Science of the Total Environment 856 (2023) 158846

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

High ambient temperatures are associated with urban crime risk in Chicago

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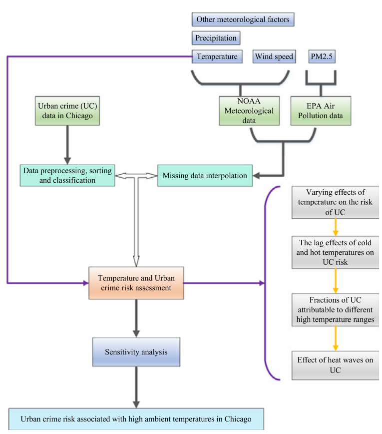
HIGHLIGHTS

- High temperature has a positive promoting effect on urban crime (UC) risk.
- The effect of low temperature is not significant for the UC risk.
- Different high temperature ranges account for different attributable risks of UC.
- Heat waves have a significant positive effect on non-domestic crime of UC.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Scott Sheridan

Keywords:
High temperatures
Urban crime
Risk
Heat waves
Lag effect

ABSTRACT

Urban crime (UC) seriously affects the security and stability of the communities and society. However, the effects of external temperatures on the risk of UC are still confusing. We quantitatively estimated the effects of high and low temperatures on UC in Chicago. After controlling for the confounding factors, we found that high temperature has a positive promoting effect on UC, for non-domestic crime, the effect occurs at lag day 0 with a maximum risk of 1.40 (95%CI, 1.34–1.46) compared to a risk of 1 at temperature of −12.3 °C, and decreased as the lag day increased. The effect of low temperature is not significant for UC. Heat waves above the 99th percentile with a duration of 4.5–5.5 days exert a significant positive impact on non-domestic crime of UC. Our findings confirm the adverse promotion effect of high temperature on UC risk, and effective individual behavior guidance and administrative intervention are of great significance for reducing the risk of UC under specific high temperature environment.

1. Introduction

Global temperatures are changing and rising at a rapid rate, which exacerbates global warming and the greenhouse effect (Evan and Eisenman, 2021). Increased concentrations of greenhouse gases in the atmosphere are expected to increase global warming by 2 °C by 2050 (Ou et al., 2021).

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http://dx.doi.org/10.1016/j.scitotenv.2022.158846
Received 29 June 2022; Received in revised form 2 September 2022; Accepted 14 September 2022
Available online 17 September 2022
0048-9697/

The direct health impacts of climate change are caused by abnormal ambient temperatures, heat waves, cold spells, and an increase in the frequency of extreme weather events such as droughts and floods (Lee et al., 2018; Lin et al., 2022; Romanello et al., 2021). Among these disasters, high temperature events have a more profound impact on human health, including high temperature-related deaths (Ban et al., 2017; Wei et al., 2021), the spread of infectious diseases (Singh et al., 2021), and mental health effects (Liu et al., 2021; Romanello et al., 2021). In 2012, approximately 23 % of global deaths can be attributed to changes in environmental factors, many of which are affected by climate change (Watts et al., 2017). Climate change threatens human health and well-being through its impacts on weather, ecosystems and human systems (Romanello et al., 2021). Previous studies have demonstrated that abnormal ambient temperatures account for a variety of adverse health outcomes related to respiratory, cardiopulmonary, unnatural death, and crime events (Burke et al., 2018; Guo et al., 2017; Schinasi and Hamra, 2017; Shen et al., 2021).

Sociodemographic characteristics including socioeconomic status, gender, and ethnicity are considered as influencing factors of urban crime (UC), and existing research exhibits fluctuating changes in criminal behavior are often not explained by sociodemographic factors, which are more influential than long term behavioral trends (Gates et al., 2019). Therefore, exploring and revealing the relationship between criminal behavior and environmental factors including meteorological variables has become the key to better understand the pattern of criminal behavior (Harp and Karnauskas, 2018; Mares and Moffett, 2016). Existing theories have partially explained the possible mechanisms behind these relationships, including the possibility that temperature affects daily activities and behavior (Berman et al., 2020; Cohen and Felson, 1979; Hipp et al., 2004). Ambient temperatures change the patterns of alcohol consumption, such that the probability of convergence between the perpetrator and the intended target can be achieved (Cohen and Felson, 1979; Gates et al., 2019). More comfortable weather and temperature conditions increase the speed of interpersonal interaction, which affects the possibility of criminal behavior (Cohen and Felson, 1979; Harp and Karnauskas, 2020). Studies have shown that the variations of temperatures or extreme abnormal weather may act as stressors that promote aggressive behavior (Anderson, 1989; Harp and Karnauskas, 2020; Lõhmus, 2018).

Investigating the linkage between criminal events or behaviors and ambient temperature has been a major focus of previous researches. Cold month conditions were found to have the highest rates of disorderly behavior and violent crime (Schinasi and Hamra, 2017). The risk of violent crime increases by 11.92 % and 10.37 % for daily temperature rises in 10 °C or deviates from multi-year stable temperature with a fluctuation range of 10 °C, respectively (Berman et al., 2020). The inter-annual variations of winter temperatures were found to be significantly positively correlated with the rates of violent and property crimes (Harp and Karnauskas, 2018). Studies in Finland showed that ambient temperature caused a 10 % increase in the change of violent crime rates between 1996 and 2013, corresponding to an increase of 1.7 % for every 1 °C (Tiihonen et al., 2017). The risk of regional conflict and violence increases with rising temperatures (O'Loughlin et al., 2014). Also, they contribute to the occurrence of violent crime assault (Williams et al., 2015). Twenty percent of the most vulnerable communities in St. Louis, Missouri, are expected to experience more than 50 % increase in criminal violence related to climate change (Mares, 2013). Non-optimal ambient temperature is exerting a significant impact on the risk of urban crime (Blakeslee et al., 2021; Heilmann et al., 2021; Shen et al., 2020; Stevens et al., 2019), especially in light of the overall trend of global warming (Harp and Karnauskas, 2020). Previous studies have explored the association between daily or monthly temperature and crime rates, yet lack of an examination of the lag effect of temperature on crime risk, which has been demonstrated in the assessment of other health effects (Alahmad et al., 2019; Elser et al., 2022; Qian et al., 2022). There are few studies on the attributable risk estimation of crime risk for different temperature ranges, and the variation pattern between heat wave, cold spell and crime risk is not clear in the previous major studies involved, which have also been mentioned several times in other studies related to health risks (Dimitrova et al., 2021; Ingole et al., 2022; McElroy et al., 2020). Overall, the quantitative relationships of the contribution of excessively high or low temperatures to UC risk remain largely unknown.

We characterized the impact of high and low temperature for UC risk based on a large adequate sample of daily crime data. In this study, we quantified the lag effect between temperature variation and UC risk, assessed the attributable UC risk caused by different temperature ranges, and calculated the additional UC risk of heat wave based on the confirmed promoting effect of high temperature on UC. Our study helps to better characterize and reveal the variation pattern of environmental temperature on UC, which has important reference significance for other temperature-related risk assessment of health outcomes. At the same time, effective outdoor activities and practical action guidance for individual behavior is recommended to be implemented in a specific high temperature environment, which is effective in reducing the negative impact of temperature on UC risk.

