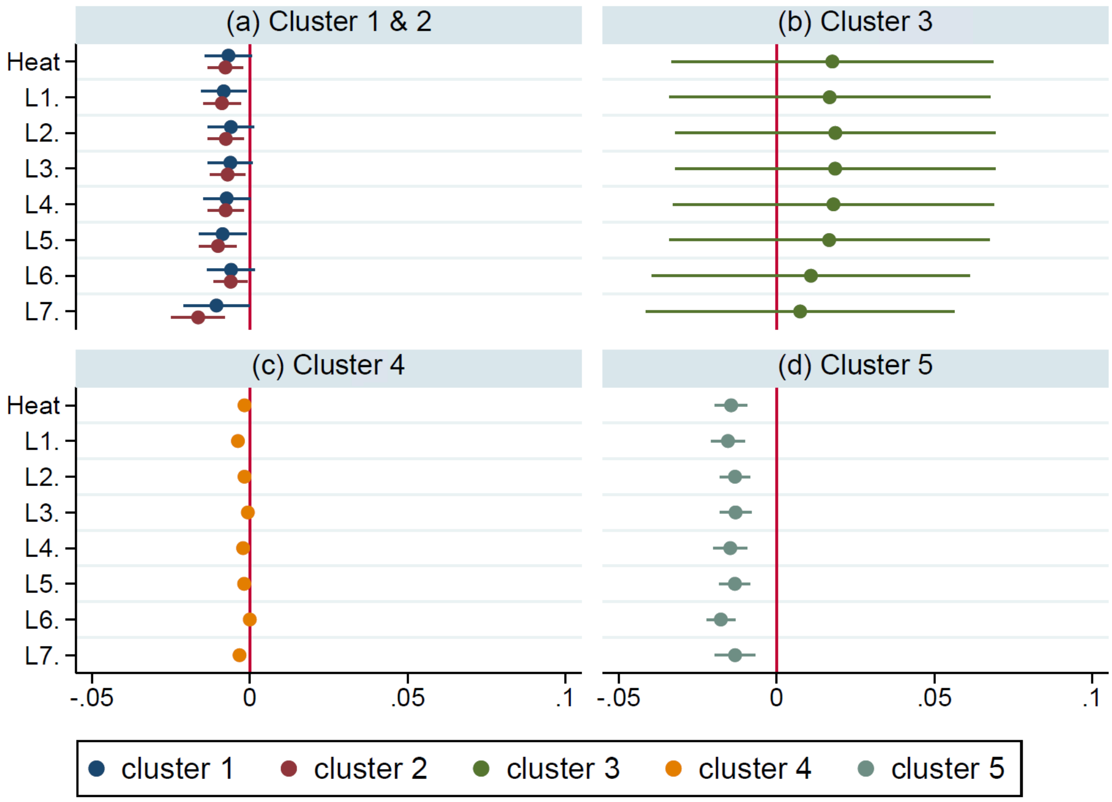


Fig. 5. Effects of extreme high temperature on nighttime lights in different clusters. Solid dots represent coefficient values that measure the 100%-point change in nighttime lights when the intensity of monthly average high temperature increased by 1°C-day. The y-axis depicts the lags of extreme heat. 'Heat' represents the current extreme heat without lags, while 'L1' to 'L7' indicate lags of 1 to 7 months for extreme heat. The bars show the 90% confidence intervals.

However, although Cluster 3 areas exhibit greater resilience to extreme heat and experience less intensity in terms of extreme precipitation, they are more profoundly affected by heavy rainfall (*Fig. 6*). This could be attributed to the lower number of dams in these areas to attenuate the adverse effects of heavy rainfall (*Table S1*), coupled with a developed economy that leaves more production facilities exposed. Note that Cluster

2 is the most economically developed areas with the highest maintenance investments, yet are vulnerable to extreme weathers such as extreme high temperature and heavy rainfall. These areas are located in the southeast of China and near the Hu Line, where most affected by extreme heat and heavy rainfall, and are therefore under high pressure to resist disasters. Clusters that are insignificantly affected by extreme precipitation have a common characteristic of being relatively less advanced economies, including clusters 1, 4 and 5. As such, these areas can focus on mitigating extreme heat waves and are under less pressure than Cluster 2 to mitigate extreme weathers.