2. Materials and methods

The research object and sample are daily crime data in Chicago from January 2011 to December 2021, with a total of more than 2 million data. Chicago was chosen mainly for the relatively wide variations in the range of temperature and high frequency of heat waves (Swainet al, n.d.). An increasing frequency of abnormal weather and extreme temperature events is emerging in the city (Bucciarelli et al., 2020; Greene et al., 2011). We explored the association between UC and temperature based on the distributed lag nonlinear model (DLNM), and controlled for the interference effects of various confounding factors in the fitting process of the model. The confounding factors involved in the final study included meteorological variables such as relative humidity and precipitation, $PM_{2.5}$, long-term temporal trends, and seasonal variables, covering the study period from January 2011 to December 2021. We revealed the variation pattern of the relationship between high and low temperatures and UC, estimated the lag effects of specific high temperatures on UC risk, conducted and calculated the attributable risk of UC exposure to high temperatures, and assessed the effect of heat waves on UC. The results of sensitivity analysis exhibit that our findings are relatively reliable.

2.1. Urban crime data

The Chicago urban crime dataset, which reflects reports of crime incidents that occurred in Chicago from 2011 to 2021, was adopted as the data source for this study. The statistical information in this dataset is of high precision and accuracy, including date of crime, geographical location, case number, brief description of crime type, area ID, etc. Exploring and tracking the data is available through the website (https://data.cityofchicago.org/). We calculated the count of UC occurrences on each independent day, and the subsequent analyses were conducted at a daily, aggregate level. We eliminated the data with the missing information, and 2,635,952 UC data of Chicago from January 2011 to December 2021 were confirmed to be valid for the study. We classified the UC data according to domestic crime and non-domestic crime (outdoor crime). The results showed that 455,791 domestic crimes and 2,180,161 non-domestic crimes were involved in the study.

2.2. Socioeconomic characteristics data

Median household income and per capita income were used to represent the socioeconomic characteristics of different neighborhoods in Chicago. We derived the data from the website of US Census Bureau (https://www.census.gov/), where the latest data on household income and per capita income for the period 2016–2020 are available. Chicago primarily consists of 77 neighborhoods, whose ZIP codes are used to retrieve the data of household income and per capita income for each neighborhood. For median household income (in dollars), we divided it into five levels based on the income ranges. Below 40,000 is the first level, 40,000–60,000 is the second level, 60,000–80,000 is the third level,

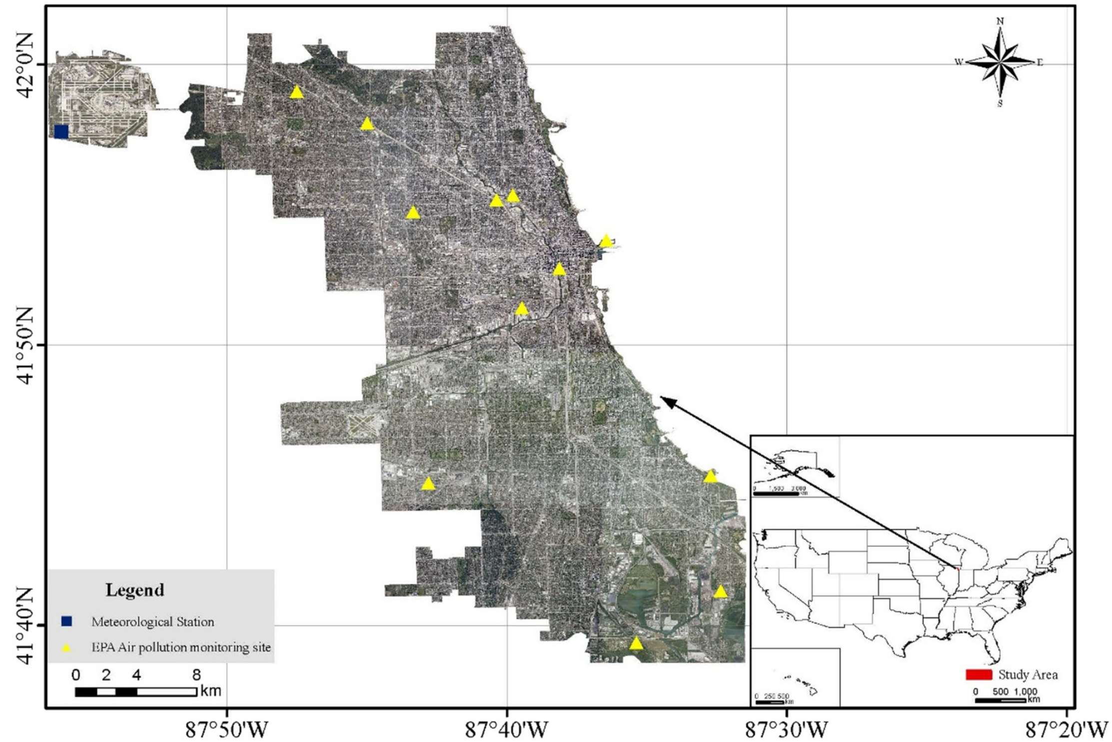

Fig. 1. The geographic locations of meteorological and air pollution sites.

80,000–100,000 is the fourth level, and above 100,000 is the fifth level. The first, second, third, fourth, and fifth levels correspond to the numbers 1, 2, 3, 4, and 5, respectively. For per capita income (in dollars), we divide it into five levels based on the income range. Below 20,000 is the first level, 20,000–30,000 is the second level, 30,000–40,000 is the third level, 40,000–50,000 is the fourth level, and above 50,000 is the fifth level. The first, second, third, fourth, and fifth levels correspond to the numbers 1, 2, 3, 4, and 5, respectively. We use the five levels of median household income and per capita income to indicate the socioeconomic effects in the model.

2.3. Meteorological data

Hourly meteorological data is derived from the weather station located 27 km southeast of Chicago, which collects the weather data from 2 m above the ground. The US National Oceanic and Atmospheric Administration (NOAA) provide the retrieval and download site (https://www.noaa.gov/) for the data. The types of meteorological data obtained include temperature, relative humidity, precipitation, and wind speed. Daily meteorological data from January 2011 to December 2021 can be obtained by averaging hourly weather data.

2.4. $PM_{2.5}$ concentrations data

The US Environmental Protection Agency (EPA) provides the daily mean air pollution data with relatively high integrity and accuracy. The daily pollutant monitoring measurement values include $PM_{2.5}$, PM_{10}, O_3, CO, and NO. Previous studies have confirmed that $PM_{2.5}$ of air pollutants associating with various types of crimes (Kuo and Putra, 2021). Thus we referred to $PM_{2.5}$ concentrations in the study to represent the interference of air pollutant on UC. Fig. 1 exhibits the geographic locations of meteorological and air pollution sites.

2.5. Imputation of the missing data

There are missing values for certain times in the data of temperature and $PM_{2.5}$. We accurately quantify the exposure levels of perpetrator by imputing to fill in the missing data. Three methods with sophistication and efficiency were used to impute the missing values as we did in previous studies (Hou et al., 2022; Hou and Xu, 2022). The primary imputation method took into account both diurnal and day-to-day variations. The second imputation method was applied when there were no adequate pairs of days with valid data, and valid data at the corresponding time in the nearest day of the missing value is used for imputation. The third method used the average of all valid data in the nearest 6 days to impute the missing data. We imputed 1 % of the temperature data and 3 % of the $PM_{2.5}$ data in this research, respectively.

Table 1 exhibits the characteristics of the relevant data used in Chicago. In total, 2,635,952 urban crime data were involved in the study. As expected, the daily temperature of Chicago varies from −26.1 °C to 33.6 °C, which is a relatively wide temperature range.

Table 1
The characteristics of the relevant data in Chicago.

Variables	Time span	Average value	Minimum value	25th percentile	50th percentile	75th percentile	Maximum value
UC	2011–2021	744	320	638	739	833	1899
Temperature (°C)	2011–2021	10.9	−26.1	2.2	11.1	20.6	33.6
$PM_{2.5}$ concentration ($\mu g/m^3$)	2011–2021	9.31	0.01	5.87	8.60	11.61	91.70
Relative humidity (%)	2011–2021	58.12	0.13	44.96	61.46	73.08	99.96
Wind speed (m/s)	2011–2021	9.59	1.34	6.96	9.17	11.63	27.96
Precipitation (mm)	2011–2021	0.11	0	0	0	0.05	6.86

2.6. Methods

2.6.1. Study design

We conducted a time-series analysis involving long-term trend, of which the number of daily urban crimes and daily temperatures were properly linked. The study covered all urban crimes in Chicago from 2011 to 2021. We chose Chicago as the study object, mainly because Chicago has a relatively wide range of temperature variations including an average daily maximum of 29 °C in July and a daily average minimum of −11 °C in January, where heat waves occur with a relatively high frequency and long duration historically and simultaneously (Abasilim and Friedman, 2022; Hartz et al., 2012). These temperature characteristics in Chicago provide a natural experimental condition for fully identifying the impacts and patterns of temperature effects on UC.

2.6.2. Investigation of the correlation for ambient temperature and UC

Relative humidity, precipitation, wind speed, and $PM_{2.5}$ concentrations were considered as the confounding factors of meteorological variables in the assessment of the association between ambient temperature and UC risk. We derived daily average data of the meteorological variables including temperature based on hourly data, and daily $PM_{2.5}$ average data is available directly (see Methods). The research time span for UC, meteorological variables, and air pollutant is consistent through January 2011 to December 2021. We adjusted for different combinations of the confounding factors in the sensitivity analysis to assess the interference of confounding factors on the results, which indicated the reliability of the research results.

We calculated the perpetrators of UC in each group in terms of the quartile of daily mean temperature, and found that the percentage of perpetrators exposed to high or low temperatures differed relative to the reference temperature. People rely on air-conditioning to cool down indoors, which mitigates the intensity of the temperature impact and alters the response mechanism of domestic versus outdoor crime (Zander et al., 2021). Therefore, we assessed the effects of temperature for domestic crime and non-domestic crime (crime outside), respectively. The definition criterion for the reference temperature is the temperature value at which the UC risk is 1. As shown below, the reference temperatures for domestic crime and non-domestic crime were eventually determined to be −14.2 °C and −12.3 °C, respectively, which we used as the reference to assess the RR of UC.

Subsequently, on the basis of DLNM, we explored the response magnitude of UC risk to variations in ambient temperature by controlling for the confounding factors involving relative humidity, precipitation, wind speed, and $PM_{2.5}$.

2.6.3. Distributed lag non-linear model (DLNM)

As in the researches (Guo et al., 2011; Yang et al., 2016), we utilized the daily average Celsius temperature denoted by °C as the criterion for temperature variable. The overall cumulative RR (OC-RR) was used to characterize the quantitative effects of temperature for UC. We derived the OC-RR in two steps (Chen et al., 2018; Gasparrini et al., 2010; Gasparrini et al., 2015). In the first step, we estimated the RR of the perpetrator with high or low temperatures exposure relative to 5.2 °C (the reference temperature) in a certain lag of days. Then we accumulate the enhancement of the individual RR of UC within the respective lag day to obtain the OC-RR.

We used the DLNM (Gasparrini et al., 2010; Gasparrini et al., 2015) to investigate the influence of temperature on UC risk, which took into account the complex nonlinear and lay effect of temperature variations for UC. The lag effect refers to the temperature exposure of a single day for the perpetrator contributes to the UC risk in subsequent days. Eq. (1) shows the basic framework of DLNM.

$$g(\mu_d) = \alpha + \sum_{j=1}^{J} f_j\left(x_{dj};\beta_j\right) + \sum_{k=1}^{K} \gamma_k u_{dk} \tag{1}$$

where Y_d (d = 1, 2, 3, …, n) represents the sequence of daily (d) counts of perpetrators with UC. The mathematical expectation of Y_d in Eq. (1) is represented by $\mu_d = E(Y_d)$. The link function g is selected according to the distribution of Y_d. In this study, Y_d approximately exhibits a Poisson distribution, and the link function is Log(μ_d).x_{dj} are the independent variables with nonlinear variations, including temperature, relative humidity, precipitation, wind speed, and $PM_{2.5}$. Other confounding factors are indicated as u_{dk}. β_j and γ_k indicate the parameters of the corresponding variables, respectively, and the intercept is denoted by α. f_j represents the basis function of the independent variable x_{dj}. A properly chosen basis function transforms x_{dj} into a new set of variables that can be summarized in the transformation matrix to quantify the effects of temperature variation and lag (Gasparrini et al., 2010).

2.6.4. Dual natural cubic spline DLNM (DDLNM)

Various fitting functions including natural cubic splines, B-splines, and polynomial functions were utilized to characterize the relationship between temperature variation, lag and UC risk, and the maximum lag time was set to 28 days (see Sensitivity analysis). We chose the best fitting of the model using Akaike Information Criterion (AIC) (Cavanaugh and Neath, 2019), of which the corresponding AIC value is the smallest.

The final fitting results exhibited that for the temperature effect, we placed five knots at the equal intervals of the distribution of temperature range using the natural cubic spline, such that it has enough flexibility at both ends of the knots to capture the temperature variation effect. For the lag effect, we placed four knots at the equal intervals of the logarithm of the lag using the natural cubic spline to achieve a full flexible characterization for various lag days. The derived model is considered as dual natural cubic spline DLNM (DDLNM), which is shown in Eq. (2).

$$\begin{aligned} log\ (\mu_d) = {} & \alpha + \beta T_{d,l} + s(PM_{2.5}, df_1) + s(RH, df_2) + s(Wind, df_3) \\ & + s(Prcp, df_4) + s(TIME, df_5) + \gamma DOW + \phi Month + \delta Season \\ & + \omega Holiday + \lambda_1 MHI + \lambda_2 PCI \end{aligned} \tag{2}$$

where $T_{d,\ l}$ is the cross-basis matrix obtained by applying the DDLNM to temperature T to describe the two-dimensional variations of temperature and lag, β is the coefficient vector of $T_{d,\ l}$, indicating the RR logarithm with respect to temperature variation on UC risk. l denotes the count of lag days following the exposure day d, and s indicates the natural cubic spline function. df is the degree of freedom (df), controlling for the influence of individual variables in the model. The confounding factors involving $PM_{2.5}$ concentrations, relative humidity, wind speed, precipitation, and the influence of long-term trend are indicated using the variables $PM_{2.5}$, *RH*, *Wind*, *Prcp*, and *TIME*, respectively. *DOW*, *Month*, and *Season* indicate the specific single day in a week, the month variable, and the effect of seasonality, respectively. *Holiday* indicates the holiday effect. For each UC event, we determine which community it belongs to based on the latitude and longitude coordinates of its occurrence, and then assign the level number of the median household income and per capita income of this community to the UC. The sum of the level numbers of median household income and per capita income for daily UC is used to reflect the impact of socioeconomic indicators. *MHI* and *PCI* represent the effect of median household income and per capita income, respectively. γ, ϕ, δ, ω, λ_1, and λ_2 are parameters for the variables.