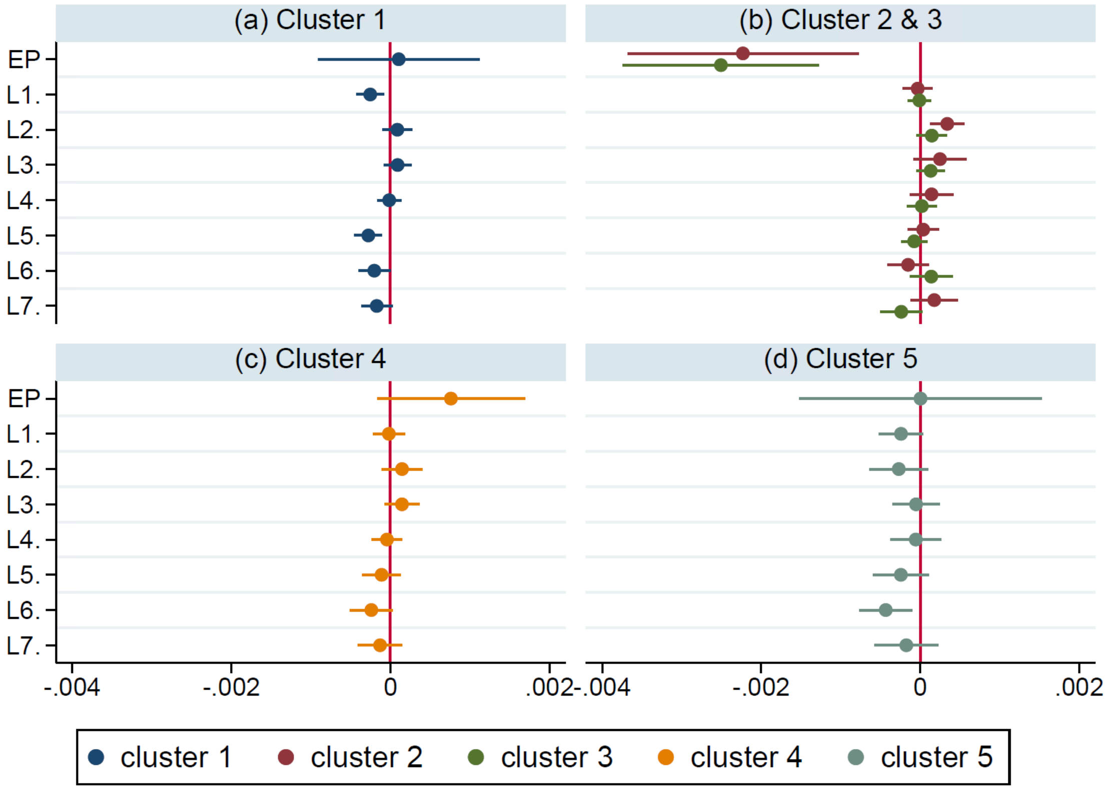


Fig. 6. Effects of extreme precipitation on nighttime lights in different clusters. Solid dots represent coefficient values that measure the 100%-point change in nighttime lights when the intensity of monthly total heavy rainfall increase by 1 mm-day. The y-

axis depicts the lags of extreme precipitation. ‘EP represents the current extreme precipitation without lags, while ‘L1’ to ‘L7’ indicate lags of 1 to 7 months for extreme precipitation. The bars show the 90% confidence intervals.

4.3.3 Sectoral heterogeneity

To further explore the sectoral heterogeneity in the impact of extreme weathers on nighttime lights, we classified cities into primary, secondary, and tertiary industry-dominated categories based on the sector with the largest share of the gross sectoral product. In regions dominated by the primary sector, urban development is relatively modest, resulting in weaker nighttime light intensity (Felbermayr et al., 2022). Conversely, regions with a dominance of tertiary sectors exhibit a heightened capacity to withstand extreme weather events due to their advanced economics and well-equipped infrastructure in this areas (Zhao et al., 2020). Consequently, our findings reveal that the influence of extreme weather on nighttime lights is statistically insignificant in regions dominated by either the primary or tertiary sectors (***Figs. S8-9***).

However, as depicted in ***Figs. S8-9***, regions mainly dominated by secondary industries suffer severe adverse effects from both extreme heat and heavy rainfall. This pattern is consistent with our main finding that cities exhibit lower resilience to extreme heat compared to extreme rainfall. This may be because that regions characterized by the dominance of the secondary sector, highly reliant on manufacturing, construction, and industrial activities, are vulnerable to extreme weather conditions (Kotz et al., 2022).

4.4 Robustness tests

We perform several robustness checks on the main results of extreme weathers. First, we test for external validity by using different extreme weather datasets and find the results to be significant and consistent with the main results (***Table S2***), confirming our main conclusions. Second, we redefine the extreme temperatures (***Tables S3***) and extreme precipitation (***Tables S4***) to test the robustness of main results. Third, we alter the fixed effects of seasonal disturbances to monthly to control monthly disturbances on nighttime lights to further test the robustness of the time fixed effects (***Table S5***). We then use duration of extreme weather, rather than the intensity of temperature and precipitation, and control for annual and seasonal fixed effects to perform robustness checks (***Table S6***). Next, we vary the time scope to 2000-2018 and average the variables into annual basis to check the long-term multiplier effects at annual and provincial fixed effects (***Table S7***).

In the above cases, the effects among extreme weathers are significant, consistent with the main results, which further confirms the results of our model and inferences.

5 Discussion

This study identifies the resilience of 356 cities in China and examines how extreme weather events pose risks to urban nighttime lights. We find that cities are less resilient to monthly extreme high temperatures than to extreme rainfall. Our results reveal, for the first time, the long-term negative impact of extreme heat on nighttime lights, leading to a reduction of 24.8%. This effect is more than 1.5 times greater than that of heavy rainfall, which results in a 15.90% decrease in nighttime lights. These findings highlight the considerable vulnerability of Chinese cities to the unprecedented challenges of climate change (Mallapaty, 2022).