We used the AIC to adjust and control for the df (i.e., knots of the spline) of each variable to achieve the best fit of the model, where the corresponding AIC value exhibited the smallest. The results of the selection of df in the natural cubic spline function of Eq. (2) show that a df of 5 for the temperature and 4 for the lag effect. For $PM_{2.5}$ concentrations, relative humidity, wind speed, and precipitation (df_1, df_2, df_3, and df_4), the df is all set to 3. The df for the long-term trend (df_5) is set to 7*11, which means 7 df of each year.

2.6.5. Number and proportion of the perpetrators with UC attributed to different high temperature ranges

Based on the DNDLNM, we quantified the perpetrators with UC caused by different high temperature ranges, which were considered as the fractions and amount of the attributable risk of temperature to UC (Gasparrini and

Leone, 2014). Similar to the research (Gasparrini and Leone, 2014), temperature from the reference temperature (the temperature at which RR equals to 1, i.e., 5.2 °C) to the 97.5th percentile (27.5 °C) was defined as moderate hot, and from the 97.5th percentile (27.5 °C) to the maximum temperature was defined as extreme hot.

We used Eq. (3) to calculate the fraction of UC caused by moderate hot and extreme hot within L days of lag, respectively. Subsequently, we used Eq. (4) to calculate the number of perpetrators of UC caused by moderate hot and extreme hot within L days of lag, respectively.

$$AF_{x,d} = 1 - \exp\left(-\sum_{l=0}^{L}\beta_{X_d,l}\right) \tag{3}$$

$$AN_{x,d} = AF_{x,d} \cdot \sum_{l=0}^{L}\frac{n_{d+l}}{L+1} \tag{4}$$

where the temperature at day d is indicated by X_d. The lag days following day d are denoted as l. L is the maximum lag scale, which is set to 28 days consistent with DNDLNM. The OC-RR of X_d of temperature at day d (including the lag risk within L days) is indicated by $\sum_{l=0}^{L}\beta_{X_d,l}$. The number of UC taking place on day $d + l$ is denoted by n_{d+l}. $AF_{x,\ d}$ and $AN_{x,\ d}$ are interpreted as the proportion and amount of potential UC attributed to a single exposure X_d occurring at day d in the future period L.

The 95 % empirical confidence intervals of $AF_{x,\ d}$ and $AN_{x,\ d}$ were obtained by using Monte Carlo simulations, which is similar to the practice of relevant researches (Chen et al., 2018; Gasparrini et al., 2015; Gasparrini and Leone, 2014).

2.6.6. The effect of heat waves on UC

Similar to the studies (Gasparrini and Armstrong, 2011; Smith et al., 2013), the impact of temperature on UC can be summarized into two parts, the main effect and the additional effect. The main effect refers to the relative risk caused by daily temperature variations, and the additional effect is interpreted as the extra risk of heat waves, where the sustained high temperature remains for a short period of days. On the basis of DDLNM, we quantitatively estimated the risk of additional effects of heat waves on UC, as shown in Eq. (6):

$$\begin{aligned} log\ (\mu_d) = {} & \alpha + \beta T_{d,l} + wT_{(i)} + s(PM_{2.5}, df_1) + s(RH, df_2) + s(Wind, df_3) \\ & + s(Prcp, df_4) + s(TIME, df_5) + \gamma DOW + \phi Month + \delta Season \\ & + \omega Holiday + \lambda_1 MHI + \lambda_2 PCI \end{aligned} \tag{6}$$

where $\beta T_{d,\ l}$ is the main effect, $wT_{(i)}$ is the additional effect, and w is a function describing the additional nonlinear effect in terms of the sustained heat waves T. The meanings of other symbols in the formula remain unchanged.

The indicator of heat waves is defined as follows:

$$T_i = \sum_{\ell=1}^{L_w}\left[I(t_{i-\ell}>t_w)\prod_{j=0}^{\ell}I\left(t_{i-j}>t_w\right)\right] \tag{7}$$

$$T_{(i)} = T_{(i)} \cdot I\left(T_{(i)} \geq 2\right) \tag{8}$$

where I denotes the indicator variable whose value is 1 when t_{i-l} is above the temperature threshold t_w, and 0 otherwise. The heat wave is usually considered as the sustained high temperature days where the temperatures are higher than the threshold t_w. L_w+1 indicates the count of sustained days of the heat wave. As in previous studies (Gasparrini and Armstrong, 2011; Guo et al., 2017), we defined the hot threshold as the 97.5th (27.5 °C) or 99th (28.9 °C) percentile of the temperature range over the entire time span of the study object. We then assessed the effect of heat waves with temperatures above 27.5 °C and 28.9 °C on the UC risk, respectively.

2.6.7. Sensitivity analysis

We varied the maximum lag length to determine that the lag effect of temperature on UC can be adequately demonstrated within the pre-assumed maximum lag days of 28 for non-domestic crime (Supplementary Table 2). We conducted different combinations of the confounding factors including $PM_{2.5}$, relative humidity, wind speed, and precipitation into the model to evaluate the impact of interference factors on the robustness of the results for non-domestic crime, and the results are shown in Supplementary Table 3.

3. Results

3.1. Relationship between high and low temperature change and UC risk

In DLNM, we used a variety of functions to test and select the best fitting of the model, and the corresponding final model was considered as dual natural cubic spline DLNM (DDLNM). The OC-RR was used to assess the magnitude of the risk of temperature to UC over the entire lag days (see Methods). The maximum lag length was set to 28 days, such that the temporally OC-RR became relatively stabilized as the maximum lag day varied.

Fig. 1 (red line) illustrates the derived exposure-response curve for temperature and UC risk, of which we can see that above the reference temperature, higher temperature increases the risk of UC. Below the reference temperature, the effect of low temperature was not significant for the UC risk (the 95 % confidence intervals (CI) of the curve cross 1 value). The RR equals to 1 at the temperature of −14.2 °C and −12.3 °C (i.e., the reference temperature) for domestic crime and non-domestic crime, respectively. We derived the OC-RR through the departure of the individual temperature from the reference temperature. For domestic crime and non-domestic crime, high temperature has a positive effect on UC above −14.2 °C and −12.3 °C, respectively, below which the effect of low temperature on UC is not significant. The impact of temperature on UC becomes substantial at hot conditions.

3.2. The lag effects of high and low temperatures on UC risk

In order to further clarify the structure of the relationship between high or low temperature and the UC risk. Based on NNDLNM, we assess the lag effects of high and low temperature on UC for domestic crime and non-domestic crime, respectively. For low temperatures, we estimate the effects of 1th (−15.0 °C) and 2.5th (−11.7 °C) percentile temperature on UC with a lag of 28 days, respectively. As shown in Fig. 3(a, b) and Fig. 4(a, b), the effects of cold temperatures of −15.0 °C and −11.7 °C for UC is similar. The exposure-response curves show that the effect of low temperatures on the UC risk is insignificant (the 95 % confidence intervals (CI) of the curve cross 1 value).

For high temperatures, we estimate the effects of 97.5th (27.5 °C) and 99th (28.9 °C) percentile temperature on UC with a lag of 28 days, respectively. As shown in Fig. 3(c, d) and Fig. 4(c, d), the effects of hot temperatures of 27.5 °C and 28.9 °C for UC is similar. The exposure-response curves show a significant positive effect on the UC risk, and the negative effect is not significant. Table 2 exhibits the RR of high temperatures for non-domestic crime of UC at different lag days. The results of RR of high temperatures for domestic crime of UC at different lag days are shown in Supplementary Table 1. The impact of high temperature on non-domestic crime of UC occurred at lag day 0, and decreased with the increase of the

Table 2
The RR of high temperatures for non-domestic crime of UC at different lag days.

High temperature	Lag days	RR and 95 % confidence interval (CI)		
		Calculated value	Lower bound of 95 % CI	Upper bound of 95 % CI
97.5th percentile	0	1.36	1.31	1.42
	2	1.00	0.98	1.03
	15	0.99	0.98	1.01
	28	1.00	0.99	1.01
99th percentile	0	1.40	1.34	1.46
	2	1.00	0.99	1.03
	15	0.99	0.98	1.01
	28	1.00	0.99	1.01

lag length. It decreased to 1 at lag day 2, and then became insignificant. The impact of high temperature on domestic crime of UC occurred at lag day 0, and decreased with the increase of the lag length. It decreased to 1 at lag day 2, beyond which the effect increased with a slight fluctuation, and then became insignificant.

The results are consistent with the exposure-response curve for temperature and UC risk shown in Fig. 2. Overall, we found that high temperature has a positive promoting effect on UC, and the effect of low temperature for UC risk is not significant.

3.3. Fractions of UC caused by various high temperature ranges

The fractions of UC caused by various high temperature ranges was quantitatively estimated (Methods). High temperature data was divided into two ranges based on the variations of temperature (see Methods), including moderate hot (from 5.2 °C, the reference temperature at which RR equals to 1, to 27.5 °C, i.e., the 97.5th percentile) and extreme hot (from 27.5 °C to 33.6 °C, i.e., the maximum temperature). As shown in Fig. 5, moderate hot accounted for 12.14 % (95 % CI, 6.45 %–18.27 %) of UC, and 1.87 % (95 % CI, 0.71 %–4.52 %) of UC could be attributed to extreme hot for domestic crime over the study period in Chicago. For non-domestic crime, moderate hot accounted for 14.25 % (95 % CI, 8.42 %–20.24 %) of UC, and 2.76 % (95 % CI, 0.82 %–4.82 %) of UC could be attributed to extreme hot for non-domestic crime over the study period in Chicago. The UC risk associated with the perpetrator exposure to moderate hot was larger than extreme hot, which were because the weather conditions of moderate hot occurred much more frequently than extreme hot.

3.4. Effect of heat waves on UC

Based on the positive effect of high temperature on UC risk, we further explored the association between heat waves and UC for domestic crime and non-domestic crime, respectively. Heat waves generally occur during the warmer months in June, July, and August. They consist of consecutive hot days above a certain temperature threshold, and are an additional effect in addition to the effect of daily temperature variations on UC risk. We used two criteria of high temperature thresholds to define heat waves. The heat waves were considered as two or more sustained high temperature days, where daily average temperature is above the 97.5th (27.5 °C) or 99th percentile (28.9 °C) of the temperature range. We then assessed the effect of heat waves on UC risk based on the two criteria separately. We set the maximum duration of heat waves to 10 days during the study period (Methods). As shown in Fig. 6, for domestic crime, the effects of heat waves are not significant for UC (the upper and lower bounds of the 95 % CI of the curve cross 0 value). As shown in Fig. 7, for non-domestic crime, the effect of heat waves above the threshold of 97.5th percentile temperature is not significant for UC, and the effect of heat waves above the threshold of 99th percentile temperature is not significant for UC except for a duration of 4.5–5.5 days, and reached the maximum value on day 5.

4. Discussion

Global temperatures are rising at an unprecedented rate, and extreme weather is occurring with greater frequency simultaneously (Evan and Eisenman, 2021; Romanello et al., 2021). The impact of abnormal temperature on human well-being and health is reflected in various aspects, ranging from a variety of negative health outcomes to public health events, of which the effects of high temperature and heat wave events is more significant (Romanello et al., 2021; Singh et al., 2021; Wei et al., 2021). Existing studies have confirmed that ambient temperatures play an important role in influencing the crime risk (Harp and Karnauskas, 2020; Stevens et al., 2019), and the attributable risk of different temperature ranges and the impact of heat waves on various health effects cannot be ignored (Ingole et al., 2022; Wei et al., 2021), which is less clear in terms of crime risk. In this study, we involved a large sample of urban crime data of Chicago over a long time scale and correlated it with daily average temperatures. We revealed the regularities and patterns of the association between UC risk and temperature, which can be explained by several potential mechanisms.

High temperatures have been found to affect crime directly or indirectly by altering daily activities and behavior (Berman et al., 2020; Cohen and Felson, 1979; Hipp et al., 2004). Ambient temperatures change the patterns of alcohol consumption, induce the emotional instability of offenders, and increase the risk of potential victimization (Cohen and Felson, 1979; Gates et al., 2019). Unusually high temperatures can trigger irritation and discomfort, which increase the aggressive behavior and performance of individual. As the heat stress and irritation increase, the individual's level

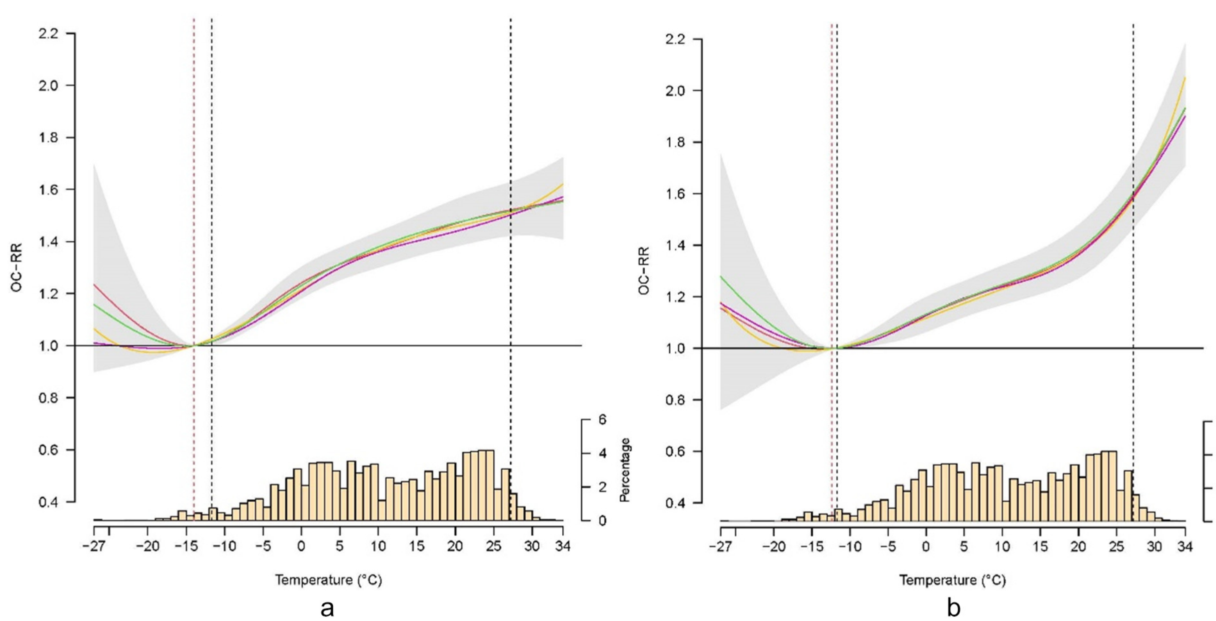

Fig. 2. The exposure-response curve for temperature and UC risk with lag days of 28 in Chicago. **a**, Domestic crime. **b**, Non-domestic crime. The colors of the curves represent the different types of fitting functions used, including polynomial (yellow), B-spline (green), and natural cubic spline with 5 knots (red) and 4 knots (violet). The gray area indicates the range of the 95 % confidence interval for the red line. The histogram above the abscissa shows the frequency percentage of daily mean temperature. The dashed red lines indicate the reference temperature (−14.2 °C and −12.3 °C), and the 2.5th and 97.5th percentile temperatures are indicated by the gray dashed lines.