Interestingly, the impact of extreme precipitation on nighttime lights in the extreme heat group can have a significantly positive time-lag effect, revealing that cities suffering from both extreme heat and extreme rainfall are not always negatively affected. Our results differ from those of previous work that merely considered the impact of extreme weather variability on annual measures (Felbermayr et al., 2022), and mostly account for short-term effects without considering the long-term impacts of extreme weathers (Wang et al., 2020; Felbermayr et al., 2022). Our research underscores the importance to mitigate both the short-term and long-term risks that extreme weather events pose to urban development.

Importantly, we find that the long-term adverse effects of extreme weathers have a distinct geographical pattern in Chinese cities. Specifically, extreme heat has the greatest negative impact on the Yangtze River basin and parts of Xinjiang province. Our results, for the first time, indicate that the regions with the most significant long-term impacts of heavy rainfall over the past few years are situated along the Hu Line, which includes Sichuan-Chongqing-Guizhou and Beijing-Tianjin-Hebei, in addition to the coastal regions of China. Therefore, our study is a wake-up call for climate managers in the areas of hazard hotspots that could contribute to targeted mitigation adaptation measures.

We further identify the channels of influence as the following three aspects. First, we explore how changes in electricity consumption respond to weather extremes. It becomes evident that individuals tend to increase their electricity usage during extreme temperatures (Auffhammer et al., 2017) but reduce it during heavy rainfall (Liu et al., 2023). This dynamic relationship allows us to deduce the underlying factors influencing changes in nighttime lights during extreme weather events. Second, we divide cities with six socioeconomic variables into five clusters and find that cities with high economic levels are adversely affected by extreme precipitation, despite their strong urban maintenance capacity. The extreme heat has a significant long-term impact on most areas, except for those with relatively advanced economies and more funding for maintenance and construction. Third, we find that regions with dominant secondary sectors need to consider the negative effects of extreme heat and rainfall (Kotz et al., 2021; Kotz et al., 2022).

We make use of monthly nighttime lights to reveal the short- and long-term impacts of extreme climate hazards. This approach offers greater objectivity and compensates for data scarcity when compared to artificial statistical variables, such as gross domestic product (Zhang et al., 2019). Given the increased intensity and frequency of extreme heat and extreme rainfall alongside future socioeconomic growth (Seneviratne et al., 2021), our study provides valuable insights for low-cost and rapid assessment of climate impacts and contributes to the city-level resilient management. In addition, our study applies empirical models to control for temporal and regional fixed effects so as to enhance the causal effects of climate hazards (Kotz et al., 2022). We cluster cities with various socioeconomic variables, which provides more in-depth and comprehensive classification than with merely one or two variables. However, nighttime lights merely represent the combined impact of urban development (Chen et al., 2023), and further analysis is required if more specific impact channels need to be identified. Regardless, our findings provide a valuable benchmark for extreme weather risk assessment, based on which contributes to the research topics of energy consumption, economic impact and inequity at a finer temporal and spatial scale.

6 Conclusions

This study reveals urban resilience by identifying both the short-term and long-term magnitude, persistent duration, and impact pathways of extreme heat and heavy rainfall on urban nighttime lights in China. Our findings first indicate that Chinese cities generally exhibit greater resilience to heavy rainfall compared to extreme heat. Furthermore, it is worth noting that the adverse long-term effects of heavy rainfall can persist for a duration of up to seven months. Our study also highlights cities and sectors that are particularly vulnerable to extreme weathers. Specifically, areas within the

Yangtze River basin are susceptible to extreme heat, while regions along the Hu Line are at risk from heavy rainfall. Additionally, areas dominated by the secondary sector need to consider the potential adverse effects of both extreme heat and heavy rainfall. This study offers valuable insights into the rapid assessment of urban resilience on a national scale, providing a high level of temporal and spatial resolution. We also identify hotspots that policymakers should prioritize on for urban sustainable management and highlights the importance of managing the short- and long-term impacts of extreme weather events.

CRediT Authorship Contribution Statement

Litiao Hu: Methodology, Software, Validation, Formal analysis, Data process, Writing - original draft, Visualization. **Jing Meng:** Conceptualization, review & editing. **Chaoying Xiong:** Investigation, Writing - review & editing. **Wen Fang:** Conceptualization, review & editing. **Jianxun Yang:** Conceptualization, review & editing. **Miaomiao Liu:** Conceptualization, review & editing. **Jun Bi:** Conceptualization, Methodology, Writing - review & editing, Funding acquisition. **Zongwei Ma:** Conceptualization, Methodology, Writing - review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interests

The authors declare no conflicts of interest.

Acknowledgement

This work was supported by the National Natural Science Foundation of China (Grants 52170189, 71921003, and 72234003), Jiangsu R&D Special Fund for Carbon Peaking and Carbon Neutrality (Grant BK20220014).

We thank Qi Wang and Xurui Wang at Nanjing University for their valuable insights in the analysis of the results. The authors declare that they have no actual or potential competing financial interests.

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