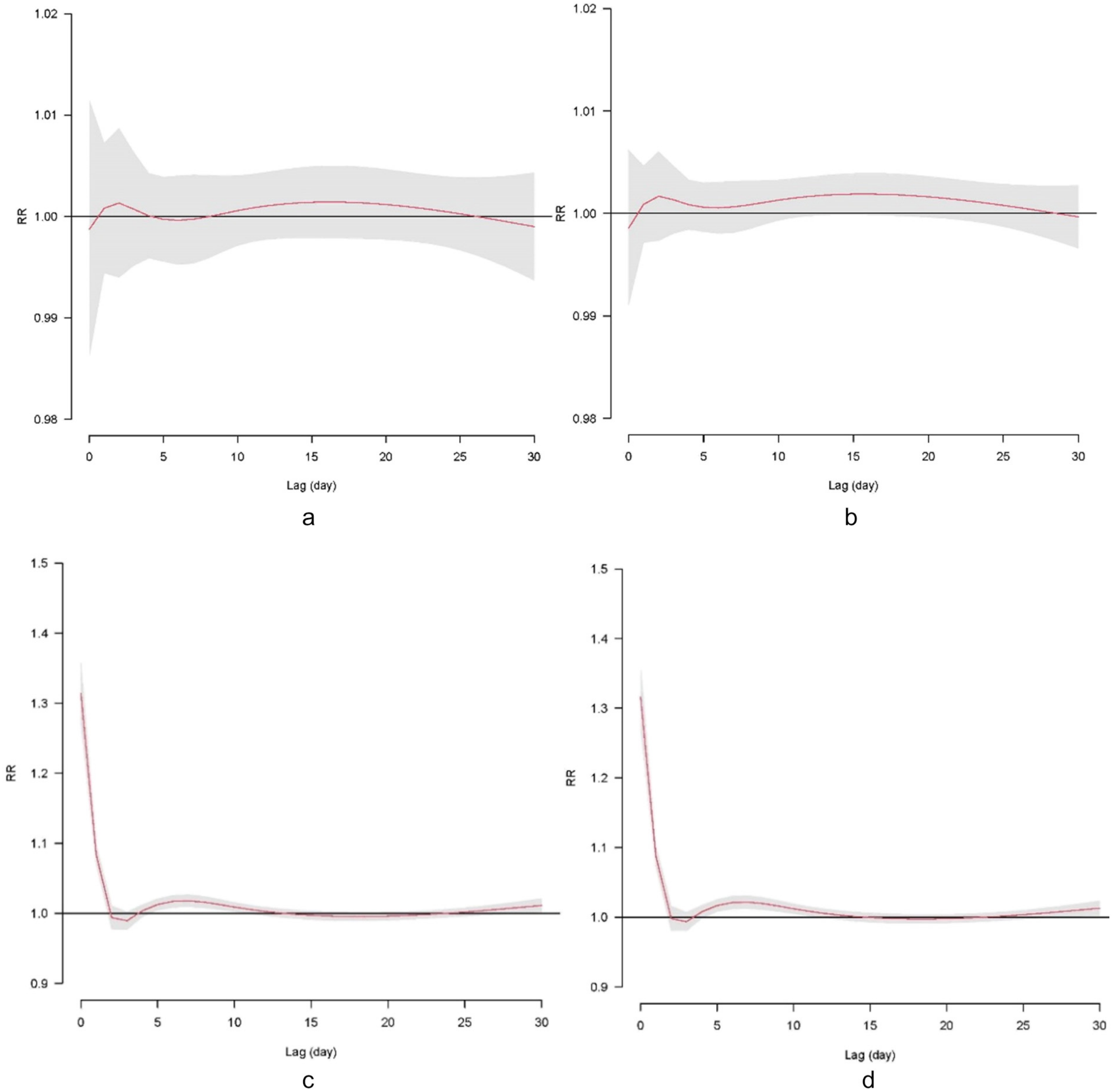

Fig. 3. The lag effects of 1th, 2.5th, 97.5th and 99th percentile temperature on UC risk in Chicago for domestic crime. The gray area indicates the 95 % CI of the curve. **a**, 1th (−15.0 °C) percentile. **b**, 2.5th (−11.7 °C) percentile. **c**, 97.5th (27.5 °C) percentile. **d**, 99th (28.9 °C) percentile.

of discomfort increases, facilitating the aggression, which leads to more crimes (Hu et al., 2017). High ambient temperature affects the psychology stability of the individual and enhances the negative emotions, which promotes the increase of aggressive behavior (Bell and Baron, 1977). High temperatures increase the anger and hostility psychologically, decrease the alertness and energy, and increase the aggression and violence (Anderson, 2000). The psychological aggression of individual can also be largely influenced by excessive heat and discomfort in the surrounding area, and increasing stress patterns and discomfort eventually lead to increased risk of crime (Salleh et al., 2012). The individuals who experience more physiological heat stress have more aggressive personal interactions than those who do not experience heat stress, such that are more prone to violent responses (Harp and Karnauskas, 2020). Heat escalates the situation by making people feel more aggressive than expected in certain behaviors (Kenrick and MacFarlane, 1986). In addition, aggression increases with the elevation of individual hostility and physical arousal caused by high temperatures. Individuals exposed to high temperatures may alter life strategies, neglect focus on the future, and reduced self-control, which together increase aggression and violent behavior (Younan et al., 2018). Elevated temperature modulates serotonin transmission and is partially mediated by the serotonin system, which promotes impulsivity and the intensity of outdoor activities, thereby increasing the risk of social interaction and violent events (Tiihonen et al., 2017). These physical reactions take a certain amount of time, which means that the changes and responses in the individual physiology to the variations in temperature on the day of exposure tend to emerge in the following days, resulting in the lag effect of temperature. Previous studies have also shown that high temperatures increase the use of air conditioning and encourage the individuals to stay indoors more often, which make people reluctant to go outside (Zander et al., 2021). The results of our study confirmed that a part of UC occurs in domestic crime, and high temperatures are prompting these individuals to reduce outdoor activities and increase the time spent indoors, which is for the families with certain financial affordable ability. However, the vast majority of UC occurs outdoors, and this part of individuals cannot achieve effective cooling due to their own economic constraints, which increases the possibility of outdoor heat exposure and potential risk of UC.

We set the meteorological variables of wind speed, precipitation and relative humidity as the confounding factors in the model, which is considered

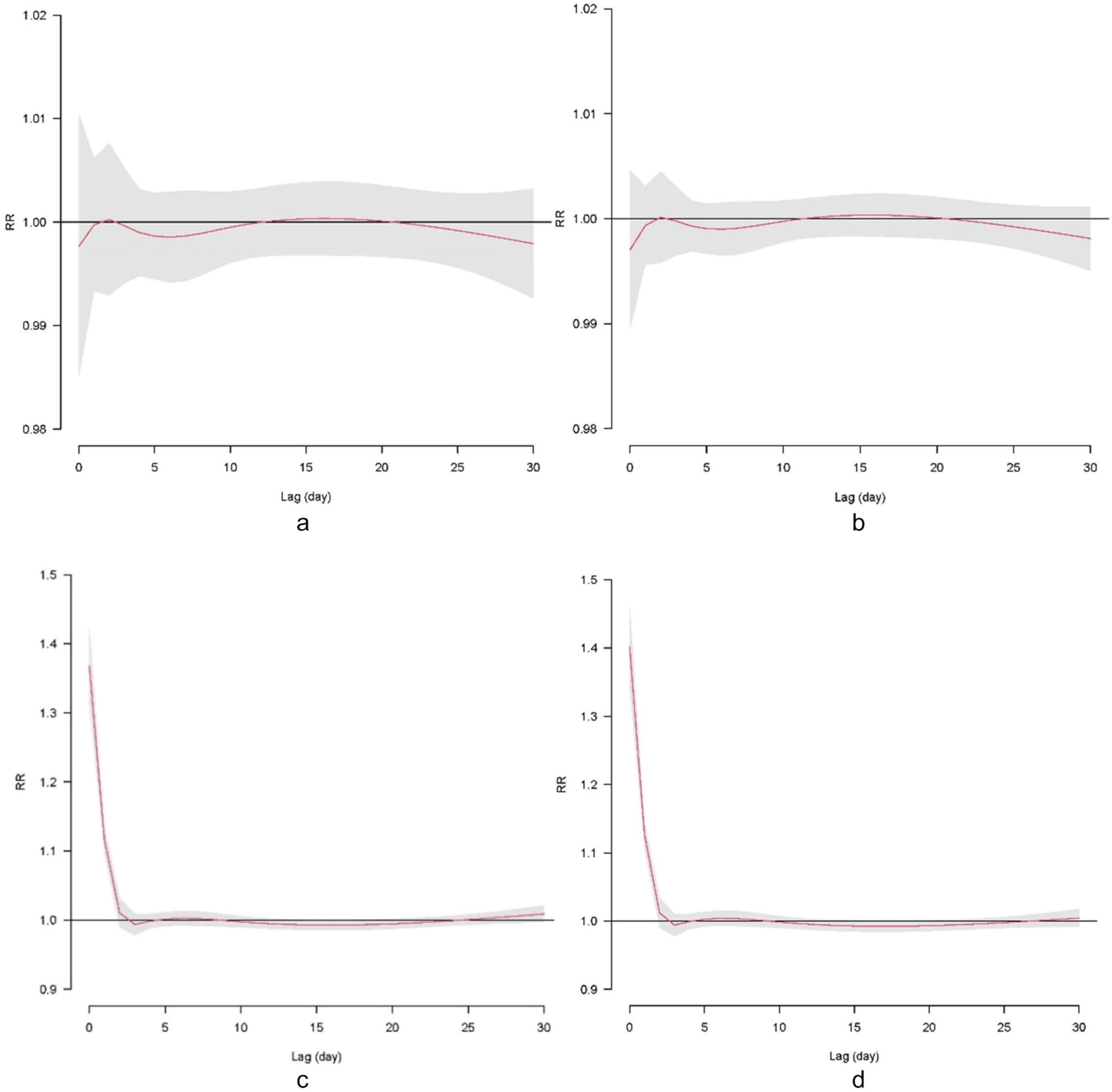

Fig. 4. The lag effects of 1th, 2.5th, 97.5th and 99th percentile temperature on UC risk in Chicago for non-domestic crime. The gray area indicates the 95 % CI of the curve. **a**, 1th (−15.0 °C) percentile. **b**, 2.5th (−11.7 °C) percentile. **c**, 97.5th (27.5 °C) percentile. **d**, 99th (28.9 °C) percentile.

to be an effective method to control for and reduce the influence of interference factors in areas with high wind speed, precipitation and relative humidity (Potgieter et al., 2022; Tiihonen et al., 2017).

There is a wide range of temperature variations in Chicago, which account for the relatively large change of exposure-response curve for temperature and UC risk. The cold and hot temperatures were found to have different impacts on the risk of urban crime, of which the positive (negative) effect of high (low) temperature is confirmed for UC. This is caused by the fact that high temperature enhances the social interaction of individual outdoor activities and promotes the behavior of individual psychological and physiological aggression (Harp and Karnauskas, 2020; Stevens et al., 2019). High temperatures were found to have a lag effect on UC with a lag of 2 days, which was consistent with other reports of a delayed facilitation effect of excessive extra heat on violent crime (Potgieter et al., 2022).

Heat waves with a duration of 4.5–5.5 days above the 99th percentile threshold was only found to be significant for UC risk, as mortality and violence were more susceptible to be affected by higher temperatures (Gasparrini and Armstrong, 2011; Sanz-Barbero et al., 2018). This study shows that moderate hot contributes a greater attributable risk for UC compared to extreme hot, which is due to the characteristic of temperature variations of Chicago that moderate hot temperatures occur much more frequently than extreme hot (Chen et al., 2018; Gasparrini et al., 2015). For specific neighborhoods and blocks in Chicago under high temperature conditions, safety guidelines for individual behavior and psychological counseling are recommended to minimize the adverse effects of high temperature on UC.

Our study included the UC sample with a large amount of data over a long time span of 11 years and various confounding factors involving $PM_{2.5}$, relative humidity, precipitation, wind speed, and other possible factors, which were representative of the research objects and had advantages compared with the small samples and less confounding factors considered in previous studies (Gates et al., 2019; Schinasi and Hamra, 2017; Tiihonen et al., 2017). A series of sophisticated DLNM-based extended models were used to describe the association between UC and temperature in the study. We identified and quantified the adverse effect of high temperature on UC risk. We quantitatively estimated the attributable risk associated with high temperature and the heat wave effect for UC risk. The combination

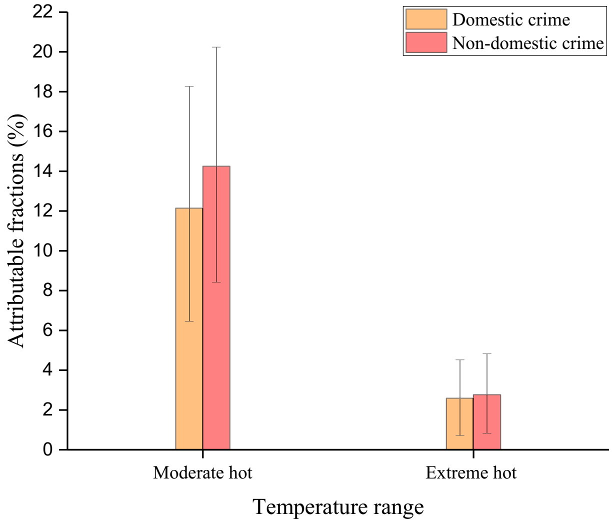

Fig. 5. Fractions of UC caused by various high temperature ranges for domestic crime and non-domestic crime.

of different confounding factors and the variation of the maximum lag length were conducted in the sensitivity analysis, where we could see the robustness of the results.

There were limitations in this study. Urban crime and the factors governing the variation of criminal behavior are complicated, and relate to the factors other than environmental variables. More than 70 % of heat waves typically have a continuous duration of less than a few days of three, adding to the indeterminacy in assessing the risk of prolonged heat waves for UC, which is consistent with the results of previous studies on heat waves and mortality (Gasparrini and Armstrong, 2011). We used three interpolation methods to interpolate the missing data for meteorological variable and air pollutant, which may lead to slight deviation of the evaluation results. More precise and accurate observational data will address this. Meteorological variables involving precipitation, relative humidity, wind speed, PM2.5 of air pollutant, and other confounding factors were controlled for in the model simultaneously. However, it has to be admitted that some of the interfering factors at the individual level relate to sex, acclimatization, attitude and health, which cannot be accurately obtained and quantified for variable control due to the limitations of monitoring conditions and the complexity of the environment. This is why we covered and included the UC sample as large as possible, aiming to reflect the impact of our primary variables of interest on UC outcomes through a

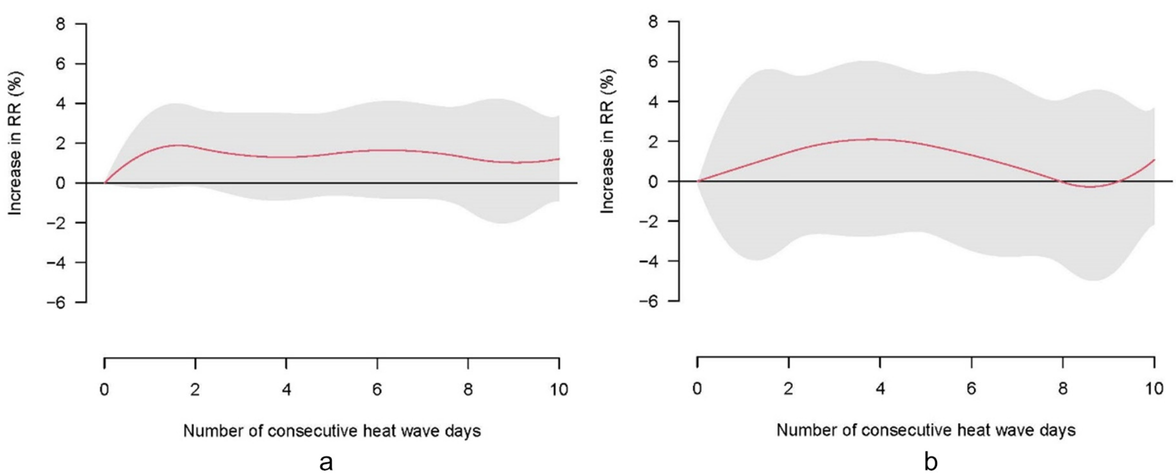

Fig. 6. Increase in the RR of heat waves to UC risk based on different high temperature thresholds for domestic crime. **a**, 97.5th (27.5 °C) percentile temperature. **b**, 99th (28.9 °C) percentile temperature.

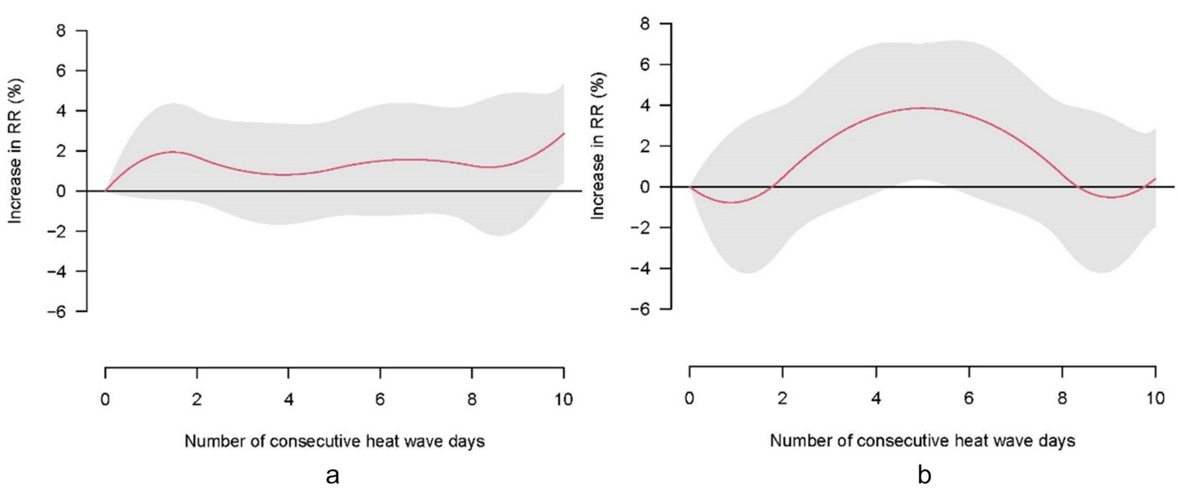

Fig. 7. Increase in the RR of heat waves to UC risk based on different high temperature thresholds for non-domestic crime. **a**, 97.5th (27.5 °C) percentile temperature. **b**, 99th (28.9 °C) percentile temperature.

large sample of data, which has been commonly used in many previous studies evaluating temperature and health risks (Elser et al., 2022; Liu et al., 2019; Wei et al., 2021). Therefore, the results of our study are of certain significance for temperature and urban crime risk assessment in light of the existing experimental conditions. We included this large sample and various confounding factors, combined with appropriate statistical methods, to accurately characterize and identify the impact of variables of interest on the UC outcomes, which was confirmed to be reliable in environmental statistics involving distributed lag nonlinear models used in the study (Elser et al., 2022; Gasparrini et al., 2010; O'Loughlin et al., 2014).

Urban crime is a serious social security issue, life threat, and considerable property loss to the individuals and communities. The adverse impact of high ambient temperature on UC cannot be underestimated. Individuals with potentially aggressive psychology and behavioral performance are recommends to avoid exposure to high temperatures whenever possible. Effective administrative measures for both victims and perpetrators of UC need to be taken and implemented in terms of the rapid climate change and frequent extreme weather phenomena. Also, our study contributes to a complete and full presentation of the relationship between urban crime outcomes and ambient temperature.

5. Conclusion

The findings of the research suggest that high temperatures have a significant positive effect on the risk of urban crime, and the effects of low temperatures are not significant for urban crime risk in Chicago. Heat waves with temperatures above the 99th percentile were found to be significant for urban crime risk. Our study provides an insight and a typical representation of how to evaluate the impact of temperature on urban crime risk under high temperature conditions, and is a significant reference for other cities and regions in terms of the assessment of impact for external environmental temperature on crime risk. At the same time, effective individual-specific practical action guidelines and necessary administrative interventions are recommended and required in specific areas of high temperature environment of the city.

CRediT authorship contribution statement

Kun Hou contributed to the conception of the study, performed the experiment and the data analyses, and wrote the manuscript. Liqiang Zhang and Xia Xu contributed significantly to analysis and manuscript preparation. Xia Xu performed the data analyses and figures. Xia Xu, Feng Yang, Baozhang Chen, Wei Hu, and Rui Shu helped perform the analysis with constructive discussions.

Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no conflict of interest and have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research was funded by The Startup Foundation for Introducing Talent of NUIST (Grant No. 2022r041).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2022.158846.

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